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Corporate governance in central state-owned enterprises: two decades of institutional evolution and research evidence

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ABSTRACT

Central state-owned enterprises (CSOEs)—a dominant force in China's national economy—must balance government authority with market mechanisms, while reconciling national interests with firm-level performance. Meanwhile, to ensure competitiveness and efficiency in the market while fulfilling state mandates, it is essential to establish effective incentive mechanisms that motivate managerial effort. Consequently, corporate governance in CSOEs is critical. This paper systematically reviews the institutional evolution and reform practices of CSOEs since the 2003 establishment of the State-owned Assets Supervision and Administration Commission. The analysis focuses on five key dimensions: mergers and acquisitions, board reform, performance evaluation, executive incentives, and auditing and internal control. By synthesizing the literature, this study highlights the theoretical underpinnings of China's distinctive SOE governance model while providing valuable insights for enterprise reform in other transition economies.

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1. Introduction

Central state-owned enterprises (CSOEs) constitute a backbone of China's economic development, playing a vital role in stabilizing growth, ensuring employment and promoting industrial upgrading. China's state-owned enterprise (SOE) system comprises two main components: CSOEs and local SOEs. CSOEs are directly supervised by central government authorities—primarily the State-owned Assets Supervision and Administra-

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tion Commission (SASAC) or the Ministry of Finance (MoF)—which exercise ownership rights on behalf of the state. In contrast, local SOEs are managed by provincial and lower-level governments through local SASACs or fiscal authorities, forming a hierarchical governance structure with clearly differentiated responsibilities. As the core entities of China's state-owned economy, CSOEs possess both strategic importance and distinctive institutional features, making them particularly valuable for theoretical inquiry. According to the 2024 Fortune Global 500, China accounts for 133 firms on the list, of which 44 are CSOEs supervised by SASAC, representing 33.1%. As of October 2024, SASAC oversaw 98 CSOEs, with combined assets exceeding RMB 90 trillion and total profits reaching RMB 2.6 trillion, accounting for 59.8% of total profits generated by all SOEs nationwide.¹ From an institutional perspective, CSOEs exhibit a distinctive dual character: they operate as market entities pursuing economic efficiency while simultaneously fulfilling national strategic objectives. This duality is particularly evident in large-scale initiatives such as the Belt and Road Initiative, where CSOEs account for more than 60% of project participation and nearly 80% of total contract value.² Such an institutional arrangement differs not only from the market-oriented operations of Western multinational corporations but also from the governance patterns of China's local SOEs, thereby providing a unique empirical setting for advancing theories of the firm. This study focuses on CSOEs precisely because of their unique position within China's economic governance system and their potential to extend existing theoretical frameworks. However, mainstream Western economic theories often approach this distinctive institutional arrangement through specific prior assumptions and evaluative lenses (Fig. 1).

In the literature, SOEs, including CSOEs, are often portrayed as entities that “command substantial resources yet exhibit low efficiency” (Megginson et al., 1994; Shleifer and Vishny, 1994; La Porta et al., 2002; Harrison et al., 2019). However, SOEs are not unique to China; they have long existed in Western economies. The theoretical rationale for state ownership in these economies is primarily rooted in Keynesian economics, which justifies government intervention in the presence of market failures. Accordingly, SOEs in Western countries have traditionally been concentrated in sectors where private investment is insufficient or absent, such as public goods provision, national security and other strategic or underdeveloped industries. In the aftermath of the Great Depression, market failure further reinforced the role of state ownership, and SOEs became important instruments for stabilizing macroeconomic fluctuations. Prior to the wave of neoliberal reforms, SOEs accounted for approximately 10% of GDP in the United Kingdom,³ 35.6% of total corporate R&D expenditure in Italy,⁴ and more than 90% of energy production, 75% of the insurance and banking sectors and 35% of industrial output in France. However, from the 1970s through the global financial crisis in the early 21st century, many capitalist economies—particularly the United Kingdom and the United States—shifted toward neoliberalism in response to stagflation. This shift advocated a more limited role for the state, confined primarily to macroeconomic regulation and the establishment of market rules, and triggered large-scale privatization of SOEs. In many developing countries, privatization was even imposed as a condition for financial assistance from the World Bank and other international institutions. These divergent historical trajectories highlight fundamental differences between Western and Chinese approaches to the role and evolution of SOEs, reflecting deeper divergences in underlying theoretical paradigms.

However, prevailing neoliberal frameworks in Western scholarship offer limited explanatory power for both the existence of China's CSOEs and their role in economic growth. Within this framework, the key distinction between CSOEs and private firms lies in state ownership, which gives rise to severe problems of ill-defined property rights. Given that transactions are inherently costly, differences in property rights arrangements can lead to variations in transaction costs and resource allocation efficiency; accordingly, the choice of property rights institutions becomes central to optimizing resource allocation (Coase, 1960). In practice, state ownership of CSOE resources often leads to ambiguity and opacity in allocation authority, making inter-

¹ https://zcgls.mof.gov.cn/qiyeyunxingdongtai/202501/t20250122_3954821.htm; <https://www.sasac.gov.cn/n4470048/n32559362/n32591461/n32591506/c32643415/content.html>.

² <https://baijiahao.baidu.com/s?id=1631755122790526604&wfr=spider&for=pc>.

³ “Privatising the UK's nationalised industries in the 1980s.” <https://www.centreforpublicimpact.org/case-study/privatisation-uk-companies-1970s/>.

⁴ “State-owned enterprises: reflections on the Italian experience.” <https://medium.com/iipp-blog/state-owned-enterprises-reflections-on-the-italian-experience-a170fbf0a1dd>.

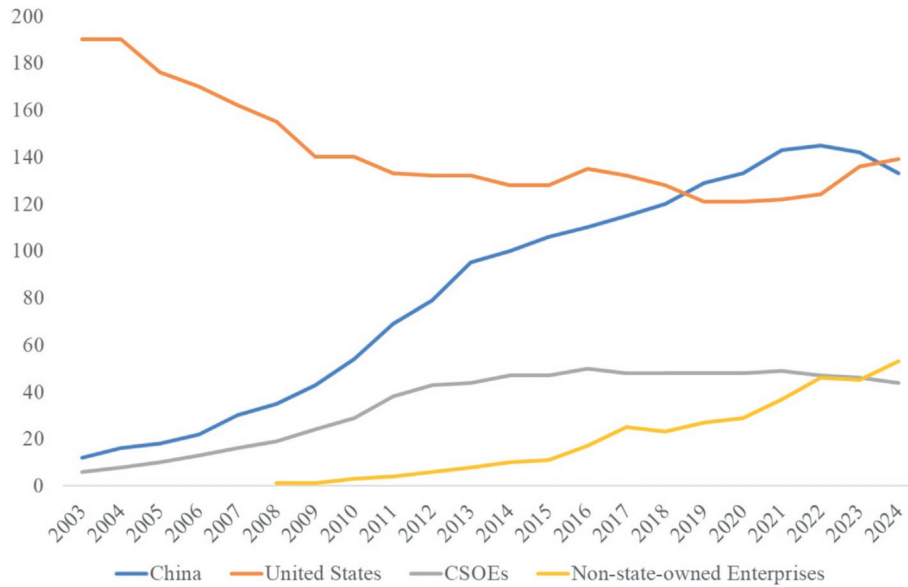


Fig. 1. China vs. U.S. firms in the *Fortune Global 500*, 2003–2024.

nal resource allocation more complex and increasing transaction costs. Moreover, decision-making in CSOEs typically requires approval from government authorities, resulting in delays and reduced responsiveness. These factors jointly constrain the flexibility and efficiency of CSOEs (Shirley, 1999). In addition, CSOEs often operate in markets with limited competition, weakening incentives to reduce costs or improve productivity and potentially leading to resource misallocation. As the government is typically the sole or dominant owner, its objectives may not align with firm-level performance, resulting in insufficient incentives for managers and employees to pursue efficiency (Shleifer and Vishny, 1994; La Porta et al., 2002). Finally, CSOEs are often tasked with fulfilling social responsibilities in addition to economic objectives. Such mandates may impose constraints that adversely affect economic performance, thereby reducing overall efficiency. To address these challenges, China has undertaken a systematic program of governance reforms for CSOEs.

Prior to the establishment of SASAC in 2003, CSOEs were administered in a highly fragmented manner by various industrial ministries, resulting in a governance structure often described as “fragmented oversight”.⁵ This administrative model gave rise to two major challenges: on the one hand, the 196 CSOEs at the time experienced severe duplication of investment and excessive competition; on the other hand, the lack of separation between government and enterprises led to low production efficiency. Institutional transformation began with the creation of SASAC in 2003, which restructured the governance system along three key dimensions. First, a unified state ownership framework was established through the promulgation of the Interim Regulations on the Supervision and Administration of State-owned Assets of Enterprises, addressing the problem of ill-defined ownership responsibility. Second, structural reforms centered on the separation of core and non-core businesses and on mergers and consolidation were implemented, reducing the number of CSOEs to 98 by 2024. These enterprises collectively control 434 listed companies at home and abroad, including 376 A-share listed firms. Third, a market-oriented operating mechanism guided by Economic Value Added (EVA) performance evaluation was introduced. These institutional changes have generated substantial outcomes. Between 2003 and 2024, the total assets of CSOEs increased from RMB 8.3 trillion to over RMB 90 trillion, while total profits rose from RMB 0.3 trillion to RMB 2.6 trillion. This evolutionary process not only reflects the distinctive trajectory of China’s SOE reform but also reveals the structural impact of institutional innovation on firm performance. More broadly, the reform path of CSOEs has been shaped by the interaction of dual institutional logics within the Chinese context (Tables 1 and 2).

⁵ <https://www.sasac.gov.cn/n2588025/n2588139/c27647167/content.html>.

Table 1
Number of CSOEs Supervised by SASAC, 2003–2024 (as of October 2024).

Year	Number	Year	Number
2003	196	2014	113
2004	179	2015	106
2005	166	2016	102
2006	150	2017	96
2007	152	2018	96
2008	145	2019	96
2009	132	2020	96
2010	121	2021	96
2011	118	2022	98
2012	113	2023	98
2013	114	2024	98

Table 2
Geographic Distribution of CSOE Headquarters (as of October 2024).

City	Number	City	Number
Beijing	70	Ganzhou	1
Shanghai	6	Harbin	1
Shenzhen	3	Qiqihar	1
Wuhan	3	Changchun	1
Hong Kong	3	Dalian	1
Xiong'an	3	Anshan	1
Guangzhou	2	Macau	1
Chengdu	1		

The governance transformation of CSOEs fundamentally reflects the deep tension between political and market logics in the development of China's socialist market economy. This institutional tension provides a key analytical lens for understanding China's distinctive model of the modern enterprise system. The agency problems of CSOEs arise from the combined effects of conflicting dual objectives—namely their political and market-oriented mandates—control inefficiencies inherent in large-scale organizational structures and the tension between administrative governance and market-based operations (Mao et al., 2022). This feature sharply distinguishes CSOEs from local SOEs, which are more commonly characterized by resource misallocation driven by local government intervention or the formation of localized interest groups. From the perspective of new institutionalism, CSOEs face a distinctive form of dual institutional pressure: they are required to conform to global, market-oriented paradigms of corporate governance while simultaneously responding to the legitimacy demands of the political system. This tension gives rise to a dual distortion in principal–agent relationships along both political and market dimensions. The implications of this institutional tension extend well beyond the firm level. More fundamentally, the tension reflects a deeper reconfiguration of the relationship between the state and the market, while also providing a distinctive empirical setting and theoretical space for advancing China's modern enterprise system. To address these challenges, CSOEs must establish clear organizational objectives that reconcile national interests with economic efficiency. At the same time, the government must balance multiple stakeholder interests when defining such objectives, ensuring that CSOEs can both fulfill state mandates and remain competitive in the market. In response to these challenges, China has initiated a systematic process of governance system development for CSOEs under the leadership of SASAC.

Since the establishment of SASAC in 2003, the Chinese government has systematically advanced governance reforms of CSOEs, seeking to address their distinctive agency problems through institutional innovation and policy guidance. In terms of governance structure, reforms have promoted the establishment of standardized board systems in CSOEs. With respect to incentive mechanisms, the *Measures for the Performance Evaluation of Heads of Central Enterprises* serve as the core framework, with increased emphasis on EVA. These are complemented by tenure-based incentives, as well as market-oriented instruments such as

excess profit-sharing schemes and equity incentives for technology-oriented enterprises. In terms of supervisory mechanisms, a coordinated system has been developed through strengthened internal controls, the regular rotation of external auditors and selective inspections by national audit authorities. To address the high leverage accumulated by CSOEs—partly due to their institutional advantages in accessing credit resources (Fang, 2007)—as well as the associated risks of excessive indebtedness (Lu et al., 2015), reforms have also targeted the underlying mechanisms through which soft budget constraints in the banking system contribute to rising leverage (Jiang and Lu, 2018). Measures such as mixed-ownership reform have facilitated structural deleveraging among highly leveraged firms (Wang et al., 2022), contributing to meaningful progress in mitigating systemic financial risks (Ferrarini and Hinojales, 2018). However, the observation that the asset-liability ratio reached a cyclical low in 2020 without a corresponding peak in performance points to deeper institutional constraints. For example, infrastructure-related CSOEs experienced declining profit margins during the COVID-19 pandemic due to policy mandates to maintain supply without raising prices, illustrating the “double-edged sword” effect of political connections identified by Borisova et al. (2015), whereby institutional advantages may translate into financial burdens when fulfilling public responsibilities. As governance reforms continue to deepen, the effectiveness of structural deleveraging increasingly depends on parallel advancements in the broader governance framework (Wang et al., 2022) (Fig. 2).

A systematic review of the literature suggests that the economic consequences of governance reforms in CSOEs are inherently multidimensional. With respect to board development, studies show that pilot reforms—through the introduction of external directors and the establishment of specialized committees—have significantly improved governance structures (Li et al., 2017; Gao et al., 2021; Mao et al., 2022). However, other studies indicate that the effectiveness of board monitoring remains constrained by institutional factors (Brown et al., 2019), as evidenced by the persistence of earnings management behavior in CSOEs following these reforms (Huang et al., 2020). Regarding incentive mechanisms, the literature confirms that improvements in performance evaluation systems have played a crucial role (Tang and Dai, 2015). In particular, combining compensation-based incentives with promotion-based incentives (Yang et al., 2013) has been shown to mitigate managerial short-termism (Yu et al., 2016). Nevertheless, evidence also suggests that strict compensation regulation alone may generate unintended adverse effects (Xu and Liu, 2013; Liu and Tai, 2020), underscoring the importance of establishing medium- and long-term incentive mechanisms (Liu and Xiao, 2015; Cao et al., 2019; Wang and Liu, 2020; Su and Alexiou, 2022). In terms of supervisory mechanisms, research shows that national auditing—particularly through the public disclosure of audit results—generates significant market reactions (Li and Wu, 2013) and enhances corporate governance efficiency (Cai and Ma, 2014). Notably, there exists a strong interaction between national audits and external audits, whereby the former exerts a disciplinary and signaling effect on the latter (Li and Ma, 2017). Taken together, these findings

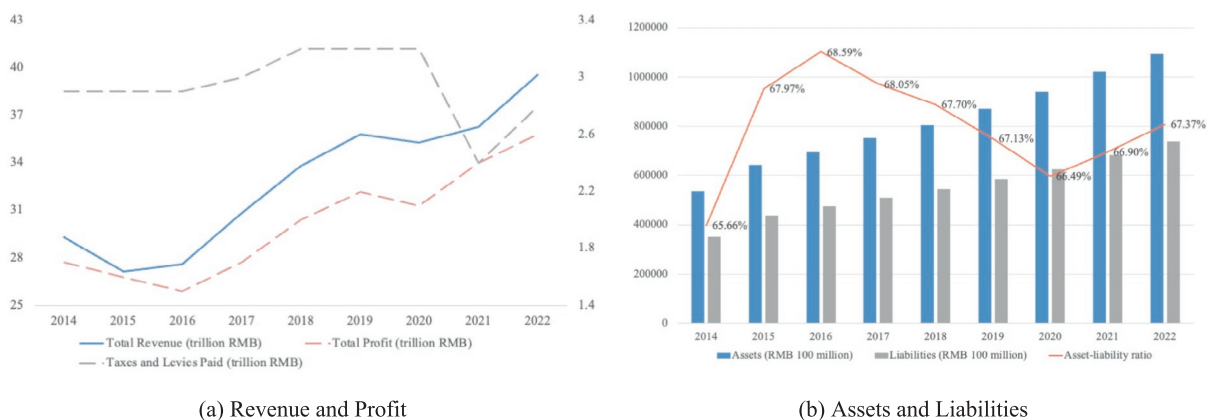


Fig. 2. Operating performance of CSOEs, 2014–2022 (Data sources: The websites of SASAC and the MoF. Financial SOEs are excluded from these data, and the same applies hereafter. Since 2019, SASAC's reports no longer disclose asset data of CSOEs. This study supplements the missing data based on the *Comprehensive Report on the Management of State-owned Assets* issued by the MoF: http://www.mof.gov.cn/zhengwuxinxi/caizhengxinwen/202110/t20211027_3761041.htm).

highlight both the complexity and the multidimensional nature of China's governance model, while also providing important insights for further deepening CSOE reforms.

The contributions of this study are threefold. First, by integrating empirical evidence across five key dimensions—mergers and acquisitions, board reform, performance evaluation, executive incentives, and auditing and internal control—this study develops a governance framework for CSOEs grounded in the dual logic of government and market. This framework extends conventional corporate governance models largely rooted in Western contexts (Jiang and Kim, 2020) and uncovers the underlying mechanisms of governance innovation in China. In particular, the dynamic weighting of EVA in performance evaluation establishes an institutionalized channel through which policy objectives are translated into market performance. These findings provide a new theoretical perspective on institutional adaptation in SOE reforms in emerging economies. Second, consistent with the macro-level insights of Chen and Rithmire (2020), this study documents a transformation of the state from a direct operator to a strategic investor. This transformation is manifested in several micro-level institutional changes: an increased proportion of external directors in board governance, which creates an institutional check on administrative intervention; a shift in executive incentive systems from administrative promotion tournaments to hybrid incentive schemes, making investor-oriented performance considerations more explicit; and a growing market orientation in mergers and acquisitions. Taken together, these micro-level institutional evolutions constitute the underlying foundation for the transition from state capitalism to an “investor state.” Third, this study systematically conceptualizes the innovation of China's supervisory regime by highlighting the integrated framework of intra-party supervision, national auditing and external auditing, thereby advancing a new paradigm for the governance of SOEs. The theoretical contribution of this institutional design lies in moving beyond the traditional dichotomy between internal and external governance in corporate governance theory and embedding political supervision within the modern enterprise system. Specifically, intra-party supervision ensures that major corporate decisions align with national strategic objectives through institutionalized compliance mechanisms; national auditing, supported by statutory independence and enforcement authority, verifies the accuracy of financial information and imposes sanctions for violations; and external auditing enhances transparency through market-based disciplinary mechanisms. This institutional innovation offers a novel approach to SOE governance globally: by integrating political governance with corporate governance, it becomes possible to maintain strategic state control while simultaneously improving firm-level efficiency. Overall, these findings not only deepen the theoretical understanding of China's socialist market economy but also contribute new insights to the broader development of global corporate governance systems.

To facilitate a systematic presentation of the analysis, the remainder of this paper is organized as follows. Section 2 examines mergers and acquisitions, highlighting the structural reforms that optimize resource allocation at the macro-level. Section 3 focuses on board reform pilots, analyzing the logic of decision-making structures and the associated system of checks and balances. Sections 4 and 5 investigate performance evaluation and executive incentives, respectively, which together constitute an incentive–constraint framework for mitigating principal–agent problems. Section 6 discusses auditing and internal control as supervisory mechanisms that ensure the stable functioning of the governance system. The paper's internal logic progresses from core to periphery and from top-level design to concrete implementation (Fig. 3), with the aim of providing a comprehensive understanding of the evolution and institutional logic of CSOE governance.

2. Mergers and acquisitions of CSOEs

2.1. Evolution in the number of CSOEs

At the time of the establishment of SASAC in 2003, a total of 196 CSOEs were under its supervision. With their large number, these enterprises exhibited excessively broad industrial coverage, dispersed resource allocation and a lack of focus on core businesses, resulting in weak core competitiveness. These features can be understood as manifestations of failures in principal–agent relationships. First, CSOEs were involved in an excessively wide range of industries. As key pillars of China's economy, they were widely distributed across sectors, leading to fragmented resource allocation. Among the 95 major industry categories in the national economy, central enterprises at or above the third tier were involved in 86 sectors. Such over-diversification

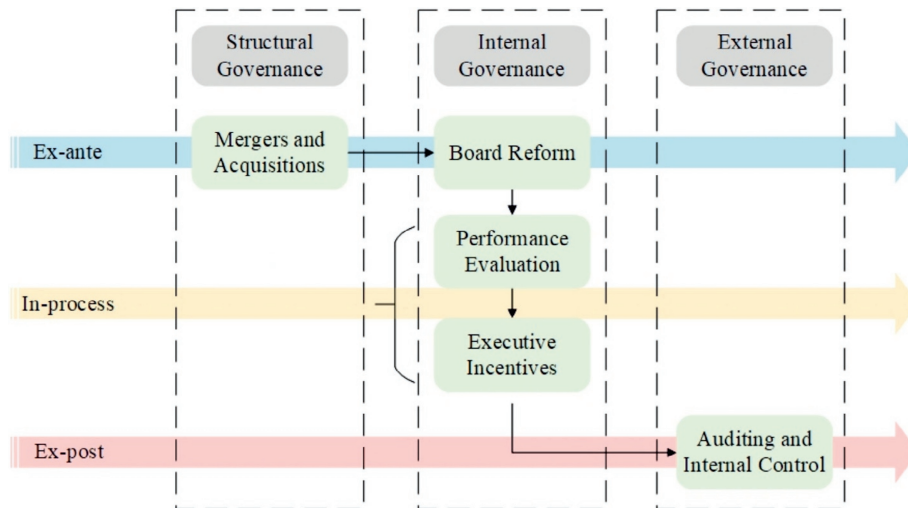


Fig. 3. Analytical framework of the study.

not only crowded out the development space of private enterprises but also led to insufficient investment in sectors critical to national welfare and strategic priorities (Zheng and Meng, 2011; Liu et al., 2020). This pattern fundamentally reflects managerial opportunism: by expanding business scope, managers increase private control benefits, thereby weakening the strategic function of state capital. Second, the strategic orientation of CSOEs was often unclear. In principle, CSOEs should concentrate on areas such as strategic security, industrial leadership, public welfare and essential services. In practice, however, many exhibited “large and all-encompassing” structures. Some enterprises established hundreds of legal entities with overlapping business scopes, leading to severe internal competition and duplication. This not only amplified operational risks but also undermined core competitiveness (Liu et al., 2020). The multi-layered corporate structures within these enterprises resembled fragmented “fiefdoms,” reflecting distortions in agency objectives, whereby subsidiary managers pursue localized interests at the expense of the strategic mandate of state capital. Third, managerial hierarchies were excessively redundant. During the early stages of reform, CSOEs adopted pyramidal organizational structures to transition from administrative governance toward more economically oriented governance. However, overly elongated hierarchies may grant managers disproportionate control and exacerbate the separation between ownership and control. As a result, both top-down information transmission and bottom-up decision-making processes become significantly less efficient (Lin et al., 2020). This corresponds to the classic agency problem of the separation between control rights and residual claims: pyramidal structures amplify information asymmetry, allowing lower-level agents to conceal moral hazard behind hierarchical barriers.

Since its establishment, SASAC has regarded the strategic restructuring of CSOEs as a key instrument for deepening SOE reform. These reforms aim to optimize the allocation of state capital, strengthen core business competitiveness and improve resource allocation efficiency. Over the past two decades, SASAC has systematically promoted three main restructuring modes. First, horizontal mergers among CSOEs within the same industry have been implemented to reduce homogeneous competition, as well as redundant investment and associated agency costs. Second, vertical integration has been pursued to enhance coordination along the value chain, internalize transaction costs and strengthen control over supply chains. Third, specialized consolidation has been carried out to address managerial control problems, realign residual claims with residual control rights and improve corporate governance structures.

Under these restructuring policies, the number of CSOEs has declined from 196 at the inception of SASAC to 98 in 2024. This consolidation has been accompanied by improvements in resource allocation efficiency and firm performance, with some restructured CSOEs emerging as global industry leaders. However, the academic literature presents divergent views on the effectiveness of these policies. Proponents emphasize the realization

of economies of scale and synergies, whereas critics argue that administratively driven mergers may suppress market competition and reduce efficiency. This debate reflects a deeper tension between market efficiency and administrative intervention in SOE reform (Fig. 4).

2.2. Economic consequences of CSOE mergers and acquisitions: a review of empirical evidence

In promoting the restructuring of CSOEs, SASAC has adopted a range of innovative approaches, including mergers among strong enterprises, acquisitions of weaker firms by more competitive CSOEs, the integration of research institutes into industrial groups and the divestiture of non-core assets to other CSOEs. These restructuring practices are intended to reduce excess capacity, alleviate debt burdens and enhance overall competitiveness, and have been shown to improve both efficiency and profitability (Zheng and Meng, 2011). Since the launch of the new phase of SOE reform in 2014, policy-coordinated restructuring among CSOEs has further contributed to sustained improvements in the performance of state capital, enhanced the efficiency of capital allocation and generated synergies with broader reform initiatives (Chu, 2022). In this sense, CSOE restructuring can be understood as a reconfiguration of relationships not only between the state and enterprises but also among enterprises themselves, thereby facilitating the optimization of asset and business structures and improving the allocation efficiency of state-owned resources (Li, 2001). Overall, the literature suggests that restructuring has strengthened the core competitiveness and functional capabilities of CSOEs, while also improving the quality of listed firms. Importantly, improvements in the performance of state capital are primarily driven by cost reduction and efficiency gains, rather than by the exercise of market power or monopolistic behavior (Chu, 2022).

However, some studies argue that large-scale mergers among CSOEs may increase market concentration and monopolistic tendencies, thereby generating organizational inefficiencies and dynamic inefficiencies in technological development, ultimately reducing resource allocation efficiency (Qi and Zhang, 2016). From this perspective, divestiture rather than consolidation is advocated, as breaking up CSOEs may enhance market competition, stimulate firm vitality and improve the quality of products and services. Moreover, in some cases, restructuring has been driven primarily by numerical consolidation, with a focus on reducing the number of

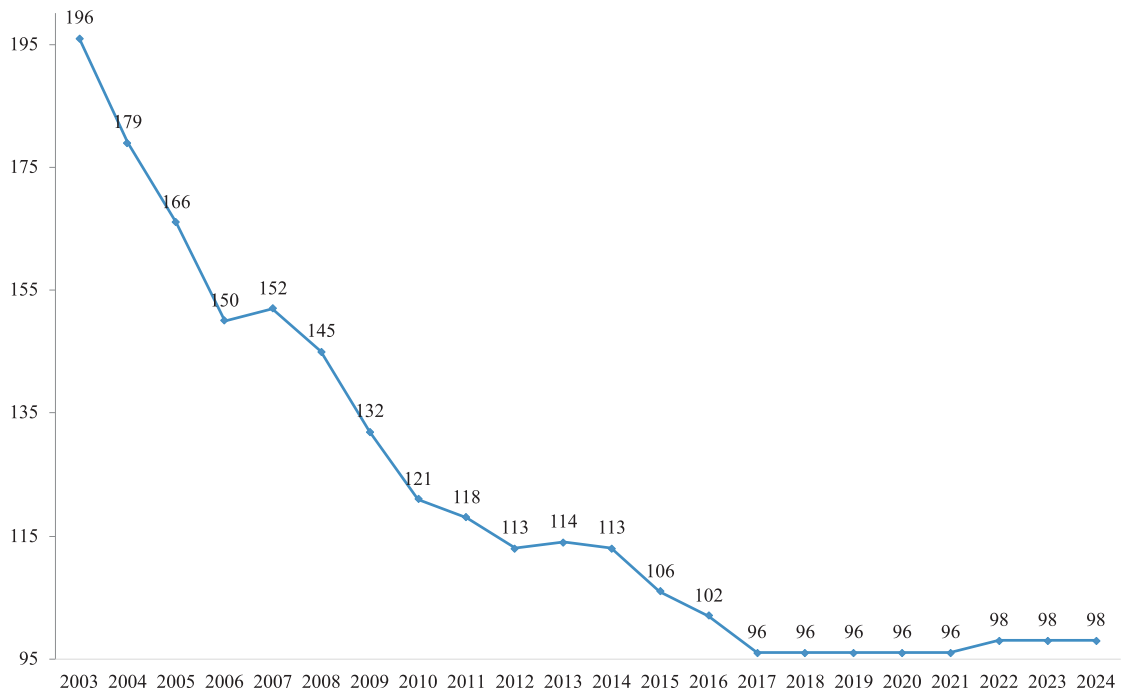


Fig. 4. Number of CSOEs supervised by SASAC, 2003–2024.

enterprises. Simply expanding firm size through mergers does not necessarily optimize industrial structure or enhance international competitiveness (Zheng and Meng, 2011). In particular, some CSOEs have pursued expansion beyond their financial capacity, engaging in mergers and acquisitions that increase interest burdens and cash flow pressures, while raising leverage ratios and undermining debt sustainability and financial stability, thereby weakening firms' financing capacity. The divergence in the existing findings largely reflects heterogeneity across industries, as differences in restructuring modes, intensity and scope lead to varied performance outcomes among CSOEs. In addition, the selection mechanisms for top executives—largely determined by government appointment systems—affect managerial quality, while incentive mechanisms and property rights arrangements further shape the extent to which managerial capabilities can be effectively realized (Li, 2001).

The restructuring and mergers of CSOEs, as a key institutional innovation for addressing the distinctive agency problems of SOEs, operate through multiple governance channels. First, at the level of property rights allocation, restructuring reconfigures multi-layered principal–agent relationships through a process of core business consolidation. The widespread presence of unrelated diversification in traditional CSOEs fundamentally reflects managerial agency problems, whereby managers pursue private benefits through the expansion of control. Strategic restructuring concentrates resource allocation authority within core business segments, thereby curbing opportunistic incentives for overexpansion. Second, at the level of supervisory mechanisms, specialized consolidation shortens and clarifies the principal–agent chain. By divesting non-core assets and compressing managerial hierarchies, restructuring reduces information distortion in transmission and enables the state, as principal, to more effectively monitor managerial behavior. In this sense, structural reorganization lowers agency costs through organizational simplification. However, administratively driven restructuring may also transform, rather than eliminate, agency problems. Mergers oriented toward scale expansion can generate bureaucratic agency costs, as managers allocate greater effort toward satisfying administrative evaluation targets rather than creating firm value. This phenomenon echoes the managerial ability hypothesis, suggesting that when restructuring is not complemented by market-oriented incentive mechanisms, managerial effort may become misaligned with organizational objectives. The key to future reform lies in complementing strategic restructuring with improvements in board authorization systems and the refinement of EVA-based performance evaluation, so that scale effects can be effectively translated into governance efficiency. Although studies present divergent views on the outcomes of restructuring, there is a broad consensus that only by combining structural reform with governance innovation can the agency problems of CSOEs be systematically addressed.

3. Board reform in CSOEs

3.1. *A review of the board reform pilot in CSOEs*

The board of directors constitutes a central mechanism in corporate governance, primarily responsible for monitoring top management. While some scholars argue that boards serve as mechanisms through which one group of managers controls another (Williamson, 1988), they are more commonly viewed as the ultimate internal monitoring body within the firm's contractual structure (Fama, 1980), and as an endogenous governance mechanism for mitigating internal agency problems (Fama and Jensen, 1983; Hermalin and Weisbach, 1998). In the context of CSOEs, the construction of an effective board is particularly critical. It directly addresses the coexistence of administrative intervention and insider control—two distinctive features of SOEs—by reshaping governance arrangements to facilitate the separation between government and enterprise. Empirical studies on boards of directors often face identification challenges, particularly reverse causality and sample selection bias. In this regard, the board reform pilot initiated by SASAC in 2004 substantially alleviates such endogeneity concerns, providing a quasi-experimental setting for examining the governance role of boards (Mao et al., 2022).

Prior to 2003, most CSOEs did not have formal boards of directors. This was largely because many large wholly state-owned companies were established under the 1988 Enterprise Law, which did not require a board structure. Even for wholly state-owned companies incorporated under the 1993 Company Law, there was often substantial overlap between board members and senior managers, resulting in a lack of separation between decision-making and execution, and limiting the effectiveness of the board. The pilot reform funda-

mentally transformed this arrangement by replacing the traditional “single leadership team” model with a corporate governance structure in which the board of directors is responsible for decision-making, the management team for execution and the supervisory board for oversight. This reform effectively separates decision rights from managerial authority (Gao et al., 2021). Taking Sinoma Group as an illustrative case (Fig. 5), in 2009 the group completed its corporate registration as China National Materials Group Corporation with the State Administration for Industry and Commerce. It subsequently convened the first meeting of its inaugural board of directors, established four specialized committees, formulated board governance rules and introduced its first cohort of external directors. In the same year, SASAC convened a board reform pilot meeting for Sinoma Group, marking the completion of its transformation in accordance with the Company Law. The board reform pilot represents a critical step in moving CSOEs away from the “top leader responsibility system” toward a modern corporate governance framework (Li et al., 2017; Mao et al., 2022). The restructured board system generates a dual agency-constraint effect: it constrains excessive intervention by the government as the owner’s representative, thereby addressing the problem of blurred boundaries between government and enterprise, while simultaneously restraining insider control by managers, thus mitigating incentive misalignment. This dual governance function constitutes a defining feature of CSOE governance compared with that of conventional firms. The successful implementation of the board reform pilot has laid the institutional foundation for establishing a standardized and efficient modern governance structure in CSOEs. As reforms have deepened, a board composition and appointment system that integrates international practices with Chinese institutional characteristics has been progressively established and refined.

The composition and appointment mechanisms of boards of directors in CSOEs reflect an institutional integration of modern corporate governance principles with arrangements featuring Chinese characteristics. At the ownership level, SASAC, as the entity exercising investor rights on behalf of the state, appoints or nominates shareholder directors in accordance with the law. In doing so, it represents the interests of state capital

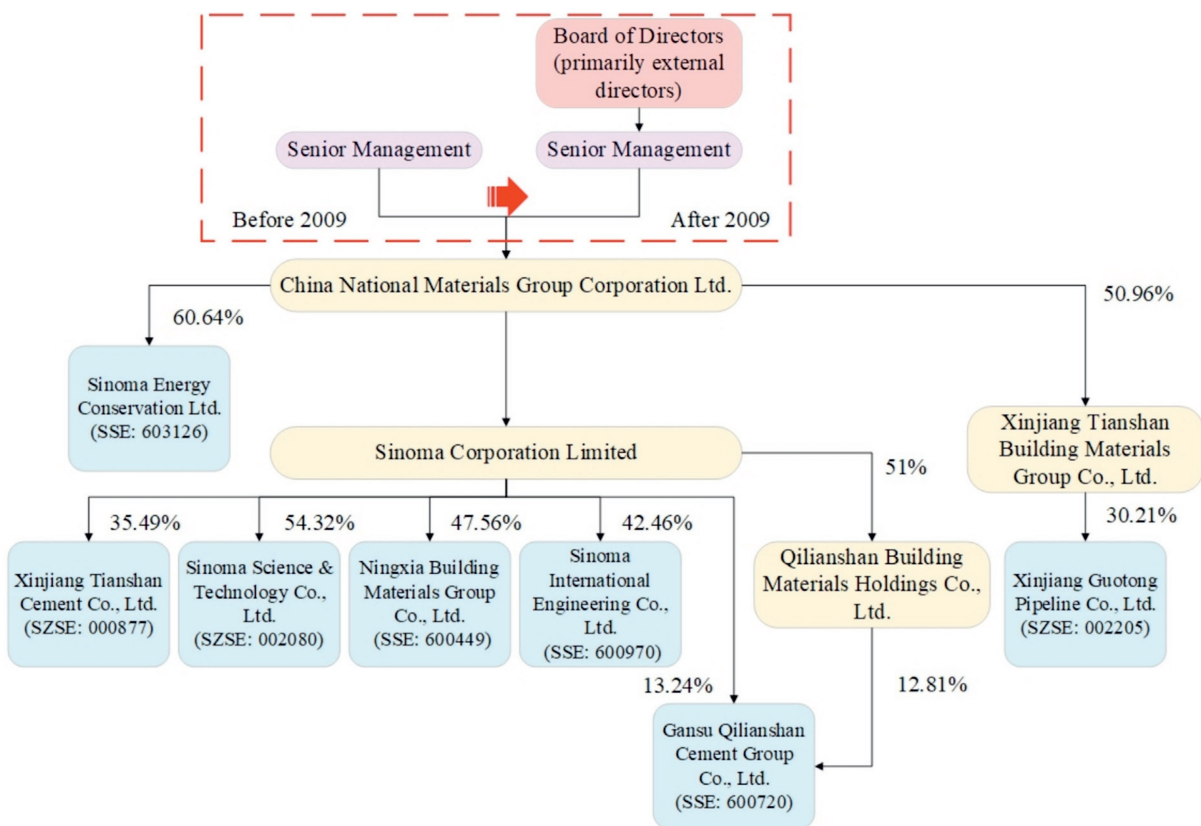


Fig. 5. Board reform pilot in CSOEs: the case of Sinoma Group (red dashed lines).

and performs its supervisory function. At the level of decision-making and execution, executive directors—typically senior managers such as the general manager and deputy general managers—facilitate the alignment between board decisions and operational implementation. To enhance board independence and professional expertise, some enterprises have introduced independent directors with specialized backgrounds and strong public credibility, in accordance with the Company Law and relevant regulatory requirements. This arrangement strengthens both the quality of decision-making and the effectiveness of independent oversight. A distinctive institutional feature of CSOEs lies in the leadership structure characterized by “dual entry and cross-appointment,” under which qualified members of the Party committee (or Party leading group) are legally incorporated into the board of directors. This arrangement ensures the central political role of Party organizations within the corporate governance structure and institutionalizes their participation in decision-making processes, thereby achieving an integrated alignment between Party leadership and corporate governance. This institutional design simultaneously reinforces the political attributes and strategic orientation of CSOEs while preserving the standardization and efficiency of modern corporate governance. Overall, the post-reform appointment process of CSOE boards constitutes a coordinated, multi-actor governance mechanism involving the state ownership authority, Party organizations and board nomination committees. Its overarching objective is to balance state objectives with market-oriented operations and to establish a modern corporate governance system characterized by clear accountability, efficient operation and effective oversight.

According to statistics released by SASAC, as of August 2018, 94 out of 96 CSOEs had established boards of directors, of which 83 had a majority of external directors (Table 3). As an increasing number of CSOEs have adopted board structures, the board system has gradually evolved into a central pillar of SOE reform. From the perspective of agency theory, this institutional evolution reflects a functional separation of decision-making authority (board of directors), executive authority (management) and supervisory authority

Table 3
Timeline of the CSOE board reform pilot.

Year	Milestones
2003	SASAC drafted policy documents to initiate the board reform pilot.
2004	SASAC proposed the pilot program for establishing boards in wholly state-owned enterprises at the 38th Executive Meeting of the State Council; the proposal was approved.
2004	SASAC issued the <i>Notice on Piloting the Establishment and Improvement of Boards of Directors in Wholly State-Owned Enterprises</i> .
2005	SASAC convened the board reform pilot meeting for Baosteel Group. The firm was restructured into a standardized wholly state-owned corporation with five external directors appointed, marking the formal launch of board construction in CSOEs.
2005	Pilot expanded to firms including Shenhua Group, China Chengtong Holdings, China Railcom, China International Travel Service, and Sinopharm Group.
2006	Additional firms included China National Real Estate Development Group, China National Building Materials Group, Sinotrans, Xinxing Ductile Iron Pipes, China Railway Engineering Corporation, China Agricultural Development Group, Panzhihua Iron and Steel Group, MCC, and China Hi-Tech Group.
2009	Expansion to Dongfang Electric Corporation, Sinoma Group, Sinomach, China Iron & Steel Research Institute Group, and China Coal Energy Group.
2010	Inclusion of China Coal Technology & Engineering Group, Poly Group, and China Energy Conservation and Environmental Protection Group.
2011	Expansion to China Datang, China Three Gorges Corporation, COFCO, Dongfeng Motor, China Mobile, Norinco Group, China Hi-Tech Group, China Railway Materials Group, and China National Aviation Fuel Group.
2012	Inclusion of CNOOC, China Shipping Group, China Telecom, Sinopec Group, and Ansteel Group.
2013	Expansion to CNNC, FAW Group, AVIC, and China National Salt Industry Corporation.
2014	Inclusion of Chinalco, China Guodian, China Light Industry Group, Genertec, CGN, Norinco Industries Group, Wuhan Iron and Steel, CASC, CASIC, and TravelSky.
2014	SASAC launched pilot programs to delegate board authority in selected firms, including China Energy Conservation, CNBM, Sinopharm, and Xinxing Cathay International Group.
2015	Expansion to ChemChina, China Huadian, State Grid, China Minmetals, CSSC, China Merchants Group, China Arts and Crafts Group, CSIC, and CETC.
2016	Inclusion of Sinochem Group, CNNC Construction, State Power Investment Corporation, and Aero Engine Corporation of China.

(Party organization), thereby addressing the coexistence of insider control and administrative intervention in traditional CSOEs. Despite over a decade of progress toward more standardized board operations and more scientific decision-making, several persistent challenges remain, including the unresolved relationship between Party organizations and boards of directors, unclear delineation of responsibilities among governance actors and misalignment in the exercise of managerial authority. These issues fundamentally reflect contractual incompleteness in principal–agent relationships. When the boundaries of authority and responsibility among Party committees (political principals), boards of directors (economic principals) and managers (agents) are blurred, a governance paradox emerges in which overlapping supervision coexists with accountability gaps. During the Three-Year Action Plan for SOE Reform (2020–2022), the General Office of the CPC Central Committee issued the *Opinions on Strengthening Party Leadership in Improving Corporate Governance of Central Enterprises*, identifying the coordination among Party organizations, boards of directors and management—particularly the relationship between Party organizations and boards—as a key institutional challenge. This “political–economic” dual governance mechanism constitutes a distinctive solution to agency problems in the Chinese context: it avoids the short-termism associated with shareholder primacy in Western models, while also mitigating the efficiency losses arising from blurred government–enterprise boundaries in traditional SOEs.

Studies evaluate the effectiveness of board reform in CSOEs from two main perspectives. On the one hand, the board reform pilot has been shown to strengthen internal checks and balances, improve governance structures, reduce agency costs and alleviate the long-standing problem of insider control in CSOEs (Li et al., 2017; Gao et al., 2021; Mao et al., 2022). On the other hand, the monitoring function of boards may be constrained or even fail in practice. Some studies suggest that firms may strategically select directors aligned with managerial interests—for example, appointing directors with multiple commitments who are less able to perform effective oversight (Brown et al., 2019). Moreover, evidence from earnings management indicates that the governance effectiveness of boards remains limited, reflecting constraints in both governance mechanisms and governance capacity (Huang et al., 2020). In addition, several structural challenges persist, including overlapping governance bodies, tensions between the administrative governance model of parent companies and the market-oriented governance of listed subsidiaries, excessive intervention by parent firms and the expropriation of minority shareholders (Yu and Qi, 2021).

3.2. Economic consequences of board reform in CSOEs: a review of empirical evidence

3.2.1. Effects on agency costs

The board of directors, as an endogenous governance mechanism for addressing internal agency problems (Fama and Jensen, 1983), plays a central role in mitigating agency costs. In the absence of effective monitoring, managers may pursue private benefits at the expense of principals, thereby exacerbating agency conflicts. One of the primary functions of the board is to monitor management (Hillman and Dalziel, 2003), and effective oversight has been shown to reduce agency costs (Zahra and Pearce, 1989; Pearce and Zahra, 1992). The board reform pilot in CSOEs delegated key powers—such as personnel appointments, performance evaluation and supervisory oversight—from SASAC to corporate boards, thereby reducing direct administrative intervention. Using the board reform as an empirical setting, Cai et al. (2019a) find that board reform significantly improves governance in Chinese CSOEs. In particular, reforms at the controlling parent company level—most notably the introduction of external directors—reduce tunneling behavior by controlling shareholders. An increase in the number of external directors at the parent level significantly curbs the expropriation of listed subsidiaries. Moreover, the participation of independent directors with professional expertise enhances the quality of decision-making, strengthens internal monitoring of management and improves the protection of shareholder interests. The effective functioning of specialized board committees further facilitates the separation of decision-making and execution, thereby strengthening internal checks and balances and promoting a more rational governance structure (Li et al., 2017; Guan et al., 2021; Yu and Qi, 2021). Overall, the empirical evidence consistently indicates that the board reform pilot significantly reduces multiple dimensions of agency costs in CSOE-controlled listed firms.

3.2.2. *Effects on investment efficiency*

Prior to the board reform, the control chain within CSOE groups extended upward to government authorities and downward to controlled subsidiaries, with major investment decisions subject to administrative approval. At the same time, the overlap between boards of directors and senior management weakened both the monitoring and advisory functions of the board. The board reform led by SASAC strengthened governance at the level of the state controlling shareholder and exerted a positive influence on the investment behavior of listed subsidiaries. Xie et al. (2019) find that board reform at the parent company level significantly reduces overinvestment in listed subsidiaries: both total new investment expenditure and excess investment decline following the reform. From the perspective of board functions, the establishment of formal board structures enhances both monitoring and advisory roles. Boards improve the screening and evaluation of investment projects, curb managerial tendencies toward overinvestment (Liu et al., 2015) and promote more efficient capital allocation. Taken together, the development of boards in CSOEs reduces excessive investment at the group level while improving investment efficiency, ultimately contributing to higher firm value (Huang and Huang, 2022; Mao et al., 2022; Yu et al., 2023).

3.2.3. *Effects on stock price crash risk*

Board governance can mitigate the accumulation of bad news within firms and curb opportunistic behavior by insiders, thereby influencing stock price crash risk (Fang et al., 2021). Board reform further strengthens both the monitoring and advisory functions of the board, reducing crash risk by improving financial transparency and enhancing investment efficiency (Hu et al., 2020). Empirical evidence shows that the board reform pilot in CSOEs helps lower the stock price crash risk of their listed subsidiaries (Cai et al., 2019b). This effect operates through several channels. First, improvements in governance at the parent company level reduce tunneling and expropriation of subsidiary firms. Second, enhanced governance at the parent company level strengthens oversight of listed subsidiaries. Third, governance improvements induced by board reform may spill over from parent companies to their subsidiaries; via improved governance quality and strengthened supervision at the parent level, the crash risk of subsidiary firms is correspondingly reduced.

3.2.4. *Effects on earnings management*

The board reform pilot in CSOEs grants greater decision-making authority to the management of CSOE-controlled listed firms, while simultaneously strengthening oversight by controlling shareholders (Huang et al., 2020). Consistent with the behavior of controlling shareholders in general firms, controlling shareholders of CSOE-affiliated listed companies both monitor managerial actions and may engage in the expropriation of firm resources. In this context, managers with incentives for earnings management weigh the costs and benefits of such behavior and may resort to real earnings management due to the timing flexibility and operational discretion it offers them. Wang et al. (2015) find that the presence of independent directors with industry expertise significantly reduces earnings management. In addition, the establishment of boards complements existing supervisory mechanisms at the parent company level (Gao et al., 2021; Huang and Huang, 2022; Yu et al., 2023). Moreover, the development of standardized boards reduces opportunistic behavior by executives driven by political promotion incentives or private benefits, thereby lowering earnings management, improving the quality of financial reporting, reducing accounting manipulation and financial fraud and enhancing audit quality (Gao et al., 2021; Kim et al., 2024).

3.2.5. *Review and discussion*

The board reform pilot in CSOEs provides a quasi-natural experimental setting for examining governance transformation under state ownership. Studies indicate that, through the introduction of external directors and the establishment of specialized committees, the reform effectively curbs tunneling by controlling shareholders and mitigates insider control, thereby reinforcing the role of the board as an endogenous governance mechanism. Beyond its direct effects at the parent company level, the reform also improves investment decision-making efficiency and generates governance spillovers within corporate groups. In particular, improvements in governance at the parent level are transmitted to listed subsidiaries, leading to reductions in stock price crash risk and earnings management. Taken together, the evidence suggests that board reform

enhances firm performance primarily by strengthening governance quality and improving the efficiency of resource allocation. These findings underscore the importance of decision-making professionalization and supervisory independence in the transition from administrative governance to market-oriented governance. At the same time, the reform is associated with a shift in the behavior of controlling shareholders, from rent extraction toward more effective monitoring, providing new evidence on the evolution of corporate governance in the Chinese institutional context. Future research should further examine the coordination mechanisms between Party organizations and boards of directors, as well as the heterogeneity of reform effects across industries, in order to more comprehensively assess the long-term implications of this institutional innovation.

4. Performance evaluation of CSOE executives

4.1. Evolution of performance evaluation systems for CSOE executives

Prior to the establishment of SASAC, the absence of clearly defined authority and accountability meant that no single agency was able to conduct comprehensive performance evaluation of CSOEs, resulting in widespread losses of state-owned assets. Multiple government bodies exercised partial oversight without bearing ultimate responsibility, leading to a governance vacuum. In the absence of effective incentive mechanisms, executives of CSOEs were often unable to obtain rewards through formal channels. As a result, they resorted to alternative forms of private benefit extraction, including earnings management and excessive perquisite consumption, in order to maximize personal utility (Chen et al., 2005; Xu and Liu, 2013). Such behavior fundamentally reflects a self-compensating response by agents under severe misalignment between residual claims and control rights (Jensen and Meckling, 1976). Since 2004, SASAC has assumed the role of the state investor and introduced formal performance evaluation systems for CSOEs. This reform established, for the first time, a unified principal and restructured the principal–agent relationship through contractual performance assessment. Performance evaluation has since become a key governance instrument for guiding managerial decision-making and strengthening internal control systems (Tang and Dai, 2015). Because performance evaluation outcomes are directly linked to executive compensation and appointment decisions, the system generates both monetary incentives and promotion incentives (Yang et al., 2013), thereby mitigating managerial short-termism and impulsive decision-making (Yu et al., 2016; Ou and Sun, 2018). This combination of explicit and implicit incentives effectively compresses rent-seeking opportunities and aligns managerial interests more closely with the objective of preserving and enhancing the value of state-owned assets.

In its early stages, the performance evaluation system exhibited several deficiencies, including poorly designed indicators, unclear evaluation cycles and limited use of assessment outcomes. These shortcomings fundamentally reflect the staged resolution of agency problems—from initially establishing the presence of supervision to progressively improving its effectiveness. Following the issuance of Order No. 2 by SASAC in November 2003, namely the *Interim Measures for the Performance Evaluation of Executives of Central Enterprises*, the system underwent six rounds of revisions and two supplementary regulations. The establishment of this performance evaluation system helped to mitigate, to some extent, the misalignment between the objectives of principals and managers in CSOEs. In the 2007 revision, EVA rankings were introduced alongside the existing evaluation framework; from 2010 onward, EVA was formally adopted as a core performance evaluation indicator for CSOEs. As a value-based metric, EVA reflects firm value maximization while incorporating considerations of innovation, growth and risk (Yu et al., 2016). The introduction of EVA marks a shift in governance from outcome-based control toward a value-creation orientation. By making the cost of capital explicit, EVA compels managers to internalize the true opportunity cost of state-owned capital (He et al., 2019). In this sense, the performance evaluation system embeds long-term value creation into managerial decision-making, thereby improving incentive alignment between principals and agents (Tables 4 and 5).

Changes in the performance evaluation system have had a significantly positive effect on the preservation and appreciation of state-owned capital, as well as on the growth of core business revenue in CSOEs. From the perspective of agency theory, these improvements stem from the effectiveness of the evaluation mechanism in alleviating the lack of supervision caused by ill-defined ownership, via internalizing the objective of preserving

Table 4
Evolution of performance evaluation regulations for CSOE executives.

Date	Policy Document	Key Indicators
2004.1.1	<i>Interim Measures for Performance Evaluation of Central SOE Executives</i>	Total profit and return on equity
2007.1.1	<i>Interim Measures for Performance Evaluation of Central SOE Executives</i>	Introduction of EVA as a performance metric
2007.12.24	<i>Supplementary Provisions on Tenure-Based Performance Evaluation of Central SOE Executives</i>	Determination of tenure performance targets; Scoring rules for core indicators
2008.2.13	<i>Supplementary Provisions on Annual Performance Evaluation of Central SOE Executives</i>	Baseline requirements for categorized performance indicators
2010.1.1	<i>Interim Measures for Performance Evaluation of Central SOE Executives</i>	Adjustment coefficients across evaluated firms; Mechanism for performance-based compensation
2013.1.1	<i>Interim Measures for Performance Evaluation of Central SOE Executives</i>	Consolidated total profit (with adjustments for legacy issues)
2016.12.8	<i>Measures for Performance Evaluation of Central SOE Executives</i>	Total profit + EVA
2019.4.1	<i>Measures for Performance Evaluation of Central SOE Executives</i>	Net profit + EVA

and increasing the value of state-owned assets into managerial decision-making through contractual performance assessment. Recent data further illustrate these outcomes. In 2024,⁶ the total assets of CSOEs exceeded RMB 90 trillion, representing a year-on-year increase of 5.9%. Value added reached RMB 10.6 trillion, total profits amounted to RMB 2.6 trillion and tax payments also reached RMB 2.6 trillion. These results suggest that by directly linking performance evaluation outcomes to compensation and promotion, a closed-loop incentive mechanism linking performance to rewards has been established, significantly reducing agency costs. In addition, SASAC publicly discloses the annual performance evaluation results of CSOEs. According to the “List of Grade A Enterprises in the 2023 Performance Evaluation of CSOE Executives,” released on 24 July 2024, a total of 49 CSOEs received an A rating (Fig. 6),⁷ among which eight enterprises have maintained A ratings for 20 consecutive years. Such sustained superior performance provides evidence of a reputation mechanism under repeated interactions: when managers anticipate that consistently strong performance will yield long-term career benefits, they are more likely to restrain short-term opportunistic behavior.

The EVA-based evaluation policy sends a clear signal to CSOE executives: SASAC emphasizes not only firms’ value creation capabilities but also their accounting performance. This institutional design directly targets the core of agency problems in CSOEs. By making the cost of capital explicit, it corrects managerial biases under traditional accounting-based evaluation, in which insufficient attention is paid to the efficiency of capital utilization. By refining the performance evaluation system, SASAC aims to better protect shareholder interests and enhance firms’ capacity for value creation. A growing body of literature exploits the implementation of EVA-based performance evaluation in CSOEs as a quasi-experimental setting. Some studies examine how new performance metrics influence managerial discretionary decision-making (Du et al., 2018), while others investigate the broader impact of government-led incentive systems on firm behavior (He et al., 2022). Empirical studies that directly test the effects of performance evaluation reform find that EVA-based evaluation significantly improves the efficiency of CSOEs (Shen et al., 2015; Ou and Sun, 2018). It also redirects R&D investment from non-core projects toward core business activities, thereby enhancing core operational performance (Yang et al., 2021). These findings reflect the role of contract design in shaping agents’ resource allocation behavior: when performance metrics are closely aligned with strategic objectives, managers are more likely to optimize their investment portfolios. Moreover, when principals establish verifiable evaluation criteria for long-term innovation investment, it becomes possible to balance short-term performance pressures with long-term development objectives. As key actors in technological innovation, CSOEs benefit from incorporat-

⁶ https://www.gov.cn/zhengce/jiedu/tujie/202501/content_6999523.htm.

⁷ <https://www.sasac.gov.cn/n2588030/n2588954/c31269659/content.html>.

Table 5
Evolution of key features in performance evaluation for CSOE executives.

	Interim Measures for Performance Evaluation of Central SOE Executives				Measures for Performance Evaluation of Central SOE Executives	
	No. 2	No. 17	No. 22	No. 30	No. 33	No. 40
Annual Performance Evaluation						
Total Profit	Consolidated total profit + absorption of prior losses	Consolidated total profit + absorption of prior losses – non-recurring gains Same as No. 2 excluding minority interests in both numerator and denominator Encouraged	Same as No. 17	Consolidated total profit (with adjustments for legacy issues) – non-recurring gains		
Return on Equity (ROE)	Net profit / average net assets (excluding minority interests)	Same as No. 2 excluding minority interests in both numerator and denominator Encouraged	—	—		
Economic Value Added (EVA)	—	—	Defined as: Net profit + (interest + R&D adjustments – 50% of non-recurring gains) × (1–25%) – adjusted capital × WACC Same as No. 2	Defined as: Net profit + (interest + R&D adjustments) × (1–25%) – non-recurring gains – adjusted capital × WACC Same as No. 2		
Tenure Performance Evaluation						
State Capital Preservation & Appreciation Ratio	Adjusted ending equity / beginning equity	Same as No. 2				
Average Growth of Main Business Revenue	Three-year compound growth rate	Same as No. 2	Same as No. 2	—		
Total Asset Turnover	—	—	—	Sum of 3-year revenue / sum of average assets	Three-tier system	Three-tier system
Annual Benchmark Indicators	Profit + EVA Net Profit + EVA	— —	— —	A–E (five grades)	A–D (four grades)	A–D (four grades)
Performance Rating	A–E (five grades)	A–E (five grades)	A–E (five grades)	Same as No. 22	Similar to No. 22 with widened differentiation	Same as No. 33
Allocation Coefficients	Legal representative = 1; others determined by firm	Same as No. 2	Principal executive = 1; others: 0.6-0.9		Monthly pre-payment with mid-year adjustment	
Performance-based Compensation	60% paid immediately; 40% deferred	Same as No. 2	70% immediate; 30% deferred	Same as No. 22		

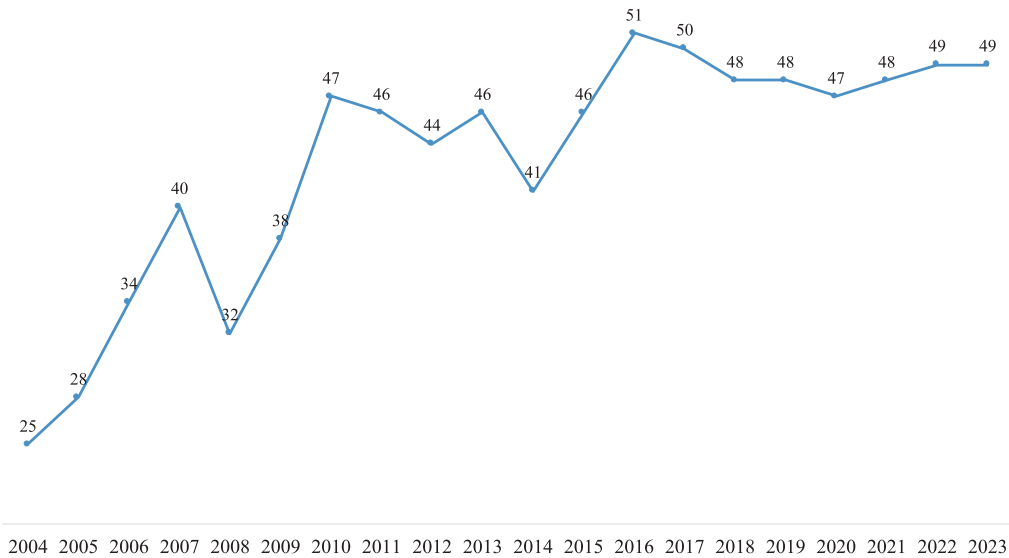


Fig. 6. Number of CSOEs rated Grade A in performance evaluations, 2004–2024.

ing innovation into performance evaluation, which facilitates high-quality development and strengthens state capital. Consistent with this shift in evaluation mechanisms, recent data show that in 2024,⁸ total R&D expenditure by CSOEs reached RMB 1.1 trillion, exceeding RMB 1 trillion for three consecutive years, while investment in strategic emerging industries amounted to RMB 2.7 trillion, representing a year-on-year increase of 21.8%.

4.2. Economic consequences of performance evaluation in CSOEs: a review of the literature

4.2.1. Effects of performance evaluation on executive promotion

Executives of CSOEs hold administrative ranks. While a small number are appointed by Party organizational departments, the vast majority are appointed and dismissed by SASAC. As “quasi-officials,” CSOE executives not only enjoy political status comparable to that of government officials at the same rank, but also face similar opportunities for political promotion. Accordingly, reforms in performance evaluation introduced by SASAC have established a dual incentive mechanism combining monetary compensation and promotion incentives, making political promotion an important instrument for motivating SOE executives. Yang et al. (2013) find that higher revenue growth increases the probability of promotion for CSOE executives, whereas Liu and Xiao (2015) report that the likelihood of demotion is negatively associated with performance, while promotion is not significantly related to performance but is positively associated with the fulfillment of social responsibilities. Although the relationship between performance evaluation and promotion remains inconclusive, it is evident that political promotion constitutes a strong and effective implicit incentive for CSOE executives (Wang et al., 2014; Lu et al., 2016) and represents an important dimension of performance evaluation reform.

4.2.2. Effects of EVA on innovation in CSOEs

In 2010, the *Interim Measures for the Performance Evaluation of Executives of Central Enterprises* replaced return on equity (ROE) with EVA as the core indicator for annual performance evaluation. By capitalizing R&D expenditures, EVA mitigates short-termism among executives who might otherwise reduce R&D spending to maintain accounting profits, thereby encouraging innovation and long-term investment (Yu et al.,

⁸ <https://www.sasac.gov.cn/n2588025/n2588139/c32643415/content.html>.

2016). Compared with ROE, EVA is widely regarded as a more value-oriented metric aligned with firm value maximization. Empirical evidence supports this view: following the adoption of EVA-based evaluation, the level of innovation in CSOEs increased significantly relative to private firms not subject to this policy (Yu et al., 2016). As a measure of shareholder value creation, EVA requires managers to evaluate their decisions from a value-creation perspective, thereby aligning the interests of shareholders and managers. On the one hand, the capitalization of R&D expenditures under EVA strengthens executives' incentives to invest in innovation; on the other hand, as a key performance indicator, EVA induces managers to prioritize innovation while improving subsequent resource allocation, integration and utilization.

4.2.3. Effects of EVA on investment in CSOEs

As a performance evaluation metric, EVA incentivizes managers to make investment decisions that maximize firm value (Rogerson, 1997). The adoption of EVA by SASAC aims to direct managers' attention to the cost of capital, encourage long-term strategic considerations and curb excessive investment (Liu and Li, 2013; Liang et al., 2019). Because EVA is linked to executive performance evaluation, rational managers take into account the cost of equity capital when making investment decisions and thus behave more cautiously. Empirical evidence shows that CSOEs respond to performance evaluation reform by adjusting their investment decisions (He et al., 2022). Compared with the pre-reform period, the introduction of EVA-based evaluation has led to more prudent investment behavior and a significant reduction in inefficient investment (Liu and Li, 2013; Du et al., 2018; Ou and Sun, 2018). However, the EVA evaluation system still has limitations. Liu and Li (2013) further show that in CSOE-controlled listed firms operating in less competitive markets, EVA-based evaluation does not achieve the expected effect of curbing overinvestment.

4.2.4. Effects of EVA on cash holdings in CSOEs

Cash plays a crucial role in corporate management and operations. While holding an appropriate level of cash helps meet operational needs and reduce financial risk, excessive cash holdings may increase the likelihood of managerial opportunism (Jensen, 1986). Prior to SOE reform, the "absence of clearly defined ownership" often led to inefficient internal allocation of cash resources. Moreover, CSOEs tended to prioritize large-scale projects rather than focusing on their core businesses, thereby reducing capital efficiency (Shen et al., 2015). Firms generally have three motives for holding cash—transactional, precautionary and agency motives (Bates et al., 2009). In CSOEs, agency problems arising from cash allocation are more often manifested as inefficient dissipation of cash resources, which reduces the value of cash holdings. Therefore, reforms in executive performance evaluation can effectively strengthen external governance through state ownership supervision. EVA-based evaluation encourages managers to make value-enhancing investment decisions (Rogerson, 1997). Studies show that after the implementation of EVA-based evaluation, the investment structure of CSOEs improves and the value of cash holdings increases significantly (Shen et al., 2015), as reflected in reduced managerial expropriation and improved efficiency of cash reallocation (Liang et al., 2019). The performance evaluation system reinforces innovation-oriented incentives and facilitates the transition of CSOEs from a focus on short-term profits to long-term value creation.

4.2.5. Review and discussion

The reform of the performance evaluation system for CSOE executives has achieved substantial progress in addressing agency problems specific to SOEs by establishing a multidimensional incentive framework. Studies show that the introduction of EVA-based evaluation, through the capitalization of R&D expenditures, effectively mitigates managerial short-termism and significantly increases innovation investment. By making the cost of capital explicit, this institutional design aligns managerial decision-making with shareholder value creation. At the same time, the reform reshapes investment behavior by curbing excessive investment and improving the efficiency of capital allocation, including more efficient cash management. Notably, political promotion, as a distinctive implicit incentive mechanism, complements EVA-based evaluation and jointly shapes managerial behavior to balance economic performance with political considerations. However, the effectiveness of EVA-based evaluation exhibits heterogeneity. Its impact is limited in firms facing underinvest-

ment constraints and in monopolistic or low-competition industries, indicating that performance evaluation systems need to be better aligned with industry characteristics and firm-specific conditions. Overall, while performance evaluation reform has made progress in mitigating agency problems arising from the absence of clearly defined ownership, further improvements are needed. In particular, future reforms should focus on balancing short-term evaluation with long-term value creation, as well as reconciling economic objectives with broader social responsibilities.

5. Executive incentives in CSOEs

5.1. Evolution of executive incentive reforms in CSOEs

Executive incentives serve both as a potential solution to agency problems and as an inherent component of those problems themselves (Bebchuk and Fried, 2003). In the context of CSOEs, this duality is particularly pronounced: insufficient incentives tend to exacerbate agency costs, whereas excessive incentives may induce managerial opportunism and the abuse of power. Managerial power theory suggests that managers may use their influence to design compensation arrangements that serve their own interests, thereby weakening the effectiveness of incentive mechanisms (Bebchuk et al., 2002). The distinctive “political-economic” dual identity of CSOEs further intensifies this issue. Executives can leverage administrative authority to reinforce their control rights, while simultaneously exploiting their market position to extract excess compensation, giving rise to a unique form of institutionally embedded managerial power.

In the early stages, CSOEs were primarily subject to administrative regulation, and their executives were directly appointed by Party organizational departments based on administrative needs. As a result, CSOE executives were widely regarded as both “entrepreneurs” and “quasi-officials” (Lee, 2001; Yang et al., 2013; Liu and Xiao, 2015; Chen et al., 2022). This personnel system led to multiple and often conflicting incentive objectives: executives were required to pursue economic performance while simultaneously satisfying political promotion requirements, resulting in severe goal conflicts within the principal-agent relationship. During this period, executive compensation in CSOEs was subject to strict government regulation and was typically benchmarked against the salary standards of government officials at equivalent ranks, thereby limiting the effectiveness of monetary incentives (Chen et al., 2005). Subsequent SOE reforms, while aiming to enhance firm vitality, further intensified agency problems arising from the absence of clearly defined ownership. The hybrid “political-commercial” nature of CSOEs endowed executives with complex and heterogeneous motivations, making it difficult for conventional incentive and constraint mechanisms to function effectively. Between 2000 and 2002, the annual growth rate of executive compensation in CSOEs was approximately 40%. Following the introduction of performance evaluation and compensation regulation by SASAC, this rate declined to 14.9% during 2003–2006. Such a sharp adjustment reflects an attempt by the principal, under conditions of information asymmetry, to forcibly reconstruct the incentive contract through administrative intervention.

However, simple compensation caps may give rise to new agency problems: when explicit incentives are insufficient, agents may seek private benefits of control through non-productive expenditures, overinvestment and other opportunistic behaviors. Studies find that the implementation of compensation regulation has had negative effects on on-the-job consumption, executive corruption and investment efficiency in CSOEs (Xu and Liu, 2013; Liu and Tai, 2020). Nevertheless, the overall direction of executive pay regulation in CSOEs remains unchanged. Policies aimed at aligning executive compensation with firm performance and restraining excessively high pay levels continue to be enforced. As incentives are an important instrument for mitigating agency problems (Jensen, 1986), compensation-based incentives alone are insufficient; alternative mechanisms such as equity-based incentives and promotion incentives can also be adopted (Liu and Xiao, 2015; Wang and Liu, 2020). In 2020, SASAC issued the *Guidelines on the Implementation of Equity Incentives for Listed Companies Controlled by Central Enterprises*, aiming to further promote the establishment of long-term incentive and constraint mechanisms in CSOE-controlled listed firms and to standardize the formulation and implementation of equity incentive plans. During the Three-Year Action Plan for SOE Reform (2020–2022), the numbers of CSOEs announcing long-term equity incentive plans were 26, 41 and 31, respectively. The promotion of equity-based incentive policies essentially operates through the sharing of residual claims, thereby aligning

managers' interests with the long-term value of the firm. This incentive-compatible mechanism effectively mitigates the distortions associated with traditional compensation regulation (Table 6).

Executive incentives in CSOEs remain an important issue that has yet to be fully resolved. Compensation-based incentives are subject to relatively strict regulation, while the economic consequences of equity-based incentives remain inconclusive. Equity incentives for managers are intended to regulate risk-taking behavior and align long-term investment decisions with shareholder interests. However, they entail both positive and negative effects, and their implementation requires a balance between these opposing outcomes. In institutional and legal environments that are not yet fully developed, equity incentives may increase the likelihood of financial misreporting and fraud (Xin and Lv, 2012; Hass et al., 2016). Although some studies on equity incentives in Chinese CSOEs suggest that such reforms help alleviate the problem of "absent ownership" and broaden existing incentive channels (Su and Alexiou, 2022), the potential drawbacks of equity incentives should not be overlooked. Promotion incentives similarly constitute a double-edged sword: while they can enhance managerial effort (Yang et al., 2013; Cao et al., 2019), they may also induce managers to engage in overinvestment and earnings management in pursuit of political advancement (Lu et al., 2016). Therefore, the design and refinement of executive incentive mechanisms in CSOEs remain important areas for further research and policy discussion. On 23 April 2020, the *Guidelines on the Implementation of Equity Incentives for Listed Companies Controlled by Central Enterprises* stipulated that for initial equity incentive plans, the number of underlying shares should not exceed 1% of total equity capital, with a higher cap of 3% for small- and medium-sized firms and technology-oriented companies.

5.2. Economic consequences of executive incentives in CSOEs: a review of the literature

5.2.1. Compensation incentives for CSOE executives

The *Interim Measures for the Performance Evaluation of Executives of Central Enterprises* link executive compensation in CSOEs to firm performance, thereby incentivizing executives to focus on improving firm performance and generating higher profits. In addition, in 2014, the central government introduced compensation regulation policies targeting CSOE executives, clarifying administrative ranks and benefits while curbing excessively high pay. Historically, the large gap between executive compensation and employee wages in CSOEs has been regarded as a reflection of managerial power; wider pay dispersion within firms may lead to

Table 6
Types of equity incentive schemes in CSOE-listed companies.

Date	Policy Document	Major Provisions
2006.1.27	<i>Trial Measures for the Implementation of Equity Incentives in Overseas-Listed State-Controlled Companies</i>	Equity grants are capped at 10% of total share capital; initial grants are typically within 1%; individual awards are limited to 1% per year; plans last up to 10 years and are granted periodically.
2006.9.30	<i>Trial Measures for the Implementation of Equity Incentives in Domestically-Listed State-Controlled Companies</i>	Total grants range from 0.1% to 10% (capped at 10% overall); initial grants are generally within 1%; individual awards are capped at 1% unless approved; plan duration is usually within 10 years.
2008.10.21	<i>Notice on Regulating Issues Concerning the Implementation of Equity Incentive Schemes in State-Controlled Listed Companies</i>	Requires performance evaluation to include shareholder returns, firm growth, and earnings quality, with at least one metric from each category.
2016.8.2	<i>Guiding Opinions on Pilot Employee Stock Ownership Plans in State-Controlled Mixed-Ownership Enterprises</i>	Clarifies rules on eligible employees, funding sources, pricing, ownership ratios, and holding structures.
2019.11.11	<i>Notice on Further Improving Equity Incentive Practices in Central SOE-Controlled Listed Companies</i>	Encourages staged (multi-tranche) incentives aligned with firm strategy, emphasizing long-term incentives and appropriate grant size.
2020.4.23	<i>Guidelines for the Implementation of Equity Incentives in Central SOE-Controlled Listed Companies</i>	Initial grants are generally capped at 1% of total share capital, with a higher cap (up to 3%) for smaller or innovation-oriented firms.

lower investment efficiency (Bebchuk and Fried, 2006). While regulating excessively high executive compensation is both reasonable and necessary, policy implementation should be differentiated rather than uniformly applied. For example, Liu and Tai (2020) find that compensation regulation reduces investment efficiency in CSOEs, with stronger negative effects in firms with lower promotion prospects and in competitive industries. Wang and Liu (2020) further show that compensation regulation has adverse effects on innovation activities. Conventional views suggest that CSOEs must consider social and political objectives rather than focusing solely on profit maximization (Jiang et al., 2014). In practice, according to their functional positioning, CSOEs are classified into three categories—public welfare, commercial type I and commercial type II—among which commercial type I firms operate in more competitive industries. Accordingly, compensation regulation policies should be adjusted based on the competitive environment. Market mechanisms tend to drive executive compensation in competitive CSOEs toward a Pareto-efficient level; excessive regulation may cause firms to lose high-quality managerial talent and thus reduce firm value. In contrast, in monopolistic CSOEs, executives place greater emphasis on promotion incentives, and compensation incentives play a relatively limited role; therefore, compensation regulation has little impact on firm value (Bu and Sun, 2021). In addition, increasing compensation dispersion among non-CEO executives can effectively reduce agency costs. This mechanism reflects performance-based differentiation among senior managers, which helps stimulate managerial effort and initiative (Xu et al., 2021).

5.2.2. *Equity incentives for CSOE executives*

Equity-based incentives, which strengthen the alignment between owners and managers, represent an important mechanism for addressing insufficient incentives among CSOE executives (Jensen and Meckling, 1976). Equity incentive plans can help attract and retain talented employees while enhancing their organizational commitment. By holding company shares, employees become more likely to perceive a shared fate with the firm and thus contribute more actively to its long-term development (Balsam et al., 2002). Given the dual identity of CSOE executives as both “officials” and “managers,” they must not only pursue political advancement but also fulfill the responsibilities of professional managers. Although some studies suggest that equity incentives in CSOEs simultaneously function as incentives, welfare and rewards—leading to ambiguity in their positioning and weakening their effectiveness (Xin and Lv, 2012)—their long-term orientation and the verifiability of performance indicators make them an essential component of executive incentive systems (Mehran, 1995; Liu and Xiao, 2015; Bu and Sun, 2021; Su and Alexiou, 2022). To participate effectively in both domestic and international market competition, CSOEs must establish compensation systems consistent with market-oriented principles. Inadequate implementation of equity-based incentives as a medium- to long-term incentive mechanism may constrain the reform and development of CSOEs. The introduction of equity incentives not only expands existing incentive channels for executives but also facilitates the optimization of ownership structures. When CSOE executives face both compensation regulation and constraints on on-the-job consumption, equity incentives and promotion incentives become the primary sources of motivation. Promotion incentives tend to drive executives to prioritize government-defined promotion criteria and non-economic targets, which may be detrimental to the preservation and appreciation of state-owned assets. In contrast, equity incentives, as a mechanism oriented toward long-term economic objectives, help mitigate agency problems (Zhang and Wang, 2018).

5.2.3. *Promotion incentives for CSOE executives*

Despite the central government’s efforts to separate government from enterprise and to de-administrativize CSOEs, the administrative ranking of executive positions remains in place, and CSOE executives continue to be managed by Party organizational departments at various levels. Although CSOE executives are not formally part of the civil service system, they are administered with reference to equivalent government ranks and enjoy comparable political status and benefits. This institutional arrangement implies that CSOE executives are not typical “professional managers” (Yang et al., 2013; Zhou and Zhang, 2016; Chen et al., 2022), but instead possess strong incentives for political career advancement. Accordingly, in addition to compensation and equity-based incentives, political promotion serves as an important mechanism for motivating CSOE executives. Empirical evidence shows that when CSOE executives face a higher probability of promotion to a higher political rank, on-the-job consumption is significantly reduced, the value-creation capacity of inno-

vation output is enhanced and overall firm performance improves (Wang et al., 2014; Zhou and Zhang, 2016; Cao et al., 2019; Wang and Liu, 2020). Nonetheless, promotion incentives may induce executives to align their behavior more closely with government preferences, thereby increasing incentives for rent-seeking through accounting manipulation and leading to a deterioration in financial reporting quality (Lu et al., 2016). In addition, the pursuit of political advancement may generate a tendency toward “performance rush,” which can adversely affect investment efficiency (Jin et al., 2016).

5.2.4. Review and discussion

The reform of executive incentive mechanisms in CSOEs exhibits distinctive Chinese characteristics. Through the combined use of compensation, equity and promotion incentives, substantial progress has been made in addressing agency problems specific to SOEs. Studies indicate that linking compensation to performance helps restrain excessive executive pay; however, rigid and uniform regulation may dampen the operational vitality of competitive CSOEs. Equity incentives, as a medium- to long-term incentive mechanism, mitigate the problem of “absent ownership” by aligning managerial interests with firm value, although their effectiveness is constrained by the dual “political-economic” identity of CSOE executives. Promotion incentives constitute the most distinctive feature in this context. Such political incentives exert a significant influence on managerial decision-making: they may restrain on-the-job consumption and promote innovation, but may also induce earnings management and overinvestment. A key direction for current reform is to implement differentiated incentive schemes based on the functional classification of CSOEs. For commercially oriented firms (commercial type I), market-based compensation and equity incentives should be strengthened; for public welfare-oriented firms, the promotion evaluation system should be further refined. Looking ahead, it is necessary to develop a more systematic incentive framework that not only prevents insufficient incentives and managerial shirking but also avoids incentive misalignment that may induce short-term behavior, ultimately achieving a balanced alignment between political and economic objectives.

6. Auditing and internal control in CSOEs

In 2004, SASAC conducted a special inspection of the financial audit reports of 181 CSOEs. The results revealed that in 120 enterprises, a substantial portion of financial information had not been included in the audit reports; in 30 enterprises, the audits were incomplete or insufficiently thorough; in 13 enterprises, audit conclusions were inconsistent with the underlying facts; and in another 13 enterprises, the audit reports contained technical deficiencies. These widespread audit failures reveal the underlying agency problems in CSOE governance: in the absence of effective monitoring mechanisms, managers have incentives to conceal agency costs through selective information disclosure. In the same year, SASAC issued the *Rules on the Financial Final Accounts Audit of Central Enterprises*, introducing a unified audit engagement system. By severing the employment relationship between audited entities and accounting firms, this reform reduced the risk of audit collusion and strengthened auditor independence.

Auditing is an integral component of the Party and state supervisory system and also an important corporate governance mechanism (Cohen et al., 2002) playing a crucial role in the development of capital markets. As one of the key forms of professional opinion in the capital market, auditors’ opinions provide important references for market regulation and investor decision-making, thereby helping to protect investor interests (Newman et al., 2005; Li and Wu, 2013; Wu and Tuttle, 2014). At the same time, state auditing is expected to play an important role in improving the governance efficiency of CSOE-controlled listed companies and constitutes a key instrument of oversight over CSOEs (Qin, 2004; Liu, 2005). In February 2006, the MoF issued a new system of accounting and auditing standards, marking the establishment of a corporate accounting and auditing framework broadly convergent with international standards. In contrast, the development of internal control systems in CSOEs started relatively late. Following the issuance of the *Basic Norms for Enterprise Internal Control* in 2008 by five government ministries, CSOEs began actively exploring the construction and implementation of internal control systems. In 2012, SASAC issued the *Notice on Accelerating the Establishment of Internal Control Systems in Central Enterprises*, initiating a comprehensive effort to build standardized internal control systems across all CSOEs, with the objective of completing this process within two years. In 2019, to further strengthen the foundational role of internal control systems, SASAC released the *Guidelines*

on *Strengthening Internal Control System Development and Supervision in Central Enterprises*, aiming to continuously optimize internal control systems and enhance their overall effectiveness. In 2021, in response to problems identified in certain CSOEs—such as deficiencies in fund management systems and weak policy implementation, which exposed serious shortcomings in internal financial controls—SASAC issued the *Notice on Strengthening Internal Control Management of Funds in Central Enterprises* to further improve the internal control framework for capital management.

6.1. External auditing

To improve the audit quality of CSOEs, regulations issued by SASAC and the MoF focus on three key measures. First, a bidding system is introduced. Through a competitive selection mechanism, this approach disrupts potential collusion between accounting firms and corporate management, thereby reducing the risk of compromised audit independence. Second, qualification restrictions are imposed on accounting firms. By setting entry thresholds, this measure ensures that auditors possess sufficient professional expertise to identify complex agency problems. Third, mandatory rotation of accounting firms is implemented. This “periodic reset” mechanism prevents auditors from developing complacency in professional judgment due to long-term engagement and helps maintain vigilance over managerial behavior. On 7 October 2005, SASAC issued the *Notice on Strengthening the Financial Final Accounts Audit of Central Enterprises*. In addition to reiterating the requirement for auditor rotation, this document introduced quantitative criteria for the selection of accounting firms. In essence, this reform reduces managerial discretion through standardized indicators, preventing managers from concealing operational problems by lowering audit quality. On 9 October 2006, SASAC released the *Answers to Issues Concerning the Financial Final Accounts Audit of Central Enterprises*, which further refined regulations on audit tenure, reflecting the principal’s dynamic calibration of the trade-off between audit tenure and independence. On 29 December 2011, the MoF issued the *Notice on Issues Concerning Accounting Firms Undertaking Financial Final Accounts Audits of Central Enterprises*, providing more detailed requirements for audit institutions. This reform extended audit supervision from a one-time annual activity to a continuous process, thereby establishing a long-term constraint mechanism on managerial behavior. Collectively, these institutional developments form a “three-pillar” audit framework: the bidding mechanism addresses adverse selection, qualification restrictions ensure monitoring capability and rotation mitigates moral hazard (Table 7).

Table 7
Core rules for the selection and rotation of accounting firms in CSOEs.

Policy Document	Audit Tenure Requirements	Auditor Qualification Requirements
<i>Notice on Issuing the Rules for Final Financial Statement Audits of Central SOEs</i>	The same accounting firm should not serve more than 5 consecutive years.	Audit firms (including participating firms) must have qualifications commensurate with firm size.
<i>Notice on Strengthening Final Financial Statement Audits of Central SOEs</i>		Standardizes the auditor selection process, including requirements on CPA staffing, professional credentials, scale, tenure, and rotation.
<i>Notice on Issues Related to the Rules for Final Financial Statement Audits of Central SOEs</i>	Audit tenure exceeding 5 but below 10 years may be extended by up to 3 years with approval; total tenure shall not exceed 10 years.	
<i>Notice on Issues Concerning Accounting Firms Undertaking Final Financial Statement Audits of Central SOEs</i>	Top-ranked audit firms (top 15) are limited to 8 years; large firms auditing H-share companies may serve up to 10 years.	Lead audit firms must rank within the top 50 nationwide; participating firms should generally rank within the top 100.
<i>Notice on Auditor Selection after SOE Restructuring and Temporary Suspension of Firms</i>		Auditor selection should be independently determined by firms in compliance with regulations.

6.2. National auditing

National auditing is not only an integral component of the national governance system but also a key instrument for overseeing CSOEs. From the perspective of agency theory, it establishes a mechanism of direct principal oversight, thereby mitigating the weakening of supervision associated with extended delegation chains under state ownership. Specifically, national auditing operates through a multi-layered framework that includes both basic monitoring functions and higher-order functions such as prevention, early warning, correction and remediation (Cai and Ma, 2014). This multi-tiered arrangement is designed to address the complex agency relationships in CSOEs by constraining managerial opportunism while also limiting potential excessive intervention by government shareholders. In 2010, the National Audit Office (NAO) began to publicly disclose the audit results of central enterprise groups, providing recommendations for improvement in areas such as accounting practices, financial management, policy implementation and compliance with central regulations. The oversight of CSOEs and the promotion of improvements in operational quality and efficiency constitute core responsibilities of national auditing (Qin, 2004; Liu, 2005). At a fundamental level, national auditing converts constitutionally mandated oversight authority into an operational mechanism for controlling agency costs. Through a closed-loop process of problem identification and rectification enforcement, it contributes to the continuous improvement of governance structures. In practice, national auditing identifies major deficiencies in CSOEs, promotes standardized corporate operations, facilitates the implementation of major policy directives, ensures effective policy transmission and reveals significant risk exposures, thereby supporting sustainable development. It also strengthens follow-up actions on audit findings, which helps institutionalize long-term rectification mechanisms. Empirical evidence shows that the disclosure of audit results by the NAO generates significant market reactions (Li and Wu, 2013), improves corporate governance efficiency (Cai and Ma, 2014), enhances internal control quality (Tang and Cong, 2020) and strengthens anti-corruption outcomes (Chi et al., 2021). In addition, national auditing is associated with reduced excessive goodwill (Zhang et al., 2022), improved corporate social responsibility performance (Pan et al., 2020) and higher-quality corporate development (Dong and Zhang, 2021). Moreover, the disclosure of irregularities identified through national auditing exerts a deterrent effect on external auditors, leading to greater caution and rigor in subsequent audits of the same CSOEs (Li and Ma, 2017) (Fig. 7).

6.3. Internal control

Internal control is an essential component of the corporate governance system, and the core issue of corporate governance lies in addressing agency problems (Jensen and Meckling, 1976). By establishing effective internal control systems, firms can regulate managerial behavior, ensure alignment with overall corporate

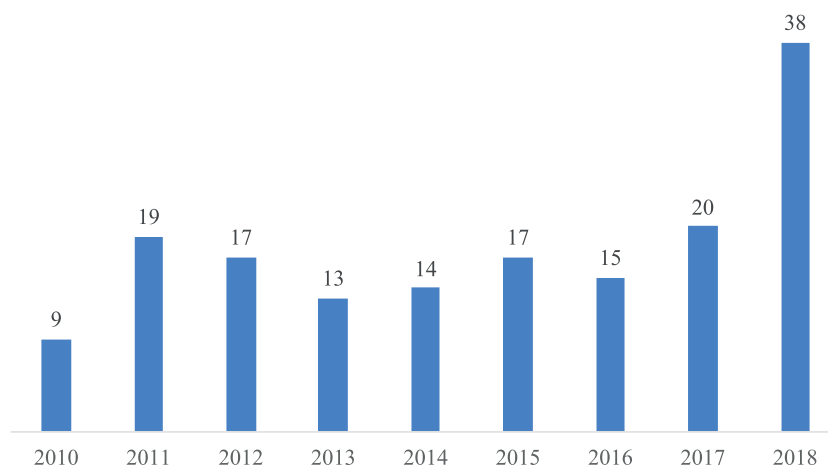


Fig. 7. Number of CSOE groups audited annually by the NAO.

interests and improve economic performance. Well-developed internal control systems also enhance transparency by enabling firms to disclose operational information more effectively to investors and other stakeholders. In CSOEs, internal control is subject to multiple layers of supervision. For example, the institutional embedding of Party organizations contributes to the development of a sound control environment. The disclosure of national audit results by the NAO significantly improves the quality of internal control in CSOEs (Tang and Cong, 2020), and Chi et al. (2021) find that stronger national auditing is associated with a lower likelihood of explicit corruption among executives. In addition, internal control and EVA-based performance evaluation jointly exert a governance effect on excessive investment. The Committee of Sponsoring Organizations of the Treadway Commission issued the *Internal Control—Integrated Framework* in 1992. In China, the MoF initiated the establishment of the Enterprise Internal Control Standards Committee in 2006, while the systematic construction of internal control systems in CSOEs only formally began in 2012. To date, there remains considerable room for further improvement and refinement of internal control systems in CSOEs. In March 2023, SASAC issued the *Notice on Strengthening Internal Control System Development and Supervision in Central Enterprises (2023)*, emphasizing the need to strengthen Party leadership over internal control management, clarify leadership responsibilities, improve accountability mechanisms and establish a well-structured and effective internal control system aligned with the standards of world-class enterprises.

6.4. Economic consequences of auditing and internal control in CSOEs: a review of the literature

6.4.1. Market reactions to the disclosure of national audit results

Most national audit reports are directed at CSOEs rather than listed firms. Li and Wu (2013) show that the magnitude of violations disclosed in audit reports helps explain differences in market reactions, as such disclosures provide incremental information about irregular economic activities to investors. This finding establishes an empirical link between the disclosure of national audit results and the economic behavior of CSOEs. According to signaling theory, markets respond positively to favorable signals and negatively to adverse information (Dechow et al., 1996). Since audit reports issued by the NAO primarily disclose problems and irregularities, they are generally interpreted as negative signals. Empirical evidence confirms that around the announcement dates of national audit reports, the stock prices of listed companies controlled by penalized CSOEs exhibit significantly negative reactions. Moreover, the more severe the violations disclosed in the reports, the stronger the negative market response (Li and Wu, 2013).

6.4.2. Corporate governance effects of national auditing

National auditing itself constitutes a form of supervision over CSOEs. During the audit process, irregularities identified in financial reporting can be addressed and sanctioned in a timely manner, thereby generating micro-level governance effects (Cai and Ma, 2014). Through the disclosure of audit results, national auditing introduces external social oversight, which strengthens deterrence against excessive on-the-job consumption and internal corruption among executives (Zhou et al., 2017). Recent studies employing textual analysis further examine the governance effects of the tone of audit reports. The tone reflects the evaluation and attitude of the state, acting as a principal, toward managerial performance, and has been shown to significantly reduce abnormal operating cash flows, abnormal production costs and abnormal discretionary expenses (Wang and Zhang, 2019). Ultimately, these effects influence real earnings management in CSOEs, thereby improving corporate governance outcomes.

6.4.3. The impact of national auditing on external auditing in CSOEs

National auditing and external auditing jointly serve as external governance mechanisms for SOEs, providing assurance on the financial reports of their common audit targets. External auditing by certified public accountants also plays an important role in national governance (Wang and Zhao, 2016). National auditing and external auditing can generate complementary supervisory effects (Pan et al., 2020). On the one hand, national auditing can make use of the outcomes of external auditing to leverage the governance advantages of different audit bodies. On the other hand, external auditing can alleviate the resource constraints faced by national auditing. In addition, national auditing affects external auditing through two channels. First, it provides reference information, generating spillover effects. Second, it transmits risk-related information to

the market, creating a warning effect. Li and Ma (2017) find that the spillover effect of national auditing reduces audit fees, whereas the warning effect increases audit fees.

6.4.4. The role of national auditing in enhancing internal control in CSOEs

Effective internal control systems provide an institutional foundation for establishing long-term governance mechanisms. The disclosure of national audit results strengthens external monitoring of internal control in CSOEs through its information effects. By revealing internal control deficiencies, national auditing promotes the development and improvement of internal control systems, thereby enhancing their effectiveness in terms of existence, underlying mechanisms and external outcomes (Tang and Cong, 2020). In addition, national auditing provides recommendations for improving specific internal control issues. During the audit process, auditors examine the design and implementation of internal controls, enabling the timely identification of deficiencies such as control failures or improper execution. By exposing weak subsidiary governance and incomplete internal control systems, national auditing facilitates in-depth analysis of the underlying causes and proposes both corrective and preventive measures. Moreover, for certain major internal control deficiencies, national auditing authorities are legally empowered to impose sanctions. Through repeated audits, national auditing further supervises and promotes the implementation of rectification measures, ensuring that recommendations are effectively carried out. Both institutional improvement and audit supervision contribute to anti-corruption governance (Chi et al., 2021).

6.4.5. Review and discussion

Research on the economic consequences of auditing and internal control in CSOEs highlights the multiple mechanisms through which national auditing improves corporate governance. From the perspective of signaling theory, the disclosure of national audit results generates significant market reactions by revealing irregularities, and the value relevance of such information reflects market recognition of national auditing. At the governance level, studies show that national auditing not only creates external pressure through the disclosure of audit results but also constrains real earnings management through the transmission of information such as the tone of audit reports. The interaction between national auditing and external auditing exhibits a dual effect: information sharing generates complementary supervision, while risk signaling affects audit pricing. In terms of internal control, national auditing promotes the transition of internal control systems in CSOEs from a compliance-oriented approach to an effectiveness-oriented approach through a closed-loop mechanism of deficiency identification, rectification recommendations and continuous supervision. Its anti-corruption effects are reflected not only in ex post enforcement but also in ex ante prevention through institutional improvement. Overall, these findings suggest that national auditing operates through multiple channels—supervision, information disclosure and prevention—in improving corporate governance in CSOEs. Future research may further examine the coordination between national auditing and Party supervision, as well as the improvement of audit effectiveness in the context of digital transformation.

7. Conclusion and implications

This study provides a theoretical and empirical analysis of the distinctive agency problems and governance mechanisms of SOEs in a transitional economy, based on the systematic reform practices of China's CSOEs since 2003. The findings show that in the process of market-oriented transformation, CSOEs exhibit agency problem characteristics that differ from those of Western firms. At the level of property rights, the features of “absent ownership” and “multi-layered delegation” inherent in state ownership give rise to a distinctive agency chain. As a result, CSOEs face a compound agency problem characterized by the coexistence of administrative intervention and insider control. This structural feature limits the direct applicability of conventional corporate governance theories, particularly with respect to standard monitoring mechanisms. With regard to incentive mechanisms, the dual “political-economic” identity of CSOE executives creates complex conditions for incentive compatibility. Managers simultaneously face dual objective functions—market performance and political evaluation. Although this institutional arrangement may generate goal conflicts, it also provides a multidimensional incentive structure that combines material incentives with promotion incentives. From the perspective of supervisory mechanisms, CSOEs have developed a hybrid governance model characterized

by Party embedding and market-based discipline. Market-oriented tools, such as EVA-based performance evaluation, provide objective benchmarks for assessing firm performance. This institutional arrangement goes beyond the traditional dichotomy between internal governance and external market discipline in corporate governance theory.

Studies have made important theoretical advances in several respects. First, the literature has gradually developed an analytical framework for agency problems in SOEs under transitional economic conditions, extending the traditional shareholder–manager perspective to a compound framework that incorporates political intervention, insider control and multi-layered delegation. This framework provides a useful perspective for understanding the governance of SOEs in emerging markets. Second, the literature has examined the institutional logic underlying China’s corporate governance practices, focusing on the interaction between political mechanisms and market-based instruments in governance. Third, research has systematically analyzed the synergistic effects of the supervisory system for SOEs, showing how Party supervision, national auditing and external auditing jointly generate governance effects through functional differentiation and institutional coordination. At the practical level, the literature provides important references for the classified reform of SOEs, particularly in terms of balancing political control and market mechanisms across firms with different functional roles.

Building on existing research progress, the governance reform of CSOEs still faces several important issues that warrant further exploration. At the level of institutional innovation, it is necessary to further advance the development of a modern enterprise system with Chinese characteristics, with a particular focus on improving market-oriented operating mechanisms and supporting measures for mixed-ownership reform. The substantive functioning of boards of directors, the more precise design of executive incentive mechanisms and the coordinated optimization of external governance mechanisms remain key factors in enhancing the efficiency of state capital allocation. At the level of reform implementation, the effectiveness of existing reform measures varies significantly across different types of CSOEs. How to implement differentiated governance based on firms’ functional roles and achieve more targeted policy implementation requires further theoretical guidance and practical exploration. At the same time, the role of CSOEs in national development strategies is becoming increasingly diversified. On the one hand, as important pillars of the national economy, CSOEs are expected to play a key role in ensuring the security of industrial and supply chains and in promoting coordinated regional development. On the other hand, under the “dual circulation” development pattern, CSOEs are required to enhance their international competitiveness and play a leading role in the restructuring of global value chains. Future reforms should focus on developing a more adaptive governance system that balances multiple dimensions, including political requirements and economic efficiency, strategic control and managerial autonomy, and scale advantages and innovation capacity. From an academic perspective, several important research directions remain open. These include the challenges posed by digital transformation to traditional governance models, cross-border governance issues in the context of globalization and the characteristics of agency relationships in mixed-ownership enterprises. Advancing research in these areas will help to further develop the governance theory of SOEs in China and provide additional perspectives for the broader study of corporate governance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Top-down monitoring and investment efficiency in state-owned enterprises: evidence from a quasi-natural experiment

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ABSTRACT

Despite their global presence, state-owned enterprises' (SOEs) corporate governance has received less attention than that of non-SOEs. Using China's central inspection team (CIT) visits as a quasi-natural experiment, we examine how central government monitoring influences local SOEs' investment efficiency. These visits may both limit local officials' interference and curb managers' pursuit of personal gains and impose excessive external responsibilities on firms. We find that investment efficiency increases after CIT visits, both in underinvesting and overinvesting firms. These effects are stronger in firms facing greater government interference, weaker internal governance or greater policy and economic uncertainty. Moreover, CIT visits affect unlisted SOEs more than listed SOEs, improve *ex-post* long-term operating performance and remain effective over time (i.e., revisit inspections). Our findings highlight the central government's role in enhancing local SOEs' investment practices, as an effective top-down corporate governance mechanism.

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1. Introduction

State-owned enterprises (SOEs) constitute a distinct and influential form of organization in both emerging and advanced economies. Their role is particularly important in regions like Europe and Asia, where they are key drivers of economic growth and strategic supervisors of critical industries. In recent decades, SOEs have

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grown significantly on the global stage, with more of them now ranking among the world's largest companies. Empirical estimates suggest that SOEs account for 13–22% of global market capitalization, contribute roughly 50% of global GDP and hold approximately US\$45 trillion in total assets (Baumöhl et al., 2019). These figures reflect their systemic importance in the global economy.

Despite their important role in economies, the corporate governance of SOEs remains less well understood. Unlike their private counterparts, SOEs have both economic and social objectives, making their governance structures and performance particularly susceptible to political interference (Wei, 2021). Agency conflicts in SOEs are especially pronounced, as managers must balance their personal ambitions, such as career advancement or alignment with government priorities, with economic efficiency. This duality often leads to adverse outcomes, such as suboptimal investment behavior, reduced operational efficiency and lower innovation and productivity (Hung et al., 2012). Moreover, traditional governance mechanisms typically used in private firms, such as director oversight and incentive-aligned compensation, often prove insufficient to address the unique agency problems of SOEs (Fan et al., 2007). Instead, the performance and accountability of SOEs often depend on the broader political and regulatory environment, emphasizing the need to study how their governance frameworks interact with government policies and enforcement.

In this study, we investigate the impact of China's central inspection team (CIT) visits—an exogenous regulatory intervention—on the investment efficiency of both listed and unlisted local SOEs. The first round of CIT visits, conducted between 2013 and 2014, was part of a national anti-corruption campaign led by the Central Commission for Discipline Inspection (CCDI). These inspections aimed to strengthen political accountability, enforce central policy directives and reduce corruption within governments and SOEs (Li et al., 2021).

This event offers a unique opportunity to study SOE governance through the lens of a top-down regulatory mechanism. Unlike market-based or internal governance mechanisms, which are often weak or compromised in SOEs (Ge et al., 2021), CIT visits represent centralized oversight from the highest level of government. This is particularly relevant because SOEs commonly suffer from soft budget constraints, limited exposure to capital market discipline and ineffective internal controls (Jian and Wong, 2010; Gu et al., 2020). In such contexts, top-down interventions may be one of the few viable tools for realigning managerial behavior with policy and economic efficiency goals. Understanding how central inspections affect SOE decision-making is therefore essential to evaluate the broader role of the state in corporate governance.

By examining whether CIT visits improve investment efficiency—a persistent challenge for SOEs due to political interference and low profit incentives (Chen et al., 2011; Song et al., 2011)—we shed light on the effectiveness and limitations of hierarchical governance in state-dominated economies. These inspections may generate a dual dynamic. On the one hand, they may constrain local officials' interference in corporate investment decisions, reduce overinvestment and policy uncertainty and enhance governance discipline. On the other hand, they may reinforce the external obligations of SOEs, potentially diverting resources from economically optimal investments. Research highlights this trade-off, showing that government influence often compromises firms' financial performance (An et al., 2016). Given these opposing forces, the overall impact of CIT visits on investment efficiency remains an open empirical question.

Using a difference-in-differences (DID) design combined with propensity score matching (PSM) to address endogeneity concerns, we find that CIT visits lead to a significant improvement in investment efficiency among local SOEs. The effects are both economically meaningful and statistically significant for firms prone to overinvestment or underinvestment, suggesting that CIT visits help to correct resource misallocation by disciplining managerial decisions. Our baseline findings are robust to various alternative specifications, including different investment efficiency measures, test windows and matching procedures.

We also explore the mechanisms behind the improvement in investment efficiency following CIT visits. Our results indicate that the impact of CIT visits is stronger for firms experiencing higher levels of local government interference, weaker internal corporate governance and greater policy and economic uncertainty. This suggests that CIT visits enhance investment efficiency by (1) curbing excessive local government intervention in SOE operations (*intervention constraint channel*), (2) compensating for weaker internal governance structures (*governance channel*) and (3) reducing the negative effects of uncertain policy and economic environments (*information channel*).

We conduct several additional analyses to better understand the scope and persistence of the effects of CIT visits. First, we examine the heterogeneity between listed and unlisted SOEs, which differ significantly in their

exposure to capital markets and their internal governance structures. We find that although CIT visits improve investment efficiency in both types of firms, the effect is stronger among unlisted SOEs, where traditional governance mechanisms tend to be weaker (Sun and Teo, 2019). This suggests that top-down government inspections can serve as an important external governance mechanism, particularly in segments of the corporate sector that are less transparent and subject to less market discipline.

Second, we extend our analysis to subsequent CIT visits—the revisit inspections conducted in 2018—and find that these subsequent inspections continue to yield improvements in investment efficiency. Our results also indicate a gradual weakening of regulatory impact over time, potentially due to reduced enforcement intensity or declining political salience in follow-up inspections, echoing the cyclical dynamics of regulatory oversight documented in prior studies (Dechenaux and Samuel, 2012).

Lastly, we assess whether CIT visits translate into real financial improvements by examining operating performance post-inspection. Our results show that firms experience sustained increases in return on assets (ROA) over 3-, 4- and 5-year windows, indicating that enhanced investment efficiency leads to increased long-term profitability. Together, these analyses offer a more comprehensive picture of how central government oversight affects not only decision-making quality but also longer-term firm outcomes in China's state sector.

Our study contributes to the literature in several ways. First, our study highlights the role of centralized government inspections as a distinct and underexplored form of external governance in SOEs. Although research has largely focused on external monitors such as institutional investors (Cao et al., 2022) and controlling shareholders (Lin et al., 2023), we examine a top-down disciplinary mechanism with formal authority: the CITs. Unlike market-based or regulatory monitoring bodies, CITs serve as exogenous enforcers of central directives and anti-corruption mandates. By focusing on how CITs affect SOE governance, our study contributes to the literature on local government intervention and central–local dynamics (e.g., Nguyen et al., 2020), providing new evidence that centralized disciplinary interventions can realign local decision-making. Specifically, we find that CIT visits reduce collusion between local governments and SOE managers, thereby curbing interference and improving investment efficiency. These findings suggest that centralized oversight can substitute for weak internal or market-based governance mechanisms in transition economies.

Second, we add to the literature on investment distortions by showing that centralized inspections not only address the commonly studied problem of overinvestment but also alleviate underinvestment. Although the corporate governance literature mainly emphasizes controlling investments driven by empire-building or soft budget constraints (Bertrand and Mullainathan, 2003; Boubakri and Saffar, 2019), we show that uncertainty and weak managerial incentives can also result in underinvestment in SOEs. CIT visits enhance policy clarity and reduce perceived risk, thus facilitating more efficient capital allocation. These findings enrich the literature on investment efficiency by highlighting how government oversight can help correct both forms of inefficiency and promote more optimal investment levels in the presence of institutional frictions and managerial risk aversion.

Third, our study contributes to the literature by distinguishing between listed and unlisted SOEs, a distinction often overlooked in prior research that focuses primarily on listed firms. Listed SOEs are typically subject to greater market scrutiny, disclosure requirements and corporate governance pressures, while unlisted SOEs tend to operate with less transparency and may be more influenced by administrative directives. Our findings show that these institutional differences significantly affect the effectiveness of CIT visits as a governance tool. By separately examining the behaviors and responses of these two types of SOEs, we shed light on the heterogeneity of state ownership.

Finally, our study responds to recent calls for more research on the real outcomes of anti-corruption campaigns (e.g., Smith, 2016). By documenting long-term improvements in operating performance and exploring heterogeneity across firm types (i.e., listed vs. unlisted SOEs), we offer a more comprehensive view of how disciplinary inspections reshape firm behavior. This provides a better understanding of how institutional enforcement, beyond deterrence, can induce organizational reform and improve economic outcomes.

The remainder of this paper proceeds as follows: Section 2 outlines the institutional background and hypothesis development; Section 3 describes the methodology and data; Section 4 presents the main results and robustness tests; Section 5 explores the underlying mechanisms; Section 6 discusses additional analyses; and Section 7 concludes the study.

2. Literature, institutional background and hypothesis development

2.1. Traditional corporate governance and SOEs

As SOEs play a more prominent role in national and global economies, their corporate governance has become an increasingly important subject of study. SOEs differ substantially from private firms, their governance structures often being characterized by government ownership and involvement. These unique characteristics make it difficult to ensure efficient investment decisions, as managers may be influenced by goals other than financial efficiency (Hung et al., 2012).

In private firms, corporate governance mechanisms are typically designed to solve principal–agent problems by aligning the interests of managers with those of shareholders. These mechanisms include performance-based compensation, board oversight, market discipline and shareholder activism. However, they often break down or operate ineffectively in the context of SOEs due to the fundamentally different nature of their ownership and control (Lin et al., 2023).

First, SOEs are characterized by a more complex and diffused principal structure. Although the state is the ultimate owner, monitoring responsibilities are delegated to bureaucrats or political representatives who often lack the incentives—or the ability—to effectively oversee managers (Quan and Zhang, 2021). This creates a classic “multiple principals” problem, where overlapping authority leads to free-riding among oversight agents, low accountability and inadequate managerial discipline (Wan et al., 2015; Su and Alexiou, 2022).

Moreover, unlike private firms where boards of directors are expected to serve the interests of shareholders, SOE boards are often composed of political appointees representing various ministries or government departments. Instead of improving governance, these boards may exacerbate agency problems by serving discretionary political agendas rather than focusing on firm performance (Bebchuk and Weisbach, 2010). The politicization of boards and executive appointments compromises meritocracy and impedes strategic decision-making based on market logic (Fan et al., 2007). This contrasts sharply with the private sector model, where board independence and shareholder pressure help to discipline underperforming managers.

Traditional incentive structures such as pay-for-performance contracts are also less effective in SOEs due to the multiplicity of objectives they pursue (Cao et al., 2019; Huang et al., 2026). While private firms focus primarily on profit maximization, SOEs often serve broader social mandates such as job creation, regional development and maintaining price stability (Shi et al., 2024). These non-commercial objectives complicate performance assessment and make it difficult to link managerial compensation to firm outcomes in a meaningful way (Bai et al., 2006; Firth et al., 2013). As a result, managers are less likely to be held accountable for inefficient investment decisions or inadequate operational underperformance.

Furthermore, the soft budget constraints prevalent in SOEs weaken the disciplining effect of financial markets (Boubakri and Saffar, 2019). Unlike private firms, which face the threat of bankruptcy or hostile takeovers if they perform poorly, SOEs often enjoy implicit state guarantees that protect them from market penalties (Dong et al., 2021). This reduces the urgency of effective management and may even encourage excessive risk-taking or resource misallocation, knowing that losses will be absorbed by the state.

Finally, principal–principal problems are especially pronounced in SOEs, where the controlling shareholder may extract resources to serve its goals at the expense of minority shareholders or long-term value. This includes practices such as requiring SOEs to sell goods below market price, forcing them to support failing firms in the same government network or diverting resources to related projects (Cheung et al., 2021). In private firms, such behavior would be classified as tunneling or expropriation, but in SOEs it is often institutionalized and opaque, undermining corporate transparency and investor trust.

Given that traditional corporate governance frameworks assume profit-driven principals and well-aligned agents, they often prove inadequate when applied to SOEs. In SOEs, government objectives, bureaucratic appointments and multiple, sometimes conflicting, mandates weaken managerial accountability and financial incentives. Therefore, we examine the role of China’s CIT visits as a potential corrective mechanism on the investment efficiency of local SOEs.

2.2. Institutional background of CIT visits

A key feature of CIT visits is their top-down design, which is crucial to their governance role. Unlike local inspections, which may be vulnerable to regional favoritism and incentives to embellish local economic performance, CIT visits are conducted by central authorities, thus limiting local interference and more closely aligning firm behavior with national priorities.

Launched in 2013 as a pillar of the anti-corruption campaign, the CIT mechanism functions as a centralized oversight tool administered by central authorities. These inspections target provincial governments, ministries and SOEs, typically on standardized 3-month cycles. Their overarching objectives are to strengthen political discipline, uncover corruption and rent-seeking behavior and ensure that local bureaucracies and SOEs remain responsive to central mandates.

The first round of CIT visits, which began in May 2013, dispatched 10 teams to provinces such as Jiangxi, Hubei, Chongqing and Guizhou, as well as to major SOEs including the China Grain Reserves Corporation. These missions marked a shift in governance philosophy, emphasizing direct vertical control over decentralized bureaucratic discretion. Operating under the authority of the CCDI, the CIT mechanism was rapidly institutionalized: the subsequent rounds, throughout 2014, extended its geographic and sectoral coverage.

What distinguishes CIT visits from other governance tools is their top-down structure and institutional independence. According to the policy document “Regulations on the Work of Inspection”, the CIT system adheres to “three non-fixed” principles: team leaders are not fixed, inspection targets are not fixed and team–target pairs are random. Each inspection team comprises approximately eight experts drawn from central agencies, selected temporarily to reduce capture and conflicts of interest.¹

The supervision model combines vertical enforcement with public participation. CITs collect complaints through online platforms, telephone hotlines and on-site visits. Since 2013, more than 1.95 million petition reports have been received, representing a 50% increase relative to the pre-inspection period. In addition, more than 43,000 interviews and 18,000 verification procedures have been conducted, establishing a factual basis for subsequent disciplinary action.²

A defining feature of CIT inspections is their “sink-in” approach to supervision. Teams review internal party documents, analyze firm-level decisions, verify personal asset disclosures and assess adherence to organizational norms. Public accountability is enforced: disciplinary measures, which often include demotions or dismissals, are widely publicized through state-controlled media. For instance, in the first wave of inspections alone, more than 32 provincial and ministerial officials were sanctioned.³

Beyond their anti-corruption mission, CIT visits serve a vital policy transmission function. They help to enforce compliance with economic and regulatory policies by directly communicating central government priorities to SOE leaders and local officials. This mechanism improves vertical coordination, reduces political uncertainty and fosters policy consistency at all levels of government (Pan et al., 2022).

Thus, as a governance mechanism, CIT visits offer a rare combination of disciplinary power and central oversight, uniquely suited to the institutional challenges of SOEs. By constraining local favoritism, imposing career consequences for mismanagement and reasserting central political authority, CIT inspections may mitigate long-standing governance deficits. At the same time, their role in enforcing political priorities may crowd out purely economic objectives. This dual role as an enforcement tool and a policy transmitter offers a novel empirical context for assessing whether centralized governance can improve investment efficiency where market-based oversight mechanisms are insufficient.

2.3. CIT visits and investment efficiency

Investment efficiency is often a major concern for SOEs because of their significant influence on national development and resource allocation. Studies show that SOEs tend to allocate capital less efficiently than private firms (Song et al., 2011), as they are more susceptible to government interference and less motivated by

¹ More details are available at https://www.ccdi.gov.cn/djfg/fgsy/201603/t20160311_114378.html.

² More details are available at https://www.ccdi.gov.cn/toutiao/201401/t20140110_123248.html.

³ More details are available at <https://fanfu.people.com.cn/n/2014/0114/c350251-24115010.html>.

profit maximization (Chen et al., 2011). In particular, SOEs in emerging markets, such as China and India, often make more inefficient investments than private firms, due to the dual pressure of government objectives and market dynamics (Chen et al., 2011; Srinivasan and Thampy, 2017). However, in some cases, SOEs with strong governance structures and limited political interference exhibit investment outcomes comparable to those of private firms, suggesting that governance mechanisms can play a major role in enhancing investment efficiency.

We argue that CIT visits can address governance challenges in SOEs and serve as an effective external mechanism to reduce inefficiencies in their investment decisions through three channels.

Intervention constraint channel: First, CIT visits help to curb political interference from local officials, a major source of distorted investment decisions in SOEs. Local governments often pressure SOEs to pursue projects aligned with regional objectives, such as job creation or GDP growth, even when these initiatives lack economic justification (Chen et al., 2011; Lyu et al., 2018). These interferences are often driven by political reasons such as electoral support or regional development rather than by commercial logic (Adelino and Dinc, 2014; Hassan et al., 2019). As a result, SOE managers frequently overinvest in politically motivated projects that undermine capital efficiency (Chen et al., 2020; Du and Heo, 2022). In highly regulated environments like China and Russia, SOEs may also be compelled to invest in infrastructure or social programs to support broader political goals (Chernykh, 2008; Duchin and Sosyura, 2012). CITs, appointed by the central authority, function as an independent oversight body that monitors and deters such interference. By investigating financial decisions and exposing cases where local officials push for politically motivated or corrupt initiatives, CITs help to protect SOEs from undue influence. Their ability to report findings to higher authorities enhances transparency and creates a deterrent effect against local-level corruption and the misuse of SOE resources (Chen and Kung, 2019; Li et al., 2021).

Governance channel: Second, CIT visits can enhance the internal governance quality of SOEs by curbing managerial opportunism and fostering greater accountability. This is particularly important because SOE managers often pursue private interests, such as political connections, personal gain or career advancement, that are misaligned with the interests of the state and other shareholders (Zheng et al., 2024; Liu et al., 2025). This misalignment may result in both overinvestment driven by empire-building or political agendas and underinvestment stemming from risk-averse behavior focused on short-term stability (Bertrand and Mullainathan, 2003; Bebchuk and Weisbach, 2010). Governance weaknesses are also reflected in SOE board structures, where political appointees can dilute the effectiveness of independent directors and hinder the board's ability to challenge poor decisions (Wang and Xu, 2022). CITs help to mitigate these issues by conducting interviews, auditing financial records and scrutinizing board activities, thereby compelling managers to justify their investment decisions and discouraging opportunistic behavior (Amiram et al., 2018). This scrutiny helps to flag economically unjustified initiatives and contributes to more efficient capital allocation (Chowdhury et al., 2021). Moreover, the presence of CITs encourages firms to strengthen their internal governance structures, such as formalizing risk assessment practices (Hope et al., 2020). Because CIT members are selected for their expertise and are independent from local interests, they provide objective evaluations that help depoliticize SOE governance.

Information channel: Finally, CIT visits help to reduce information asymmetry in two critical directions: upward, by ensuring that accurate financial and operational data from SOEs reach central authorities; and downward, by clarifying central government policies for local implementation. Through on-site inspections and review of internal reports, CITs provide central decision-makers with credible, firsthand information, enhancing oversight quality and informing more effective policy design. Simultaneously, by communicating policy expectations and resolving ambiguities of interpretation, CITs help SOEs better understand and align with national objectives.

This dual flow of information is especially important given that uncertainty is a well-documented barrier to corporate investment, including in innovation, R&D and M&A activities (Chen et al., 2024; Dube, 2024). By minimizing policy ambiguity and regional inconsistencies, CITs reduce uncertainty and promote more strategic and informed investment decisions (Amore and Minichilli, 2018; Bird et al., 2023). Moreover, this channel is crucial to ensuring the effectiveness of the first channel, namely curbing government interference. For CITs to be able to guide local officials without introducing their own political agendas or biases, their decisions must be grounded in comprehensive and accurate information. The legitimacy and success of their oversight role

depend on their ability to make informed, objective judgments that align with the firm's long-term interests rather than short-term political considerations. As such, reducing information asymmetry is not only beneficial; it is fundamental to the sound and unbiased governance that CITs are meant to provide.

Despite these positive channels, we also acknowledge that CIT visits may harm investment efficiency by imposing additional obligations on SOEs, which could have important implications for their decision-making and resource allocation. These visits may pressure SOEs to increase their investments in politically sensitive or socially priority sectors, even if such investments are not aligned with the firms' long-term strategic goals or market conditions. Moreover, the need to comply with increased political scrutiny and social expectations can generate substantial compliance costs, which may reduce operational flexibility and hinder the ability of SOEs to respond quickly to market changes. These factors may lead to inefficiencies and distortions in the allocation of capital and managerial attention. Finally, the impact of external monitoring on investment efficiency may not always be immediate or predictable. Overconfident managers or controlling shareholders may resist change, thereby delaying the reduction of overinvestment or underinvestment. Therefore, although CIT visits aim to strengthen oversight and governance, their actual effects on SOE performance and behavior are complex and multifaceted. Hence, the real impact of CIT visits remains an empirical question that warrants rigorous investigation. As such, we propose the following hypotheses:

Hypothesis 1a: *CIT visits increase local SOEs' investment efficiency.*

Hypothesis 1b: *CIT visits reduce local SOEs' investment efficiency.*

The empirical evidence we present allows us to determine whether CIT visits are indeed an effective institutional mechanism for addressing agency problems and curbing political distortions in SOE governance.

3. Sample, variables and methodology

3.1. Sample and identification strategy

Our initial sample includes both listed and unlisted local SOEs. Listed SOEs are traded publicly on the Shanghai and Shenzhen stock exchanges, while unlisted SOEs refer to firms that are not publicly listed but have issued public bonds, as only these firms are required to disclose financial data. This addresses a limitation of prior studies, which focus solely on publicly traded firms, potentially overlooking the heterogeneity of how state ownership interacts with market oversight through different financing channels.

Our sample period extends from 2009 to 2018, covering 4 years before and after the CIT visit years (2013–2014).⁴ We exclude financial firms due to their distinct accounting standards and regulatory requirements. Central SOEs are also excluded because they are directly monitored by the State-owned Assets Supervision and Administration Commission (SASAC) of the State Council and are only required to submit their annual budget plans and financial reports to SASAC, rather than being subject to local government oversight. To improve data consistency and reliability, we further remove firms that have received special treatment (ST), have been warned of delisting risks, have defaulted on bonds or lack key financial variables needed for analysis.

Our identification strategy relies on the variation in exposure to CIT inspections across provinces and firm types. Given that CIT inspections are designed to monitor and penalize misconduct by provincial-level bureaucrats and corporate executives, local SOEs are more directly targeted by these inspections than non-SOEs. Accordingly, we define the treatment and control groups as follows (Kim et al., 2023; Tan and Cui, 2026): the treatment group includes local SOEs located in provinces that received a CIT visit during the sample period, while the control group comprises non-SOEs in the same provinces and years.

To mitigate selection bias from observable firm characteristics, we adopt the PSM approach (Shipman et al., 2017). This strategy enables a quasi-experimental comparison between SOEs and observationally similar

⁴ We use a longer sample period of 4 years before and after CIT inspections rather than the three quarters used in Pan et al. (2022), because it may take longer for a firm to adjust its investment preferences and improve its corporate investment efficiency than to reduce its earnings management. Chay et al. (2023) argue that it takes several years for firms to optimize their investment decisions, supporting our choice of test windows. We also use alternative test windows in robustness tests and our main results still hold.

Table 1
Covariate balance after PSM procedure and descriptive statistics.

Panel A: Covariate balance after propensity score matching procedure.

Variable	Mean		Mean Difference	P Value
	Treatment	Control		
SIZE	22.406	22.356	0.050	0.08
LEV	0.109	0.105	0.004	0.19
ROA	0.028	0.029	−0.001	0.51
CFLOW	0.038	0.040	−0.002	0.32

Panel B: Descriptive statistics.

Variable	N	Mean	S.D.	Q1	Median	Q3
INVEST	6867	0.055	0.095	0.004	0.034	0.083
UNDER	6867	0.465	0.262	0.200	0.400	0.600
TOUR	6867	0.487	0.500	0.000	0.000	1.000
SIZE	6867	22.640	1.338	21.670	22.610	23.650
LEV	6867	0.152	0.137	0.031	0.117	0.245
TANG	6867	0.429	0.195	0.288	0.426	0.578
CFLOW	6867	0.049	0.537	−0.010	0.068	0.188
LOSS	6867	0.906	0.292	1.000	1.000	1.000
SLACK	6867	8.600	58.790	0.243	0.682	2.139
FLOW_SD	6867	0.549	2.232	0.049	0.091	0.258
SALE_SD	6867	0.133	0.145	0.042	0.088	0.169
INV_SD	6867	0.076	0.105	0.026	0.048	0.087
LEV_IN	6867	0.146	0.086	0.073	0.138	0.209
SOE	6867	0.813	0.390	1.000	1.000	1.000
LIST	6867	0.791	0.406	1.000	1.000	1.000

Notes: Panel A compares the differences in the key firm-level characteristics between local SOEs and private firms after propensity score matching procedure. We use firm size (SIZE), long-term debt-to-assets ratio (LEV), return-on-assets ratio (ROA), and cash-to-assets ratio (CFLOW) as matching covariates. We use one-to-one nearest neighbor matching without replacement and we set the caliper to 0.05. The results show that the bias between the treatment and control groups decreases after propensity-score-match procedure. Panel B reports the descriptive statistics for the main variables.

non-SOEs by matching them on pre-treatment characteristics, thereby improving the balance of covariates and internal validity.

We implement one-to-one nearest neighbor matching without replacement, using a caliper width of 0.05, following Allen et al. (2023). The logit model includes pre-treatment firm characteristics, firm size (SIZE), long-term leverage (LEV), return on assets (ROA) and cash flow (CFLOW), either in 2012 or 2013 (the year before the CIT visits). These covariates proxy for firms' investment capacity, financial health and operational efficiency.

After the matching procedure, we compare the means and standardized differences of the matching covariates between the treatment and control firms. As shown in Table 1, Panel A, the differences in firm characteristics between SOEs and matched non-SOEs are not statistically significant, and all standardized mean differences fall below 5%, indicating that our matching achieves covariate balance. This result suggests that, conditional on observable characteristics, the SOEs and non-SOEs in our final matched sample are comparable.

The final PSM-matched sample consists of 6867 firm-year observations with 826 unique firms spanning the symmetric event window from 2009 to 2018.⁵ This window allows us to capture the short-term and medium-term effects of CIT visits while minimizing bias from long-term macroeconomic changes or firm-specific time trends. Of the 826 firms, 627 are publicly listed SOEs and 199 are unlisted SOEs.

⁵ As robustness checks, we use alternative matching procedures, placebo tests and additional sensitivity analyses, which are reported in Section 4.

For all listed SOEs, their financial data used in the analysis are obtained from the China Stock Market and Accounting Research (CSMAR) database and the Wind Financial Terminal (WIND). For unlisted SOEs, we manually collect their annual financial reports from the WIND Bond Datasets. It is important to note that because our sample includes unlisted firms, the covariates available for matching and the regression controls are often limited due to the scarcity of data for these firms. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers, and all standard errors are clustered at the firm level to correct for heteroskedasticity and serial correlation.

3.2. Variables and descriptive statistics

The key dependent variable in our analysis is INVEST, which captures firm-level investment activity. Following Aghamolla and Hashimoto (2023), INVEST is measured as the sum of capital and acquisition expenditures less the proceeds from the sale of property, plant and equipment, scaled by lagged total assets.

Our primary independent variables include TOUR and UNDER. TOUR is a dummy variable equal to 1 if, in a given year, the province where the firm is located is subject to a CIT visit or for any year following the inspection. This variable captures the treatment effect of central inspections.

UNDER is a proxy used to detect settings in which there is a greater likelihood of underinvestment or overinvestment problems. Following García Lara et al. (2016), we identify industry-year combinations where there is aggregate underinvestment or overinvestment at the industry level. To do so, we estimate the following regression:

$$INVEST_{I,t} = \alpha_0 + \alpha_1 \times GROWTH_{I,t} + \mu_{I,t} \quad (1)$$

In Eq. (1), the dependent variable INVEST is the average investment of all firms in each industry-year group (I, t). The independent variable GROWTH, a proxy for investment opportunities, is the average sales growth of all firms in each industry-year group, where the sales growth of each firm is calculated as $\Delta SALES_{i,t-1} / SALES_{i,t-2}$. To ensure the reliability of the computed averages, we require a minimum of 20 firms per industry-year. The industry groups correspond to the two-digit industry classifications provided by the WIND datasets. To determine whether underinvestment or overinvestment is more frequent at the industry-year level, we proceed as follows. First, we multiply the residuals of Eq. (1) by -1 . Next, we rank these values into deciles and normalize the rankings on a 0–1 scale. We call this final measure UNDER. Each firm is then assigned the corresponding UNDER value based on its industry and year. High values of UNDER indicate settings where underinvestment is more likely, while low values suggest a greater likelihood of overinvestment.

We include control variables commonly used in the literature on investment efficiency (García Lara et al., 2016). These include firm size (SIZE), leverage ratio (LEV), asset tangibility (TANG), cash flow from operations scaled by assets (CFLOW), an indicator of frequent losses (LOSS), financial slack (SLACK), cash flow volatility (FLOW_SD), sales volatility (SALE_SD) and investment volatility (INV_SD). We also include the industry capital structure (LEV_IN) to control for industry-wide financial conditions. Importantly, we include firm fixed effects to absorb time-invariant unobservable characteristics at the firm level, such as baseline corporate governance quality and political connections, which may systematically differ between SOEs and non-SOEs. Given the inclusion of unlisted SOEs, whose data availability limits the range of observable firm-level indicators, these firm fixed effects are especially important for addressing omitted variable bias. Year fixed effects are also included to account for macroeconomic shocks and policy changes over time. All variables are defined in Appendix A.

Table 1, Panel B, reports the summary statistics of the main variables in the PSM sample. The mean value of INVEST is 0.055, suggesting that capital investments average 5.5% of total assets. The coefficient of variation for INVEST is 1.72 (0.095/0.055), which aligns closely with the findings of prior research (e.g., Jiang et al., 2018). The descriptive statistics of the remaining control variables are also broadly consistent with those reported in previous studies, reinforcing the representativeness of our sample.

Panel C reports the correlation matrix for the key variables in our analysis. Notably, our primary dependent variable, INVEST, exhibits a statistically significant negative correlation with TOUR, consistent with the idea that firms that overinvest reduce their capital expenditures after CIT visits. Given the variation in correlation magnitudes across variables, we compute the variance inflation factors (VIFs) for all regression speci-

fications (Lennox et al., 2012). The VIFs remain well below the threshold of 10.0 in each model, indicating that multicollinearity is not a major concern in our empirical analysis (Bae et al., 2017).

3.3. Research methodology

Corporate investment decisions and financial performance often take considerably more time to adjust than leverage, cash holdings or payout policies (Chay et al., 2023). Therefore, a longer sample period is desirable to fully capture the impact of CIT visits on investment efficiency. However, using an extended observation window increases the risk of confounding from unobserved factors such as national time trends (Yagan, 2015) or business cycle fluctuations (Winberry, 2021), which may influence investment efficiency independently of CIT visits.

To address these concerns, we adopt a DID methodology to estimate the causal effect of CIT visits. The core idea of this approach is to compare changes in investment efficiency over time between a treatment group (local SOEs in CIT-visited provinces) and a control group (non-SOEs in the same province-years), effectively removing bias from time-invariant differences and common time shocks. Combined with PSM and firm fixed effects, the DID framework allows us to more credibly identify the causal impact of CIT visits on investment behavior.

Our tests are based on the methodology of García Lara et al. (2016), which allows us to analyze how financial reporting quality affects both overinvestment and underinvestment. We adapt their model to examine the impact of CIT visits on investment efficiency as follows:

$$INVEST_{i,t} = \beta_0 + \beta_1 \times TOUR_{i,t} + \beta_2 \times TOUR_{i,t} \times UNDER_{i,t} + \beta_3 \times UNDER_{i,t} + \delta_i Controls_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

In Eq. (2), the dependent variable $INVEST_{i,t}$ is the total investment, where i and t denote the firm and the year, respectively; the independent variable $TOUR_{i,t}$ is an indicator of CIT visits; and the independent variable $UNDER_{i,t}$ is the likelihood of underinvestment or overinvestment problems.

We use Eq. (2) to test our main hypotheses, that is, whether CIT visits increase the investment efficiency of both underinvesting and overinvesting firms. β_1 and β_2 are the coefficients of interest and represent the effect of CIT visits on corporate investment efficiency. When overinvestment is more likely (i.e., $UNDER = 0$), β_2 reflects the effect of CIT visits. A significant and negative β_1 would suggest that CIT visits prompt overinvesting firms to reduce their excessive investments. When underinvestment is more likely (i.e., $UNDER = 1$), the relevant effect is captured by the sum of $\beta_1 + \beta_2$. A significant and positive value would indicate that underinvesting firms increase their investments following CIT visits.

4. CIT visits and investment efficiency

4.1. Main results

We begin by examining the relationship between CIT visits and corporate investment efficiency. Table 2, Panel A, presents the regression results based on Eq. (2). Columns (1) and (2) report the univariate and multivariate analyses for $INVEST$, respectively. The coefficients on $TOUR$ are -0.024 and -0.030 , both statistically significant at the 1% level. These results indicate that CIT visits are associated with a significant reduction in subsequent investment expenditures for firms with a greater likelihood of overinvestment, suggesting that CIT oversight constrains excessive investment behavior.

To assess the net effect of CIT visits on underinvesting firms, we examine the sum of the coefficients on $TOUR$ and the interaction term $TOUR \times UNDER$, following García Lara et al. (2016). In Column (2), the sum of $TOUR$ and $TOUR \times UNDER$ is positive and significant (i.e., $\beta_1 + \beta_2 = 0.007$, $F\text{-stat} = 8.33$). This finding supports the idea that CIT visits lead firms more likely to underinvest to increase their investments, effectively alleviating underinvestment problems.

Notably, the effects of CIT visits appear to be better at curbing overinvestment than underinvestment. This asymmetry is consistent with the idea that government oversight is particularly effective at constraining man-

Table 2
Effect of the CIT visits on firms' investment efficiency.

Panel A: Main results.

Dependent variable	(1) INVEST	(2) INVEST
TOUR	−0.024*** (−3.06)	−0.030*** (−3.80)
TOUR × UNDER	0.030*** (3.02)	0.037*** (3.80)
TOUR + TOUR × UNDER	0.006*** (5.27)	0.007*** (8.33)
UNDER	−0.090*** (−8.77)	−0.094*** (−8.67)
SIZE		−0.029*** (−5.42)
LEV		−0.031 (−1.40)
TANG		−0.053*** (−3.22)
CFLOW		0.000 (0.04)
LOSS		0.034*** (6.18)
SLACK		0.000 (0.58)
FLOW_SD		−0.000 (−0.15)
SALE_SD		0.038** (2.16)
INV_SD		−0.062** (−2.56)
LEV_IN		−0.003 (−0.13)
Intercept	0.102*** (18.24)	0.749*** (6.18)
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	6867	6867
Adj. R-squared	0.017	0.057

Panel B: Timing tests.

Dependent variable	(1) INVEST	(2) INVEST
BEFORE ^{−4}	0.011 (0.77)	0.022 (1.45)
BEFORE ^{−4} × UNDER	−0.008 (−0.43)	−0.015 (−0.65)
BEFORE ^{−4} + BEFORE ^{−4} × UNDER	0.003 (0.31)	0.007 (1.30)
BEFORE ^{−3}	−0.008 (−0.67)	−0.003 (−0.25)
BEFORE ^{−3} × UNDER	0.010 (0.62)	0.011 (0.66)
BEFORE ^{−3} + BEFORE ^{−3} × UNDER	0.002 (0.24)	0.008 (0.33)
BEFORE ^{−2}	0.002 (0.20)	0.004 (0.39)
BEFORE ^{−2} × UNDER	0.008 (0.50)	0.008 (0.51)

(continued on next page)

Table 2 (continued)

Panel B: Timing tests.

Dependent variable	(1) INVEST	(2) INVEST
BEFORE ⁻² + BEFORE ⁻² × UNDER	0.010 (0.88)	0.012 (1.45)
CURRENT	-0.022** (-2.33)	-0.024** (-2.56)
CURRENT × UNDER	0.041*** (2.77)	0.046*** (3.19)
CURRENT + CURRENT × UNDER	0.019** (3.85)	0.022*** (5.24)
AFTER ¹⁺	-0.029*** (-2.82)	-0.033*** (-3.34)
AFTER ¹⁺ × UNDER	0.029** (2.28)	0.038*** (3.03)
AFTER ¹⁺ + AFTER ¹⁺ × UNDER	0.000** (3.98)	0.005*** (5.88)
Controls included	No	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	6867	6867
Adj. R-squared	0.018	0.058

Notes: This table presents the main results and parallel trends assumption tests from regressions of CIT visits on firms' investment efficiency using the difference-in-differences design. Panel A presents the main results. INVEST is the total investment measured as the sum of capital expenditures, research and development, and acquisition expenditures; less the sales of property, plant, and equipment; scaled by the lagged total assets. TOUR is an indicator of the CIT visits, and it equals one for years during which the province of firm *i* is experiencing an inspection and for the following years after the CIT visits. Panel B presents the timing tests from regressions of CIT visits on firms' investment efficiency. We break down the variable timing indicator variable into dimensions corresponding to the four, three, and two years before (BEFORE⁻⁴, BEFORE⁻³, BEFORE⁻²), during (CURRENT), and after the central inspection (AFTER¹⁺). Other variables are as defined in Appendix A. The standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

agerial empire-building and reducing wasteful capital expenditures, but less effective at promoting risk-taking or innovation, which are often needed to remedy underinvestment.

The coefficients of the control variables are both qualitatively and statistically consistent with those reported in Chen et al. (2017), confirming the robustness of our specification. Collectively, these results demonstrate that CIT visits effectively enhance corporate investment efficiency by curbing overinvestment while mitigating underinvestment problems.

To validate the key identification assumption underlying our DID approach, namely the parallel trend assumption, we conduct a dynamic timing test. Specifically, we include a series of lead and lag time indicators and their interactions with the treatment indicator. BEFORE⁻⁴, BEFORE⁻³ and BEFORE⁻² are dummy variables for the 4th, 3rd and 2nd years preceding the CIT visit, respectively. Statistically significant coefficients on these lead time indicators would indicate pre-existing differences in investment behavior between the treatment and control firms, thus violating the parallel trend assumption (Chay et al., 2023).

We also include contemporaneous and post-treatment dummies, CURRENT and AFTER¹⁺, to capture the immediate and subsequent effects of CIT visits. Beyond testing the validity of our DID design, this dynamic specification helps to mitigate endogeneity concerns by revealing the temporal evolution of treatment effects (Bertrand and Mullainathan, 2003).

We examine the parallel trend assumption in Table 2, Panel B. Column (1) reports the results without controls, while Column (2) includes all controls. In both columns, the coefficients on BEFORE⁻⁴, BEFORE⁻³ and BEFORE⁻² are not statistically significant, indicating that the pre-treatment investment trends between the treatment and control firms are not significantly different. This validates the parallel trend assumption.

Importantly, the coefficients on CURRENT and AFTER¹⁺ are significant and negative, while the interaction terms are positive and significant at the 1% level. These findings suggest that CIT visits improve investment efficiency immediately and that the external monitoring effect persists over time. In summary, the results highlight the ability of CIT visits to effectively oversee and discipline managerial investment decisions in local SOEs.

4.2. Robustness tests

Alternative measure of investment efficiency: To further validate our findings, we use an alternative measure of investment efficiency based on the deviation between a firm's actual investment and its optimal investment level (Chay et al., 2023). Following prior research (Godsell et al., 2023), we define optimal investment as a function of growth opportunities, proxied by sales growth. This approach is based on the theoretical premise that, in frictionless markets, investment should be positively correlated with growth opportunities. Our empirical procedure involves estimating optimal investment as the predicted values from industry-year regressions of firm-level investment on lagged sales growth. Following Choi et al. (2020), we perform the regression analysis in Eq. (1) separately for each two-digit industry-year combination with at least 20 observations.

We then construct our investment efficiency measure, INVEFF, as the negative absolute value of the residuals from these investment regressions. This transformation ensures that higher values indicate greater investment efficiency, as smaller deviations from the optimal investment level reflect more efficient allocation. Using this alternative measure, we re-estimate our DID specification.

Table 3, Column (1), presents the results in support of Hypothesis 1a. The coefficient on TOUR and the sum of $\beta_1 + \beta_2$ are positive and statistically significant, indicating that CIT visits enhance the investment efficiency of local SOEs using the alternative dependent variable that directly captures investment efficiency.

Alternative test windows: While our primary analysis uses an 8-year window (4 years before and after CIT visits), we conduct supplementary tests using alternative windows of 1, 2, 3 and 5 years around the inspections. Research shows that government monitoring can mitigate managerial myopia, particularly in the context of earnings management (Guedhami et al., 2014; Hadley, 2019), although these effects are often short-lived (Pan

Table 3
Alternative measures of investment efficiency, test windows, and entropy balancing procedure.

Dependent Variable	(1) INVEFF	(2) INVEST_ 1 YEAR	(3) INVEST_ 2 YEARS	(4) INVEST_ 3 YEARS	(5) INVEST_ 5 YEARS	(6) ENTROPY BALANCE
TOUR	0.013** (2.57)	−0.023** (−2.28)	−0.025*** (−2.87)	−0.026*** (−3.20)	−0.033*** (−4.38)	−0.034*** (−5.06)
TOUR × UNDER	−0.004 (−0.63)	0.041*** (2.82)	0.033*** (2.70)	0.030*** (2.73)	0.041*** (4.52)	0.035*** (3.94)
TOUR + TOUR × UNDER	0.009*** (4.98)	0.018** (3.96)	0.008** (4.41)	0.004*** (5.25)	0.008*** (11.40)	0.001*** (12.58)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6862	2463	4004	5474	8219	17,218
Adj. R-squared	0.070	0.060	0.061	0.056	0.055	0.059

Notes: This table presents the results from regressions of CIT visits on local SOEs' investment inefficiency using the alternative measures of investment efficiency, test windows, and entropy balancing procedure. In Column (1), the dependent variable INVEFF equals −1 times absolute value of residual from the following regression: $INVEST_{i,t} = \alpha_0 + \beta_1 GROWTH_{i,t} + \varepsilon_{i,t}$. Column (2) to (5) are based on a one, two, three, and five years before and after the CIT visits, respectively. Column (6) reports the results after entropy balancing procedure with respect to the first and second moments of observable firm characteristics for SOE. In all columns, TOUR is an indicator of the CIT visits, and it equals one for years during which the province of firm *i* is experiencing an inspection and for the following years after the CIT visits in different test windows. Other variables are as defined in Appendix A. The standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

et al., 2022). We expect the effects on corporate investment decisions to be more persistent, as these decisions typically involve larger capital outlays, longer time horizons and more substantial economic consequences than earnings manipulation. CIT visits help to reduce excessive interference from local officials. By easing political pressure, they enable managers to shift their focus from short-term outcomes to more value-enhancing, long-term investment strategies.

In Table 3, Columns (2) to (5), we report the results for 1, 2, 3 and 5 years around CIT visits, respectively. We show that our main results hold across all alternative windows. Notably, the economic magnitude of the negative coefficient for firms more likely to overinvest increases from -0.023 to -0.033 as the window expands, suggesting stronger long-term effects on curbing overinvestment. For underinvesting firms, the sum of TOUR and the interaction term $\text{TOUR} \times \text{UNDER}$ remains significant and positive in all windows, thus confirming the lasting influence of CIT visits, even if the effect does not appear to strengthen over time. These findings contribute to the literature on government monitoring by highlighting its lasting impact on improving corporate investment efficiency (Deng et al., 2023).

Alternative matching methods: One potential concern is that observable differences between SOEs (treatment group) and non-SOEs (control group) may drive differences in investment behavior. To address this, our main analysis uses several strategies, including PSM, controlling for observable firm characteristics in the regression models and incorporating firm fixed effects to account for the linear effects of these observable characteristics. In this section, we adopt an alternative matching approach to further mitigate this concern by addressing potential nonlinear effects, following Godsell et al. (2023). Specifically, we apply entropy balancing to align the distribution of observable characteristics between local SOEs and private firms.

Using the method developed by Francoeur et al. (2023), we balance the first and second moments of the main firm characteristics to ensure that SOEs and private firms have comparable distributions. This procedure successfully achieves a balance of the covariates (untabulated results). We then re-estimate Eq. (2) using this entropy-balanced sample. The results, reported in Panel A, Column (6), show that the coefficient on TOUR remains negative for overinvesting firms, while the sum of TOUR and $\text{TOUR} \times \text{UNDER}$ remains positive for underinvesting firms. These findings confirm that the monitoring effects of CIT visits persist even when accounting for nonlinear differences in observable characteristics.

Alternative measure of underinvestment and overinvestment: In our baseline model, we follow García Lara et al. (2016) and construct a continuous variable, UNDER, to capture the likelihood of underinvestment or overinvestment at the industry-year level. As a robustness check, we adopt an alternative approach using dummy variables to identify underinvesting and overinvesting firms. Specifically, we follow Chen et al. (2011) and estimate the following regression:

$$\text{INVEST}_{i,t} = \alpha_0 + \beta_1 \text{NEG}_{i,t-1} + \beta_1 \text{GROWTH}_{i,t-1} + \beta_1 \text{NEG}_{i,t-1} \times \text{GROWTH}_{i,t-1} + \varepsilon_{i,t}$$

where INVEST represents capital expenditures and is equal to investments in tangibles and acquisitions scaled by lagged total assets. GROWTH represents sales growth. NEG is an indicator equal to 1 for negative sales growth, and 0 otherwise. Based on the residuals of this regression, we define dummy variables for underinvestment and overinvestment. In Table 4, Columns (1) and (2), UNDER2 is set to 1 for firms in the bottom tercile of the residuals (indicating underinvestment), and OVER2 is set to 1 for firms in the top tercile (indicating overinvestment). In Columns (3) and (4), UNDER3 and OVER3 are defined using the bottom and top quartiles of the residuals, respectively. In both specifications, the results are consistent with our main findings, suggesting that our conclusions are robust to alternative definitions of underinvestment/overinvestment.

Controlling for the effects of corporate governance quality: Corporate governance quality is an important determinant of firms' investment and financing decisions. A key concern in our baseline analysis is that the inclusion of unlisted firms may limit our ability to control for important corporate governance differences, as many relevant variables are only available for listed firms. To address this concern, we proceed in two steps. We first rerun PSM among listed firms, adding corporate governance variables to the matching process. Specifically, we include INS, the percentage of shares held by institutional investors; ATT, the number of analysts covering the firm; and IND, the number of independent directors on the board. We then re-estimate the baseline model using this matched sample of listed firms and include these corporate governance variables as additional controls in the regression. We report our results in Column (5), which confirm that our main findings remain robust when we restrict our sample to listed firms and account for corporate governance quality.

Table 4

Alternative measures of under-investment and controlling the corporate governance quality.

Dependent Variable	(1) INVEST_ UNDER2	(2) INVEST_ OVER2	(3) INVEST_ UNDER3	(4) INVEST_ OVER3	(5) PSM_ CG	(6) ADD CG CONTROLS
TOUR	−0.020*** (−3.68)	−0.011*** (−2.86)	−0.017*** (−3.17)	−0.009** (−2.45)	−0.020** (−2.47)	−0.029*** (−3.85)
TOUR × UNDER					0.022** (2.01)	0.038*** (3.87)
TOUR + TOUR × UNDER					0.002** (3.09)	0.009*** (8.57)
TOUR × UNDER2	0.021*** (4.72)	0.011*** (3.57)				
TOUR + TOUR × UNDER2	0.001*** (12.05)	0.000*** (8.30)				
TOUR × OVER2		−0.016*** (−3.18)				
TOUR + TOUR × OVER2		−0.027*** (8.60)				
TOUR × UNDER3			0.019*** (4.17)	0.012*** (3.66)		
TOUR + TOUR × UNDER3			0.002*** (9.77)	0.003*** (8.20)		
TOUR × OVER3				−0.016*** (−2.66)		
TOUR + TOUR × OVER3				−0.025*** (6.13)		
INS						0.001*** (3.21)
INS_DUM						0.018** (2.39)
ATT						0.001*** (2.88)
ATT_DUM						0.016*** (3.39)
IND						−0.037 (−0.87)
IND_DUM						0.003 (0.14)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6867	6867	6867	6867	6430	6867
Adj. R-squared	0.252	0.418	0.229	0.474	0.067	0.088

Notes: This table presents the results from regressions of CIT visits on local SOEs' investment inefficiency using the alternative measure of under-investment and controlling the corporate governance quality. In Column (1) and (2), UNDER2(OVER2) is a dummy variable defined as observations in the third(first) tercile of the residuals from the regression following Chen et al. (2011). In Column (3) and (4), UNDER3(OVER3) is a dummy variable defined as observations in the bottom(top) quartile of the residuals from the regression following Chen et al. (2011). In Column (5), we re-perform propensity score matching across listed firms after controlling INS, ATT and IND. In Column (6), we re-estimate the baseline model with additional control variables INS, ATT, IND, INS_DUM, ATT_DUM and IND_DUM. In all columns, TOUR is an indicator of the CIT visits, and it equals one for years during which the province of firm *i* is experiencing an inspection and for the following years after the CIT visits in different test windows. Other variables are as defined in Appendix A. The standard errors are clustered at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Second, we re-estimate the baseline model by incorporating additional control variables for corporate governance characteristics, namely INS, ATT and IND. Because these variables are not available for unlisted firms, we also incorporate INS_DUM, ATT_DUM and IND_DUM, dummy variables equal to 1 when

INS, ATT or IND is missing and 0 otherwise, respectively. The results in Column (6) suggest that CIT visits still influence investment efficiency after controlling for the effects of corporate governance quality.

5. Channels linking CIT visits to enhanced investment efficiency

As discussed above, we argue that CIT visits can enhance investment efficiency through three main channels: reducing excessive interference from local officials, improving corporate governance quality and mitigating political and economic uncertainty. In this section, we test these proposed mechanisms by looking at government interference, corporate governance and uncertainty as important moderating factors.

5.1. Intervention constraint channel: Reducing interference from local officials

The first channel through which CIT visits enhance investment efficiency is by disciplining local officials who may otherwise interfere with corporate decision-making. The superior oversight authority of CITs exerts considerable pressure on local officials in the inspected provinces. These visits are a key mechanism for enforcing central government directives and ensuring compliance with national policies and regulations. Through comprehensive investigations and audits, CITs help to uncover and address cases where local officials prioritize politically expedient or image-driven projects over economically sound investments (Hu, 2021; Li et al., 2021). This corrective function fosters a more disciplined and accountable governance environment.

The increased scrutiny brought by CIT visits constitutes a credible disciplinary mechanism against politically motivated overinvestment, often aimed at achieving short-term goals or enhancing the promotion prospects of local officials. In the absence of such oversight, local authorities may pressure SOE managers to allocate capital to “vanity projects” or sectors aligned with local agendas, even when these investments are economically inefficient. CIT visits disrupt this dynamic by increasing the expected cost of such behavior, both in terms of career risk for local officials and reputational consequences for the firms involved (Zhou and Chu, 2025). With reduced interference from local governments, managers can better focus on long-term value creation, allocate capital more efficiently and avoid both overinvestment and underinvestment.

To test this mechanism, we use two proxies that measure the degree of local interference. If CIT visits improve investment efficiency by reducing local government intervention, we should observe stronger effects in firms and locations that experienced greater intervention prior to these visits. Our first measure, INTERVENE, is an index that captures the degree of local government interference in the local economy, incorporating both direct intervention and control of resource allocation (Xie et al., 2022). We obtain the relevant data from the China Provincial Marketization Index Report, a widely recognized and comprehensive dataset on regional market development compiled by the China Society of Economic Reform Institution.⁶ The second measure, PROMOTION, is a binary variable equal to 1 if the provincial governor is 50 years old or younger (Chen et al., 2020). Younger governors typically face stronger career incentives, increasing the likelihood of excessive intervention.

Table 5 presents the results, using INTERVENE and PROMOTION as proxies for government interference. In both columns, the interaction term $\text{TOUR} \times \text{INTERVENE}$ is negative and significant, while $\text{TOUR} \times \text{UNDER} \times \text{INTERVENE}$ is positive and significant. These findings indicate that CIT visits are more likely to increase (decrease) investment in underinvesting (overinvesting) firms located in regions with high government interference compared with those located in regions with lower interference. The results are consistent with the notion that CIT visits improve investment efficiency by restraining undue involvement of local officials in firm-level decision-making.

⁶ Based on the systematic analysis of large sets of standardized data, the index evaluates the overall and the different aspects of the progress of marketization reforms across Chinese provinces. We adopt one of its components, the government–market relationship, as our measure. For more information, visit <https://www.cser.org.cn/plus/list.php?tid=81>.

Table 5

Potential mechanisms: Local officials' interference.

Dependent Variable	(1) INVEST	(2) INVEST
TOUR	−0.032*** (−4.12)	−0.030*** (−3.78)
TOUR × UNDER	0.040*** (4.05)	0.037*** (3.79)
TOUR × INTERVENE	−0.010** (−2.41)	
TOUR + TOUR × INTERVENE	−0.042*** (−10.49)	
TOUR × UNDER × INTERVENE	0.015** (2.17)	
TOUR + TOUR × INTERVENE +TOUR × UNDER + TOUR × UNDER × INTERVENE	0.013*** (5.81)	
TOUR × PROMOTION		−0.047*** (−4.14)
TOUR + TOUR × PROMOTION		−0.077*** (−19.91)
TOUR × UNDER × PROMOTION		0.051** (2.45)
TOUR + TOUR × PROMOTION +TOUR × UNDER + TOUR × UNDER × PROMOTION		0.011*** (16.14)
Controls included	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	6867	6867
Adj. R-squared	0.058	0.057

Notes: This table presents the effects of CIT visits on firms' investment inefficiency in curbing local officials' interference. INVEST is the total investment measured. TOUR is an indicator of the CIT visits. INTERVENE is an interference level index, which measures the degree of the interference of local government in local firms. PROMOTION is an indicator variable, and it equals one if the provincial governor is 50 or younger. The standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.2. Governance channel: Enhancing corporate governance quality

We also propose that CIT visits enhance local firms' investment efficiency by improving their corporate governance quality. This improvement operates through two key mechanisms: (1) the power of the CITs to sanction executive misconduct and (2) their ability to identify governance deficiencies. The literature highlights two primary forms of corporate corruption: collusion with corrupt officials and coercion exercised by these officials (Armand et al., 2020). As independent external monitors, CIT members present a lower risk of collusion due to their limited prior relationships with local executives and their strict anti-corruption protocols. Additionally, their access to key decision-making documents, such as project proposals, feasibility studies and voting records, along with their forensic accounting expertise, enable them to effectively detect governance weaknesses (Denis, 2012). Accordingly, we posit that CIT visits significantly strengthen governance mechanisms and raise compliance standards in corporate investment decisions. If this is the case, we expect CIT visits to be more effective in firms with worse internal governance prior to these visits.

To empirically test this, we examine the moderating effect of corporate governance on the relationship between CIT visits and firm investment. Because our sample includes both listed and unlisted firms, we cannot use many of the conventional corporate governance measures due to the lack of data for unlisted firms. Therefore, we use two alternative proxies. Following Gogineni et al. (2022), the first is administrative inefficiency (ADE), calculated as administrative expenses divided by total assets. Although not a direct measure of governance, ADE reflects the organizational inefficiency that can stem from weak governance or excessive bureaucracy. Improvements in governance are expected to reduce administrative waste, making ADE particularly

Table 6

Potential mechanisms: Corporate governance quality.

Dependent Variable	(1) INVEST	(2) INVEST
TOUR	−0.028*** (−3.56)	−0.023*** (−2.86)
TOUR × UNDER	0.035*** (3.49)	0.033*** (3.24)
TOUR × ADE	−0.701** (−2.39)	
TOUR + TOUR × ADE	−0.729*** (11.09)	
TOUR × UNDER × ADE	1.042** (2.25)	
TOUR + TOUR × ADE + TOUR × UNDER + TOUR × UNDER × ADE	0.278*** (6.09)	
TOUR × EM		−0.000*** (−3.02)
TOUR + TOUR × EM		−0.023*** (−11.78)
TOUR × UNDER × EM		0.000*** (2.82)
TOUR + TOUR × EM + TOUR × UNDER + TOUR × UNDER × EM		0.010*** (6.69)
Controls included	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	6867	6867
Adj. R-squared	0.060	0.058

Notes: This table presents the effects of CIT visits as an additional external monitoring on firms' investment inefficiency. INVEST is the total investment. TOUR is an indicator of the CIT visits. ADE is an indicator variable for administrative inefficiency, measured as administrative expenses divided by total assets. EM is the rank-based absolute value of discretionary total accruals, that is, the residuals from the performance matched modified Jones model. The standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

informative for firms with initially high inefficiency. The second proxy is earnings management (EM), measured as the rank-based absolute value of discretionary accruals using the performance-matched modified Jones model. Higher EM values indicate greater earnings manipulation and, consequently, weaker internal controls.

Table 6 presents the empirical results examining how CIT visits influence investment efficiency through the governance channel. The interaction terms TOUR × ADE and TOUR × EM show consistent negative and significant patterns, indicating that for overinvesting firms, CIT visits are associated with reduced investment in firms exhibiting higher administrative inefficiency or greater earnings manipulation, both indicating weaker governance and internal controls. Conversely, for underinvesting firms, the interaction terms TOUR × UNDER × ADE and TOUR × UNDER × EM are positive and significant, suggesting that CIT visits encourage increased investment in firms previously constrained by governance weaknesses. These findings support the view that CIT inspections enhance investment efficiency by addressing internal inefficiencies and governance shortcomings, consistent with the role of external monitoring in mitigating organizational inefficiencies in politicized or bureaucratic environments.

5.3. Information channel: Mitigating policy and economic uncertainty

We propose that CIT visits improve investment efficiency by reducing policy and economic uncertainty. Uncertainty is a major barrier to investment (Chen et al., 2024; Dube, 2024). CITs help to address this by clar-

ifying central policy priorities and reducing inconsistencies in local implementation (Amore and Minichilli, 2018; Bird et al., 2023). This greater policy clarity is especially valuable for underinvesting firms, which often face financing frictions. With clearer signals and reduced ambiguity, these firms can more effectively obtain external funding (Bonaime et al., 2018), enabling them to make more confident and efficient investment decisions. At the same time, CITs gather first-hand financial and operational data from local firms, reducing information asymmetry for central authorities. This improves the quality of oversight and enables more informed, targeted policy decisions.

To measure policy and economic uncertainty, we use two proxies. First, policy uncertainty (PU) is a binary variable equal to 1 if the city where the firm's headquarters is located has experienced a turnover of key government officials, either a new mayor or a new party secretary, during the fiscal year.⁷ A value of 1 for PU indicates increased policy uncertainty, as leadership changes often introduce changes in local policy priorities, administrative styles or regulatory enforcement, creating ambiguity for firms operating in that region. Second, economic policy uncertainty (EPU) is measured as the 12-month moving average of the monthly Economic Policy Uncertainty Index developed by Baker et al. (2016).⁸ This index is constructed from a textual analysis of policy-related news coverage and official documents, capturing the frequency and intensity of economic policy uncertainty at the national level. Higher EPU values reflect a more volatile or ambiguous economic policy environment, which may discourage firms from committing to long-term investments.

Table 7 presents the empirical results. Column (1) shows a statistically significant and negative coefficient on $\text{TOUR} \times \text{PU}$, while $\text{TOUR} \times \text{UNDER} \times \text{PU}$ remains significant and positive. Column (2) shows similar patterns for economic policy uncertainty. These findings suggest that the effects of CIT visits are more pronounced for firms operating in highly uncertain environments prior to inspections, supporting the hypothesis that CIT visits enhance investment efficiency by mitigating both policy and economic uncertainty.

Overall, our moderation analysis suggests that reducing local political interference, enhancing internal governance and mitigating policy and economic uncertainty are three key channels through which CIT visits enhance corporate investment efficiency. By strengthening oversight, improving transparency and governance and aligning local implementation with central policy objectives, CIT visits help to address traditional governance issues, ultimately leading to more effective and disciplined investment behavior.

6. Additional analyses

6.1. Listed versus unlisted SOEs

We further examine how CIT visits differently affect publicly listed and unlisted SOEs. Compared with unlisted firms, listed firms face more stringent regulatory requirements and disclosure standards imposed by securities regulators (Hou and Wang, 2023), as well as greater analyst coverage and media scrutiny that enhance external monitoring (He et al., 2019). Additionally, the presence of minority shareholders in listed firms strengthens market discipline through the threat of exit (Jiang and Liu, 2021).

In contrast, unlisted firms tend to have more opaque governance structures and are subject to less external oversight, resulting in more severe agency problems (Gogineni et al., 2022). This distinction is particularly important in the Chinese institutional context, where state ownership and political objectives strongly influence corporate operations. Unlike market economies with clearer separations between commercial and administrative roles, China's fragmented governance system grants local officials considerable informal control over unlisted SOEs. Consequently, unlisted firms are more susceptible to political interference and managerial discretion, which may deviate from maximizing shareholder value. This highlights the critical role of external monitoring mechanisms, such as CIT visits, in enhancing governance quality and investment efficiency in these firms.

⁷ We manually collect data on the registered cities of all sample firms, as well as the names of the mayors and party secretaries of each city. By cross-referencing biographical information and online news, we compile local official turnover records in different cities throughout the sample period.

⁸ More details are available at https://www.policyuncertainty.com/scmp_monthly.html.

Table 7
Potential mechanisms: Uncertainty in corporate investment.

Dependent Variable	(1) INVEST	(2) INVEST
TOUR	−0.024** (−2.31)	−0.027*** (−2.74)
TOUR × UNDER	0.045*** (2.98)	0.049*** (3.17)
TOUR × PU	−0.030*** (−2.74)	
TOUR + TOUR × PU	−0.054*** (−13.89)	
TOUR × UNDER × PU	0.040** (2.38)	
TOUR + TOUR × PU + TOUR × UNDER + TOUR × UNDER × PU	0.031*** (9.44)	
TOUR × EPU		−0.007** (−2.33)
TOUR + TOUR × EPU		−0.034*** (−10.87)
TOUR × UNDER × EPU		0.007* (1.79)
TOUR + TOUR × EPU + TOUR × UNDER + TOUR × UNDER × EPU		0.022*** (6.87)
Controls included	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	6867	6867
Adj. R-squared	0.073	0.073

Notes: This table presents the effects of CIT visits on corporate investment in policy and economic uncertainty. INVEST is the total investment. TOUR is an indicator of the CIT visits. PU is an indicator variable for political uncertainty, and it equals one when the city of firm's headquarters experiences a government official turnover and zero otherwise. EPU is the economic policy uncertainty index related to newspaper coverage frequency. The standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Given these differences, we hypothesize that the monitoring effects of CIT visits will be more pronounced in unlisted SOEs. Analyzing the heterogeneity between publicly listed and unlisted SOEs is especially valuable because prior research predominantly focuses on listed firms, leaving the governance and oversight dynamics of unlisted SOEs largely underexplored. By addressing this gap, our study contributes new insights into the distinct challenges and oversight needs of unlisted SOEs.

We divide the sample into subgroups based on firms' public listing status. Table 8 shows that the coefficients on TOUR are negative and statistically significant, while the sum of the coefficients on TOUR + TOUR*UNDER are positive and statistically significant for both listed and unlisted firms. These results confirm that CIT visits effectively improve investment efficiency in both publicly listed and unlisted SOEs. However, the F-tests comparing the coefficients between the two groups reveal that CIT visits have a stronger effect on improving the investment efficiency of unlisted firms. This finding suggests that CIT visits serve as an effective monitoring mechanism, particularly in contexts where traditional governance structures are typically weaker.

6.2. Impact of revisit inspections

A key question when evaluating the effectiveness of government oversight mechanisms like CIT visits is whether repeated inspections continue to produce meaningful governance improvements or whether their

Table 8
Heterogeneity between publicly-listed and unlisted firms.

Dependent Variable	(1) Listed firms	(2) Unlisted firms
TOUR	−0.028*** (−3.30)	−0.034*** (−2.82)
TOUR × UNDER	0.034*** (3.09)	0.044** (2.50)
TOUR + TOUR × UNDER	0.006*** (6.03)	0.010** (4.04)
Compare coefficient across partitions:		
TOUR	p value (one-tailed) = 0.040**	
TOUR × UNDER	p value (one-tailed) = 0.020**	
TOUR + TOUR × UNDER	p value (one-tailed) = 0.040**	
Controls included	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	5434	1433
Adj. R-squared	0.076	0.051

Notes: This table presents the results from regressions of CIT visits on firms' investment inefficiency in cross-sectional heterogeneity between publicly-listed firms and unlisted firms. INVEST is the total investment. TOUR is an indicator of the CIT visits. We grouped the whole samples into two partitions based on whether the firm issues traded publicly shares in stock market. The standard errors are clustered at the firm level and t-stats are presented in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

impact is primarily front-loaded and diminishes over time. To investigate this, we conduct a comparative analysis between the first inspection round in 2013–2014 and the second “revisit inspections” round in 2018.

Unlike the initial round, which introduced the CIT mechanism and generated a strong disciplinary shock, the second-round inspections focused on assessing local compliance with prior rectification directives and reinforcing political accountability through follow-up pressure. This setup allows us to examine whether CIT visits maintain their effectiveness after the initial round, when local firms and governments may have adapted their behavior or become desensitized to external scrutiny.

Using our primary research design, we reconstruct the sample period to cover the 2016–2020 period and apply the same methodological framework. If the revisit inspections continue to improve investment efficiency, we expect similar results: a significant and negative coefficient on TOUR and a significant and positive combined effect of TOUR and TOUR × UNDER.

The results presented in Table 9 reveal important dynamics in monitoring effectiveness. This pattern suggests that the initial CIT visits played a particularly potent external monitoring role, effectively curbing agency problems in local SOEs. The reduced impact in later rounds could stem from decreased enforcement intensity or attention in later rounds, as the initial shock effect of the inspection regime wears off. These interpretations align with the literature on regulatory enforcement cycles (Dechenaux and Samuel, 2012), which documents similar patterns of weaker effect in repeated interventions (e.g., regulatory fatigue or compliance drift).

6.3. Ex-post financial consequences

Finally, we examine how CIT visits affect operating performance. This extension allows us to better understand whether the regulatory impact on investment efficiency translates into measurable financial outcomes.

The predicted effects of CIT visits on firms' financial performance are not necessarily straightforward. In settings prone to overinvestment, we expect that after CIT visits, firms may reduce their investments in projects with negative net present value and divest from underperforming assets, thereby increasing their future ROA. The prediction for underinvesting firms is less clear. In underinvesting firms, CIT visits may encourage increased capital spending by reducing policy uncertainty and strengthening accountability. However, this investment is not necessarily geared toward high-return projects. Firms typically prioritize the most profitable

Table 9

Effect of the subsequent CIT visits on investment efficiency.

Dependent variable	(1) INVEST	(2) INVEST
TOUR	−0.030*** (−3.80)	−0.026* (−1.87)
TOUR × UNDER	0.037*** (3.80)	0.031** (2.10)
TOUR + TOUR × UNDER	0.007*** (8.33)	0.005* (2.24)
Controls included	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	6867	3614
Adj. R-squared	0.057	0.067

Notes: This table presents the results from regressions of subsequent CIT visits on corporate investment efficiency using the difference-in-differences design. INVEST is the total investment measured. TOUR is an indicator of the subsequent central inspection, and it equals one for years during which the province of firm *i* is experiencing an inspection and for the following years after the subsequent CIT visits. Other variables are as defined in Appendix A. The regressions include firm and year fixed effects. Robust standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10

Long-term operating performance after CIT visits.

Dependent Variable	(1) F1_ROA	(2) F2_ROA	(3) F3_ROA	(4) F4_ROA	(5) F5_ROA
TOUR	−0.001 (−0.35)	0.001 (0.24)	0.011** (2.51)	0.016*** (3.41)	0.015*** (3.15)
TOUR × UNDER	0.003 (0.61)	−0.000 (−0.03)	−0.007 (−1.14)	−0.015** (−2.50)	−0.004 (−0.75)
TOUR + TOUR × UNDER	0.002 (0.19)	0.001 (0.04)	0.004** (3.39)	0.001*** (5.95)	0.009*** (5.98)
Controls included	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	6867	6867	6867	6299	5469
Adj. R-squared	0.032	0.039	0.029	0.014	0.010

Notes: This table presents the results from regressions of CIT visits on firms' operating performance in the following years. The dependent variable F1_ROA, F2_ROA, F3_ROA, F4_ROA, and F5_ROA is the net income scaled by average total assets in year $t + 1$, $t + 2$, $t + 3$, $t + 4$, and $t + 5$, respectively. TOUR is an indicator of the CIT visits. The other control variables are defined in Appendix A. The regressions include firm and year fixed effects. Reported t-statistics are based on robust standard errors adjusted using a cluster at the firm level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

opportunities; thus, the new investments generated may flow into lower-return, albeit acceptable, projects. As a result, although investment levels rise, financial performance may show limited improvement or even stagnate, consistent with diminishing marginal returns to capital (García Lara et al., 2016).

In Table 10, we examine the impact of CIT visits on ROA. Given that changes in corporate investment planning and governance structures typically take time to materialize, and that the disciplinary effects of CIT visits on local officials are likely to persist beyond the short term, we assess financial performance over an extended horizon. Specifically, we use five forward-looking ROA measures, F1_ROA to F5_ROA, defined as net income divided by average total assets in years $t + 1$ through $t + 5$, respectively. These measures enable us to capture both the immediate and longer-term financial outcomes associated with CIT visits, providing a more comprehensive view of their impact on firm performance.

In Columns (1) and (2), the coefficient on TOUR is not statistically significant, suggesting that CIT visits do not have an immediate impact on short-term financial performance. In contrast, Columns (3) to (5) show positive and statistically significant coefficients on TOUR, indicating that overinvesting firms experience improved financial performance in the years following the inspections. For underinvesting firms, the sum of the coefficients on TOUR + TOUR $\times$ UNDER becomes significant and positive from the 3rd year onward, suggesting that these firms also benefit from CIT visits, but that the effects appear later.

7. Conclusion

This paper explores how centralized government oversight influences the investment efficiency of local SOEs, using China's CIT visits. Although such interventions may discipline self-serving behavior by local officials and firm managers, they may also exacerbate non-commercial obligations imposed on firms. To isolate the causal effects of CIT visits, we exploit their staggered rollout as a quasi-natural experiment and apply a DID model with PSM to address selection bias and endogeneity concerns.

We document significant improvements in investment efficiency following CIT visits for both listed and unlisted local SOEs. The effect is more pronounced in unlisted firms, consistent with the notion that external government monitoring is more effective when internal governance and market discipline are weaker. Our analysis also suggests that central inspections constitute an effective top-down governance mechanism for SOEs, by reducing local government interference, strengthening internal governance and lowering uncertainty related to policy and regulatory environments. Unlike previous studies focused on short-term earnings management adjustments (e.g., Chen et al., 2020), our results highlight sustained real activity-based changes, suggesting that CIT inspections influence long-term investment behavior rather than merely prompting superficial compliance.

Our study contributes to the broader literature on corporate governance and political economy by illustrating how centralized regulatory mechanisms can be effective external monitoring tools. Although our findings are based on Chinese SOEs, a context with unique institutional characteristics, they have broader implications for other developing economies seeking to strengthen corporate compliance and reduce government interference in firm decision-making. Our results also have policy relevance. Amid China's economic headwinds and continued emphasis on regulatory enforcement, our evidence suggests that centrally driven oversight can help restore investor confidence by promoting more disciplined corporate behavior.

Finally, our findings raise important questions about the long-term sustainability of such oversight mechanisms. While our revisit inspections analysis indicates that CIT visits continue to have a positive impact, the effect appears to be somewhat weaker than that observed during the initial inspection round. This suggests that even if these inspections remain effective, their influence may decline once the initial shock wears off. Understanding how to sustain or institutionalize the monitoring role of central government inspections, without causing regulatory fatigue or imposing excessive compliance burdens, remains an important area for future research and policy consideration.

CRedit authorship contribution statement

Ruiyao Zhang: Writing – original draft. **Xiaowei Xu:** Visualization, Writing – review & editing. **Bingxuan Lin:** Conceptualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Variable definitions

Variable name	Definition	Source
Dependent variables		
INVEST	Total investment measured as the sum of capital and acquisition expenditures less the sale of property, plant, and equipment multiplied and scaled by the lagged total assets.	WIND
INEFF	–1 times absolute value of residual from the following regression: $INVEST_{i,t} = \alpha_0 + \beta_1 GROWTH_{i,t} + \varepsilon_{i,t}$ where INVEST represents capital expenditures. GROWTH represents sales growth. We also control industry and year fixed effects.	WIND
F1_ROA	Net income scaled by average total assets in year t + 1.	WIND
F2_ROA,	Net income scaled by average total assets in year t + 2.	WIND
F3_ROA	Net income scaled by average total assets in year t + 3.	WIND
F4_ROA	Net income scaled by average total assets in year t + 4.	WIND
F5_ROA	Net income scaled by average total assets in year t + 5.	WIND
Independent variables		
TOUR	An indicator of the CIT visits, and it equals 1 for years during which the province of firm i is experiencing an inspection and for the following years after the CIT visits, and 0 otherwise.	CIT Visits Website
INTERVENE	Interference level index, which measures the degree of the interference of local government in local firms.	China Provincial Marketization Index Report
PROMOTION	An indicator whether the provincial governor is 50 or younger.	Local Official Website
ADE	An indicator variable for administrative inefficiency, measured as administrative expenses divided by total assets.	WIND
EM	Rank-based absolute value of discretionary total accruals in modified Jones model.	WIND
PU	An indicator for political uncertainty, and it equals 1 when the city where the firm's headquarters are located experiences a government official turnover (i.e., a mayor or community party secretary) and 0 otherwise.	Local Official Website
EPU	Economic policy uncertainty index related to newspaper coverage frequency, using textual analysis.	SCMP Website
Other variables and controls		
UNDER	An indicator of the likelihood of under- or over-investment problems.	WIND
SIZE	Natural log of total assets at the end of year.	WIND
LEV	Total long-term liabilities divided by total assets at the end of year.	WIND
TANG	Ratio of property, plant, and equipment to total assets.	WIND
CFLOW	Operating cash flow divided by average total assets this year.	WIND
LOSS	An indicator of the loss, and it equals 1 if net income before extraordinary items is negative and 0 otherwise.	WIND
SLACK	Ratio of cash to net property, plant, and equipment.	WIND
FLOW_SD	Standard deviation of the cash flow from operations scaled by average total assets, for years t – 5 to t – 1.	WIND

(continued)

Variable name	Definition	Source
SALE_SD	Standard deviation of annual sales deflated by average total assets, for years $t - 5$ to $t - 1$.	WIND
INV_SD	Standard deviation of annual investment for years $t - 5$ to $t - 1$.	WIND
LEV_IN	Mean of leverage for firms in the same WIND two-digit industry group, where leverage is the ratio of total long-term liabilities divided by total assets at the end of year.	WIND
INS	Percentage of the firm's shares held by institutional investors	CSMAR
IND_DUM	An indicator that equals 1 if INS is missing and 0 otherwise.	CSMAR
ATT	Number of analysts following the firm.	CSMAR
ATT_DUM	An indicator that equals 1 if ATT is missing and 0 otherwise.	CSMAR
IND	Number of the firm's independent directors	CSMAR
IND_DUM	An indicator that equals 1 if IND is missing and 0 otherwise.	CSMAR
Industry	Indicator variables for the industries, defined based on the two-digit industry group published by Wind Financial Terminal (WIND) databases.	WIND
Year	Indicator variables for the fiscal year.	WIND

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How does the U.S. Entity List affect the narrative information disclosure strategies of Chinese firms?

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ABSTRACT

Against the backdrop of volatile global trade and the expanding U.S. Entity List targeting Chinese enterprises, this study examines how firms adjust their narrative disclosures in response to external trade policy risks, specifically, the strategic choice between opacity and explicitness. Using data from A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2011 to 2024, we find that firms added to the U.S. Entity List exhibit significantly higher textual ambiguity in their narrative disclosures than non-sanctioned firms. This effect is primarily driven by firms' strategic choice to adopt an obscure disclosure stance. Mechanism analyses reveal that inclusion on the U.S. Entity List triggers negative discussions on Guba and increases negative coverage by the financial media, thereby heightening the firms' perceived supply chain risks. In turn, this perception drives firms to incorporate more positive forward-looking statements in their Management Discussion and Analysis. Heterogeneity tests indicate that the increase in textual ambiguity is more pronounced among firms facing higher managerial performance pressure, with inferior market positions, greater international exposure or weaker institutional investor oversight. Further analysis of the economic consequences shows that elevated textual ambiguity significantly increases both analyst forecast dispersion and stock price crash risk, thereby impairing the informativeness of the capital market and financial market stability. This study contributes to the literature on the economic consequences of the U.S. Entity List from an information disclosure perspective, elucidates how external risks can lead to corporate textual manipulation and provides valuable empirical insights for improving disclosure regulation within a complex international trade environment.

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1. Introduction

The globalization process currently faces structural challenges, with strategic rivalries among major powers profoundly reshaping the international economic and trade order. As one of the world's most consequential bilateral relationships, the competitive and cooperative dynamics between China and the United States in areas such as trade rules, technological dominance and industrial chain security have become pivotal in shaping global supply chain configurations and national economic development trajectories. Since 2018, U.S. trade competition policies toward China have grown increasingly politicized, securitized and weaponized, gradually forging a systemic containment framework encompassing entity lists, critical technology barriers and supply chain reviews (Zhao, 2020). The “Entity List” policy has moved beyond trade restrictions; its core strategy is to exclude Chinese enterprises from the “walled garden” constructed by the United States and its allies (Yu et al., 2025). This sanctions policy has significantly restructured the global industrial division of labor and innovation cooperation, posing severe challenges to the resilience and efficiency of global supply chains. It has also directly disrupted the pace of innovation and international collaboration networks in China's high-tech industries. Enterprises in relevant sectors face pressures across multiple dimensions, including access to core inputs, international market expansion and technological R&D iteration. Consequently, the processes of industrial upgrading and independent innovation have been substantially constrained (Benguria et al., 2022; Shao et al., 2025; Wang et al., 2025).

Under the framework of the Export Control Reform Act, the U.S. government has continuously expanded its Entity List on the grounds of “national security,” regularly adding Chinese government agencies, research institutions and high-tech enterprises to the list. Since 2018, Chinese enterprises have been subject to systemic risks arising from this list-based containment, with the number of affected companies increasing dramatically. In 2024 alone, 252 new entities were added (Fig. 1). Extensive empirical research indicates that the intensifying external institutional shocks have exerted significant and far-reaching impacts on the technological innovation capacity, supply chain stability and operational performance of Chinese firms (Yu et al., 2022; Chor and Li, 2024; Han et al., 2024). However, a critical question that remains under-explored is as follows: How do firms adjust their core communication strategies to promptly address capital market concerns amid severe unilateral trade protectionism? Specifically, do firms exhibit abnormal disclosure behavior in narrative texts rich in qualitative content, such as the Management Discussion and Analysis (MD&A), that convey management's intentions and risk perceptions?

Information disclosure serves as the cornerstone of capital markets, with its quality directly determining market efficiency and resource allocation optimization (Fama, 1970; Tong, 2007). Compared with standardized quantitative financial data, narrative texts such as the MD&A hold unique value. They present non-financial information, including operational performance, significant events, risk factors, strategic planning and future outlook, from the perspective of corporate management. This effectively bridges the

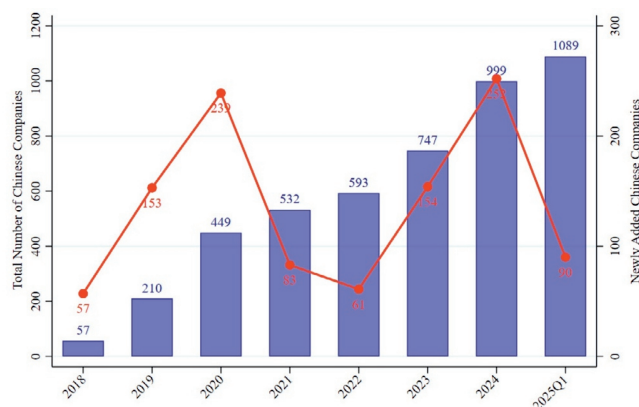


Fig. 1. Number of Chinese companies included in the U.S. Entity List (2018–2025Q1).

gap between financial statements and business substance (Merkley, 2014), offering advantages in relevance and timeliness (Liu et al., 2025a, 2025b). Consequently, the quality of narrative texts, particularly the clarity and comprehensibility of the information conveyed, has a profound impact on the decision-making efficiency and accuracy of stakeholders such as investors and creditors (Clarkson et al., 1999; Cole and Jones, 2004). As a fundamental dimension of quality, text readability directly affects recipients' comprehension efficiency and cognitive load, with variations leading readers to form distinctly different judgments (Tan et al., 2015; Xu et al., 2019). Notably, management has significant scope to manipulate textual characteristics. Beyond the selective disclosure of content, they can strategically adjust text readability or tone to influence the perceptions and judgments of information users (Li, 2008; Huang et al., 2014). Moreover, the level of readability is significantly influenced by multiple factors, including earnings management motives, shareholder litigation risk and equity pledge pressure (Nelson and Pritchard, 2007; Lo et al., 2017; Lu et al., 2020). Against this backdrop, analyzing the readability of narrative texts offers a critical perspective on how management adjusts its disclosure strategies in response to external trade uncertainties and U.S. sanctions (Fig. 2).

Focusing on the negative exogenous shock of the U.S. Entity List, this paper addresses the following core question: What characteristics emerge in firms' narrative disclosure strategies when they are suddenly subjected to such sanctions? Facing pressure from external stakeholders and regulators, will firms opt for “full disclosure,” enhancing textual clarity by detailing impacts, potential risks and countermeasures to stabilize market expectations? Or, driven by considerations such as avoiding liability, buying response time and preserving market image, do they tend toward “obfuscatory disclosure”—strategically obscuring textual expressions and increasing linguistic opacity to delay or mitigate market reactions to negative information? The answer will not only shed light on the logic of corporate governance under political risks but also be crucial for assessing the actual information environment and the stable functioning of capital markets amid the impacts of sanctions.

To examine whether Entity List sanctions induce obfuscation in firms' narrative disclosures, this study uses a sample of Shanghai and Shenzhen A-share listed companies from 2011 to 2024. It adopts the Fog Index, a text readability metric proposed by Xu et al. (2019) for Chinese contexts, to measure textual ambiguity. A multi-period difference-in-differences (DID) model is constructed for empirical testing. The results strongly support the “obfuscation hypothesis”: firms targeted by the Entity List exhibit significantly greater ambiguity in their narrative text, primarily driven by management's deliberate concealment rather than by objective increases in information complexity. The benchmark results remain robust across a series of stability tests. Mechanism analysis indicates that heightened external scrutiny, increased supply chain risk perceptions and conveying “false confidence” in forward-looking statements collectively drive manipulative narrative practices. Further heterogeneity analysis demonstrates that the Entity List's impact on text ambiguity is more pronounced when management faces high performance pressure, or when the firm occupies a weaker market

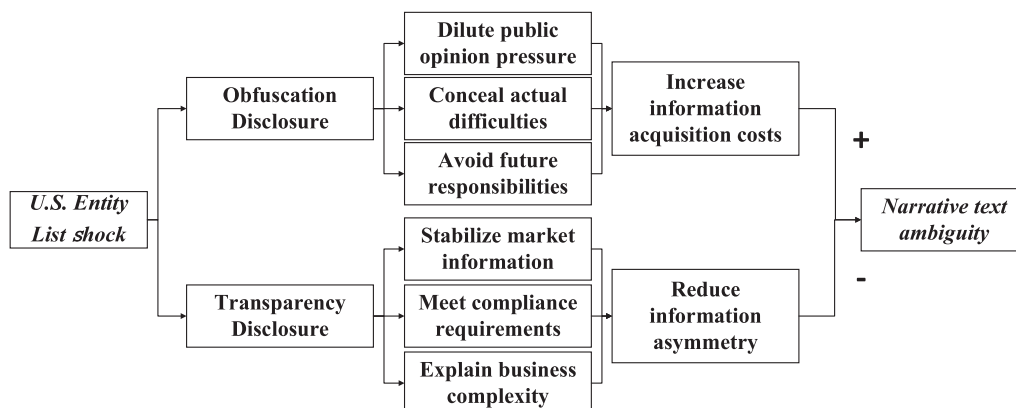


Fig. 2. Theoretical analysis framework.

position, exhibits greater internationalization or operates under weaker institutional investor oversight. Research on the economic consequences reveals that Entity List sanctions not only amplify future analyst-forecast biases for listed companies but also heighten the risk of stock price crashes. This adverse effect is particularly pronounced in firms with higher textual ambiguity, suggesting that the interaction between Entity List sanctions and ambiguous disclosure strategies exacerbates the information environment in securities markets, thereby triggering financial market volatility.

This study makes three potential contributions. First, it broadens the analytical dimensions for evaluating the economic impact of the Entity List on China, thereby enhancing the understanding of corporate behavioral responses to sanctions. While existing literature primarily focuses on the Entity List's impact on economic outcomes—mainly corporate innovation activities—and coping strategies such as building supply chain resilience (Yu et al., 2022; Han et al., 2024; Liu et al., 2025a, 2025b), it pays insufficient attention to how such lists shape firms' information communication behaviors. This study extends the research perspective to include corporate disclosure, providing empirical evidence of the negative policy shocks on firms' disclosure practices. It provides empirical evidence from the disclosure dimension to comprehensively assess the microeconomic effects of trade sanctions, thereby contributing to a systematic understanding of firms' overall response logic and behavioral patterns under external trade policy pressures. Second, it enriches the research framework on drivers of narrative text disclosure by revealing the pivotal role of external policy uncertainty and sanction risk. Previous studies predominantly explain textual ambiguity in terms of internal factors such as corporate performance, earnings management or managerial self-interest (Li, 2008; Lo et al., 2017; Wang et al., 2018), paying relatively little attention to how external pressures trigger abnormal disclosures. Unlike Mekhaime et al.'s (2024) generalized discussion of the broad impacts of political uncertainty, our study confirms the targeted effects of precision-hunting trade sanctions on covered firms. The practical value of this finding lies in clarifying the research context and revealing potential distortions in corporate disclosure strategies in highly sensitive areas such as national security and technological embargoes. It provides a more refined theoretical basis for understanding corporate communication dilemmas in trade conflict scenarios. Third, the findings provide references for decision-making to enhance the efficiency of capital market information and maintain financial stability. The results of analyst forecasts and capital market outcomes reveal the profoundly disruptive effects that the interaction between external political risks and firm-specific disclosure strategies has on the market information environment and operational efficiency. This alerts regulators to the potential systemic deterioration in disclosure quality under external shocks and underscores the importance of strengthening disclosure oversight, enhancing transparency and improving the comprehensibility of information within complex international economic and trade environments. The analysis provides direct and compelling empirical evidence to inform the refinement of regulatory policies and safeguard industrial security.

2. Policy context, literature review and theoretical analysis

2.1. Policy background of the Entity List for China

The U.S. Entity List policy targeting China is rooted in the United States' long-standing export control framework and has developed alongside the intensifying strategic competition between the two nations. The policy's origins can be traced back to the early 20th century. The Trading with the Enemy Act of 1917 established the legal basis for wartime trade restrictions. The subsequent formation of the Coordinating Committee for Multilateral Export Controls in 1949 marked the beginning of the Cold War era, during which the United States formalized export controls as a tool for the technological containment of the Soviet bloc. The Export Administration Act of 1979 formally established the Entity List system, authorizing the Bureau of Industry and Security, which is part of the U.S. Department of Commerce, to impose stringent trade restrictions on entities deemed to threaten national security or foreign policy interests. These restrictions apply not only to local goods but also to products from third countries that depend on U.S. technology. As China's technological capabilities advanced rapidly in the 21st century, the focus of the U.S. Entity List policy gradually shifted toward strategic containment of China. The 2018 Sino-U.S. trade friction served as a turning point, with the United States significantly expanding the scope of its export controls against China under the rationales of "national security" and "technology protection." Enacted in the same year, the Export Control

Reform Act further intensified these controls by introducing provisions for “emerging and foundational technologies,” thereby subjecting cutting-edge fields such as artificial intelligence, quantum computing and semiconductors to enhanced regulatory scrutiny. Since then, the frequency of Entity List updates has accelerated markedly, with numerous Chinese entities being successively added to the control regime.

The Entity List policy currently exhibits three core characteristics. First, it precisely targets China’s strategic and emerging industries, with a focus on high-tech sectors such as telecommunications, electronic equipment manufacturing and aerospace. This scope effectively covers the 10 key areas outlined in the “Made in China 2025” initiative, aiming to impede China’s progress in critical technologies such as 5G, supercomputing and semiconductors. Leading Chinese companies in communications, supercomputing and semiconductor manufacturing, such as Huawei, Sugon and SMIC, have been subjected to repeated rounds of sanctions. Second, the policy reinforces legal mechanisms and “long arm jurisdiction.” Under the Export Administration Regulations, it implements a “presumption of denial” licensing review policy for listed entities. Furthermore, it extends U.S. jurisdictional reach through rules such as the “de minimis rule” and the “direct product rule,” thereby restricting non-U.S. companies that utilize U.S. technology from exporting certain items to China. Third, a multidimensional sanctions system has been established that operates in synergy with other U.S. restrictive lists. These include the U.S. Department of Defense’s “Chinese Military Companies” list and the Treasury Department’s Specially Designated Nationals list. This coordinated approach aims to impose comprehensive financial, technological and market constraints on targeted Chinese enterprises.

2.2. Review of relevant literature

2.2.1. Research on Sino-U.S. trade frictions

Since 2018, Sino-U.S. trade frictions have exerted a profound impact on Chinese enterprises. One such effect is represented by the innovation challenges arising from restricted access to technology resulting from Entity List sanctions, which have become a key driver for corporate strategic adjustments and industrial chain restructuring, and thus represent a primary focus of current research. At the macro level, Sino-U.S. trade frictions have profoundly reshaped global industrial chains and trade patterns. Trade sanctions have not only directly reduced per capita income in Chinese regions with high trade exposure, with the impact concentrated in highly open, key nodal areas (Chor and Li, 2024), but also left U.S. enterprises reliant on Chinese suppliers confronting inventory backlogs and deteriorating profitability. This problem intensifies as supply chain complexity increases (Fan et al., 2022). At the micro-enterprise level, trade friction has initially suppressed short-term innovation output (Li et al., 2024a, 2024b, 2024c). Furthermore, tariff shocks have significantly increased trade policy uncertainty, causing firms to reduce investment expenditures, postpone capital allocation decisions and accept poorer short-term performance (Benguria et al., 2022; Shao et al., 2025). However, the long-term effects reveal a strong trend of “forced innovation” under external pressure, spurring Chinese enterprises to substantially increase investment in independent innovation to maintain strategic flexibility (Shao et al., 2025), accelerate digital transformation (Yu et al., 2022; Li et al., 2024a, 2024b, 2024c; Ma et al., 2025) and rapidly improve the innovation quality among upstream firms (Han et al., 2024). To address external challenges and build industrial chain resilience, firms have pursued various core strategic initiatives. These include ramping up R&D intensity (Liu and Li, 2023), optimizing supply chain layouts (Lv et al., 2019), scaling up venture capital investments (Wan et al., 2025), reconfiguring transnational innovation networks (Liu et al., 2025a, 2025b) and leveraging regional cooperation frameworks such as the Belt and Road Initiative (Li et al., 2024a, 2024b, 2024c). Meanwhile, macro-policy efforts have centered on establishing institutional support systems, including strategies to strengthen domestic industrial chain coordination (Wang and Qian, 2025), implement differentiated countermeasures (Wei and Lu, 2024) and optimize export tax rebate mechanisms (Fang and Yu, 2024), aiming to systematically elevate the overall resilience and risk resistance capacity of industrial chains.

2.2.2. Research on text readability

Text readability, as a key indicator of information disclosure quality, has been widely studied in corporate finance and accounting for its influence on the efficiency of information transmission, including its determinants and consequences (Rameezdeen and Rajapakse, 2007; Tan et al., 2015). Research in this area can be

traced back to the pioneering work of Soper and Dolphin (1964) on the relationship between readability and information comprehension. Li (2008) established the theoretical foundation by systematically introducing readability into empirical accounting research, revealing that underperforming firms tend to reduce the readability of their annual reports to hide negative information. This strategic disclosure behavior is particularly evident in firms with strong motives for earnings management (Lo et al., 2017) or low risk of shareholder litigation (Nelson and Pritchard, 2007). Subsequent research has focused on two dimensions: drivers and market effects. Factors such as short-selling pressure (Li and Zhang, 2015), controlling shareholders' equity pledges (Lu et al., 2020) and managerial self-interest (Wang et al., 2018) have been shown to increase textual obfuscation. Regarding market effects, recent studies also examine the impact of the external macroeconomic environment on readability. Mekhaimer et al. (2024) find that political uncertainty significantly increases the complexity of narrative disclosures, as management possesses a strong incentive to conceal adverse information. Conversely, low readability triggers multiple market inefficiencies, manifested in increased investor information-processing costs (Bushee et al., 2018), greater credit rating divergence (Bonsall and Miller, 2017) and increased borrowing costs (Ertugrul et al., 2017).

In terms of its impact mechanisms, ambiguous textual expression primarily distorts market efficiency through three key pathways. First, it creates information barriers that slow down market reaction speeds (You and Zhang, 2009). This, in turn, reduces stock liquidity (Miller, 2010) and lowers analyst coverage (Qiu et al., 2016). Second, heightened information asymmetry has been demonstrated to exacerbate agency costs (Luo et al., 2018), affording opportunities for managerial compensation manipulation (Wang et al., 2018) and misconduct (Guo et al., 2022). Finally, obfuscated text has been shown to increase semantic confusion (Ertugrul et al., 2017), thereby undermining the incremental information value of the disclosure. Recent research increasingly emphasizes the regulatory implications of text readability. For instance, the "information amplification effect" arising from the interaction between low readability and a highly negative tone in annual reports has been shown to significantly improve the accuracy of predicting corporate misconduct risk (Guo et al., 2022). Concurrently, flexible regulatory measures have proven effective in incentivizing high-ability managers to enhance the readability of their responses to regulatory inquiries (Wang et al., 2020). Strategic disclosure behavior also manifests in innovation-driven contexts: to balance disclosure requirements against proprietary costs, highly innovative firms tend to enrich the information content of their MD&A while deliberately reducing its readability (Yu et al., 2024).

2.2.3. Research gap and this study's positioning

Existing research on Sino-U.S. trade friction extensively reveals its broad microeconomic consequences for firms and their diverse coping strategies. However, when firms encounter a substantial negative shock to their status on the Entity List, their communication with the market, especially their information disclosure strategy, is equally critical yet remains underexplored. Prior literature clearly indicates that managers have incentives to strategically manipulate disclosures, particularly during periods of poor performance or pressure, tending to reduce text readability and increase linguistic ambiguity to conceal adverse information (Li, 2008; Kothari et al., 2009; Lo et al., 2017). Such opaque disclosure practices exacerbate information asymmetry and impair market efficiency (Bushee et al., 2018; Mekhaimer et al., 2024). Thus, when confronting the adverse shock of Entity List sanctions, firms are confronted with a fundamental disclosure dilemma: should they explicitly disclose relevant risks and countermeasures under pressure from external stakeholders and regulators, or deliberately adopt more ambiguous and obscure linguistic expressions to obfuscate information for users, thereby delaying or weakening market recognition of and reaction to the adverse news? Building on the identified research gaps and the established contextual framework, this paper investigates the strategic choices that firms make regarding the readability of their disclosure texts when facing Entity List sanctions, systematically examining the underlying motivational mechanisms and subsequent economic consequences.

2.3. Theoretical analysis and research hypotheses

According to obfuscatory disclosure theory, when firms encounter significant negative shocks, management has strong incentives to conceal adverse information by intentionally reducing the readability of disclosure texts and increasing linguistic ambiguity (Rutherford, 2003; Li, 2008). Such strategic textual manipulation

can be viewed as a “self-preservation” tactic adopted by management in response to corporate distress (Abu Bakar and Ameer, 2011). The U.S. sanctions system targeting Chinese entities systematically disrupts companies’ access to core technologies, critical production resources and global supply chain networks, exerting a direct, multidimensional impact on daily operations and strategic advancement. This has resulted in considerable disruption and poses significant threats to firms in both domestic and international markets. Such incidents are prone to triggering market panic and intensive negative media coverage. Consequently, management has strong incentives to increase the ambiguity of narrative texts, thereby raising the cost of extracting and interpreting information. The creation of obstacles to an accurate market assessment of real risks (Bloomfield, 2002; Chakrabarty et al., 2018) is intended to delay the rapid, concentrated release of “bad news” in the short term. Three primary motivations underlie this behavior. First, to dilute the consequences of sensitive information and avoid triggering excessive speculation, regulatory inquiries or litigation (Skinner, 1994; Rogers et al., 2009; Kim et al., 2016), management may deliberately utilize ambiguous language to “wrap” bad news (Bloomfield, 2002). Second, as sanctions directly threaten the supply of critical technologies and components, companies are legally obligated to disclose detailed response measures to comply with regulatory requirements. Management may seize this opportunity to insert redundant and obscure language, portraying risk mitigation measures as complex and unpredictable. This approach formally addresses concerns while substantially concealing the true extent of the damage and deficiencies in recovery capabilities, thereby avoiding the potential exacerbation of financing constraints or a collapse in market confidence that could result from a clear disclosure of negative news (Zhang, 2008). Finally, to guard against liability for unmet expectations (Kothari et al., 2009), management may emphasize potential technological breakthroughs or recovery prospects in forward-looking statements. By employing vague optimistic phrasing such as “expected to improve” or “anticipated to enhance,” they project a false sense of confidence while avoiding verifiable specific commitments (Doyle et al., 2013; Huang et al., 2014; Mekhaimer et al., 2024). Moreover, the cultural norms of implicit and indirect communication in China (Gu, 1992) may provide additional scope for the covert implementation of this strategy. Thus, according to the obfuscatory disclosure hypothesis, under immense pressure from Entity List shocks, management is more likely to increase the ambiguity of narrative texts to strategically conceal bad news, evade responsibility and manage market expectations.

In contrast, the transparent disclosure hypothesis presents a distinct perspective. It posits that when faced with significant negative external shocks, managers may provide clearer, more detailed disclosures to address concerns about oversight (El Ghouli et al., 2021). Given its high openness and far-reaching influence, an Entity List designation inevitably triggers extensive discussion and intense public scrutiny from investors, creditors, regulators and other stakeholders. In such circumstances, corporate silence or ambiguous statements can be easily interpreted by the market as inadequate responses or attempts at concealment. This would exacerbate market skepticism, inflate information risk premiums and trigger financing constraints and trust crises (Healy and Palepu, 2001). Therefore, proactively adopting a “frank and open” disclosure strategy can generate a positive informational effect. First, providing detailed explanations of the specific impacts of the sanctions, potential risks and the countermeasures that management has implemented or intends to implement—such as supply chain diversification, technological innovation or sourcing alternative suppliers—effectively signals to the market that management is in control. This demonstrates their ability to address challenges, thereby stabilizing investor sentiment and safeguarding corporate reputation and market value (Bloomfield, 2008). Second, clear risk disclosure serves as a crucial means to meet regulatory compliance requirements and address stakeholder concerns, helping to mitigate potential regulatory penalties and litigation risks (Skinner, 1994). Finally, from a business complexity perspective, the Entity List incident itself may increase operational volatility and make strategic adjustments more difficult. To accurately describe these more complex business conditions, newly emerging risk factors and the details of countermeasures, management may need to provide more detailed explanations with greater technical specificity (Bushee et al., 2018). The resulting increase in textual comprehension difficulty is an inevitable consequence of meeting stakeholders’ demand for in-depth information, rather than a deliberate strategy of management obfuscation. In summary, according to the transparent disclosure hypothesis, when confronted with substantial external information demands and heightened business complexity stemming from Entity List impacts, management is more likely to reduce (or at least not significantly increase) the ambiguity of narrative texts. Instead, they will opt for clear, transparent

communication to effectively manage market expectations, reduce information asymmetry and ultimately maintain market confidence.

Based on the two theoretical perspectives outlined above, this paper proposes the following pair of competing research hypotheses:

H_{1a}: Entity List sanctions increase the ambiguity of corporate narrative texts.

H_{1b}: Entity List sanctions decrease (or do not materially increase) the ambiguity of corporate narrative texts.

3. Research design

3.1. Sample selection and data sources

To comprehensively assess the impact of the U.S. Entity List policy on the narrative disclosure practices within the MD&A section of Chinese listed firms, this study selects all A-share listed firms on the Shanghai and Shenzhen stock exchanges from 2011 to 2024 as the initial research sample. The sample is refined through the following screening procedures: (1) excluding firms in the financial industry; (2) excluding ST and *ST companies; (3) removing observations with missing data for key variables. After applying these filters, the final sample consists of 44,917 firm-year observations, among which 232 firms are directly affected by the Entity List. The data regarding the U.S. Entity List designations targeting Chinese entities are primarily collected and translated from official announcements issued by the Bureau of Industry and Security under the U.S. Department of Commerce. The dataset is then matched with the listed companies' basic information to identify the affected firms. The narrative disclosure texts, stock forum data, financial news data and overseas shareholding data are sourced from the China Research Data Services (CNRDS) database. Macroeconomic variables, such as provincial GDP, are obtained from provincial statistical yearbooks. All other firm-level financial data come from the China Stock Market & Accounting Research database. To mitigate potential bias from outliers, all continuous variables are winsorized at the top and bottom 1% levels. In subsequent regression analyses, standard errors are clustered at the firm level.

3.2. Model specification

The U.S. Entity List policy targeting Chinese firms, which was formally enacted under the Export Control Reform Act of 2018 and expanded through incremental additions in subsequent years, is treated as an exogenous shock. This study utilizes it as a quasi-natural experiment and constructs a staggered DID model to examine its effect on the narrative disclosure behavior of Chinese firms. The model is specified as follows:

$$Fog_Index = \alpha_0 + \alpha_1 Regulation + Controls + FirmFE + YearFE + \varepsilon \quad (1)$$

In Eq. (1), the dependent variable *Fog_Index* measures the linguistic ambiguity (or “fog”) of a firm's narrative text. The core explanatory variable *Regulation* is a binary indicator for the exogenous shock of Entity List designation. *Controls* represents a vector of firm-level, industry-level and macro-level control variables. ε denotes the random error term. To account for unobserved time-invariant firm heterogeneity and common temporal trends, the model includes both firm fixed effects (*FirmFE*) and year fixed effects (*YearFE*).

The primary coefficient of interest is α_1 on *Regulation*. If the Entity List policy leads firms to increase the ambiguity of their MD&A narrative disclosures, α_1 is expected to be significantly positive. Conversely, if the policy incentivizes firms to improve the readability and clarity of their disclosures, α_1 is expected to be significantly negative.

3.3. Variable definitions

3.3.1. Dependent variable: narrative text ambiguity (*Fog_Index*)

The Fog Index has been widely adopted in academic research since Li's (2008) seminal work as a standard measure of the readability of English texts. Originating from Gunning's (1952) study on English writing, it is calculated based on two core dimensions—the average number of words per sentence and the percentage of complex words—as specified in Eq. (2).

$$\text{Fog Index} = 0.4 \times (\text{Average words per sentence} + \text{Percentage of complex words}) \quad (2)$$

By integrating features of sentence length and lexical complexity, this metric demonstrates reasonable validity within the English linguistic context. However, it is not directly applicable to Chinese texts. In English, word length—often measured by syllable or letter count—serves as a proxy for lexical complexity, whereas individual Chinese characters do not inherently convey such compositional information. Fundamental differences in ideographic word formation render English text readability standards inapplicable to Chinese contexts. Furthermore, using text length alone to gauge readability may conflate information content with comprehension difficulty. For instance, a longer text might simply contain more detailed content rather than being inherently more obscure (Eng and Mak, 2003; Francis et al., 2008).

Therefore, this study uses the Chinese Text Fog Index, which was proposed by Xu et al. (2019). This index is constructed from two perspectives. The first consideration is the deviation of the average number of characters per clause from the industry mean (*Readability1*). Although existing research on Chinese text supports the use of average sentence length as a valid classifier for text difficulty, the readability of a Chinese sentence is also significantly influenced by its structure. Given the same number of characters, a sentence with a clear structure and well-segmented clauses is easier to understand. Consequently, this paper uses the more granular measure of average characters per clause as a foundational metric. The second consideration is the deviation of the density of specific function words (adverbs and conjunctions) from the industry mean (*Readability2*). Research on the Chinese language indicates that an increased use of function words, particularly adverbs and conjunctions, significantly increases the ambiguity in logical relationships and comprehension difficulty (Xu et al., 2019). The final Chinese Text Fog Index is constructed as shown in Eq. (3). A higher index value indicates greater textual ambiguity and lower readability.

$$\text{Fog_Index} = 0.5 \times (\text{Readability1} + \text{Readability2}) \quad (3)$$

3.3.2. Core explanatory variable: U.S. Entity List shock (*Regulation*)

The core explanatory variable *Regulation* is a dummy variable indicating whether a firm is subject to Entity List restrictions: if a firm is directly added to the Entity List during the sample period, the variable takes a value of 1 for that year and all subsequent years; otherwise, it is 0. This study focuses exclusively on the sample of firms directly designated on the Entity List, excluding non-listed firms indirectly affected through supply chains, technology linkages or controlled-product matches (Yu et al., 2022). This approach enables clearer identification of the direct causal effect of Entity List restrictions on corporate disclosure behavior.

3.3.3. Control variables (*Controls*)

Model (1) controls for firm-level, industry-level and macro-level variables. The firm-level controls are firm size (*Size*), firm age (*Age*), leverage ratio (*Lev*), return on assets (*Roa*), total asset turnover (*Ato*), cash flow ratio (*Cashflow*), fixed asset investment (*Fixed*), revenue growth rate (*Growth*), loss status (*Loss*), firm value (*TobinQ*), board size (*Board*), proportion of independent directors (*Indep*), CEO duality (*Dual*), ownership concentration (*Top1*) and whether the auditor is a Big Four firm (*Big4*). The industry-level controls are industry leadership position (*LNI_Industry*) and high-tech industry status (*Tech_Industry*). The macro-level controls are provincial per capita GDP (*PerGDP*), provincial GDP growth rate (*GDPGrowth*) and the marketization index (*Marketization*). Detailed definitions for all variables are provided in Table 1.

4. Empirical results and analysis

4.1. Descriptive statistics and correlation analysis

Table 2 presents the descriptive statistics for the main variables. The mean value of the narrative text ambiguity variable (*Fog_Index*) is 0.0008, with a standard deviation of 0.1087. This indicates that the overall level of textual ambiguity in the MD&A sections released by the sample firms is close to the industry average, albeit with some variation. The minimum and maximum values are −0.2437 and 0.2999, respectively, revealing significant differences in narrative text ambiguity among firms. The core explanatory variable, U.S. Entity List

Table 1
Variable definitions.

Variable name	Variable symbol	Variable definition
Narrative text ambiguity	<i>Fog_Index</i>	The arithmetic mean of (1) the average number of characters per sentence in the MD&A section minus its industry-year average, and (2) the proportion of conjunctions and adverbs per sentence in the MD&A section minus its industry-year average.
U.S. Entity List shock	<i>Regulation</i>	Equals 1 for the fiscal year in which a firm is added to the U.S. Entity List and all subsequent years, and 0 otherwise.
Firm size	<i>Size</i>	The natural logarithm of total assets at the end of the fiscal year.
Firm age	<i>Age</i>	The natural logarithm of (the number of years since listing + 1).
Leverage ratio	<i>Lev</i>	Total liabilities at the end of the fiscal year divided by total assets at the end of the fiscal year.
Return on assets	<i>Roa</i>	Net income for the fiscal year divided by total assets at the end of the fiscal year.
Total asset turnover	<i>Ato</i>	Operating revenue for the fiscal year divided by the average total assets (beginning and end of the year).
Cash flow ratio	<i>Cashflow</i>	Net cash flow from operating activities for the fiscal year divided by total assets at the end of the fiscal year.
Fixed asset ratio	<i>Fixed</i>	Net fixed assets at the end of the fiscal year divided by total assets at the end of the fiscal year.
Revenue growth rate	<i>Growth</i>	(Operating revenue in year t minus operating revenue in year $t-1$) divided by operating revenue in year $t-1$.
Loss status	<i>Loss</i>	Equals 1 if the firm reports a net loss for the fiscal year, and 0 otherwise.
Firm value	<i>TobinQ</i>	Market value of equity divided by total assets at the fiscal year-end.
Board size	<i>Board</i>	The natural logarithm of the total number of directors on the board.
Proportion of independent directors	<i>Indep</i>	The number of independent directors divided by the total number of directors on the board.
CEO duality	<i>Dual</i>	Equals 1 if the positions of Chairman of the Board and Chief Executive Officer are held by the same individual, and 0 otherwise.
Ownership concentration	<i>Top1</i>	The number of shares held by the largest shareholder divided by the total number of shares outstanding.
Big Four auditor	<i>Big4</i>	Equals 1 if the firm's annual financial statements are audited by one of the Big Four international accounting firms (PwC, Deloitte, EY or KPMG), and 0 otherwise.
Industry position	<i>LNI_Industry</i>	The weighted average of the Lerner index for each firm in the industry, where the weights are the firm's operating revenue as a proportion of the total industry operating revenue.
High-tech industry	<i>Tech_Industry</i>	Equals 1 for firms belonging to industries classified as high-tech (manufacturing) according to the 2017 official Chinese classification standard ^a , and 0 otherwise.
Provincial GDP per capita	<i>PerGDP</i>	The provincial gross domestic product (GDP) per capita divided by 10,000.
Provincial GDP growth rate	<i>GDPGrowth</i>	The year-on-year growth rate of the provincial GDP.
Marketization index	<i>Marketization</i>	The total marketization index score for the province, reflecting the level of market development.

^a How high-tech industries are defined and measured: https://www.stats.gov.cn/zs/tjws/tjbz/202301/t20230101_1903766.html.

shock (*Regulation*), has a mean of 0.0199 (standard deviation of 0.1398), suggesting that around 1.99% of observations correspond to periods in or after the year a firm was added to the Entity List. Furthermore, the descriptive results for the control variables indicate that the sample covers listed firms at various stages of development. Notably, firms in high-tech industries—a primary target of U.S. sanctions—account for over 60% of the sample. The distribution range and dispersion of each variable suggest that the sample has sufficient variability to meet the requirements for subsequent empirical analysis.

This study also performs a correlation analysis on the main variables.¹ The variable *Regulation* exhibits a significant positive correlation with *Fog_Index* at the 5% level. This finding provides preliminary support for Hypothesis H_{1a} , namely that the Entity List targeting China has complicated firms' narrative text disclosures,

¹ Due to space constraints, the correlation coefficient analysis table is temporarily withheld for reference.

Table 2
Descriptive statistics.

Variables	N	Mean	Min	P25	P50	P75	Max	STD
<i>Fog_Index</i>	44,917	0.0008	−0.2437	−0.0718	−0.0049	0.0674	0.2999	0.1087
<i>Regulation</i>	44,917	0.0199	0.0000	0.0000	0.0000	0.0000	1.0000	0.1398
<i>Size</i>	44,917	22.2250	19.9545	21.2977	22.0158	22.9428	26.2728	1.2884
<i>Age</i>	44,917	2.0665	0.0000	1.3863	2.1972	2.8904	3.4012	0.9424
<i>Lev</i>	44,917	0.4138	0.0512	0.2454	0.4032	0.5663	0.9063	0.2079
<i>Roa</i>	44,917	0.0380	−0.2278	0.0120	0.0380	0.0715	0.2167	0.0660
<i>Ato</i>	44,917	0.6266	0.0735	0.3521	0.5351	0.7750	2.5613	0.4237
<i>Cashflow</i>	44,917	0.0462	−0.1559	0.0083	0.0456	0.0858	0.2382	0.0678
<i>Fixed</i>	44,917	0.2030	0.0020	0.0821	0.1708	0.2901	0.6749	0.1541
<i>Growth</i>	44,917	0.1366	−0.5636	−0.0435	0.0872	0.2400	2.0284	0.3555
<i>Loss</i>	44,917	0.1583	0.0000	0.0000	0.0000	0.0000	1.0000	0.3650
<i>TobinQ</i>	44,917	1.9839	0.8313	1.2293	1.5781	2.2533	8.2042	1.2476
<i>Board</i>	44,917	2.1091	1.6094	1.9459	2.1972	2.1972	2.6391	0.1973
<i>Indep</i>	44,917	0.3778	0.3333	0.3333	0.3636	0.4286	0.5714	0.0535
<i>Dual</i>	44,917	0.3056	0.0000	0.0000	0.0000	1.0000	1.0000	0.4607
<i>Top1</i>	44,917	0.3369	0.0822	0.2219	0.3131	0.4350	0.7425	0.1485
<i>Big4</i>	44,917	0.0587	0.0000	0.0000	0.0000	0.0000	1.0000	0.2350
<i>LNI_Industry</i>	44,917	0.1232	0.0188	0.0756	0.1138	0.1609	0.3737	0.0656
<i>Tech_Industry</i>	44,917	0.6070	0.0000	0.0000	1.0000	1.0000	1.0000	0.4884
<i>PerGDP</i>	44,917	9.2091	2.6416	5.8942	8.5871	11.6650	21.7140	4.3287
<i>GDPGrowth</i>	44,917	0.0832	0.0045	0.0516	0.0807	0.1084	0.2194	0.0413
<i>Marketization</i>	44,917	9.6681	4.4480	8.9080	9.9360	10.8270	11.4940	1.5698

thereby increasing textual ambiguity. Meanwhile, the absolute values of the correlation coefficients between the independent variable and the control variables are all below 0.1. The mean variance inflation factor is 1.46, which is well below the commonly accepted threshold of 10. This suggests that the selection of control variables in this study is appropriate and that the model is not affected by severe multicollinearity, thereby laying a solid foundation for the robustness of the empirical results.

4.2. Benchmark regression results

Table 3 reports the regression results on the impact of the Entity List on the ambiguity of corporate narrative texts. Columns (1) to (3) present the results for the univariate specification, the specification with fixed effects and the specification with both fixed effects and control variables, respectively. The results in Column (3) show that the estimated coefficient for *Regulation* is 0.0276 and statistically significant at the 1% level. This implies that firms added to the Entity List experience an average increase of 0.0276 units in the ambiguity of their MD&A texts compared with unaffected firms, corresponding to a 25.39% change in the standard deviation, which is economically significant. This finding supports Hypothesis H_{1a} , indicating that the U.S. Entity List policy increases the ambiguity of firms' narrative disclosures. This disclosure strategy is likely rooted in two motivations. First, sanctioned firms are required to disclose more details about their strategies for addressing regulatory scrutiny of supply. This, in turn, increases the texts' complexity. Second, management proactively employs ambiguous language to avoid leaking sensitive information or to mitigate investors' excessive reactions to the negative impacts of sanctions. To determine whether textual ambiguity stems from the inherent complexity of the information or from strategic obfuscation by management, a further analysis of the primary drivers of ambiguity is required.

We first employ text analysis techniques to extract six key categories of features (*Text_Feature*) from MD&A texts, including named entities (*NER*), financial information (*Fin*), trading information (*Trading*), entity list information (*BisList*), supply chain information (*SupplyChain*) and risk information (*Risk*). Subsequently, as specified in Model (4), we regress *Fog_Index* on these textual feature variables along with

Table 3
Benchmark regression and indicator tests.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	<i>Fog_Index</i>	<i>Fog_Index</i>	<i>Fog_Index</i>	<i>Info</i>	<i>Obfu</i>	<i>ASY</i>	<i>ASY</i>
<i>Regulation</i>	0.0090** (2.45)	0.0298*** (5.10)	0.0276*** (4.71)	0.0016 (1.29)	0.0252*** (4.51)		
<i>Info</i>						−0.2576** (−2.22)	
<i>Obfu</i>							0.0655** (2.51)
<i>Controls</i>	No	No	Yes	Yes	Yes	Yes	Yes
<i>FirmFE</i>	No	Yes	Yes	Yes	Yes	Yes	Yes
<i>YearFE</i>	No	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	44,917	44,917	44,917	44,917	44,917	44,701	44,701
<i>R</i> ²	0.0001	0.5735	0.5752	0.6419	0.0028	0.7534	0.7533
<i>Adj_R</i> ²	0.0001	0.5202	0.5219	0.5970	0.0000	0.7224	0.7223

Note: ***, ** and * denote significance levels of 1%, 5% and 10%, respectively. The values in parentheses represent the *t*-statistics of the parameter estimates. The same applies to the table below.

the control variables from Model (1). The predicted value from this regression measures objective information complexity (*Info*), while the residual, ε , represents opaque disclosure (*Obfu*). The rationale for this decomposition is that objective information complexity should reflect the objective association between firm fundamentals and textual features, whereas the residual captures strategic textual manipulation not explained by fundamentals (Bushee et al., 2018; Mekhaimer et al., 2024). Furthermore, we separately regress *Regulation* on the complexity derived from information itself (*Info*) and on the ambiguity disclosure resulting from management manipulation (*Obfu*), as shown in Model (5). The results in Columns (4) and (5) of Table 3 show that the coefficient on *Regulation* is statistically nonsignificant for *Info* (0.0016), but positively significant at the 1% level for *Obfu* (0.0252). This suggests that the Entity List shock primarily induces management to proactively increase ambiguous disclosure, rather than to change the objective complexity of the information itself.

$$Fog_Index = \alpha_0 + \alpha_1 Text_Feature + Controls + FirmFE + YearFE + \varepsilon \quad (4)$$

$$Info/Obfu = \alpha_0 + \alpha_1 Regulation + Controls + FirmFE + YearFE + \varepsilon \quad (5)$$

To validate the rationality of decomposing text ambiguity, we follow the approach of Bushee et al. (2018) and Mekhaimer et al. (2024) and examine the relationship between *Info/Obfu* and information asymmetry (*ASY*) based on Model (6).

$$ASY = \alpha_0 + \alpha_1 Info/Obfu + Controls + FirmFE + YearFE + \varepsilon \quad (6)$$

The measurement of information asymmetry (*ASY*) is primarily derived from Bharath et al. (2009), constructed from three stock liquidity-based proxies: the liquidity ratio (*LR*), the illiquidity ratio (*ILL*) and the gamma (*GAM*) yield reversal measure. Poorer stock liquidity implies a higher degree of information asymmetry. Principal component analysis is performed on *LR*, *ILL* and *GAM* to construct a composite *ASY* index. In accordance with the efficient market hypothesis, informative disclosure should reduce information asymmetry, whereas ambiguous disclosure exacerbates information frictions. The regression results in Columns (6) and (7) of Table 3 align with this expectation: *Info* is significantly negatively correlated with *ASY* at the 5% level, indicating that information complexity indeed reflects more transparent disclosure; *Obfu* is significantly positively correlated with *ASY* at the 5% level, confirming that ambiguous language hinders information transmission. This finding supports the validity of our classification of complexity sources and further confirms that the Entity List targeting Chinese firms incentivizes management to engage in more opaque disclosure, thereby obfuscating narrative disclosures.

4.3. Robustness tests

4.3.1. Parallel trend test

The parallel trend assumption is a prerequisite for applying the DID model, requiring that there be no systematic differences in textual ambiguity (*Fog_Index*) between the treatment and control groups prior to the exogenous policy shock (Bertrand et al., 2004). To test this assumption, we conduct a parallel trend test for our model. Specifically, we set the fifth year before the policy implementation as the base period, construct a series of time-varying dummy variables covering the period from five years pre-designation to five years post-designation, and incorporate these dummy variables into Model (1) for estimation. As shown in Fig. 3, prior to being included in the Entity List, the coefficient estimates for all corresponding time dummies are statistically indistinguishable from zero at the 90% confidence level. This indicates that there is no substantial discrepancy in MD&A textual ambiguity between the treatment and control groups during the base period, and no discernible pre-trend divergence prior to the policy shock, thereby satisfying the parallel trend assumption.

4.3.2. Heterogeneity of treatment effects

Given that the multi-period two-way fixed effects DID estimator is essentially a weighted average of multiple two-period DID estimates, the signs of the weights and the time-varying nature of treatment effects may introduce bias due to treatment effect heterogeneity. To rigorously assess the reliability of the estimated impact from the Entity List and to rule out bias from heterogeneous treatment effects, this study employs a combination of three methods: 2×2 DD decomposition, Bacon decomposition (Baker et al., 2022) and the CSDID estimator (Callaway and Sant'Anna, 2021).

First, Baker et al. (2022) demonstrate that multi-period treatment effects can be decomposed into a weighted average of four types of 2×2 comparisons: early-treated versus never-treated, late-treated versus never-treated, early-treated versus late-treated, and late-treated versus early-treated. Bias may arise if a comparison with a large weight yields a coefficient with an opposite sign to the theoretical expectation. The results of the 2×2 DD decomposition in Panel A of Table 4 show an overall weighted-average coefficient of 0.0271, which is significantly positive at the 1% level. This effect can be attributed primarily to three sets of positive

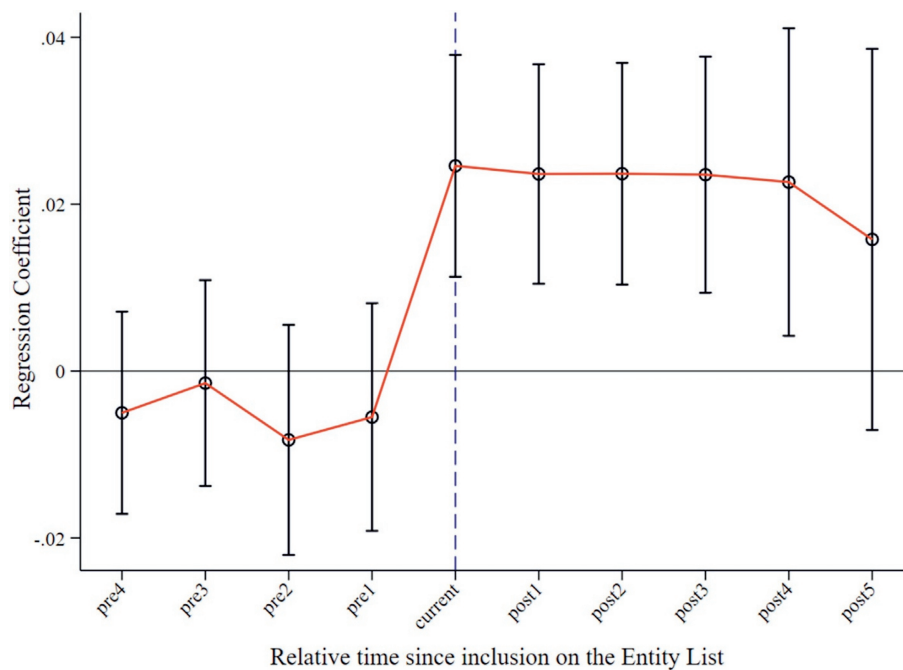


Fig. 3. Parallel trend test.

Table 4
Heterogeneity of treatment effects.

Panel A: 2×2 DD decomposition results

Variable	<i>Fog_Index</i>	DD comparison	<i>Avg DD</i>	<i>Weight</i>
<i>Regulation</i>	0.0271*** (2.82)	<i>Earlier T vs Later C</i> <i>Later T vs Earlier C</i>	0.014 0.045	0.010 0.003
<i>Controls</i>	No	<i>T vs Never T</i>	0.027	0.986

Panel B: Bacon decomposition results

Variable	<i>Fog_Index</i>	Bacon decomposition	<i>Beta</i>	<i>Weight</i>
<i>Regulation</i>	0.0240** (2.49)	<i>Timing_groups</i> <i>Never_v_timing</i>	0.0213 0.0273	0.014 0.972
<i>Controls</i>	Yes	<i>Within</i>	−0.1937	0.015

decomposition results, with the comparison between the treated and the never-treated groups (*T vs Never T*) carrying the greatest *Weight* (0.986), which is consistent with the benchmark regression.

Second, the Bacon decomposition method further breaks down the overall treatment effect into comparisons between groups treated at different times (*Timing_groups*) and comparisons between the treated and the never-treated groups (*Never_v_timing*). Panel B of Table 4 indicates that the predominant source of the treatment effect stems from the treated-versus-never-treated comparison (*Weight* = 0.972), while the contribution from comparisons across various treatment timing groups is negligible, aligning with the 2×2 DD decomposition results.²

Finally, to further guard against estimation bias from a potentially misspecified multi-period DID model, we employ the CSDID method for validation. Fig. 4 shows no significant difference in *Fog_Index* between the control and treatment groups prior to the Entity List shock. However, a significant increase becomes apparent subsequently. In summary, the results of these three tests collectively confirm that the increase in textual ambiguity following the Entity List shock stems from genuine differences between the treated and untreated groups, rather than model specification errors, thus supporting the robustness of our findings.

4.3.3. Placebo test

To ensure the robustness and reliability of the benchmark regression results and to eliminate spurious correlations arising from randomness, we conduct a rigorous placebo test. The specific procedure is as follows: we randomly generate 1000 simulated treatment assignments (pseudo-“Entity List” indicators) and use these to replace the actual *Regulation* variable in Model (1) for regression analysis. This yields a distribution of estimated coefficients under the null hypothesis of no treatment effect. Fig. 5 shows the results of the placebo test. Both the distribution of simulated *p*-values and the kernel density plot of the simulated coefficients approximate a normal distribution centered around zero. Furthermore, the simulated coefficients are predominantly concentrated within the range of −0.01 to 0.01, which is statistically distinct from the actual estimated coefficient (0.0276). These results confirm that our main findings are unlikely to be due to chance and that the impact of the U.S. Entity List on firms’ strategic disclosure in narrative text is statistically significant.

4.3.4. Heckman two-stage method

To address the potential sample selection bias, the Heckman two-stage method is employed to correct for endogeneity. In the first stage, a probit model is estimated to predict the probability of a firm being included on the Entity List, using the control variables from Model (1) to explain *Regulation*. In the second stage, the inverse Mills ratio (*IMR*) is computed from the first-stage estimation and included as an additional control variable in Model (1) to re-test our hypothesis. The results in Column (1) of Table 5 show that after control-

² The overall small weighted coefficients in both the 2×2 DD and Bacon decompositions stem primarily from the requirement for balanced panel data in both experimental and control groups. After balancing, only 1056 listed companies and 14,784 data points remain.

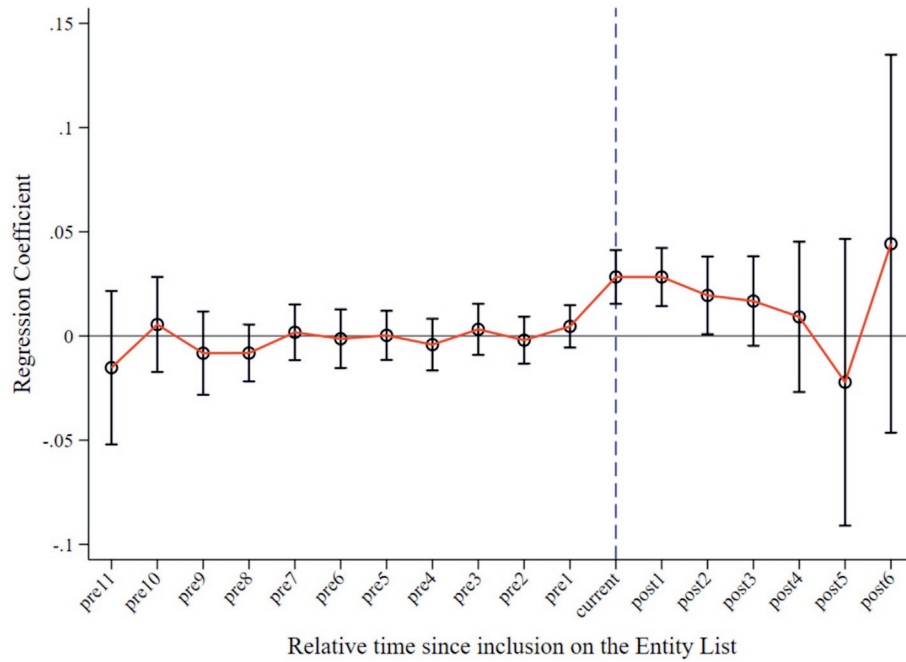


Fig. 4. CSDID trend results.

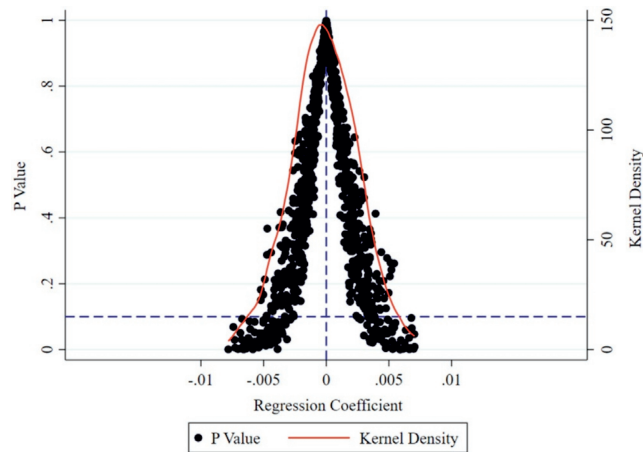


Fig. 5. Placebo test.

ling for *IMR*, the coefficient on the Entity List shock (*Regulation*) remains positively significant at the 1% level, indicating a significant increase in the narrative text ambiguity of regulated firms. Meanwhile, the coefficient on *IMR* itself is statistically nonsignificant. This further corroborates the robustness of our conclusion, and hypothesis H_{1a} remains valid.

4.3.5. Propensity score matching

To address potential systematic differences in fundamental characteristics between firms on the Entity List and other firms, and to mitigate endogeneity concerns, this study employs the propensity score matching (PSM) method to match treated firms with control firms of similar characteristics (Shipman et al., 2017). Specifically, given the strong industry-specific nature of the U.S. Entity List targeting Chinese firms, we ensure

Table 5
Endogeneity tests.

Variable	(1)	(2)	(3)
	Heckman two-stage	Propensity score matching	Entropy balancing
	<i>Fog_Index</i>	<i>Fog_Index</i>	<i>Fog_Index</i>
<i>Regulation</i>	0.0268*** (4.53)	0.0268*** (4.17)	0.0277*** (2.62)
<i>IMR</i>	0.0550 (0.87)		
<i>Controls</i>	Yes	Yes	Yes
<i>FirmFE</i>	Yes	Yes	Yes
<i>YearFE</i>	Yes	Yes	Yes
<i>N</i>	44,917	1207	44,917
<i>R</i> ²	0.5752	0.6917	0.7109
<i>Adj_R</i> ²	0.5219	0.5657	0.6747

sample comparability by matching each treated firm with a control firm within the same industry and year from the full sample, using firm-level characteristic variables (*FirmControls*) as covariates. We implement a 1:1 nearest-neighbor matching strategy without replacement, ensuring that each treated observation is matched to a unique, most similar control observation. This avoids the reuse of control observations, thereby enabling more precise estimation of the treatment effect and reducing sample selection bias. The regression results in Column (2) of Table 5 show that after adjusting for selection bias via PSM, the shock from the Entity List still significantly increases the ambiguity of corporate MD&A texts, further confirming the robustness of Hypothesis *H*_{1a}.

4.3.6. Entropy balancing

The application of PSM has two main limitations: first, its performance heavily relies on the correct specification of the first-stage logit model; second, the 1:1 nearest-neighbor matching may discard unmatched samples, which might lead to information loss. To address these issues, this study employs the entropy balancing method for control group matching (Hainmueller, 2012). The method does not rely on propensity-score prediction. Instead, it calculates a set of weights for the control group such that the reweighted group matches the treatment group on pre-specified moments (e.g., mean, variance and skewness) of the covariate distributions. This “optimal weighting” mechanism ensures a high degree of comparability in the distribution of key covariates between the two groups while preserving the full sample, thereby providing a more robust methodological foundation for causal inference. As shown in Column (3) of Table 5, after reweighting via entropy balancing, the effect of *Regulation* on *Fog_Index* remains significantly positive at the 1% level, which enhances the credibility of our findings.

4.3.7. Alternative measures of the dependent variable

To enhance the robustness of our conclusions, we validate the results using multiple alternative proxies of text readability. Following the approach of Wang et al. (2018), we select alternative indicators for textual obscurity from dimensions such as logical structure and lexical features. First, we use the density of adverse conjunctive components (*Adverse*) as a substitute for *Fog_Index*. This metric, based on the adverse component list, counts the number of adverse conjunctive words per 100 words in the MD&A text to capture the complexity of logical relationships. Second, we utilize the density of underused Chinese characters (*UCDensity*) to measure the usage of obscure characters. A higher frequency of such characters typically indicates poorer readability. Drawing on the 1988 List of Modern Chinese Underused Characters, we measure textual obscurity by calculating the frequency of underused characters per 100 words. Third, a high density of specialized accounting terminology (*ATDensity*) may also negatively impact readability (Loughran and McDonald, 2014). Therefore, using the 2008 Lingges Chinese–English Accounting Dictionary, we count the number of accounting terms per 100 words to reflect each text’s level of specialization. The regression results in Columns

Table 6
Other robustness tests.

Variable	(1)	(2)	(3)	(4)	(5)
	Replacing the dependent variable			Changing the identification strategy	Excluding the impact of the COVID-19 pandemic
	<i>Adverse</i>	<i>UCDensity</i>	<i>ATDensity</i>	<i>Fog_Index</i>	<i>Fog_Index</i>
<i>Regulation</i>	0.0151*** (5.22)	0.0270** (2.03)	0.0369** (2.48)		0.0415*** (3.05)
<i>Regulation_Industry</i>				0.0110*** (5.16)	
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes
<i>YearFE</i>	Yes	Yes	Yes	Yes	Yes
<i>FirmFE</i>	Yes	Yes	Yes	Yes	Yes
<i>N</i>	44,917	44,917	44,917	44,917	23,385
<i>R</i> ²	0.5391	0.7244	0.6926	0.5752	0.6218
<i>Adj_R</i> ²	0.4813	0.6898	0.6540	0.5219	0.5567

(1) to (3) of Table 6 show that regardless of which alternative proxy is used for textual ambiguity, the shock from the U.S. Entity List still significantly increases the obscurity of narrative disclosure. This consistent finding further supports our Hypothesis H_{1a} .

4.3.8. Alternative identification strategy

To examine the aggregate industry-level effect of the Entity List policy, we further refine our identification strategy for the policy shock. In view of the marked industry-specific targeting of the U.S. Entity List, the objective of which is to curtail technological advancement in specific sectors, and given that firms within the same industry generally face analogous competitive environments, R&D trajectories and supply chain relationships, sanctions against individual firms may precipitate cascading effects throughout the industry. Following the methodology of Yang and Zheng (2024), we construct an industry-level policy shock variable (*Regulation_Industry*). This variable takes the value of 1 for all firms within an industry in the year when any firm in that industry is added to the Entity List and in all subsequent years, and 0 otherwise. The regression results in Column (4) of Table 6 show that the industry-level Entity List shock also significantly increases corporate textual ambiguity. The *Fog_Index* of firms in affected industries rises by 0.0110 units on average compared with unaffected firms, equivalent to a 10.12% increase relative to its standard deviation. This finding further validates that the Entity List policy not only directly affects sanctioned firms but also amplifies disclosure ambiguity among peer firms through industry contagion effects, thereby strengthening the robustness of the conclusions.

4.3.9. Controlling for the impact of the COVID-19 pandemic

The COVID-19 pandemic, as a major and persistent public crisis, created a highly uncertain environment that could have significantly influenced corporate disclosure behavior. To prevent the pandemic from confounding our core findings, we restrict the sample period to the pre-pandemic years of 2011–2019 and re-estimate our model. The results in Column (5) of Table 6 show that after controlling for potential pandemic-related interference, the significant positive impact of the Entity List shock on corporate textual ambiguity remains robust.³ This further reinforces the reliability of our core conclusion, indicating that the Entity List shock itself is the primary driver behind increased textual ambiguity, rather than a spurious effect stemming from external environmental upheavals, such as the pandemic.

³ To ensure symmetry in the sample periods before and after the implementation of the Entity List policy, the sample is further restricted to 2016–2019, and the findings remain robust. Furthermore, regression results using data from 2011–2019 and 2023–2024 (while excluding the pandemic peak period of 2020–2022) also demonstrate that the external shock from the Entity List significantly increases the complexity of firms' narrative disclosures.

4.4. Mechanism analysis

Theoretical analysis suggests that the Entity List event significantly amplifies external public pressure, heightens perceptions of supply chain risk and increases uncertainty regarding future business prospects for sanctioned firms. In this context, corporate management tends to employ strategic obfuscation in their MD&A to mitigate the perceived negative impact, evade accountability and manage market expectations. To empirically test the primary mechanisms through which the Entity List shock affects narrative text ambiguity, this study constructs Model (7), where *Mechanism* represents the mediating variable.

$$Mechanism = \alpha_0 + \alpha_1 Regulation + Controls + FirmFE + YearFE + \varepsilon \quad (7)$$

4.4.1. External public sentiment environment

The Entity List event has been observed to exacerbate market panic, raising concerns about corporate operational resilience and supply chain security. This negatively affects investor sentiment and attracts intense negative media coverage. Facing a sudden surge in external public pressure, firms tend to adopt strategically ambiguous language in their MD&A section to dilute the impact of negative information, thereby avoiding potential overinterpretation of sensitive details or drawing additional regulatory scrutiny (Fei, 2021; Jiang et al., 2021). Accordingly, this study constructs proxy variables for external public pressure using stock forum posts and financial news report data from the CNRDS database. Specifically, we measure negative stock forum sentiment (*Guba_Neg*) as the annual ratio of negative posts to total posts in a listed firm's designated online stock forum. Negative media sentiment (*Media_Neg*) is measured as the annual ratio of negative news reports about the firm in mainstream financial media to the total number of reports about the firm. The regression results in Columns (1) and (2) of Table 7 show that the Entity List shock (*Regulation*) has a significantly positive effect on both *Guba_Neg* and *Media_Neg* at the 5% level (with coefficients of 0.0055 and 0.0178, respectively). This indicates that firms added to the Entity List encounter a more unfavorable public sentiment environment. This finding lends support to the notion that in the face of heightened negative public pressure, corporate management is inclined to apply more ambiguous narrative disclosures to mitigate excessive market reactions to the sanctions while avoiding direct exposure of sensitive information.

4.4.2. Supply chain risk perception

The restrictions imposed by the Entity List policy on access to key technologies and market channels have a significant impact on supply chain risks for sanctioned firms (Yu et al., 2025). Confronted with this external uncertainty, management opts to “wrap” bad news in ambiguous language. This approach serves a dual purpose: it avoids quantifying the specific severity of supply chain risks while simultaneously presenting countermeasures in an overly complex, “defensively packaged” manner, ostensibly to demonstrate effort and diligence. Such deliberate phrasing inherently increases the ambiguity (*Fog_Index*) of MD&A texts. Artificially erecting barriers to information comprehension substantially hinders stakeholders' capacity to accurately assess the firm's actual damages and its resilience to recovery. Drawing on Wu (2024), this study constructs a supply chain risk perception index (*SCRisk*). The specific steps are as follows. First, based on Chinese and English literature, we identify seed words for risk (e.g., “risk,” “crisis,” “uncertainty”) and supply chain (e.g., “supplier,” “customer,” “logistics”). We then use Word2Vec to calculate cosine similarity, thereby expanding the synonym libraries, and supplement them with a corpus of Chinese government work reports. Finally, following Hassan et al. (2019) and Benguria et al. (2022), we count the frequency of co-occurrence between supply chain words and risk words within a 15-word window in the MD&A text. *SCRisk* is measured as the percentage of such co-occurrences relative to the total word count (multiplied by 100). A higher index value indicates a stronger perception of supply chain risk by the firm. The results in column (3) of Table 7 show that the Entity List policy significantly increases firms' *SCRisk*, implying that after being listed, firms are more inclined to closely associate “risk” with “supply chain” in their disclosures. This shift in disclosure patterns may reflect either a genuine increase in operational pressures perceived by management or a strategic intent to obscure the specific attribution of negative impacts.

Table 7
Mechanism tests.

Variable	(1)	(2)	(3)	(4)	(5)
	<i>External public sentiment environment</i>		<i>Supply chain risk perception</i>	<i>Forward-looking disclosure</i>	
	<i>Guba_Neg</i>	<i>Media_Neg</i>	<i>SCRisk</i>	<i>Future</i>	<i>Future_Tone</i>
<i>Regulation</i>	0.0055** (2.17)	0.0178** (2.26)	0.0985*** (2.91)	0.1058** (2.55)	0.0100*** (2.62)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes
<i>FirmFE</i>	Yes	Yes	Yes	Yes	Yes
<i>YearFE</i>	Yes	Yes	Yes	Yes	Yes
<i>N</i>	44,873	42,892	44,917	44,917	44,917
<i>R</i> ²	0.7024	0.3002	0.5089	0.6386	0.5925
<i>Adj_R</i> ²	0.6652	0.2097	0.4473	0.5933	0.5414

4.4.3. Forward-looking disclosure

The Entity List shock heightens uncertainty surrounding firms' business prospects, prompting management to manage investor expectations by adjusting their forward-looking disclosure strategy. On the one hand, firms may proactively increase optimistic descriptions of future prospects to boost market confidence. On the other hand, to avoid potential liability for unmet expectations, management may resort to vague or hollow forward-looking statements to obfuscate the real-time impact of the negative shock. Consequently, this study constructs forward-looking disclosure indicators following the methodologies of Muslu et al. (2015) and Wang et al. (2020a, 2020b). Specifically, using a forward-looking dictionary expanded via Word2Vec technology, we calculate the frequency of forward-looking words per 100 words (*Future*) in the narrative text. Concurrently, we extract sentences containing forward-looking vocabulary. Following Huang et al. (2014), we utilize a sentiment dictionary to calculate the tone of these forward-looking sentences (*Future_Tone*), defined as the ratio of positive words to negative words, expressed as (number of positive words – number of negative words)/(number of positive words + number of negative words). A higher value indicates a more optimistic tone. The regression results in Column (4) of Table 7 show that inclusion on the Entity List significantly increases the frequency of forward-looking words (coefficient = 0.1058, significant at the 5% level). This suggests that firms attempt to divert investor attention from the immediate sanction shock by increasing forward-looking statements, which aligns with strategic disclosure motives. Furthermore, the results in Column (5) indicate that the tone of forward-looking text becomes significantly more positive (coefficient = 0.0100, significant at the 1% level). Despite substantial operational risks, managers adopt a deliberate approach in their forward-looking statements, employing a more optimistic vocabulary and emphasizing opportunities over potential hazards. This approach enables them to avoid direct responsibility for explaining the current negative impact while simultaneously alleviating market pessimism to a certain degree.

5. Further analysis

5.1. Heterogeneity analysis

5.1.1. Management performance pressure

In circumstances where management is under high pressure to perform well, the Entity List shock may further strengthen its incentive to strategically obfuscate disclosures. First, management tends to conceal bad news or shirk responsibility to evade accountability for any decline in performance that may be attributed to the imposition of sanctions (Huang et al., 2014). Second, the uncertainty engendered by the Entity List provides a “convenient excuse,” enabling management to attribute unfavorable outcomes to external, uncontrollable factors through ambiguous language. Consequently, performance pressure may amplify the Entity List's positive effect on textual ambiguity. This paper defines management performance pressure (*Pressure*) as the difference between analysts' forecasted net profit and the actual net profit, normalized by the actual net profit

to reflect the extent to which actual performance falls short of expectations. Since the pressure perceived by management in the current year is predominantly attributable to the performance shortfall in the prior period, we lag the *Pressure* variable by one year ($Pressure_{t-1}$) and construct an interaction term with the Entity List shock variable (*Regulation*), which is then incorporated into Model (1) for regression. The results in Column (1) of Table 8 show that the coefficient of this interaction term is significantly positive (at the 1% level), indicating that performance pressure significantly amplifies the positive effect of the Entity List shock on textual ambiguity. This finding supports the theoretical expectation that management under performance pressure is more likely to use the Entity List shock as a “smokescreen,” employing ambiguous language to obfuscate disclosure content and thereby shift the blame for performance issues to uncontrollable external factors. This highlights the combined distortionary effect of performance pressure and external uncertainty on disclosure quality.

5.1.2. Corporate market power

Firms with greater market power are typically in a stronger position to negotiate, have greater access to resources and demonstrate higher levels of risk resilience (Burkart and Ellingsen, 2004; Chen et al., 2022). When confronted with the Entity List shock, such firms typically opt for transparency to bolster their market reputation and investor trust, thereby avoiding ambiguous disclosures that could raise market concerns about their operational stability. In contrast, firms with weaker market positions, constrained by limited resources and insufficient risk resilience, fear that detailed and truthful disclosure might further jeopardize their market standing (Huang et al., 2017). Consequently, they prefer to use ambiguous language to deflect the attribution of negative shocks, blaming adverse information and performance pressures on uncontrollable external factors, thereby exacerbating disclosure opacity. Drawing on the methodology of Hu et al. (2023), this paper constructs a market power indicator (*Market_Position*) as (Operating Revenue – Cost of Goods Sold – Selling

Table 8
Heterogeneity analysis.

Variable	(1)	(2)	(3)	(4)
	<i>Performance pressure</i>	<i>Market power</i>	<i>Corporate internationalization</i>	<i>Institutional shareholding</i>
	<i>Fog_Index</i>	<i>Fog_Index</i>	<i>Fog_Index</i>	<i>Fog_Index</i>
<i>Regulation</i> × <i>Pressure</i> _{<i>t</i>-1}	0.5826*** (2.62)			
<i>Regulation</i> × <i>Market_Position</i>		-0.0890** (-2.19)		
<i>Regulation</i> × <i>International</i>			0.0116** (2.26)	
<i>Regulation</i> × <i>INST</i>				-0.0595** (-2.41)
<i>Regulation</i>	0.0257*** (3.59)	0.0357*** (5.13)	0.0184** (2.46)	0.0535*** (4.29)
<i>Pressure</i> _{<i>t</i>-1}	0.0535 (1.05)			
<i>Market_Position</i>		-0.0127 (-1.57)		
<i>International</i>			-0.0003 (-0.22)	
<i>INST</i>				-0.0032 (-0.42)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>FirmFE</i>	Yes	Yes	Yes	Yes
<i>YearFE</i>	Yes	Yes	Yes	Yes
<i>N</i>	32,719	44,917	44,917	44,882
<i>R</i> ²	0.5958	0.5754	0.5753	0.5757
<i>Adj_R</i> ²	0.5366	0.5221	0.5220	0.5224

Expenses – Administrative Expenses)/Operating Revenue. This metric measures a firm's core business profitability, with higher values indicating a stronger market position. We then incorporate *Market_Position* and its interaction term with *Regulation* into the baseline Model (1). The results, shown in Column (2) of Table 8, indicate that the coefficient for *Regulation* $\times$ *Market_Position* is -0.0890 , significantly negative at the 5% level. This suggests that market power mitigates the text-amplifying effect of the Entity List. The empirical findings confirm that firms with high market power, leveraging their resource buffers and supply chain adjustment capabilities, are more likely to convey risk-resilience signals through transparent disclosure, thereby avoiding undermining their market credibility with ambiguous statements. For instance, industry leaders may proactively disclose their technology substitution plans or progress in supply chain diversification to alleviate investor concerns. Conversely, weaker firms face greater survival pressure, and the Entity List exacerbates their operational fragility, increasing the likelihood that their management will obscure the actual impact of U.S. sanctions through the use of ambiguous language.

5.1.3. Degree of corporate internationalization

Firms with overseas operations are typically deeply embedded in global supply chains, involving the cross-border procurement of raw materials, technological collaboration or sales in foreign markets. The Entity List policy imposes direct restrictions on their access to U.S. technology, equipment and critical components, significantly increasing the risk of overseas supply chain disruptions. This compels management to strategically utilize ambiguous language to avoid disclosing sensitive information or to conceal potential negative impacts. Simultaneously, overseas subsidiaries must navigate dual institutional pressures from U.S. “long arm jurisdiction” and host-country regulations. Although objectively necessitating more detailed disclosure, management may seize this opportunity to insert ambiguous statements as a precaution against potential future retrospective scrutiny. Following Yang et al. (2022), this paper constructs a measure of corporate internationalization (*International*) based on the natural logarithm of the annual number of overseas subsidiaries (including both controlled and non-controlled interests) held by the listed firm. We introduce *International* and its interaction term with *Regulation* into Model (1). The regression results, presented in Column (3) of Table 8, show that the coefficient for the interaction term *Regulation* $\times$ *International* is 0.0116 , significantly positive at the 5% level. This suggests that greater corporate internationalization intensifies the Entity List's positive impact on textual ambiguity. When firms deeply embedded in global production networks encounter sanction shocks, the combined pressures of supply chain vulnerability risks and compliance disclosure requirements strengthen management's motivation to strategically manipulate texts, thereby significantly increasing textual ambiguity.

5.1.4. Institutional shareholding

Institutional investors possess professional investment analysis capabilities and monitoring incentives. Their shareholding proportion is commonly regarded as an important indicator of corporate governance quality (Gompers and Metrick, 2001) and can effectively constrain management's strategic text obfuscation. First, their status as long-term holders incentivizes firms to prioritize transparency in their information to maintain stable investor relations. Second, institutional investors' superior ability to decipher ambiguous texts reduces management's incentive to obscure information. Consequently, firms with higher institutional ownership exhibit a significantly lower propensity to engage in ambiguous disclosure in response to the Entity List shock. Conversely, lower institutional ownership affords management greater latitude to employ ambiguous disclosure strategies. This paper constructs an interaction term between *Regulation* and the proportion of institutional shareholding (*INST*), and includes both *INST* and this interaction term in Model (1). The regression results, shown in Column (4) of Table 8, indicate that the coefficient of the interaction term is significantly negative at the 5% level. This suggests that for every one-unit increase in institutional ownership, the Entity List's positive effect on textual ambiguity decreases by approximately 5.95%. This result validates the critical role of institutional investors as an external monitoring mechanism: when institutional ownership is high, their demand for information transparency curbs management's use of ambiguous language for strategic disclosure purposes, thereby mitigating the narrative obfuscation problem induced by the Entity List shock.

5.2. Analysis of economic consequences

5.2.1. Securities market information environment

The Entity List shock significantly distorts the efficiency of information transmission in the securities market by increasing corporate textual ambiguity (Loughran and McDonald, 2014). First, ambiguous disclosure raises the cost of information extraction, hindering analysts and investors from accurately assessing firms' true risks. Second, management's strategic use of vague language to conceal negative information may cause market expectations to diverge from corporate fundamentals, leading to pricing distortions. The deterioration of the information environment could amplify the negative impact of the Entity List and exacerbate market volatility. Following Clement (1999), we use the analyst forecast error for the next period ($Error_{t+1}$), defined as the absolute difference between the mean analyst earnings forecast and actual earnings, scaled by the absolute value of actual earnings, as a proxy for the securities market information environment. The results in Column (1) of Table 9 show that the Entity List shock directly leads to a significant increase of 0.5074 units in the future analyst forecast error. This suggests that the sanction event itself exacerbates information asymmetry, significantly increasing analysts' difficulty in forecasting the earnings of sanctioned firms. In Column (2), the coefficient on the interaction term between *Regulation* and *Fog_Index* is significantly positive, further confirming that the amplifying effect of the shock on analyst forecast errors is more pronounced when sanctioned firms have higher textual ambiguity. This validates the adverse effect of ambiguous disclosure: management's deliberate elevation of textual ambiguity obscures critical information, making it difficult for analysts to effectively interpret the firm's true condition, thereby significantly widening forecast errors. In summary, the Entity List shock significantly worsens the information environment in the securities market by inducing ambiguous disclosure, highlighting the negative economic consequences arising from the interaction between external environmental uncertainty and management's strategic disclosure behavior.

5.2.2. Financial market stability

The increase in disclosure ambiguity triggered by the Entity List shock exacerbates information asymmetry, leading to the concealment, obfuscation and continuous accumulation of negative information within firms. When such information accumulates to a point where it can no longer be concealed, its concentrated release delivers a severe shock to investors, causing stock price crashes and disrupting financial market stability (Chen et al., 2001). Following Kim et al. (2011), we employ the down-to-up volatility ratio ($DUVOL_{t+1}$) and the negative coefficient of skewness ($NCSKEW_{t+1}$) to measure stock price crash risk, controlling for the mean (*Ret*)

Table 9
Analysis of economic consequences.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Analyst forecast bias		Stock price crash risk			
	$Error_{t+1}$		$DUVOL_{t+1}$		$NCSKEW_{t+1}$	
<i>Regulation</i>	0.5074** (2.07)	0.4409* (1.80)	0.0473** (2.39)	0.0416** (2.09)	0.0715** (2.39)	0.0637** (2.13)
<i>Regulation</i> × <i>Fog_Index</i>		5.0544** (2.55)		0.4858*** (2.69)		0.6038** (2.24)
<i>Fog_Index</i>		−0.3078 (−0.73)		−0.0186 (−0.55)		0.0028 (0.05)
<i>Ret</i>			3.7091*** (10.98)	3.7117*** (10.99)	5.1435*** (10.30)	5.1459*** (10.30)
<i>Sigma</i>			−1.7333*** (−7.63)	−1.7325*** (−7.63)	−1.7914*** (−5.24)	−1.7912*** (−5.24)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>FirmFE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>YearFE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	32,371	32,371	38,119	38,119	38,119	38,119
<i>R</i> ²	0.2641	0.2642	0.1921	0.1922	0.1836	0.1837
<i>Adj_R</i> ²	0.1467	0.1467	0.0775	0.0775	0.0678	0.0678

and standard deviation (*Sigma*) of weekly returns in the regression models. The regression results in Columns (3) and (5) of Table 9 show that the Entity List shock directly increases the stock price crash risk, with the coefficients on *Regulation* being significantly positive at the 5% level. This indicates that the shock itself significantly raises the crash risk of sanctioned firms by intensifying operational uncertainty. Furthermore, the coefficients on the interaction term *Regulation* $\times$ *Fog_Index* are significantly positive in Columns (4) and (6) (with coefficients of 0.4858 and 0.6038, respectively). This suggests that when firms engage in disclosure manipulation through strategic textual obfuscation, the aggravating effect of the Entity List on crash risk becomes more pronounced. These findings support the view that management's strategic text obfuscation impedes the timely release of negative information, leading to the accumulation of latent risk. Once these shocks are concentrated and exposed, market panic is amplified, resulting in sharp declines in stock prices and significantly undermining financial market stability. This highlights the profoundly disruptive effect of the interaction between external political risks and firm-specific disclosure strategies on capital market quality.

6. Conclusions and policy recommendations

The U.S. Entity List sanctions have constituted a major exogenous shock in recent years, with the potential to disrupt the supply chain security and technological pathways of Chinese enterprises. Taking these sanctions as a natural experiment, this study investigates the impact of asymmetric trade policy shocks on corporate disclosure behavior. We construct a measure of narrative text ambiguity based on the MD&A texts of Chinese A-share listed companies from 2011 to 2024. The findings reveal that firms added to the Entity List significantly increase the ambiguity of their narrative disclosures in comparison with non-sanctioned firms. A decomposition of the sources of textual ambiguity indicates that such textual obfuscation stems primarily from management's deliberate strategic manipulation rather than from an increase in the objective complexity of the underlying information. The mechanism analysis identifies three channels through which the Entity List sanctions drive strategic ambiguous disclosure: intensifying external public scrutiny pressure, heightening supply chain risk perception, and inducing management to convey a facade of confidence in forward-looking statements. Heterogeneity analyses show that the ambiguity-amplifying effect of sanctions is more pronounced for firms with higher management performance pressure, lower market power, greater internationalization and weaker oversight by institutional investors. Further analysis of economic consequences demonstrates that the elevated textual ambiguity induced by the Entity List significantly exacerbates analyst forecast inaccuracies and stock crash risk, thereby compromising the integrity of the information environment in securities markets and jeopardizing financial market stability.

The policy implications of our findings are as follows:

First, at the firm level, companies should strengthen their endogenous resilience through governance upgrading, striking a balance between compliant information disclosure and strategic response. Disclosure strategy should be integrated into the overarching corporate risk management framework. In addressing external sanctions, firms should enhance disclosure quality and market trust through governance optimization. It is imperative that the management of firms impacted by the Entity List avoid adopting short-sighted secrecy. Instead, the focus should be on providing clear, transparent disclosures, including details on supply chain alternatives and R&D progress, with a view to stabilizing investor confidence. Concurrently, internal governance structures should be refined to bolster the board's oversight of disclosure practices, thereby preventing management from manipulating textual content to evade accountability. This is particularly crucial for firms operating under high performance pressure or with extensive overseas business involvement, for which more stringent and prudent disclosure review mechanisms are necessary. Furthermore, firms should enhance their capacity to anticipate and respond to policy risks. To reduce reliance on external technologies and markets, businesses should diversify their operations and pursue independent technological innovation. This approach addresses the root cause by diminishing the incentive to manipulate disclosure triggered by sanction shocks, fostering a virtuous cycle between effective governance and transparent disclosure to lay a solid foundation for sustainable development.

Second, at the regulatory level for information disclosure, authorities should employ targeted oversight to enhance transparency and solidify the informational foundation of capital markets. Regulators must closely monitor the potential for systemic deterioration in the quality of corporate narrative disclosures amid external

shocks. By strengthening the enforcement of disclosure rules and innovating regulatory tools, they should ensure the authenticity and comprehensibility of market information. Specifically, differentiated disclosure guidelines should be formulated for major risk events, such as Entity List designations, mandating that firms explicitly disclose the impacts of sanctions, the countermeasures taken and the potential risks. This would reduce the space for ambiguous statements and strategic manipulation. Moreover, the establishment of a dynamic monitoring system for narrative disclosure quality, utilizing advanced technologies such as text analytics and artificial intelligence, is imperative. Disclosures exhibiting abnormally low readability, high ambiguity or a distorted tone should initiate targeted regulatory inquiries, compelling firms to improve transparency. Furthermore, there is a need to enhance cross-border disclosure coordination mechanisms to prevent firms from exploiting the complexities of international operations to evade disclosure obligations. Through such effective regulation, regulators can strike a balance between information transparency and trade secrets protection, provide investors with clear and reliable decision-making information and uphold the “efficient market” hypothesis in capital market operations.

Furthermore, at the capital market level, optimizing resource allocation through mechanism refinement is imperative for enhancing the market’s capacity for accurate risk pricing. Capital markets need to improve their efficiency in responding to external policy shocks and corporate disclosure practices via institutional innovations, thereby alleviating resource misallocation caused by information asymmetry. Institutional investors should be guided to leverage their professional monitoring role. It is recommended that firms be encouraged to conduct in-depth research based on the quality of textual disclosures, with a view to constraining the ambiguous disclosure practices through the exercise of voting rights and engagement pressure. Concurrently, policies should be implemented to facilitate the inflow of long-term institutional capital, which can help stabilize rational market expectations regarding Entity List-affected firms and reduce speculative market volatility. Meanwhile, the professional environment for financial analysts is also a matter for concern. Targeted training programs should be launched to enhance analysts’ ability to decode ambiguous narrative disclosures and identify information obfuscation, thereby reducing earnings forecast errors caused by textual manipulation. Establishing an evaluation mechanism for the quality of analyst reports would incentivize them to uncover the true impact of sanction shocks. Additionally, capital market infrastructure should be strengthened by improving stock price stabilization mechanisms and market-risk early-warning systems to prevent abnormal price fluctuations induced by low-quality or ambiguous disclosures. The price-discovery function of an “efficient market” can be harnessed to channel capital toward firms with genuine risk resilience and innovative potential.

Ultimately, at the national trade policy level, a proactive and effective government is necessary to coordinate strategic responses and establish a self-reliant and controllable industrial chain ecosystem. Amid intensifying deglobalization and technological containment, the state is obliged to enhance the strategic synergy of trade policies and to provide institutional safeguards for firms to withstand external shocks through top-level design and planning. First, it is crucial to implement targeted R&D investment increments and preferential policy support for high-tech industries and key sectors in the Entity List. By improving the national collaborative innovation system to tackle core “bottleneck” technologies, we can reduce dependence on single sources of technology and fundamentally strengthen the resilience of industrial chains. Second, efforts should be made to deepen technological cooperation and mutually beneficial trade linkages with Belt and Road partner countries and friendly economies. Supply chain diversification helps mitigate sanctions risks, while multilateral mechanisms can be utilized to counter unreasonable applications of “extraterritorial jurisdiction,” thereby fostering a fair international competitive environment for firms. Furthermore, policy formulation must strike a balance between short-term relief and long-term development goals. Measures such as export tax rebates and credit support can alleviate the operational pressure on sanctioned firms. Simultaneously, policies should guide industrial upgrading and transformation, promoting the high-end and autonomous development of key sectors. In this way, an effective government can efficiently guide market-oriented resource allocation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The impact of global major customers on corporate carbon disclosure: a quasi-natural experiment from Apple's supply chain in China

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ABSTRACT

This study investigates whether and how global major customers affect corporate carbon disclosure. Leveraging the unique quasi-natural experiment of Apple's supply chain from 2008 to 2023 in China, we employ a difference-in-differences design and examine the impact of major customers on suppliers' carbon-disclosure quality. Baseline results indicate that the carbon-disclosure quality increases by approximately 6.76% following a firm's entry into the supply chain. Mechanism analysis indicates Apple plays a disciplining role through direct governance and indirect exposure effects. Cross-sectional analyses reveal that the impact is more pronounced among suppliers with stronger financial capacity and lower agency costs. Real effects, measured by carbon emission intensity and green innovation, demonstrate that the influence of global major customers extends beyond symbolic disclosure to substantive environmental action. These findings underscore the influential role of major customers in promoting environmental transparency along global supply chains.

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1. Introduction

Climate change has emerged as a global challenge of increasing importance for society and politics (World Economic Forum, 2020). Corporations can be both sources of and solutions for carbon emissions. To fulfill a firm's environmental responsibilities, transparent and comprehensive disclosure practices are necessary. It is

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difficult for external stakeholders (e.g., investors, regulatory authorities, the public) to directly observe the real emission reduction actions and achievements within an enterprise. Therefore, effective carbon disclosure is conducive to alleviating such information asymmetry. The key issue is how to motivate firms to disclose high-quality carbon information. Prior literature has explored pressure from internal governance (Ben-Amar et al., 2017; Flammer et al., 2019) and external pressure from government regulation (Wang et al., 2019; Downar et al., 2021), capital markets (Döring et al., 2023), public media (Li et al., 2018) and others. Nevertheless, systematic studies on the carbon-related governance role of global supply chains are scant. Major customers, especially global major customers, are equipped with information, incentives and the power to monitor their suppliers effectively (Dai et al., 2021; Distelhorst and Shin, 2023; Chen et al., 2025). To address this gap, our study investigates whether global major customers improve suppliers' carbon-disclosure quality.

In general, carbon disclosure reflects a firm's emission reduction target, management strategy, progress, analysis of climate-related risks and opportunities, and greenhouse gas (GHG) emissions information. GHG emissions can be divided into three scopes: Scope 1 includes direct emissions from owned or controlled sources; Scope 2 covers indirect emissions from the generation of purchased electricity, heat or steam consumed by the firm; and Scope 3 encompasses all other indirect emissions in the company's value chain. Prior to 2020, carbon disclosure was primarily driven by non-official initiatives, such as the Carbon Disclosure Project (CDP) and the Task Force on Climate-Related Financial Disclosures. Since 2020, a growing number of countries and regions have begun promoting mandatory carbon disclosure, including the European Union's Corporate Sustainability Reporting Directive, California's SB 253 and the U.S. Securities and Exchange Commission climate disclosure rules, as well as the climate-related provisions within China's corporate sustainability disclosure standards. Supply chain carbon responsibility also attracts growing attention: for example, California's SB 253 requires enterprises to disclose Scope 3 emissions, highlighting the expanding trend of supply chain responsibility.

Analyzing supply chain carbon disclosure is crucial in the context of global efforts to mitigate carbon emissions. Of the three types of carbon emissions, Scope 3 emissions are often the most significant. McKinsey (2024) estimates that Scope 3 emissions account for about 90% of a company's total emissions. Effective management of Scope 3 emissions through monitoring and reporting carbon emissions is imperative for reducing a company's carbon footprint, which necessitates collaborative efforts across the entire value chain (Lintukangas et al., 2023). Global major customers, who typically possess considerable bargaining power over suppliers, can act as rule-setters and facilitators, effectively incentivizing suppliers to adopt carbon management practices (Bhattacharyya and Nain, 2011; Distelhorst and Shin, 2023; Chen et al., 2025). This trend is becoming a norm in global business practices. In recent years, a growing number of global major customers have actively engaged in managing sustainability practices across their supply chains, e.g., Microsoft¹ and Walmart.² However, it remains unclear whether those global major customers' carbon reduction commitments can serve as a beneficial complement to formal institutional arrangements to improve supply chain carbon transparency.

We focus on Apple as a global major customer to explore this pivotal research question. Beyond its market capitalization and consistent recognition by Interbrand as the world's most valuable brand,³ Apple's leadership is prominently demonstrated by its supply chain capabilities. Apple Inc. has been consistently recognized as a Supply Chain Master by Gartner since 2015. For most focal firms, Apple is a major customer according to the thresholds of top-5 customer or 10% of sales. We cannot acquire specific sales amounts from each supplier to Apple as most suppliers only disclose the sales proportions of their top 5 customers without disclosing their identity. However, media reports have scrupulously inferred from clues regarding purchase amounts and products' unit prices that Apple is the largest or a top-5 customer of these suppliers, with sales even exceeding

¹ Microsoft, "Microsoft Supplier Code of Conduct," 2025, available at <https://cdn-dynmedia-1.microsoft.com/is/content/microsoftcorp/microsoft/accex/documents/presentations/Microsoft%20Supplier%20Code%20of%20Conduct.pdf>.

² Walmart, "Walmart Suppliers Lead the Charge, Help Deliver Project Gigaton Goal More Than Six Years Early," available at <https://corporate.walmart.com/news/2024/02/21/walmart-suppliers-lead-the-charge-help-deliver-project-gigaton-goal-more-than-six-years-early>.

³ Apple has been ranked as the world's most valuable brand by Interbrand since 2013.

50% for some suppliers.⁴ Even for corporations that do not meet this threshold, Apple still has enormous power over them as a globally renowned client that exerts substantial influence in the global market.

The unique setting of Apple suppliers in China has several advantages for this study. First, China is the largest emerging-market country, with increasingly intense carbon emissions, and is in the early stage of carbon disclosure (Li et al., 2018), making it significant to explore the governance role of international major customers in enhancing carbon disclosure in China. Second, different from general major customers, global major customers are internationally recognized, coordinating global supply chains and distribution networks, and thereby exert profound pressure on their suppliers (Distelhorst and Shin, 2023). Using customer concentration alone to measure the influence of major customers may fail to capture the asymmetric dependence between customers and suppliers. While a large sales share indicates a customer's importance to a supplier, it can simultaneously reflect the customer's own reliance on that supplier. Finally, information about Apple's suppliers is transparent and publicly available. Apple has published a list of its top 200 suppliers annually since fiscal year 2011. Given that Apple ultimately decides suppliers' entry and exit from its supply chain, the timing of these events provides a quasi-natural experiment setting. We employ a difference-in-differences (DID) design to disentangle Apple's impact on supply-chain carbon disclosure, alleviating endogeneity concerns. Transparency also enhances the high visibility of the supply chain, resulting in an exposure effect through which Apple can discipline its suppliers.

While Apple has established a comprehensive *Supplier Code of Conduct*⁵ and regularly publishes supplier responsibility reports, prior research highlights persistent ethical and environmental challenges within its supply chain. For instance, Clarke and Boersma (2017) document unresolved human rights and environmental dilemmas in Apple's global value chains. These findings suggest that despite Apple's formal commitments, the effectiveness and depth of its supply chain governance warrant further research. Our study focuses on carbon disclosure to examine whether Apple as a major customer can exert a substantive influence on its suppliers in the context of combating global climate change.

This study uses a DID approach to study how Apple affects suppliers' carbon disclosure behavior. The supplier list data are manually collected from the Apple supplier list released annually. The initial sample includes Chinese A-share companies listed on the Shanghai and Shenzhen Stock Exchanges from 2008 to 2023. We then restrict the sample to non-state-owned enterprises and the computer, communication and other electronic equipment manufacturing industry. Our final sample consists of 3226 firm-year observations covering 530 unique firms over the period 2008–2023.

The baseline results show that there is a positive relationship between entry into Apple's supply chain and carbon-disclosure quality. Controlling for other factors, the average carbon-disclosure quality of Apple suppliers is 6.76% higher than that of non-participating suppliers. We conduct a series of robustness tests to examine the sensitivity of our results to different research design choices, including using alternative measures for the dependent variable (e.g., carbon-disclosure word frequency), employing a Poisson regression model for the count nature of the disclosure score and re-estimating the model using alternative samples (e.g., different industries, including SOEs or varying the sample period). Furthermore, we incorporate additional control variables, such as regional economic factors and corporate ESG/environmental performance, to mitigate potential omitted variable bias. The results remain consistently significant across these alternative specifications.

To mitigate endogeneity concerns, we conduct the following analysis. First, we perform parallel trend tests. Second, placebo tests are conducted to further assess the validity of our findings by randomly assigning treatment group status to firms in our sample and keeping the year-specific number of Apple suppliers the same as in the actual data. Third, to reduce the bias resulting from systematic differences between Apple's suppliers and non-Apple suppliers, we employ the propensity score matching (PSM) and entropy balancing methods. Fourth, we also rule out certain alternative explanations.

Mechanism analysis indicates that Apple's influence on suppliers' carbon disclosure is primarily driven by a direct governance effect and an indirect exposure effect. Regarding the governance effect, we find that Apple's

⁴ Retrieved from <https://cj.sina.com.cn/articles/view/2587691232/9a3d08e002001etvy?froms=ggmp> (in Chinese).

⁵ Apple, "Apple Supplier Code of Conduct," available at <https://www.apple.com/hk/en/supplier-responsibility/pdf/Apple-Supplier-Code-of-Conduct-and-Supplier-Responsibility-Standards.pdf>.

influence is significantly stronger when suppliers are more economically dependent on Apple, measured by higher sales concentration and larger relationship-specific investments. Regarding the exposure effect, our evidence shows that the positive effect is more pronounced for suppliers receiving greater media and investor attention. Heterogeneity analyses show that the positive impact of Apple on suppliers' carbon disclosure is more pronounced for suppliers with stronger financial capacity and lower agency costs. These findings underscore the importance of both internal slack financial resources and governance capacity in facilitating effective environmental governance along the supply chain. Finally, we observe that the improvements in carbon transparency are accompanied by the real effects of carbon emission reduction and green innovations.

This study makes three main contributions to the literature. First, it offers critical insights into the growing literature on the influence of global major customers. Although existing research generally emphasizes the governance role of global major customers in disciplining supplier behavior (Dai et al., 2021; Chen et al., 2025; Deng et al., 2025), some studies find a decoupling effect of environmental responsibility and the outsourcing of carbon emissions within global supply chains (Dai et al., 2024; Chen and Zhao, 2025). By focusing on Apple's supply chain in China, we hold customer identity constant and restrict our sample to suppliers from the same country, which allows us to more cleanly isolate the effect of global major customer. We find that as a global major customer, Apple is uniquely positioned due to its strong market dominance, high reputational exposure and substantial bargaining power, allowing it to exert governance over suppliers in developing countries.

Second, this paper contributes to the literature on the determinants of corporate carbon disclosure. Prior research examines how internal corporate governance shapes corporate carbon disclosure behavior (Peters and Romi, 2014; Ben-Amar and McIlkenny, 2015; Flammer et al., 2019). Corporate carbon disclosure is also influenced by formal regulations (Wang et al., 2019; Downar et al., 2021; Kim et al., 2023; Tomar, 2023), institutional investors (Cohen et al., 2023; Döring et al., 2023; Ilhan et al., 2023), underwriters (Tian et al., 2025) and the media (Guenther et al., 2016). However, existing literature overlooks an important stakeholder, i.e., supply chain partners, especially global major customers. Apple, as a global major customer, is more likely to actively promote supply-chain carbon footprint reduction. We add to corporate carbon disclosure research by documenting that the monitoring role of major customers can serve as a complement to traditional regulatory mechanisms.

Third, we exploit the distinctive "Apple-supplier" setting to construct a quasi-natural experiment to alleviate potential endogeneity. The empirical challenge of employing customer concentration to measure the impact of major customers lies in the potential for reverse causality and omitted bias concerns (Chen et al., 2025; Deng et al., 2025). Studies often rely on cross-customer comparisons, where unobserved differences in customer characteristics may be driven by supplier selection (Naidu and Ranjeeni, 2024). We employ a DID approach to identify the causal effect of Apple as a major customer, thereby mitigating the potential endogeneity of supplier selection.

The remainder of this paper is organized as follows. Section 2 provides the literature review and hypothesis development. The data and methods are described in Section 3. The main empirical findings are presented in Section 4. Section 5 concludes the paper.

2. Literature review and hypothesis development

2.1. Literature review

2.1.1. Research on corporate carbon disclosure

(1) The motivation for corporate carbon disclosure

For a firm to fulfill its environmental responsibilities, transparent, comprehensive and standardized disclosure practices are necessary. Although an increasing number of mandatory environmental disclosure regulations have been issued, most environmental disclosure is voluntary, leaving the issuance and scope of reports to firms' discretion. In our framework, we adopt three theoretical perspectives to explain firms' voluntary carbon disclosure: legitimacy theory, signaling theory and stakeholder theory.

According to legitimacy theory, firms proactively disclose carbon information to convey their legitimacy to the public and to demonstrate that their behavior is consistent with social norms, values and beliefs (Suchman,

1995). Firms disclose more environmental information when facing an environmental crisis or when their environmental reputation suffers (De Villiers and Van Staden, 2011). Environmental disclosure also helps alleviate exposures to political and regulatory concerns (Cho et al., 2012). However, some companies use disclosure as a legitimizing tool to mask their environmental misconduct. U.K. firms, particularly those with high environmental sensitivity, tend to disclose symbolic soft or semi-hard environmental targets to manage stakeholder perceptions and legitimize their existence (Moussa et al., 2022). Ding et al. (2023) show that firms with higher levels of carbon emissions disclose more climate-related information.

Based on signaling theory, firms with superior environmental performance distinguish themselves in information-asymmetric markets by incurring high and difficult-to-imitate disclosure costs, thereby conveying credible signals of their superior quality to secure economic benefits (Spence, 1973). In general, disclosure reduces information asymmetry between the firm and outsiders (Healy and Palepu, 2001). Social disclosure reduces investor uncertainty about a firm's social performance-related regulatory risks and implicitly signals sufficient resources and operational stability (Anderson and Frankle, 1980). Voluntarily disclosing CSR activities demonstrates firms' confidence in their CSR performance, which sends a positive signal to investors (Dhaliwal et al., 2011). As an important form of non-financial disclosure, carbon disclosure is associated with favorable economic consequences. Firms disclosing their carbon emissions experienced a smaller increase in the cost of capital after the Fukushima nuclear disaster as such disclosure alleviated investor uncertainty about the energy supply shortage (Bonetti et al., 2024). Matsumura et al. (2014) also find that the median value of firms disclosing carbon emissions is about \$2.3 billion higher than that of comparable non-disclosing firms.

Stakeholder theory proposes that a firm's responsibility is not only to serve shareholders' interests but also to respond to demands for business ethics from diverse stakeholders (Freeman, 1984). Increasing regulation and societal pressure compel firms to prioritize environmentally responsible behavior.

(2) The impact of stakeholders on corporate carbon disclosure

Internal corporate governance mechanisms, including shareholders, the board and employees, play a crucial role in encouraging firms to disclose carbon information. Flammer et al. (2019) find that environmental shareholder activism increases the voluntary disclosure of climate change risks. As the center of contemporary corporate governance, boards can help to improve carbon disclosure levels. The likelihood of climate change-related disclosure increases with the percentage of women on boards, as female directors contribute distinct environmental awareness and external network resources (Ben-Amar et al., 2017). Board effectiveness and the presence of an environmental committee and a chief sustainability officer are positively associated with the likelihood of carbon disclosure as well as disclosure quality due to superior supervision and resource support (Peters and Romi, 2014; Ben-Amar and McIlkenny, 2015). Employees are concerned about carbon emission-related risks in the working environment and demand through labor unions that enterprises disclose emission reduction measures (Guenther et al., 2016).

Studies have also examined external pressure from various external stakeholders. As global warming intensifies, governments are taking actions to enhance corporate carbon disclosure, for example the U.K.'s mandatory carbon disclosure regulations introduced in 2013 (Downar et al., 2021), the SEC's 2010 climate change risk disclosure regulation (Kim et al., 2023), the U.S. GHG reporting program (Tomar, 2023), the EU emissions trading scheme and Global Reporting Initiative guidelines (Comyns, 2016). Capital markets are also paying more attention to climate risk and requiring firms to disclose carbon information. Institutional investors, especially those who are from civil law countries and who are CDP signatories, have a strong demand for climate risk disclosure, and many actively engage with their portfolio firms to secure improvements through influence and selection effects (Cohen et al., 2023; Döring et al., 2023; Ilhan et al., 2023). However, common ownership decreases a firm's propensity to disclose carbon information as well as the disclosure quality by lowering industry competition and hence regulatory and divestment risks (Choi et al., 2026). Green underwriters significantly improve disclosure levels through information and monitoring effects (Tian et al., 2025). The media shapes public attention to climate change concerns and corporate carbon disclosure through agenda-setting, pressuring firms to increase their carbon disclosure (Guenther et al., 2016). When enterprises face negative media reports, carbon disclosure becomes a "defensive tool" to restore legitimacy (Li et al., 2018).

Although the literature extensively explores the pressure from internal corporate governance entities and external stakeholders on enterprises to disclose carbon information, current research pays less attention to the role of supply chains, which is directly relevant due to Scope 3 emissions.

2.1.2. Research on global major customers

Research on the impact of major customers, including global major customers, has gained increasing attention. Studies document both the positive and negative impacts of major customers on suppliers.

Since suppliers' negative behaviors have potential spillover effects on customers, major customers play a monitoring role to avoid such risks to suppliers' sustainability performance and disclosure (Yu et al., 2024; Deng et al., 2025; Liang and Pan, 2025), green innovation (Huang et al., 2023) and corporate conduct (Chen et al., 2025). Additionally, the threat of relationship termination serves as a powerful incentive mechanism for suppliers, given that losing major customers represents a significant business risk (Dai et al., 2021; Darendeli et al., 2022). With global attention on sustainable development and supply chain network globalization (Feng et al., 2022), international customers attract scholarly interest. Global major customers exert pressure on their suppliers through supply chain relationships to disclose transparent carbon emission information (Shen et al., 2025). Dai et al. (2021), employing international databases, find that socially responsible corporate customers can infuse similar socially responsible business behaviors into their suppliers. A multinational clothing retailer, H&M, directly monitors its suppliers and may require them to increase factory workers' wages (Distelhorst and Shin, 2023).

However, cooperation with major customers is often accompanied by unethical supplier exploitation (Schleper et al., 2017), squeezing of suppliers' profits (Bhattacharyya and Nain, 2011; Murfin and Njoroge, 2015; Hui et al., 2019), highly relationship-specific investments (Banerjee et al., 2008), risk of losing substantial future sales (Hertzel and Officer, 2012) and increased cost of capital (Campello and Gao, 2017). Several scholars criticize the failure of major customers of this type to act on environmental issues (Clarke and Boersma, 2017). Dai et al. (2024), using U.S. firms as a sample, find that firms outsource part of their carbon emissions to foreign suppliers. Chen and Zhao (2025) find that a higher proportion of sales to major overseas customers increases the likelihood of supplier firms' decoupling from environmental responsibility due to inadequate supervision resulting from geographic distance.

2.2. Hypothesis development

Apple's influence extends beyond private compliance to actively shaping public disclosure norms across its value chain. As a global major customer, Apple exerts governance over its suppliers' carbon disclosure through a dual-pronged mechanism combining direct rigorous monitoring and the consequential exposure effect.

Apple has strong motivation and enormous bargaining power to directly supervise its suppliers to conduct carbon management practices, which constitutes a foundation for public carbon disclosure. Regulatory scrutiny and public oversight due to high visibility, as well as its production and carbon emission structure, require Apple to participate in the management of carbon reduction in the supply chain. First, Apple is one of the world's most influential and visible firms. Environmental violations by its suppliers will have spillover effects on Apple, thereby causing reputational and substantial financial losses (Hartmann and Moeller, 2014; Villena et al., 2021). For example, in 2011, five Chinese environmental protection organizations issued the report *Apple's Other Face: Pollution Spreads Behind the Screen* to blame Apple for environmental pollution by its suspected Chinese suppliers.⁶ Second, Apple operates relatively few manufacturing plants of its own, resulting in low Scope 1 and Scope 2 emissions, but very high Scope 3 emissions. According to Apple's 2022 Environmental Progress Report,⁷ Apple's Scope 1 emissions amounted to 55,000 metric tons of CO₂ equivalent, and its Scope 2 emissions were 2780 metric tons, while its Scope 3 emissions reached as high as 23.13 million metric

⁶ Retrieved from <https://www.reuters.com/article/business/environment/apple-criticized-for-china-supply-chain-pollution-idUSTRE77U4M6/> on 14 September 2025.

⁷ Apple, "2022 Environmental Progress Report," available at https://www.apple.com/environment/pdf/Apple_Environmental_Progress_Report_2022.pdf.

tons of CO₂ equivalent. For Apple, carbon footprint reduction depends on mitigating Scope 3 emissions across its supply chain.

Based on stakeholder theory and resource dependence theory (Freeman, 1984; Mitchell et al., 1997), Apple has the power, legitimacy and urgency to compel suppliers to consider their carbon performance, given its impact on supplier profitability, pricing procedures, contract conditions and operational risk (Bhattacharyya and Nain, 2011; Murfin and Njoroge, 2015; Hui et al., 2019). Apple has committed to 100% total carbon neutrality across its supply chain and products by 2030.⁸ Moreover Apple's *Supplier Code of Conduct* proposes that "Suppliers shall, in accordance with Apple's requirements, report to Apple annually on the progress of their greenhouse gas emission targets, reduction amounts and 'covered carbon footprint'." Apple may monitor suppliers' adherence to stringent carbon emission standards in production processes to deliver the final output in a more environmentally responsible way (She, 2022; Tao et al., 2023). One potential outcome is that Apple may revise supplier portfolios by terminating relationships with suppliers that do not meet carbon commitments (Darendeli et al., 2022). Such termination threatens to severely impact suppliers' profitability and prospects, as evidenced by O-Film, which was removed from Apple supply chain in 2021 and suffered a sharp revenue decline of about 53%.⁹ Consequently, suppliers may be more motivated to establish carbon management systems and accurately measure their GHG emissions, which lays the foundation for improving its carbon-disclosure quality.

The public disclosure of Apple's supplier list also constitutes a critical governance mechanism to force suppliers to disclose high-quality carbon information to maintain legitimacy. First, disclosure significantly enhances the visibility of suppliers to external stakeholders such as media and institutional investors. This heightened scrutiny amplifies the reputational and market risks for both Apple and its suppliers in the event of non-compliance, thereby intensifying the supervisory pressure on Apple and the compliance pressure on suppliers (Campbell, 2007; Ilhan et al., 2023). Consequently, because of public scrutiny, suppliers have stronger incentives to demonstrate their carbon reduction endeavors. Moreover, disclosure serves as a credible signal of Apple's commitment to supply chain responsibilities (Spence, 1973). It also creates extremely high public expectations, as stakeholders tacitly assume that Apple's suppliers should meet high environmental standards, thereby adding pressure on suppliers to enhance carbon disclosure. Therefore, we propose the following hypothesis:

Hypothesis 1a: There is a positive association between entry into Apple's supply chain and subsequent carbon-disclosure quality.

However, the opposite effect may occur for several reasons. First, from a monitoring perspective, Apple's influence over supplier carbon disclosure may be limited. Apple may focus on avoiding reputational damage from supplier carbon-related scandals, rather than on ensuring the continuous improvement of suppliers' carbon reduction. This asymmetry may reduce Apple's incentives to rigorously monitor suppliers' carbon management. Even when Apple does prioritize carbon transparency, geographic distance may hinder effective oversight (Chen and Zhao, 2025). Ineffective oversight by Apple would fail to improve suppliers' internal carbon management practices, and consequently would not translate into improved external carbon disclosure.

Second, from a financial constraint perspective, clients with strong bargaining power, such as Apple, may excessively squeeze suppliers' profit margins in their pursuit of cost efficiency and rapid product iteration (Bhattacharyya and Nain, 2011). Suppliers also face heightened cash pressure due to investment in relationship-specific assets (Banerjee et al., 2008). Their ability to allocate resources to costly carbon reduction and carbon disclosure practices becomes severely constrained.

Third, from a disclosure cost perspective, firms may be reluctant to disclose carbon information because it can reveal their exposure to potential vulnerabilities, and entail direct costs and proprietary costs (Healy and Palepu, 2001; Flammer et al., 2019).

Based on the perspectives of weak monitoring, financial constraints and disclosure costs, we propose the following competing hypothesis:

⁸ Apple, "2020 Environmental Progress Report," available at https://www.apple.com.cn/environment/pdf/Apple_Environmental_Progress_Report_2020.pdf.

⁹ Retrieved from <https://pandaily.com/ofilms-nanchang-subsidiary-removed-from-us-entity-list>.

Hypothesis 1b: There is a negative association between entry into Apple's supply chain and subsequent carbon-disclosure quality.

3. Research design

3.1. Sample selection

The sample includes Chinese A-share companies listed on the Shenzhen and Shanghai Stock Exchanges from 2008 to 2023. The sample period begins in 2008 because data on carbon disclosures are available from that year. As China is the largest emerging-market country and is at an early stage of research on carbon disclosure, it is significant to explore the governance role of international major customers in enhancing carbon disclosure in China. State-owned enterprises (SOEs) are confronted with additional institutional and legitimacy pressures, compelling them to adopt more pro-environmental actions (Earnhart and Lizal, 2006; Li and Zhang, 2010).¹⁰ Therefore, we choose non-SOEs to examine the net effect of Apple being a major customer. We further restrict the sample to the computer, communication and other electronic equipment manufacturing industry (denoted C39 in the "Guidelines for Industry Classification of Listed Companies in China" (2012)). We focus on this specific industry for three main reasons. First, among Apple's suppliers in China, those in this industry account for 66.91%. Second, the environmental impact of the electronics manufacturing industry in terms of energy consumption and carbon emissions is also becoming increasingly prominent, with more than 4% of GHG emissions coming from this industry globally.¹¹ Third, restricting the sample to a single industry helps ensure comparability by aligning firms with similar business models. To ensure robustness, we conduct the analysis using the full industry sample. Table 1 Panel A lists details regarding the sample selection procedure. To address potential outliers, we winsorize all continuous variables at the 1st and 99th percentiles. Following this procedure, our primary sample comprises 530 unique firms and 3226 firm-year observations. Panel B of Table 1 shows the Apple supplier distribution by year.

Apple's supplier data are manually collected from the Apple supplier list reported on its official website. The carbon disclosure data and control variable data are from the China Stock Market & Accounting Research (CSMAR) database.

3.2. Definitions of variables

3.2.1. Carbon disclosure

Carbon disclosure data are obtained from the Research Database of Carbon Disclosure Index of Chinese Listed Companies in the CSMAR database. Specifically, the index constructs detailed indicators in accordance with the framework of "governance, strategy, risk and opportunity management, and indicators and goals." Carbon information can be divided into six categories: (1) Governance includes board supervision, management responsibilities and employee engagement. (2) Strategy means a low-carbon transformation strategy. (3) Risk management encompasses risk management systems, risk identification and assessment. (4) Opportunity management encompasses opportunity identification and management. (5) The indicators include Scope 1 GHG emissions, Scope 2 GHG emissions, Scope 3 GHG emissions, carbon emission intensity, changes in emissions, Scope 1 emission decomposition, Scope 2 emission decomposition, value chain interaction, upstream and downstream customer management, other climate information, and verifiability. (6) The goals include carbon reduction targets, other climate management targets, reduction measures and progress in busi-

¹⁰ In China's institutional context, SOEs are often the pioneer responders to national strategies, and their decisions will be influenced by direct intervention and preferential resource allocation, as well as non-economic objectives (e.g., employment security and environmental protection) from central and local governments (Earnhart and Lizal, 2006; Li and Zhang, 2010). Such intrinsic policy embeddedness makes it difficult to screen out the noise of government intervention when analyzing the impact of external market pressures on their behavior. Since 2008, the State-owned Assets Supervision and Administration Commission (SASAC) has actively taken measures to promote ESG development among SOEs, establishing and improving the ESG ecosystem.

¹¹ Wei Li, Guangxu Wang, and Meng Wang, Towards Net-Zero Electronics: Unlocking the power of energy efficiency in manufacturing facilities, RMI, 2025, <https://rmi.org/insight/towards-net-zero-electronics/>.

Table 1
Sample selection.

Panel A. Sample selection procedure				
Initial sample of Chinese A-share companies listed in the Shenzhen and Shanghai Stock Exchanges from 2008 to 2023				62,329
Delete ST and PT samples				(1860)
Delete the sample of state-owned enterprises				(29,366)
Delete samples from other industries except electronics manufacturing industries				(27,665)
Delete samples with missing values				(212)
Firm-year observations				3226
Unique firms				530
Panel B. Distribution of Apple supplier over sample-years				
Sample-Year	New entry supplier	Remained supplier	Exit supplier	Total Apple supplier
2008	0	0	0	0
2009	0	0	0	0
2010	0	0	0	0
2011	4	0	0	4
2012	1	4	0	5
2013	1	4	1	5
2014	2	5	0	7
2015	1	6	1	7
2016	3	5	2	8
2017	1	7	1	8
2018	8	8	0	16
2019	0	16	0	16
2020	3	13	3	16
2021	1	13	2	15
2022	4	14	1	18
2023	0	16	2	16
Total	—	—	—	141

ness transformation. We use the comprehensive carbon disclosure index (CD_score) in the database to measure corporate carbon-disclosure quality, which is the summed score of all 22 sub-indicators, and ranges from 0 to 50. Finally, we construct the independent variable, $CDI_{i,t}$, as the natural logarithm of CD_score plus one. In Online Appendix A, we use the case of Luxshare Precision's 2022 carbon disclosure scores to illustrate this index.

3.2.2. The impact of Apple as a major customer—becoming a supplier

The Apple supplier list, which represents 97–98% of Apple's direct spending on materials, manufacturing and assembly of its products worldwide, has been released since fiscal year 2011. We manually collect the supplier data of Apple in China. However, as Apple did not release data for fiscal year 2019, we replace it with the list for fiscal year 2018. Apple's fiscal year ends on the last Saturday of September, unlike the 31 December calendar-year end commonly used by Chinese companies. We adjust Apple's fiscal year to the fiscal year used in China. For instance, if a company is on Apple's supplier list for fiscal year 2012, it is considered that the company is a supplier of Apple in both fiscal years 2011 and 2012 of China. We then construct a treatment indicator, $Treat_{i,t}$, which equals one if a firm is an Apple supplier and zero otherwise. We define $Post_{i,t}$ as a dummy variable that takes the value of one if a firm enters Apple's supply chain, and zero otherwise.

3.2.3. Control variables

Following prior research (Flammer et al., 2021; Cohen et al., 2023; Döring et al., 2023), we include a variety of characteristics of firms as control variables: firm size ($Size$), leverage ratio (Lev), return on total assets (ROA), firm growth ($Growth$), book-to-market ratio (MB), cash holding ratio ($Cash\ holdings$), tangible asset ratio ($Tangibility$), dividend payout ratio ($Dividend$), top 1 shareholder's ownership ($Top1$), CEO duality

(*Dual*) and board independence (*Boardindep*). The detailed definitions and constructions of the variables are shown in Appendix A.

3.3. Research model

To disentangle the impact of Apple's influence on supply chain carbon disclosure, we use a DID design and ordinary least squares regressions as specified in Eq. (1):

$$CDI_{i,t} = \alpha + \beta Treat_{i,t} * Post_{i,t} + \gamma Controls_{i,t} + FirmFE + YearFE + \varepsilon_{i,t} \quad (1)$$

where i indicates the firm and t indicates the year. The variable of interest is $Treat_{i,t} * Post_{i,t}$, which captures whether a firm enters Apple's supply chain. $Treat_{i,t}$ is a dummy variable that takes the value of one if firm i is an Apple supplier, and zero otherwise. $Post_{i,t}$ is a dummy variable that takes the value of one if a firm enters Apple's supply chain, and zero otherwise. The dependent variable is the carbon disclosure index, $CDI_{i,t}$, measured as the natural logarithm of the total score of carbon disclosure plus one. Following Flammer et al. (2021), Cohen et al. (2023) and Döring et al. (2023), we control for several firm-level factors that may have impacts on corporate carbon disclosure. We also control for year fixed effects and firm fixed effects, and cluster the standard errors by firm.

4. Empirical results

4.1. Descriptive statistics and correlations

Table 2 presents the descriptive statistics for our sample. The sample consists of 3226 firm-year observations. The mean values of *Treat* and *Post* are 0.082 and 0.044, respectively, indicating that 8.2% of the sample firms are Apple suppliers and 4.4% are observed after entering the supply chain. The mean value of *CDI* is 1.974, and firms' average carbon disclosure score (*CD_score*) is 9.554. The statistics of the control variables are consistent with prior literature and exhibit no outlier values.

Table 3 reports the Pearson correlations of the main test variables. Specifically, the Pearson coefficient between entering Apple's supply chain ($Treat * Post$) and corporate carbon-disclosure quality (*CDI*) is positive and significant at the 1% confidence level. This result shows that without controlling for other variables,

Table 2
Descriptive statistics.

Variable	N	Mean	SD	Min	Median	Max
<i>Treat</i>	3226	0.082	0.274	0.000	0.000	1.000
<i>Post</i>	3226	0.044	0.204	0.000	0.000	1.000
<i>CD_score</i>	3226	9.554	8.766	0.000	7.000	49.000
<i>CDI</i>	3226	1.974	0.970	0.000	2.079	3.761
<i>Size</i>	3226	21.674	1.036	19.812	21.532	25.008
<i>Lev</i>	3226	0.336	0.181	0.040	0.317	0.767
<i>ROA</i>	3226	0.036	0.066	−0.258	0.042	0.182
<i>Growth</i>	3226	0.212	0.515	−0.646	0.094	2.959
<i>MB</i>	3226	0.342	0.155	0.064	0.319	0.759
<i>Cash_holdings</i>	3226	0.200	0.147	0.015	0.157	0.698
<i>Tangibility</i>	3226	0.182	0.124	0.006	0.159	0.534
<i>Dividend</i>	3226	0.276	0.318	0.000	0.212	1.922
<i>Top1</i>	3226	0.310	0.138	0.088	0.289	0.698
<i>Dual</i>	3226	0.507	0.500	0.000	1.000	1.000
<i>Boardindep</i>	3226	0.388	0.054	0.333	0.400	0.571

Note: Variable definitions are shown in Appendix A.

Table 3
Correlation coefficients.

	<i>CDI</i>	<i>Treat*Post</i>	<i>Size</i>	<i>Lev</i>	<i>ROA</i>	<i>Growth</i>	<i>MB</i>
<i>CDI</i>	1						
<i>Treat*Post</i>	0.128***	1					
<i>Size</i>	0.383***	0.329***	1				
<i>Lev</i>	0.171***	0.123***	0.448***	1			
<i>ROA</i>	−0.030*	0.030*	0.039**	−0.322***	1		
<i>Growth</i>	−0.104***	−0.047***	−0.068***	−0.053***	−0.021	1	
<i>MB</i>	−0.043**	−0.046***	−0.100***	−0.482***	0.069***	−0.004	1
<i>Cash_holdings</i>	−0.125***	−0.045**	−0.221***	−0.490***	0.217***	0.070***	0.323***
<i>Tangibility</i>	0.126***	0.098***	0.084***	0.248***	−0.138***	−0.224***	−0.124***
<i>Dividend</i>	−0.011	0.007	−0.061***	−0.259***	0.251***	−0.048***	0.234***
<i>Top1</i>	−0.067***	0.053***	−0.040**	−0.097***	0.194***	0.019	0.125***
<i>Dual</i>	−0.0230	−0.00100	−0.137***	−0.100***	−0.028	0.024	0.048***
<i>Boardindep</i>	−0.0110	0.050***	−0.0240	0.0220	−0.050***	0.082***	−0.047***
	<i>Cash_holdings</i>	<i>Tangibility</i>	<i>Dividend</i>	<i>Top1</i>	<i>Dual</i>	<i>Boardindep</i>	
<i>Cash_holdings</i>	1						
<i>Tangibility</i>	−0.368***	1					
<i>Dividend</i>	0.209***	−0.0200	1				
<i>Top1</i>	0.109***	0.00300	0.158***	1			
<i>Dual</i>	0.052***	−0.040**	0.00300	0.047***	1		
<i>Boardindep</i>	−0.047***	0.0280	−0.055***	0.073***	0.078***	1	

becoming an Apple supplier is significantly positively associated with carbon-disclosure quality, which is in line with H1a.

4.2. Regression analyses

Table 4 shows the baseline results concerning the relationship between entering Apple's supply chain and suppliers' carbon-disclosure quality. In Column (1), we find that higher carbon-disclosure quality is associated with becoming an Apple supplier when including only fixed effects. In Column (2), the coefficient of *Treat*Post* is 0.498 and is significant at the 1% level when including both control variables and fixed effects. This suggests that Apple suppliers experience a 6.76%¹² relative increase in carbon-disclosure quality compared with those that do not enter the Apple supply chain, supporting H1a.

4.3. Robustness tests

4.3.1. Alternative measures of the dependent variable

In a robustness test, we use the carbon disclosure-related word frequency in annual reports, obtained from the Chinese Research Data Services (CNRDS) database, as a substitute for the carbon disclosure index (*CDI*). We adopt three specific indicators for this measurement: (1) *CD_wordfreq1*: carbon disclosure-related word frequency divided by total word count of annual financial reports (excluding English and figures). (2) *CD_wordfreq2*: carbon disclosure-related word frequency divided by total number of terms used in annual financial reports (excluding stop words). (3) *CD_wordfreq3*: carbon disclosure-related word frequency divided by total number of sentences in annual financial reports. The results are shown in Panel A of Table 5; the coefficient of *Treat*Post* is still positive and significant at least at the 10% level. Overall, these results suggest that our main findings are robust to different measures of carbon disclosure.

¹² Using the standard $e^{\beta} - 1$ transformation, the implied economic effect is about 0.0676 ($(e^{0.498} - 1)/9.554$).

Table 4
Baseline results: The effect of entry into Apple's supply chain on suppliers' carbon disclosure quality.

<i>Variables</i>	(1) <i>CDI</i>	(2) <i>CDI</i>
<i>Treat*Post</i>	0.701*** (3.80)	0.498*** (2.98)
<i>Size</i>		0.339*** (6.38)
<i>Lev</i>		−0.481** (−1.99)
<i>ROA</i>		−0.480* (−1.76)
<i>Growth</i>		−0.025 (−0.72)
<i>MB</i>		−0.574*** (−3.65)
<i>Cash_holdings</i>		0.085 (0.53)
<i>Tangibility</i>		0.567** (2.16)
<i>Dividend</i>		0.038 (0.94)
<i>Top1</i>		−0.668* (−1.77)
<i>Dual</i>		0.033 (0.62)
<i>Boardindep</i>		0.055 (0.14)
<i>Constant</i>	1.943*** (241.09)	−4.985*** (−4.35)
<i>Year FE</i>	Yes	Yes
<i>Firm FE</i>	Yes	Yes
<i>N</i>	3226	3226
<i>Adj. R²</i>	0.63	0.65

Note: All variables are defined in Appendix A. Estimates are based on ordinary least square regressions with standard errors adjusted for heteroscedasticity and within firm clustering. T-statistics, in parentheses, are based on two-sided tests. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

4.3.2. Alternative model

We estimate Eq. (1) using a Poisson regression, with the carbon disclosure index (*CD_score*) as the dependent variable, to take into consideration the count nature of *CD_score* and the advantage of Poisson regression over other regression models (Cohn et al., 2022). Panel B Column (1) of Table 5 reports the coefficients of the Poisson regression. The empirical results are consistent with the baseline results.

4.3.3. Alternative sample

We conduct a series of robustness checks using alternative sample selections to ensure our findings are not driven by specific sample choices. These include (1) using all industries in which Apple's suppliers operate, rather than restricting the analysis to a specific sector; (2) retaining SOEs in the sample; (3) starting the sample period from 2010, when Apple began disclosing its supplier list; and (4) terminating the sample in 2020, prior to China's announcement of its dual-carbon commitments. The results, presented in Panel B Columns (2)–(5) of Table 5, show that the coefficients of *Treat*Post* remain positive and statistically significant, which helps mitigate concerns that our main results are attributable to a particular sample construction.

Table 5
Robustness tests.

Panel A. Alternative measures of the dependent variable								
Variables	(1) <i>CD_wordfreq1</i>	(2) <i>CD_wordfreq2</i>	(3) <i>CD_wordfreq3</i>					
<i>Treat*Post</i>	0.006* (1.75)	0.015* (1.75)	0.542* (1.81)					
<i>Controls</i>	Yes	Yes	Yes					
<i>Year FE</i>	Yes	Yes	Yes					
<i>Firm FE</i>	Yes	Yes	Yes					
<i>N</i>	3203	3203	3203					
<i>Adj. R²</i>	0.61	0.61	0.61					
Panel B. Alternative model and alternative sample								
	Alternative model	Alternative sample of all industries in which Apple's suppliers operate	Alternative sample of retaining the state-owned enterprises	Alternative sample starting from 2010 when Apple began disclosure its supplier list	Alternative sample restricted before 2020 when China announced dual carbon commitments			
Variables	(1) <i>CD_score</i>	(2) <i>CDI</i>	(3) <i>CDI</i>	(4) <i>CDI</i>	(5) <i>CDI</i>			
<i>Treat*Post</i>	0.275* (1.74)	0.345** (2.31)	0.265* (1.94)	0.487*** (2.89)	0.548*** (3.69)			
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes			
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes			
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes			
<i>N</i>	3192	10,101	4437	3122	2059			
<i>Adj. R²</i>	—	0.66	0.64	0.66	0.60			
Panel C. Control for more variables								
	Control for regional level factors (1) <i>CDI</i>		Control for ESG performance (2) <i>CDI</i>		Control for environmental performance (3) <i>CDI</i>			
<i>Treat*Post</i>	0.474*** (2.81)		0.469*** (3.01)		0.432*** (2.92)			
<i>Eco_development</i>	0.134 (0.71)							
<i>SecondaryInd</i>	−0.019 (−0.02)							
<i>FDI</i>	−0.149 (−0.24)							
<i>ESGperformance</i>			0.011** (2.46)					
<i>Eperformance</i>					0.019*** (5.49)			
<i>Controls</i>	Yes		Yes		Yes			
<i>Year FE</i>	Yes		Yes		Yes			
<i>Firm FE</i>	Yes		Yes		Yes			
<i>N</i>	2717		3037		3037			
<i>Adj. R²</i>	0.66		0.65		0.66			
Panel D. Detailed carbon disclosure index								
Variables	(1) <i>Governance</i>	(2) <i>Risk Opportunities</i>	(3) <i>Strategy</i>	(4) <i>Targets</i>	(5) <i>Indicator_ emissions</i>	(6) <i>Indicator_ decomposition</i>	(7) <i>Indicator_ valuesupply</i>	(8) <i>Indicator_ others</i>
<i>Treat*Post</i>	0.198** (2.06)	0.240*** (2.92)	0.132** (2.33)	0.338** (2.50)	0.169 (1.18)	0.228** (2.16)	0.093 (1.07)	0.117 (1.59)

(continued on next page)

Table 5 (continued)

Panel D. Detailed carbon disclosure index								
Variables	(1) <i>Governance</i>	(2) <i>Risk Opportunities</i>	(3) <i>Strategy</i>	(4) <i>Targets</i>	(5) <i>Indicator_ emissions</i>	(6) <i>Indicator_ decomposition</i>	(7) <i>Indicator_ valuesupply</i>	(8) <i>Indicator_ others</i>
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	3226	3226	3226	3226	3226	3226	3226	3226
<i>Adj. R²</i>	0.55	0.57	0.43	0.57	0.43	0.59	0.44	0.62

*, **, and *** denote significance at 0.10, 0.05, and 0.01 levels in a two-tailed test. Robust t-statistics are in parentheses.

4.3.4. Additional control variables

To avoid any bias from omitted variables in our baseline analysis, we incorporate a set of additional control variables that may be associated with carbon reporting quality.

(1) Controlling for region-level factors

We address potential endogeneity concerns by considering the possibility that, for firms, unobservable regional characteristics may simultaneously influence both entering Apple's supply chain and carbon disclosure practices. The degree of economic openness, the industrial structure and economic development directly affects whether Apple selects companies from a particular region to enter its supply chain. Specifically, the economic openness degree (*FDI*) is measured by the ratio of actual utilized foreign direct investment to GDP. Industrial structure (*SecondaryInd*) is measured by the ratio of secondary industry value added to GDP. Economic development (*Eco_development*) is measured by the natural logarithm of per capita GDP. After controlling for these region-level factors, we find that Apple continues to significantly promote suppliers' carbon disclosure, further validating our main conclusion. The result is reported in Column (1) of Panel C in Table 5.

(2) Controlling for ESG performance and environmental performance

An alternative explanation, rather than Apple exerting a governance effect, is that enterprises that are more environmentally friendly are more likely to be selected by Apple as its suppliers. Such firms are more willing and able to provide high-quality carbon disclosure. To control for the endogenous bias caused by this omitted variable, we include corporate ESG performance and environmental (E) performance in the model, using the Sino ESG ratings of firms in China. In Panel C of Table 5, Column (2) controls for ESG performance and Column (3) controls for E performance. The results show that the coefficient of *Treat*Post* is still significant at the 1% level (although the effect is slightly weakened), which indicates that Apple's governance effect is independent of firms' own ESG or environmental performance.

4.3.5. Detailed carbon disclosure index

We further use the sub-indicators of the carbon disclosure index (*CD_score*) to examine whether becoming an Apple supplier consistently affects different dimensions of carbon disclosure, namely carbon governance (*Governance*), carbon risk and opportunities (*RiskOpportunities*), low-carbon transformation strategy (*Strategy*), carbon-related targets (*Targets*), GHG emissions (*Indicator_emissions*), GHG emission decomposition (*Indicator_decomposition*), value chain interaction (*Indicator_valuesupply*) and other climate information and verifiability (*Indicator_others*). Appendix A provides the detailed definitions of these variables. The regression results in Table 5 Panel D show that Apple's governance role as a major customer primarily enhances suppliers' carbon-disclosure quality in core managerial areas, including governance (Column (1)), risk and

opportunity management (Column (2)), strategy (Column (3)) and targets (Column (4)), with a significant effect also observed on the indicator for decomposition (Column (6)). However, its influence is weaker and nonsignificant for more technical or peripheral information, i.e., all-scope emissions (Column (5)), value chain interactions (Column (7)) and other information (Column (8)). This pattern suggests that Apple's governance focuses on motivating suppliers to establish and improve their institutional frameworks and strategic commitments for carbon management, but neglects supply chain carbon management by suppliers.

4.4. Addressing endogeneity

4.4.1. Parallel trend test

The DID identifying assumption underlying our research design is that Apple's suppliers and non-Apple suppliers would exhibit similar carbon-disclosure quality in the absence of Apple. To validate the parallel trend assumption, we construct Eq. (2):

$$CDI_{i,t} = \alpha + \beta_{-4}Before_{i,t}^4 + \beta_{-3}Before_{i,t}^3 + \beta_{-2}Before_{i,t}^2 + \beta_{-1}Before_{i,t}^1 + Current_{i,t} + \beta_1After_{i,t}^1 + \beta_2After_{i,t}^2 + \beta_3After_{i,t}^3 + \beta_4After_{i,t}^4 + \beta_5After_{i,t}^{5+} + \gamma Controls_{i,t} + Firm\ FE + Year\ FE + \varepsilon_{i,t} \quad (2)$$

where $Current_{i,t}$ indicates period 0, during which suppliers enter Apple's supply chain, $Before^k$ indicates year k prior to period 0, and $After^k_{i,t}$ indicates year k after period 0, with $Before^5$ omitted and used as the benchmark. We report the estimated coefficients in Panel A of Table 6 and plot the coefficients and corresponding confidence intervals of $Current_{i,t}$, $Before^k$ and $After^k_{i,t}$ in Fig. 1. The results validate the parallel trend assumption by showing that the coefficients are statistically not different from 0 in the pre-entering period. However, suppliers' carbon-disclosure quality significantly increases in the first years after entering Apple's supply chain.

4.4.2. Placebo tests

To assess the validity of the findings, placebo tests are conducted by randomly assigning treatment group status to firms in our sample and keeping the year-specific number of Apple suppliers the same as in the actual data. We rerun the baseline regression and save the coefficient of the placebo $Treat*Post$. This procedure is performed for 500 replicates, and the distribution of the estimated placebo coefficients of $Treat*Post$ is plotted in Fig. 2, where the dashed line represents the actual coefficient of $Treat*Post$ from Column (4) of Table 4. As shown, the actual coefficient of $Treat*Post$ falls in the extreme right tail of the distribution of the placebo estimates, suggesting that the significant effect of carbon disclosure governance documented in our main analysis is unlikely to be spurious.

4.4.3. PSM and entropy balancing

Considering the potential selection problem, we use PSM to reduce the endogeneity resulting from selection bias. We estimate the propensity scores using a logit model, wherein the dependent variable is a dummy variable (*supplier_dummy*) in the first stage, and the explanatory variables are all control variables, as specified in Eq. (1). We then use one-to-five matching and one-to-one matching to match each control group with a treatment group with similar propensity scores, using a caliper of 0.01. After PSM, the covariates are well balanced, as shown in Panel A and Panel B of Online Appendix B. The standard deviations after matching are all less than 10% and the t-statistics are nonsignificant, indicating that there is no significant difference between the matched treatment and control groups. The regression results using the PSM sample, presented in Column (1) and Column (2) of Panel B of Table 6, indicate that the coefficients of $Treat*Post$ remain significantly positive. These findings generally corroborate our baseline results.

To mitigate potential sample selection bias, we also employ entropy balancing. This technique retains the original sample size by reweighting the covariates in a manner that ensures no significant post-weighting differences in the mean, variance and skewness of these covariates (Hainmueller, 2012). We balance the mean and variance of our covariates. The sample statistics before and after entropy balancing are reported in Panel C and Panel D in Online Appendix B, respectively. Column (3) of Panel B in Table 6 reports the regression results after entropy balancing, which remain robust.

Table 6
Addressing endogeneity.

Panel A. Parallel trend test	
Variables	(1) CDI
Before ⁴	−0.332 (−1.13)
Before ³	0.199 (0.64)
Before ²	0.249 (1.24)
Before ¹	0.263 (1.12)
Current	0.298 (1.23)
After ¹	0.440* (1.77)
After ²	0.625*** (2.71)
After ³	0.783*** (2.97)
After ⁴	0.654** (2.54)
After ⁵	0.565* (1.91)
Controls	Yes
Year FE	Yes
Firm FE	Yes
N	3226
Adj. R ²	0.65

Panel B. Regression results after PSM or entropy balancing			
Variables	Regression Results after PSM (1:5) (1) CDI	Regression Results after PSM (1:1) (2) CDI	Regression Results after Entropy Balancing (3) CDI
Treat*Post	0.556*** (3.53)	0.484*** (3.00)	0.453*** (3.01)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	1014	429	3226
Adj. R ²	0.60	0.63	0.66

Panel C. Excluding Alternative Explanations						
Variables	Excluding the Impact of Carbon Related Policy		Excluding the Impact of CDP Signatories			
	(1) CDI	(2) CDI	(3) RequestCDP	(4) ProvideCDP	(5) CDI	(6) CDI
Treat*Post	0.497*** (2.97)	0.498*** (3.00)	0.100 (1.54)	0.026 (0.46)	0.487*** (3.44)	0.496*** (3.42)
CEtradingDID	0.064 (0.57)					
LowCarbonDID		0.164 (1.41)				
RequestCDP					0.103 (1.37)	
ProvideCDP						0.051 (0.52)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 6 (continued)

Panel C. Excluding Alternative Explanations

Variables	Excluding the Impact of Carbon Related Policy		Excluding the Impact of CDP Signatories			
	(1) <i>CDI</i>	(2) <i>CDI</i>	(3) <i>RequestCDP</i>	(4) <i>ProvideCDP</i>	(5) <i>CDI</i>	(6) <i>CDI</i>
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	3226	3226	2767	2767	2767	2767
<i>Adj. R²</i>	0.65	0.65	0.47	0.39	0.63	0.63

*, **, and *** denote significance at 0.10, 0.05, and 0.01 levels in a two-tailed test. Robust t-statistics are in parentheses.

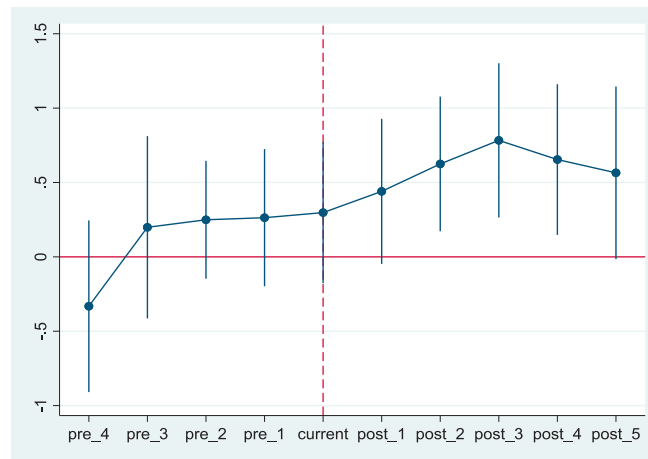


Fig. 1. Equilibrium trend chart.

4.4.4. Excluding alternative explanations

China has introduced several carbon reduction regulations to meet its commitment to peaking carbon emissions before 2030 and reaching carbon neutrality before 2060, e.g., a carbon emission trading policy¹³ and low-carbon city construction.¹⁴ These policies are highly relevant to carbon reduction management and may have a direct impact on corporate carbon disclosure behavior (Chen et al., 2022). To eliminate the potential impact of these policies, we add the corresponding policy variables to the regression model. In Panel C of Table 6, Column (1) and Column (2) show that after controlling for those policies, our empirical results remain robust.

We use the CDP setting to exclude the impact of capital providers and other potential supply chain partners by isolating disclosure prompted by CDP requests. Based on CDP data from 2009 to 2022, we construct two variables: CDP disclosure request (*RequestCDP*) and CDP information provision (*ProvideCDP*). Specifically,

¹³ The carbon trading policy has been implemented in many provinces and cities in China, such as Beijing, Shanghai, Tianjin, Chongqing, Shenzhen, Hubei and Guangdong, since 2013. We assign cities in pilot areas to the experimental group while other cities are categorized as the control group. The year 2013 is selected as the time of the first round of the carbon trading pilot policy. If a city has implemented the pilot policy, *CEtradingDID* takes the value of one, and zero otherwise.

¹⁴ Information about the low-carbon city construction policy is obtained from the three batches of the “Low-Carbon City Pilot List” released by the National Development and Reform Commission. If a city has implemented the low-carbon city construction policy, *LowCarbonDID* takes the value of one, and zero otherwise.

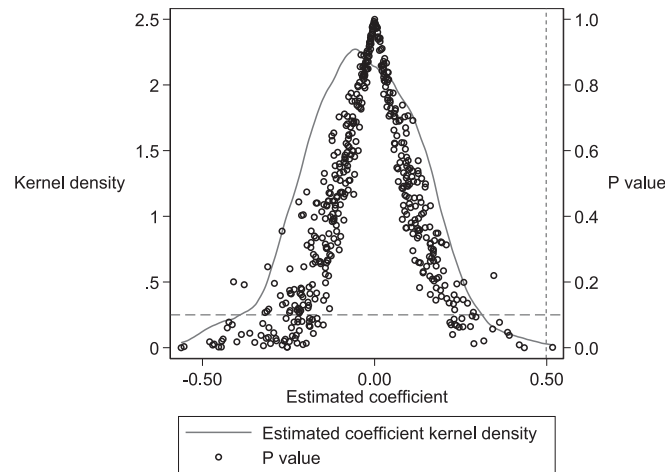


Fig. 2. Placebo tests.

we examine the following two explanations: (1) Becoming an Apple supplier may enhance a firm's visibility in capital markets, which subsequently attracts greater attention and demands for carbon disclosure from external stakeholders, such as institutional investors who are CDP signatories. (2) Firms may be subject to requests from CDP signatories to disclose material carbon information through the CDP platform and improve their disclosure quality. First, we replace the dependent variable *CDI* by *RequestCDP* and *ProvideCDP* in Eq. (1). Next, we incorporate *RequestCDP* and *ProvideCDP* into Eq. (1) to control for the impact of CDP signatories. The results are presented in Table 6 Panel C. In Column (3) and Column (4), the coefficient on *Treat*Post* is statistically nonsignificant. This suggests that becoming an Apple supplier does not prompt CDP signatories or other supply chain members to request more carbon disclosure through the CDP platform. In Column (5) and Column (6), *Treat*Post* is still significant at the 1% level, whereas the coefficients of *RequestCDP* and *ProvideCDP* are nonsignificant, thereby excluding the alternative explanation that the observed improvement stems from external pressures via the CDP.

4.5. Mechanism analysis

4.5.1. Direct governance effect

Regarding the direct governance effect, Apple directly oversees the carbon management practices of its suppliers through formal mechanisms. This governance is operationalized via a carrot-and-stick approach, combining incentives with sanctions. Since the direct governance process is unobservable, we proxy its strength by each supplier's asymmetric reliance on Apple. We posit that stronger Apple bargaining power, lower customer switching costs and higher supplier relationship-specific investments lead to greater supplier adherence to Apple's carbon management mandates, which will externalize as higher carbon-disclosure quality.

(1) The effect of Apple's bargaining power

We expect the effect of Apple on suppliers' carbon disclosure behavior to be stronger when Apple has stronger bargaining power, given that the negative consequences of obeying Apple's Supplier Code of Conduct are more severe in such cases. We measure Apple's bargaining power using (1) *Custo_reliance1*: the percentage of sales from the top customer, and (2) *Custo_reliance2*: the percentage of sales from the top five customers.¹⁵ We

¹⁵ Since corporate annual reports typically do not disclose the identities of major customers, we are unable to directly identify the specific amounts of sales to Apple. To address this problem, we employ two indirect proxies to capture the potential purchasing share and strategic importance represented by Apple. Extensive public reports and industry analyses confirm that Apple is indeed among the top five customers for many key suppliers, particularly in consumer electronics manufacturing, and is often the largest customer. Hence, these proxies reasonably reflect a supplier's dependence on Apple.

Table 7

Mechanism analysis: direct governance effect.

Variables	Custo_reliance1		Custo_reliance2		Spatial Location Competition		Relationship-specific Investments	
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CDI	CDI	CDI	CDI	CDI	CDI	CDI	CDI
<i>Treat*Post</i>	0.440** (2.50)	0.068 (0.34)	0.567** (2.52)	−0.128 (−0.79)	0.559** (2.46)	0.343 (1.37)	0.537*** (2.85)	0.088 (0.44)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value of difference	0.088		0.012		0.223		0.047	
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	1351	1354	1579	1578	1611	1615	1610	1616
<i>Adj. R²</i>	0.66	0.66	0.65	0.67	0.64	0.66	0.68	0.63

*, **, and *** denote significance at 0.10, 0.05, and 0.01 levels in a two-tailed test. Robust t-statistics are in parentheses.

partition the sample into high- and low-reliance groups based on the year median of these measures and estimate regressions separately for each subsample. The results are presented in Table 7. The coefficients of *Treat*Post* are all significantly positive at the 5% level in the subgroups with higher sales reliance, as shown in Column (1) and Column (3). In contrast, these coefficients are nonsignificant or even negative in the subgroups with lower sales reliance, as shown in Column (2) and Column (4). The p-values of the differences between the two groups of coefficients are 0.088 and 0.012, which are significant at the 10% level and 5% level, respectively. These findings imply that higher sales concentration enhances Apple's bargaining power and supervisory role as a major customer, thereby increasing suppliers' propensity to comply with Apple's carbon management demands.

(2) The impact of customer switching costs

Apple can promote carbon management practices by its suppliers through threatening to switch suppliers. In this context, low switching costs enhance the customer's bargaining power and make its claims more salient. We measure the customer's switching costs in terms of competition in the supplier's spatial location (*Spatial_competition*), calculated as the natural logarithm of the average geographic distance to the supplier's five closest same-industry competitors. This measure is inversely related to competitive intensity, with closer proximity indicating stronger competition. Higher spatial-location competition implies lower switching costs, as there are more suppliers that the customer can purchase from. We classify observations in which the supplier's spatial-location competition is lower (higher) than the sample year median of *Spatial_competition* as the subgroup with higher (lower) customer switching costs. The empirical results are shown in Table 7. In the high spatial-location competition group (Column (5)), the coefficient of the interaction *Treat*Post* is 0.559 and is significant at the 5% level, while in the low spatial-location competition group (Column (6)), the coefficient of the interaction term *Treat*Post* is not significant. The p-value of the difference between the two coefficients is 0.223 and nonsignificant. Overall, the results are consistent with our expectation that the effect of Apple on suppliers' carbon disclosure is stronger in firms facing higher spatial-location competition (higher customer switching costs).

(3) The impact of relationship-specific investments

Suppliers often make substantial relationship-specific investments (e.g., customized equipment, dedicated production lines or environmental technology R&D) to meet Apple's technical and sustainability standards. The hold-up effect implies that the cost of exiting Apple's supply chain is then extremely high, as it would

result in redundant equipment and a sharp decline in revenue. To avoid being removed from the supply chain, suppliers are strongly motivated to comply with Apple's carbon requirements.

Following prior studies (Dhaliwal et al., 2016), we capture relationship-specific investments using a firm's R&D intensity (*R&D_intensity*), defined as the ratio of a firm's R&D expenditure to its total assets. We divide the sample according to the year median of *R&D_intensity* into high and low relationship-specific investment subgroups and rerun the regression separately for the two subgroups. The coefficient of the interaction *Treat*Post* in Column (7) of Table 7 is significantly positive in the high relationship-specific investment group, whereas it is nonsignificant in the low relationship-specific investment group, as shown in Column (8). The p-value of the difference between the two coefficients is 0.047, which is significant at the 5% level. These results are consistent with our expectations.

4.5.2. Indirect exposure effect

Apple's annual release of its supplier list establishes reputational bonding with Apple and motivates market monitoring, thereby generating an indirect exposure effect that exerts disciplining pressure on its suppliers. This heightened scrutiny amplifies the reputational and market risks for both Apple and its suppliers in the event of non-compliance, thereby intensifying the supervisory pressure on Apple and the compliance pressure on suppliers (Campbell, 2007; Ilhan et al., 2023). Moreover, it places suppliers under the sustained scrutiny of diverse stakeholders (e.g., media and investors). Therefore, suppliers have stronger incentives to publicize their endeavor in the carbon reduction field to mitigate public scrutiny.

We use media attention (*Media_attention*)—the natural logarithm of total media coverage plus one—and investor attention (*Investor_attention*)—the natural logarithm of the Web Searches Index with stock codes as keywords plus one—as proxies for the indirect exposure effect. Both media attention and investor attention data are obtained from the CNRDS database. Then, we classify the sample into high and low media (investor) attention groups based on the median of *Media_attention* (*Investor_attention*), and conduct separate regressions for each subsample. The results are shown in Table 8. In the high media attention group in Column (1), the coefficient of the interaction term *Treat*Post* is 0.648, which is significant at the 1% level, whereas in the low media attention group in Column (2), the coefficient of is 0.050 and statistically nonsignificant. The p-value of the difference between the two coefficients is 0.026, which is significant at the 5% level. Similarly, in the high investor attention group in Column (3), the coefficient of *Treat*Post* is 0.508, significant at the 5% level, whereas in the low investor attention group Column (4), the coefficient is −0.102 and statistically nonsignificant. The p-value of the difference between the two coefficients is 0.032, which is significant at the 5% level. These findings indicate that Apple's governance effect on suppliers' carbon disclosure becomes more pronounced when suppliers are subject to greater media or investor attention.

Table 8
Mechanism analysis: indirect exposure effect.

Variables	Media Attention		Investor Attention	
	High (1) <i>CDI</i>	Low (2) <i>CDI</i>	High (3) <i>CDI</i>	Low (4) <i>CDI</i>
<i>Treat*Post</i>	0.648*** (2.88)	0.050 (0.23)	0.508** (2.47)	−0.102 (−0.34)
Controls	Yes	Yes	Yes	Yes
P-value of difference	0.026		0.032	
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes
<i>N</i>	1545	1548	1387	1388
<i>Adj. R²</i>	0.64	0.66	0.63	0.70

*, **, and *** denote significance at 0.10, 0.05, and 0.01 levels in a two-tailed test. Robust t-statistics are in parentheses.

4.6. Cross-sectional analyses

Our cross-sectional analysis explores the boundary conditions that shape the strength of Apple's supply chain governance effect. We focus on two dimensions that collectively constitute the preconditions through which external governance demands are transformed into firm-level responses: financial capacity (financing constraints) and corporate governance (agency costs).

4.6.1. The impact of financial constraints

Enterprises with lower financial constraints are more able and willing to respond to Apple's carbon disclosure requirements because they possess more abundant financial resources and greater strategic flexibility to invest in carbon management and the collection and accounting of carbon information while withstanding financial pressure from Apple. We predict that Apple will have a disproportionately larger impact on corporate carbon disclosure practices when suppliers experience lower financial constraints. We employ the FC index and SA index as the proxies for suppliers' financial constraints.

By dividing the sample based on the median value in each year of the *FC_index* and *SA_index*, we separate companies with strong financial constraints from those with weak financial constraints. The regression results are reported in Table 9. In Column (2) and Column (4), which show the results for companies with lower financial constraints, Apple has a significant positive influence on enterprises' carbon disclosure at the 5% level. However, *Treat*Post* is negative and significant in the high financial constraints group, as shown in Column (1). This indicates that for suppliers currently in short-term financial distress (Hadlock and Pierce, 2010), the high costs associated with becoming an Apple partner and the encroachment on resources suppress their ability and willingness to disclose carbon emission information. The p-value of the difference between the high and low *FC_index* coefficients is 0.014, which is significant at the 5% level. Meanwhile, the coefficient is significantly positive for the low *SA_index* group but nonsignificant for the high *SA_index* group. However, the difference between these two coefficients is not statistically significant ($p = 0.191$). These results show that sufficient financial resources are an important premise for the effective implementation of environmental governance in the supply chain.

4.6.2. The impact of agency costs

In the cross-sectional analysis of agency costs, we examine the governance effect of carbon disclosure in Apple's supply chain from two dimensions: (1) Separation of ownership and control (*Separation*), defined as the divergence between control and cash-flow ownership; and (2) Managerial ownership ratio (*Mshare*), defined as the number of shares held by directors, supervisors and senior management divided by the total

Table 9
Cross-sectional analyses: the impact of financial constraints.

Variables	FC index		SA index	
	High (1) <i>CDI</i>	Low (2) <i>CDI</i>	High (3) <i>CDI</i>	Low (4) <i>CDI</i>
<i>Treat*Post</i>	−0.313*** (−2.93)	0.360** (2.11)	0.370 (1.59)	0.623** (2.19)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	−3.890* (−1.79)	−5.451*** (−2.77)	−7.638*** (−5.56)	−1.974 (−1.23)
P-value of difference	0.014		0.191	
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes
<i>N</i>	1409	1412	1611	1615
<i>Adj. R²</i>	0.66	0.63	0.71	0.59

*, **, and *** denote significance at 0.10, 0.05, and 0.01 levels in a two-tailed test. Robust t-statistics are in parentheses.

number of shares. Lower separation of ownership and control reduces the incentives of controlling shareholders to expropriate minority shareholders. Higher managerial ownership ratios are associated with a greater interest alignment between management and shareholders. We partition the sample into high- and low-agency concern groups based on the median of *Separation* and *Mshare* within each year. We then rerun the regressions in Eq. (1) separately for the two subgroups. Table 10 Columns (1)–(4) report the results, revealing that Apple's carbon disclosure governance effect is more significant in the group with lower agency costs. The p-values of the differences between the coefficients for the two measures are 0.059 and 0.053, respectively, both of which are significant at the 10% level. These results indicate that only suppliers with effective internal governance respond actively to the environmental requirements of the external customer.

4.7. Further analyses

4.7.1. Carbon emission intensity

We further analyze whether carbon disclosure truly reflects substantive carbon reduction practices using the carbon emission intensity of subsidiaries and grand subsidiaries. The data are obtained from the Emissions Database for Global Atmospheric Research. We construct Eq. (3):

$$Carbon_intensity_{i,j,t} = \alpha + \beta Treat_{i,t} * Post_{i,t} + \gamma Controls_{i,t} + FirmFE + YearFE + \varepsilon_{i,t} \quad (3)$$

where i indicates the firm, j indicates subsidiaries or grand subsidiaries of the firm and t indicates the year. The variable of interest is $Treat*Post$, which captures whether a firm enters Apple's supply chain. We use the carbon emission intensity of subsidiaries or grand subsidiaries within 10 km (*Carbon_intensity10km*) and the carbon emission intensity of subsidiaries or grand subsidiaries within 30 km (*Carbon_intensity30km*) to measure a firm's actual carbon management practice. The control variables are the same as in Eq. (1). The detailed definitions and constructions of the variables are shown in Appendix A. We also control for year fixed effects and firm fixed effects, and cluster the standard errors by firm. As reported in Table 11 Columns (1) and (2), the coefficients on $Treat*Post$ are significantly negative for *Carbon_intensity10km* and *Carbon_intensity30km*, indicating that suppliers' higher carbon-disclosure quality is accompanied by real improvements in carbon emission reduction behavior.

4.7.2. Green innovation

To investigate whether Apple's influence extends beyond symbolic disclosure to substantive environmental action, we also examine its impact on suppliers' green innovation. The data are obtained from CNRDS. We construct Eq. (4):

Table 10
Cross-sectional analyses: the impact of agency costs.

Variables	Separation of Ownership and Control		Managerial Ownership	
	High (1) <i>CDI</i>	Low (2) <i>CDI</i>	High (3) <i>CDI</i>	Low (4) <i>CDI</i>
<i>Treat*Post</i>	0.231 (1.29)	0.672*** (2.98)	0.784*** (3.35)	0.367* (1.77)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	−1.601 (−1.15)	−6.095*** (−4.20)	−2.835 (−1.21)	−3.923** (−2.05)
P-value of difference	0.059		0.053	
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes
<i>N</i>	1523	1703	1614	1612
<i>Adj. R²</i>	0.71	0.64	0.64	0.68

*, **, and *** denote significance at 0.10, 0.05, and 0.01 levels in a two-tailed test. Robust t-statistics are in parentheses.

Table 11

Further analyses: carbon emission intensity and green innovation as the real effects.

Variables	(1) <i>Carbon_intensity10km</i>	(2) <i>Carbon_intensity30km</i>	(3) <i>GI_Apply</i>	(4) <i>GI_Grant</i>
<i>Treat*Post</i>	−3.254** (−1.98)	−22.696* (−1.96)	0.293* (1.77)	0.302* (1.73)
<i>Size</i>	−0.311 (−0.85)	−2.116 (−0.80)	0.082 (1.60)	0.149*** (3.74)
<i>Lev</i>	−1.597 (−1.04)	−11.197 (−1.03)	0.206 (1.16)	0.088 (0.57)
<i>ROA</i>	−1.894 (−0.94)	−19.165 (−1.29)	0.391 (1.54)	−0.018 (−0.09)
<i>Tangibility</i>	2.926* (1.81)	16.864 (1.48)	0.348* (1.71)	0.172 (0.93)
<i>Growth</i>	0.708*** (2.84)	4.434** (2.54)		
<i>MB</i>	−1.251 (−1.03)	−9.625 (−1.08)		
<i>Cash_holdings</i>	−0.467 (−0.33)	−2.747 (−0.27)		
<i>Dividend</i>	−0.011 (−0.04)	−0.113 (−0.06)		
<i>Top1</i>	1.170 (0.87)	11.405 (1.17)		
<i>Dual</i>	−0.589* (−1.69)	−3.926 (−1.53)		
<i>Boardindep</i>	−4.931* (−1.74)	−30.077 (−1.47)		
<i>Age</i>			−0.136* (−1.70)	−0.148*** (−4.50)
<i>R&D_Intensity</i>			0.780 (0.47)	1.436 (1.08)
<i>TobinQ</i>			0.019 (1.19)	0.042*** (3.14)
<i>KZ_index</i>			−0.000 (−0.02)	−0.000 (−0.03)
<i>Capex.Asset</i>			0.133** (2.48)	0.052 (1.31)
<i>InsInvestorProp</i>			0.000 (0.30)	0.001 (0.97)
<i>Illiquidity</i>			−0.312 (−0.75)	0.422 (1.19)
<i>Constant</i>	10.544 (1.28)	71.509 (1.20)	0.610 (0.40)	−0.767 (−0.74)
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Firm FE</i>	Yes	Yes	Yes	Yes
<i>N</i>	10,500	10,500	2861	2861
<i>Adj. R²</i>	0.14	0.14	0.51	0.53

*, **, and *** denote significance at 0.10, 0.05, and 0.01 levels in a two-tailed test. Robust t-statistics are in parentheses.

$$GI_Apply_{i,t+2}/GI_Grant_{t+2} = \alpha + \beta Treat_{i,t} * Post_{i,t} + \gamma Controls_{i,t} + FirmFE + YearFE + \varepsilon_{i,t} \quad (4)$$

where i indicates the firm and t indicates the year. The variable of interest is $Treat*Post$, which captures whether a firm enters Apple's supply chain. We use green innovation application (GI_Apply) and green innovation grants (GI_Grant) to measure a firm's green innovation. To account for the time lag in the innovation process, we employ a two-period lag of the green innovation. Following He and Tian (2013), we control for

firm size (*Size*), leverage ratio (*Lev*), return on total assets (*ROA*), firm age (*Age*), R&D intensity (*R&D_Intensity*), firm value (*TobinQ*), tangible asset ratio (*Tangibility*), financing constraints (*KZ_index*), capital expenditure (*CapexAsset*) and institutional investor ownership (*InsInvestorProp*). The detailed definitions and constructions of the variables are shown in Appendix A. We also control for year fixed effects and firm fixed effects, and cluster the standard errors by firm.

As presented in Table 11 Columns (3) and (4), the coefficients on *Treat*Post* are significantly positive for *GI_Apply* and *GI_Grant*, indicating that becoming an Apple supplier improves green innovation. These findings suggest that the observed improvement in carbon disclosure is underpinned by genuine efforts in sustainable innovation.

5. Conclusion and future research

This study examines the impact of global major customers on corporate carbon transparency through observing changes in corporate carbon-disclosure quality after suppliers' entry into Apple's supply chain. We show that suppliers significantly improve their carbon-disclosure quality after entering Apple's supply chain, which indicates a strong disciplining effect exerted by Apple as a major customer. The two channels through which Apple influences its suppliers are direct governance and exposure, the latter an indirect governance effect. The effect is stronger among suppliers with greater financial capacity and lower agency costs. These results indicate that only suppliers with slack financial resources and effective internal governance have a stronger willingness and ability to respond actively to the environmental requirements of this external customer. Finally, further analysis confirms that Apple's influence extends beyond symbolic disclosure to real improvements in carbon emission reduction and substantive green innovation among suppliers. In conclusion, our findings collectively demonstrate that influential global major customers like Apple can play a critical role in advancing carbon transparency and sustainability in global supply chains.

Although we believe that our results offer a more nuanced understanding of the governance role of major customers in environmental transparency, we acknowledge three limitations of our study. First, our analysis focuses solely on Apple as a global major customer, implying a lack of variation in customer characteristics. We acknowledge that several other global leading customers (e.g., Microsoft, Tesla, Boeing) have similar bargaining power over their suppliers and act to promote sustainable governance in supply chains. The biggest challenge for us in exploring the impact of those customers on suppliers' carbon disclosure is the lack of access to their complete supplier lists. We believe that our findings regarding Apple can be generalized to other similar customers because such firms' governance mechanisms over suppliers (e.g., code of conduct enforcement, bargaining power, and visibility associated with supplying a global major customer) are widely regarded as universal. We do believe it is an important and interesting problem to discuss such customers' sustainable governance role, and we encourage future research to explore other global major customers' carbon-related commitments in this field.

Second, our sample is restricted to a specific industry with distinct features, such as globalized supply chains, high visibility to consumers and specific carbon emission profiles (e.g., significant Scope 3 emissions). These characteristics are likely to enable supply chain governance to play a significant role in this sector. Third, we solely focus on Apple's suppliers in China, a representative emerging market; future research could extend this analysis to global suppliers.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Variable definitions

Variables	Definition
Variables in the baseline results	
<i>Treat</i>	Dummy variable that equals one if a firm is Apple's supplier, zero otherwise.
<i>Post</i>	Dummy variable that takes the value of one after entry into Apple's supply chain, zero otherwise.
<i>CDI</i>	The natural logarithm of the total carbon disclosure score plus one.
<i>Size</i>	The natural logarithm of total assets.
<i>Lev</i>	The sum of the long-term debt and the debt in current liabilities over the firm's total assets.
<i>ROA</i>	Net income scaled by total assets.
<i>Growth</i>	Current-year revenue divided by last-period revenue minus 1.
<i>MB</i>	Book value of equity divided by market value of equity.
<i>Cash_holdings</i>	The ratio of cash and short-term investments to the book value of total assets.
<i>Tangibility</i>	The ratio of property, plant, and equipment over the firm's total assets.
<i>Dividend</i>	Total amount of dividends scaled by net income.
<i>Top1</i>	The number of shares held by the largest shareholder divided by the total number of shares.
<i>Dual</i>	Dummy variable indicating whether the CEO is also chairman of the board.
<i>Boardindep</i>	Proportion of independent directors.
Additional variables in Table 5	
<i>CD_wordfreq1</i>	Carbon disclosure word frequency divided by total word number of annual financial report (excluding English and figures)
<i>CD_wordfreq2</i>	Carbon disclosure word frequency divided by total term number of annual financial report (excluding stop words).
<i>CD_wordfreq2</i>	Carbon disclosure word frequency divided by total sentence number of annual financial report.
<i>Eco_development</i>	The natural logarithm of per capita GDP.
<i>SecondaryInd</i>	The ratio of secondary industry value added to GDP.
<i>FDI</i>	The ratio of actual utilized foreign direct investment to GDP.
<i>ESGperformance</i>	The comprehensive score of Sino ESG rating in China.
<i>Eperformance</i>	The environmental score of Sino ESG rating in China.
<i>Governance</i>	The natural logarithm of one plus the disclosure score of board supervision, manager responsibility and employee engagement.
<i>RiskOpportunities</i>	The natural logarithm of one plus the disclosure score of carbon risk managing system, carbon risk identification and assessment, and carbon opportunity identification and management.

(continued on next page)

Appendix A (continued)

Variables	Definition
<i>Strategy</i>	The natural logarithm of one plus the disclosure score of low carbon transformation strategy.
<i>Targets</i>	The natural logarithm of one plus the disclosure score of carbon reduction targets, other climate managing targets, emission reduction measures targets, and business transformation progress targets.
<i>Indicator_emissions</i>	The natural logarithm of one plus the disclosure score of GHG emission Scope1, Scope2, Scope3 and carbon emission intensity.
<i>Indicator_decomposition</i>	The natural logarithm of one plus the disclosure score of emission changes, Scope1 emission decomposition, and Scope2 emission decomposition.
<i>Indicator_valuesupply</i>	The natural logarithm of one plus the disclosure score of value chain interaction and up and down customer management.
<i>Indicator_others</i>	The natural logarithm of one plus the disclosure score of other climate information and verifiability.
Additional variables in Table 6	
<i>CEtradingDID</i>	If a city has implemented carbon emissions trading pilot policy, <i>CEtradingDID</i> takes the value of 1, and 0 otherwise.
<i>LowCarbonDID</i>	If a city has implemented low-carbon city construction policy, <i>LowCarbonDID</i> takes the value of 1, and 0 otherwise.
<i>RequestCDP</i>	Dummy variable that takes one if a firm is requested to report climate change information to CDP in a year.
<i>ProvideCDP</i>	Dummy variable that takes one if a firm responds to CDP's request in a year.
Additional variables in Table 7	
<i>Custo_reliance1</i>	Percentage of sales from the top one customer.
<i>Custo_reliance2</i>	Percentage of sales from the top five customer.
<i>Spatial_Competition</i>	The natural logarithm of the average geographic distance to its five closest same-industry competitors.
<i>R&D_Intensity</i>	The ratio of a firm's R&D expenditure scaled by total assets.
Additional variables in Table 8	
<i>Media_attention</i>	The natural logarithm of total media coverage plus one.
<i>Investor_attention</i>	The natural logarithm of the Web Searches Index with stock codes as keywords plus one.
Additional variables in Table 9	
<i>FC_index</i>	Constructed following Kaplan and Zingales (1997).
<i>SA_index</i>	Constructed following Hadlock and Pierce (2010).
Additional variables in Table 10	
<i>Separation</i>	The divergence between control and cash-flow ownership.
<i>Mshare</i>	The number of shares held by directors, supervisors and senior management to the total number of shares.
Additional variables in Table 11	
<i>Carbon_intensity10</i>	Carbon emission in 10 km around subsidiaries (grand subsidiaries) scaled by their total assets.
<i>Carbon_intensity30</i>	Carbon emission in 30 km around subsidiaries (grand subsidiaries) scaled by their total assets.
<i>GI_Apply</i>	The natural logarithm of green innovation application number plus one.
<i>GI_Grant</i>	The natural logarithm of green innovation grant number plus one.
<i>TobinQ</i>	Firm's market value divided by book value of assets.
<i>KZ_index</i>	Constructed following Kaplan and Zingales.

Appendix A (continued)

Variables	Definition
<i>CapexAsset</i>	Capital expenditure scaled by book value of total assets.
<i>InsInvestorProp</i>	The number of shares held by institutional investors.
<i>Illiquidity</i>	Absolute value of the difference between the execution price and the mid-point of the prevailing bid-ask quote divided by the mid-point of the prevailing bid-ask quote (daily), then averaged arithmetically from daily to annual data.

Online Appendix A and B. Supplementary material

Supplementary material to this article can be found online at <https://doi.org/10.1016/j.cjar.2026.100501>.

Online Appendix A illustrates the construction of the carbon disclosure score index using Luxshare Precision's 2022 carbon disclosure report as an example. Online Appendix B reports the covariate balance tests for the propensity score matching and entropy balancing procedures.

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Green transformation along the supply chain: Spillover effects from backward vertical partnerships

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ABSTRACT

This paper employs natural language processing to construct a firm-level green-transition score and examines how downstream companies' greening shapes upstream suppliers' environmental upgrading. Our findings demonstrate that downstream firms' green transition exerts significant positive spillovers on upstream suppliers' environmental practices. This conclusion remains robust across multiple identification strategies, including instrumental variable estimation, difference-in-differences analysis and Heckman two-step selection correction. Heterogeneity analysis reveals that these spillover effects are amplified under three conditions: (1) strong supplier absorptive capacity, (2) narrow green-technology gaps between buyers and suppliers and (3) large market size in the buyer's regional market. Mechanism tests indicate that downstream firms' green transformation facilitates upstream suppliers' environmental upgrading through two channels: knowledge–technology transfer and norm diffusion of environmental standards. This study advances the literature on corporate greening and supply chain coordination and provides policy levers to foster integration and amplify green spillovers.

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1. Introduction

The conflict between environmental conservation and economic progress remains a pressing global concern. Corporate greening is pivotal to addressing environmental issues globally and advancing sustainable development (Liu et al., 2023; Cheng et al., 2024; Wang et al., 2024). The existing literature examines the drivers of firms' transition towards environmentally friendly practices. Specifically, it focuses on command regulation

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policies (Carrión-Flores et al., 2013; Wesseh and Lin, 2019; Zhang et al., 2019; Pan et al., 2022; Liu et al., 2024; Wang et al., 2024), market-based regulation policies (Weber and Neuhoff, 2010; Fan et al., 2021; Helm and Mier, 2021; Qi et al., 2023) and company structure (Amore and Bennedsen, 2016; Krueger et al., 2020; Shive and Forster, 2020; Xu and Hu, 2024). However, insufficient attention has been accorded to the role of green spillovers from downstream customers in shaping upstream suppliers' environmental strategies. Enterprise green transformation is innovative in nature. Diffusion of innovation theory posits that innovations require dissemination through certain channels that are consistently embraced by adopters within the system (Papazoglou and Spanos, 2018; Kertcher et al., 2020). From a supply chain standpoint, the green transformation of downstream customers serves as a holistic innovation practice. Downstream customers' experience and knowledge act as a catalyst for innovation that spreads within upstream and downstream enterprises, which provides valuable external assets for upstream suppliers to acquire, embrace and advocate for green transformation. However, the majority of the present research concerning supply chains revolves around the business connections between upstream and downstream companies, as well as factor flows and knowledge diffusion among enterprises (Lu et al., 2017; Ding et al., 2024; Ersahin et al., 2024a, 2024b; Ouyang et al., 2024). A clear understanding remains elusive regarding whether and how the green transformation of customer firms influences upstream suppliers, and how suppliers can effectively leverage customer resources to facilitate their own green transitions. This paper seeks to investigate three specific questions: (1) Does the green transformation of downstream firms diffuse to upstream suppliers within the supply chain? (2) Through what mechanisms does this diffusion occur? (3) How can upstream suppliers better absorb the green spillover from the client company?

To analyze environmental spillovers from consumers along supply chains, we first establish a Gounod game theoretical framework that incorporates the upstream and downstream enterprises. Second, using the top five customer lists and financial data of Chinese Shanghai and Shenzhen A-share listed companies from 2008 to 2022, we construct a unique supplier–customer database through matching. Third, with Python, we crawl annual reports from the CNINF Network and quantify firms' green transformation using natural language processing (NLP). Finally, the measures are used to assess the presence of green spillovers across supply chain networks. The findings indicate that green transformation in downstream enterprises can significantly boost that in upstream enterprises. Heterogeneity analysis shows that the environmental spillover effects within supply chains exhibit asymmetric characteristics, and downstream customers exert more pronounced environmental spillovers in the case of the strong absorptive capacity of the supplier, a small green-technology gap between the customer and the supplier and a large market size of the customer's region. In addition, the mechanism test finds that knowledge and technology spillover and environmental standards and norms spillover are effective mechanisms by which downstream customers' green transformation can promote upstream suppliers' green transformation.

We focus on Chinese firms for three reasons. To begin with, China has entered the decisive phase of ecological restructuring. While it claims the title of the world's largest energy user and CO₂ polluter, its Environmental Performance Index score still places it in the lowest third of countries worldwide—a sharp disparity relative to its position as the globe's second-largest economic power.¹ Therefore, the central authorities have implemented a range of policy initiatives designed to foster environmental conservation and sustainable growth. Second, Chinese companies have moved quickly along the green-technology frontier. As presented in Fig. 1, green patent applications filed by Chinese companies expanded from 3028 in 2002 to 98,278 in 2020, representing an average annual growth rate of 22.3%. This growth demonstrates Chinese firms' progress in sustainable transition and offers valuable insights into supply chain environmental spillovers.

Third, the disclosure rules governing Chinese listed firms yield granular supply chain data. Since 2001, Chinese listed companies have been required to report the revenue share of their five largest customers in annual reports, and customer name disclosure remains encouraged under China Securities Regulatory Commission (CSRC) guidelines. As shown in Fig. 2, from 2002 to 2022, the number of Chinese listed firms disclosing customer names rose from 65 to 871 (13.5% annual growth), while disclosed customers increased from 310 to 2788 (11.8% annual growth). Therefore, these disclosure policies provide robust support for building accurate supply chain datasets.

¹ Source: <https://epi.yale.edu/epi-results/2022/component/epi>.

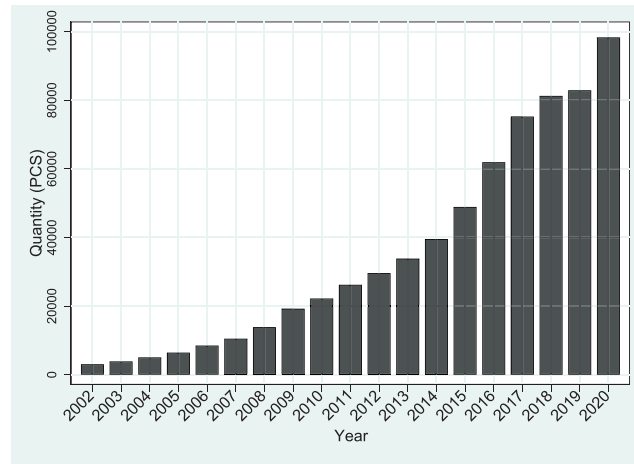


Fig. 1. Number of green and low-carbon patent applications in China, 2002–2020. Notes: The bar graph displays the quantity of eco-friendly and sustainable technology patents. The dataset is provided by the China National Intellectual Property Administration.

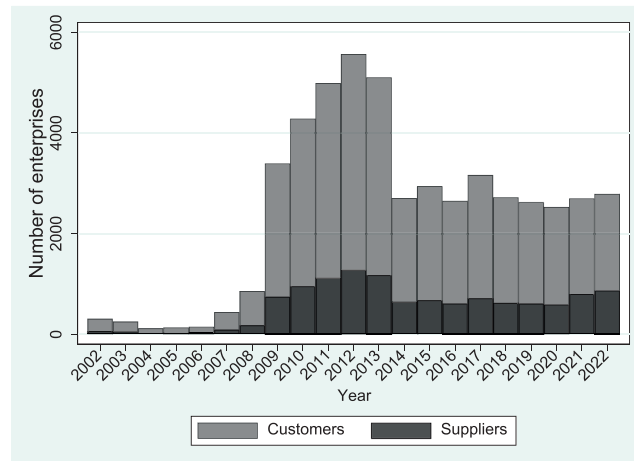


Fig. 2. Disclosure of major customers by China's public companies, 2002–2022. Notes: The gray bar shows disclosed customer counts, while the black bar represents firms disclosing customer names (CSMAR data).

The present paper advances two distinct branches of academic literature. First and foremost, it supplements existing scholarship pertaining to supply chain spillovers. Extant work focuses on how import-trade liberalization, financing constraints, operational risk and outward foreign direct investment (FDI) propagate upstream and downstream (Amiti and Konings, 2007; Lu et al., 2017; Newman et al., 2023; David et al., 2024; Ding et al., 2024; Ersahin et al., 2024a, 2024b). This paper investigates how downstream customers' green transformation spills over to their upstream suppliers, adding a new dimension to the supply chain spillover literature. Second, it speaks to research on the drivers of corporate environmental upgrading. Existing studies typically treat firms as isolated individuals, yet in practice, enterprises exert spatial spillover (Shang et al., 2012), herding effects (Xue et al., 2023) and enterprise group spillover (Desai et al., 2006). Furthermore, supply chain linkages create strong economic interdependence between suppliers and customers, so corporate transformation may also be affected by the spillover effects of other enterprises in the supply chain. By examining how downstream customers' green transformation shapes upstream suppliers through vertical supply chain spillovers, the present paper supplements existing scholarship pertaining to the factors driving firms' environmental upgrading.

2. Literature review and research gap

2.1. Green transformation of enterprises

As Table 1 summarizes, the prevailing proxies for corporate green transformation are green patents (Amore and Bannedsen, 2016; Tang et al., 2025), pollutant emissions or emission intensity (Qi et al., 2023), ESG indices (Liang et al., 2024; Sun et al., 2024) and green total factor productivity (Kuosmanen and Maczulskij, 2024). Recent literature shows that machine learning-based measurement can mitigate interference from problems such as cross-sectional errors (Battistoni et al., 2023; Shao et al., 2024), measurement errors (Ning et al., 2023) and reverse causality (Shao et al., 2024). Thus, we use cutting-edge textual NLP techniques to measure the green transformation in enterprises, aiming to further improve the evaluation system for corporate ecological performance.

Table 1 shows that the drivers of corporate green transformation have mainly been studied through the lens of command-and-control regulatory policies (Carrión-Flores et al., 2013; Wesseh and Lin, 2019; Zhang et al., 2019; Wang et al., 2024), market-based regulatory policies (Weber and Neuhoﬀ, 2010; Fan et al., 2021; Helm and Mier, 2021; Qi et al., 2023) and enterprise organizational structure (Amore and Bannedsen, 2016; Krueger et al., 2020; Shive and Forster, 2020; Xu and Lin, 2025), while vertical supply chain spillovers have received comparatively little attention (Chen et al., 2019; Hsieh and Lathifah, 2024; Yang et al., 2024a, 2024b). This study expands corporate green transformation research by analyzing supply chain spillover effects.

2.2. Supply chain spillover effect

The literature documents supply chain spillovers arising from financial flows, environmental regulation, trade liberalization, enterprise innovation, enterprise internationalization (Javorcik, 2004; Isaksson et al., 2016; Linarello, 2018; Minetti et al., 2019; Dhyne et al., 2021; Lin et al., 2024). Panel A of Table 2 shows that previous empirical studies mostly measure supply chain spillover effects based on macro input–output tables (Javorcik, 2004; Blalock and Veloso, 2007; Linarello, 2018; Newman et al., 2023; Ding et al., 2024; Olurotimi et al., 2025). However, Chakraborty et al. (2024) argue that this approach can only portray inter-industry vertical linkages between upstream and downstream sectors, which makes it difficult to capture the intra-industry heterogeneity of firms in terms of the quality and composition of inputs. An emerging alternative is to exploit firm-level data on disclosed suppliers and customers (Geng et al., 2024; Lin et al., 2024), and we adopt this micro approach here.

Table 1
Literature review on the green transformation of enterprises.

Research authors	Independent variables	Main findings	Proxy indicator
Amore and Bannedsen (2016); Lan et al. (2024); Xu and Lin (2025)	Corporate governance, establishment of environmental protection courts, green credit policies	Command-and-control policies, market-based regulatory policies and enterprise organizational structures are important factors that influence enterprise green innovation.	Green patent
Qi et al. (2023); Shang et al. (2023); Zhou et al. (2024a, 2024b)	Tax incentives, market-based environmental regulations and the establishment of environmental courts	Industrial policies, command-and-control policies and market-based regulatory policies are important factors affecting the pollutant emissions of enterprises.	Pollutant discharge or discharge intensity
Liang et al. (2024); Zhang et al. (2024)	Extreme temperatures, artificial intelligence	External geographical conditions and an enterprise's own technological application are important factors affecting the enterprise's ESG.	ESG index
Nieto and Santamaría (2007); Dai and Zhu (2024); Kuosmanen and Maczulskij (2024); Liu et al. (2024)	Changes in corporate structure, uncertainty in climate policy, pilot policies for low carbon emissions	Command-and-control policies and corporate organizational structures are important factors influencing the green total factor productivity of enterprises.	Green total factor productivity

Table 2
Literature review on supply chain spillover effects.

Panel A: Supply chain spillover studies				
Authors	Perspectives	Core data	Major findings	
Javorcik (2004)	FDI	Input–output table	FDI brings positive productivity-enhancing effects through the interaction between its affiliates and local suppliers in upstream industries.	
Blalock and Veloso (2007)	Import competition	Input–output table	Vertical supply linkages serve as conduits for import-driven technology transfer.	
Isaksson et al. (2016)	Enterprise innovation	Enterprise supply chain networks	Buyer innovation positively affects supplier innovation.	
Linarello (2018)	Trade liberalization	Input–output table	Tariff reductions benefit downstream industries, while also boosting productivity in supplier industries. Indirect effects account for 22.5% of the total effect.	
Minetti et al. (2019)	Financial flows	Enterprise supply chain networks	For credit-constrained small and medium-sized enterprises, supply chain integration enhances liquidity access and unlocks asset liquidity.	
Dhyne et al. (2021)	Corporate import trade	Enterprise supply chain networks	Most firms use large quantities of foreign inputs, but only a few do so through direct imports, with most firms exporting indirectly.	
Newman et al. (2023)	Import competition	Input–output table	Imports can influence the productivity of domestic business entities, competitors, direct importers of intermediates and downstream sector businesses within the supply chain.	
Dankyira et al. (2024)	Supply chain disruption	Questionnaire	Disruptions in the supply chain heighten threat interpretation bias, thereby diminishing operational resilience.	
Lin et al. (2024)	Environmental regulation	Enterprise supply chain networks	Customer firms' environmental regulatory pressures spur supplier green innovation, as buyers leverage bargaining power to transfer compliance demands upstream.	
Ding et al. (2024)	FDI	Input–output table	FDI generates financial spillovers to domestic providers, mainly through trade credit and bank lending channels.	
Geng et al. (2024)	Digital transformation	Enterprise supply chain networks	Organizational digital transformation drives upstream and downstream digitalization, with stronger spillover effects on suppliers. Enterprises' digital shifts enhance supplier transformation through reverse spillover mechanisms.	
Olurotimi et al. (2025)	FDI	Input–output table	Increased FDI in the downstream and upstream sectors favors the export performance of business sector firms.	
Panel B: Research on green spillovers in supply chains				
Authors	Research sample	Methodology	Major findings	
Green et al. (2012)	Sample plant-level executives employed by U.S. manufacturing enterprises	Structural model	The implementation of joint environmental practices and supervision across supply chain collaborators can boost the dual performance of both environmental and organizational dimensions.	
Chen et al. (2019)	Not applicable	Theoretical model	Supply chain green R&D collaboration boosts environmental performance, consumer surplus and social welfare.	
Lin (2022)	Taiwanese listed manufacturing companies	Structural model	The internal integration and external collaboration of e-green supply chain management can enhance both environmental performance and competitiveness.	
Hsieh and Lathifah (2024)	Not applicable	Theoretical model	Green supply chain coordination achieves mutual benefits for partners through spillover effects.	

As Panel A of Table 2 shows, existing work on supply chain spillovers typically estimates their aggregate impact (Isaksson et al., 2016; Dankyira et al., 2024) while remaining silent on the underlying mechanisms. Ding et al. (2024) find that downstream customers can achieve financial spillovers to upstream and downstream firms through the transaction credit channel and the bank loan channel. The present study scrutinizes the mechanisms related to green knowledge and technology spillovers, as well as the spillovers of environmental standards and norms, thereby enhancing the comprehension of green spillover mechanisms within supply chains.

As shown in Panel B of Table 2, research on green spillovers along supply chains is still scarce but is beginning to attract interest (Hsieh and Lathifah, 2024). The majority of these studies investigate the collaborative behavior of upstream and downstream business entities in their ecological transformation through the lens of green supply chain collaboration (Green et al., 2012; Hsieh and Lathifah, 2024), and most of them focus on theoretical research (Chen et al., 2019; Hsieh and Lathifah, 2024). Empirical evidence on corporate unilateral green spillovers in supply chains remains limited, and our study seeks to help fill this gap.

3. Theoretical model

This study examines how downstream firms' adoption of green practices affects upstream suppliers. To do so, we build a game-theoretic framework that explicitly models both tiers of the supply chain, where upstream output serves as the intermediate input for downstream production.

3.1. Downstream firm behaviors

Consider a downstream industry with n identical firms, facing the following market demand function:

$$P_d = a - \sum_{i=1}^n q_{di} \quad (1)$$

Let $Q_d = \sum_{i=1}^n q_{di}$ denote the total output of the downstream industry, P_d its market price and q_{di} the output of an individual downstream firm. We assume a unit input–output ratio (i.e., equal to 1) for the downstream firm, but the specific value of this ratio does not influence the main conclusions. Furthermore, the price of the intermediate input (produced by the upstream firm) is denoted as P_u and is exogenous to the downstream industry. To mitigate pollution externalities, the government imposes an environmental tax proportional to firm output, with a specified levy intensity of t_d . Corporate green transformation is defined by green innovation. Accordingly, the model is built upon the following assumptions. First, building on De Bettignies et al. (2018) and Aghion et al. (2024), we assume that green transformation reduces the marginal cost of downstream firms from P_u to $P_u - bg_{di}$. A downstream firm's green transformation cost is given by $\lambda g_{di}^2/2$. Second, drawing on Porter and Linde (1995), who argue that green transformation lowers environmental compliance costs, we assume that downstream firms' compliance cost decreases from $t_d q_{di}$ to $(1 - g_{di})t_d q_{di}$. The profit of the downstream firm i can be represented in the following manner:

$$\pi_{diq_{di},g_{di}} = (P_d - P_u + bg_{di})q_{di} - \frac{\lambda g_{di}^2}{2} - (1 - g_{di})t_d q_{di} \quad (2)$$

We calculate the partial derivative of Eq. (2) with respect to q_{di} to obtain the first-order condition for profit maximization by the downstream firm:

$$\frac{\partial \pi_{di}}{\partial q_{di}} = a - 2q_{di} - \sum_{j \neq i} q_{dj} - P_u + bg_{di} - (1 - g_{di})t_d = 0 \quad (3)$$

Due to the symmetry of the behavior of the firms in the Gounod model, we have $q_{di} = q_{dj}$. Solving Eq. (3) yields the optimal output of the downstream firm:

$$q_{di}^* = \frac{a - P_u + bg_{di} - (1 - g_{di})t_d}{n + 1} \quad (4)$$

3.2. Upstream firm behaviors

Let there be n homogeneous upstream firms. Downstream firms are assumed to have a production technology that requires one unit of the intermediate input for each unit of output produced. This implies the following relationship:

$$\sum_{i=1}^n q_{di} = \sum_{k=1}^m q_{uk} \quad (5)$$

The output of the upstream firm k is q_{uk} . By incorporating Eq. (4) into Eq. (5), Eq. (6) is obtained:

$$\frac{[a - P_u + bg_{di} - (1 - g_{di})t_d]n}{n+1} = \sum_{k=1}^m q_{uk} \iff P_u = a + bg_{di} - (1 - g_{di})t_d - \frac{n+1}{n} \sum_{k=1}^m q_{uk} \quad (6)$$

The upstream industry faces the market demand given in Eq. (6). We denote the upstream firms' marginal cost as c , their green transformation level as g_{uk} and the environmental tax rate as t_u . Accordingly, the profit of an upstream firm k is

$$\begin{aligned} \pi_{uk|q_{uk}, g_{uk}} &= (P_u - c + dg_{uk})q_{uk} - \frac{\mu g_{uk}^2}{2} - (1 - g_{uk})t_u q_{uk} \\ &= [a + bg_{di} - (1 - g_{di})t_d - \frac{n+1}{n} \sum_{k=1}^m q_{uk} - c + dg_{uk}]q_{uk} - \frac{\mu g_{uk}^2}{2} - (1 - g_{uk})t_u q_{uk} \end{aligned} \quad (7)$$

We calculate the partial derivatives of Eq. (7) with respect to the output of upstream firm (q_{uk}) and its green transformation effort (g_{uk}).

The equations representing the first-order conditions for maximizing the profits of the upstream firm k are as follows:

$$\frac{\partial \pi_{uk}}{\partial q_{uk}} = \left(a + bg_{di} - (1 - g_{di})t_d - \frac{2(n+1)}{n} q_{uk} - \frac{n+1}{n} \sum_{j \neq k}^m q_{uj} - c + dg_{uk} \right) - (1 - g_{uk})t_u = 0 \quad (8)$$

$$\frac{\partial \pi_{uk}}{\partial g_{uk}} = dq_{uk} - \mu g_{uk} + t_u q_{uk} = 0 \quad (9)$$

Given the symmetry among upstream firms, we combine Eqs. (8) and (9) to solve for the optimal green transformation level g_{uk}^* for the upstream firm k :

$$g_{uk}^* = \frac{n(d + t_u)[-a + c + t_d - g_{di}(b + t_d) + t_u]}{d^2 n - (1 + m)(1 + n)\mu + nt_u(2d + t_u)} \quad (10)$$

3.3. Comparative static analysis

Differentiating Eq. (10) with respect to g_{di} (the downstream firms' green transformation) yields the following equation:

$$\frac{\partial g_{uk}^*}{\partial g_{di}} = \frac{-n(b + t_d)(d + t_u)}{d^2 n - (1 + m)(1 + n)\mu + nt_u(2d + t_u)} \quad (11)$$

If $(1 + m)(1 + \frac{1}{n})\mu > d^2 + t_u(2d + t_u)$, then $\frac{\partial g_{uk}^*}{\partial g_{di}} > 0$, implying that downstream green transformation promotes its upstream counterpart. Conversely, if $(1 + m)(1 + \frac{1}{n})\mu < d^2 + t_u(2d + t_u)$, then $\frac{\partial g_{uk}^*}{\partial g_{di}} < 0$, suggesting that downstream efforts impede upstream transition. Furthermore, we highlight three key findings. First, the probability that downstream green transformation induces upstream adoption is increasing in the size of the upstream industry. This effect arises because a larger number of upstream enterprises provides downstream firms with a wider selection of suppliers. As downstream firms advance their green transformation, they are not dependent on any single upstream partner and can exert pressure by switching partners. To avoid losing orders, upstream firms will be more proactive in responding to green demands and undergoing green transfor-

mation (Wang et al., 2024). Second, the positive effect of downstream green transformation on upstream adoption is augmented by a higher concentration level in the downstream industry. This is because downstream firms possess higher bargaining power when they dominate a significant share of upstream orders. In this case, the green transformation demands of downstream firms impose rigid constraints on upstream firms. If upstream firms fail to meet these demands, they may directly lose their core customers, forcing them to proactively respond to downstream green requirements. Third, lower environmental tax stringency in upstream industries strengthens the positive effect of downstream green transformation on upstream adoption. We contend that reduced tax rates attenuate the external policy pressures forcing upstream firms to cut their carbon emissions. This, in turn, allows the market demand from downstream green transformation to become the primary driving force for upstream emissions reduction. This effectively mitigates the cost conflict between policy and the market (Zhang, 2022), facilitating a more effective transmission of downstream demand into upstream action. Furthermore, a cost–benefit analysis provided in Appendix A supports this logic. Drawing on this theoretical model, we put forward the following core hypotheses:

H1: *The green transformation of downstream enterprises promotes the green transformation of upstream enterprises.*

H2: *The green transformation of downstream enterprises inhibits the green transformation of upstream enterprises.*

3.4. Mechanism analysis

Spillovers of knowledge and technology can occur. As firms implement green innovations—including new technologies, management practices and production processes—the benefits often extend beyond firm boundaries through supply chain linkages (Nieto and Santamaría, 2007). This process operates through two main channels. The first is technological diffusion: downstream customer firms may adopt advanced green technologies and production methods (Cheng et al., 2024), which not only improve downstream customers' own production efficiency (Xu and Hu, 2024) but also provide opportunities for upstream suppliers to learn and imitate (Berliant et al., 2006; Byun et al., 2021). Through technological exchanges and cooperation, green technologies can be disseminated in the supply chain, thus promoting technological upgrading and green transformation of upstream supplier firms. The second channel is knowledge transfer. Green transformation involves not only technological innovation but also the updating of management concepts and the enhancement of environmental awareness (Chen et al., 2019; Wang et al., 2024). The environmental knowledge and management experience accumulated by downstream customer firms in the green transformation process can be transferred to upstream suppliers through the supply chain. This sharing of green knowledge helps upstream supplier firms to develop environmental capabilities, optimize production, reduce pollution and achieve their transformation goals.

Spillovers of environmental standards and norms can also occur. Enterprises tend to upgrade their own environmental standards and norms during green transformation. These standards not only influence their own operations but also cascade upstream through the supply chain (Wang et al., 2024). First, from a market demand-driven perspective, downstream customer firms' raising their environmental standards implies an increased demand for green products. This compels upstream supplier firms to adapt their production strategies to meet these new requirements (Dai et al., 2021). As consumer preference for green products grows, this trend further incentivizes downstream firms to elevate their standards, thereby indirectly driving upstream green transformation. Second, from a standards-diffusion perspective, the eco-friendly shift by downstream buyers typically involves implementing stringent environmental requirements. These requirements are transmitted to upstream suppliers, who must provide compliant products or services to maintain their commercial relationships (Wang et al., 2024). Consequently, the necessity of adhering to these standards promotes green transformation among upstream firms.

Furthermore, Appendix B presents supporting case studies on knowledge–technology spillovers and environmental standards spillovers. Based on the theoretical mechanism and this empirical evidence, we propose the following hypotheses:

H2a: *The green transformation of downstream enterprises can promote the green transformation of upstream enterprises through the path of knowledge and technology spillover.*

H2b: *The green transformation of downstream enterprises can promote the green transformation of upstream enterprises through the path of environmental standards and norms spillover.*

4. Research design and description of variables

4.1. Data sources and data processing

Our empirical analysis relies on three primary data sources: (1) Firm-level financial data: We obtain fundamental and financial information for Chinese A-share listed companies in Shanghai and Shenzhen from the China Stock Market & Accounting Research (CSMAR) database. (2) Supply chain data: Data on the major customers of these listed firms are also sourced from CSMAR. This dataset includes client identities and the sales volume and proportion of sales from the listed firm to each client. (3) Macroeconomic data: Regional-level economic indicators are collected from the *China Statistical Yearbook*, the *China Urban Statistical Yearbook* and the CEIC database.

This study applies several data filters to ensure sample quality. Observations are excluded if they (1) lack essential firm identifiers (e.g., missing company names); (2) exhibit financial anomalies (e.g., Special Treatment [ST] or Particular Transfer [PT] status); (3) have missing critical variables; or (4) violate fundamental accounting principles (e.g., reporting negative net fixed assets). To alleviate the impact of outliers, all continuous variables are winsorized at the 1st and 99th percentile levels.

The core of our data construction involves matching listed companies with their customer lists. We first perform an exact match based on official company names and year. To improve the matching efficacy, we standardize company names by removing common legal suffixes (e.g., “Limited Company,” “Limited Liability Company” and “Group Limited Liability Company”). A fuzzy matching algorithm is then applied using these standardized names and year information. Following the approach of Isaksson et al. (2016), we construct a supplier–customer–year-level dataset since a single supplier (denoted as S_i) may have multiple customers (denoted as C_j , where $j = 1, 2, 3, \dots$) in a given year (e.g., 2019). The resulting dataset, designated S_i-C_j-2019 , comprises 2060 observations.

4.2. Research design

This study examines Chinese A-share listed companies in Shanghai and Shenzhen from 2008 to 2022. It investigates how the adoption of environmentally friendly practices by downstream firms influences the adoption of such practices by their upstream suppliers in the supply chain. Following the methodologies of Isaksson et al. (2016), Amore and Bennedsen (2016) and Chu et al. (2019), we employ a fixed effects model:

$$UGreenTrans_{itpj} = \beta_0 + \beta_1 DGreenTrans_{it} + \gamma X + \delta_i + \mu_t + \varepsilon_{itpj} \quad (12)$$

where i , t , p and j index the upstream supplier, year, province and industry, respectively, $UGreenTrans_{itpj}$ measures the degree of upstream suppliers' green transformation; $DGreenTrans_{it}$ is the core independent variable indicating the green transformation of downstream customers corresponding to firm i ; X encompasses control variables affecting the green transformation of upstream suppliers; δ_i and μ_t are the firm fixed effects and time fixed effects, respectively; and ε_{itpj} is the idiosyncratic error term.

4.3. Description of variables

4.3.1. Dependent variables

This study gauges the degree of green transformation among upstream business entities ($UGreenTrans$), which is the dependent variable. Existing literature primarily employs four approaches to assess corporate green transformation. First, some studies utilize the quantity of green patents applied for or granted to evaluate a company's green transformation (Amore and Bennedsen, 2016). However, this approach predominantly captures green innovation while potentially overlooking other parts of the green transition, such as the development of green consciousness. Second, another method evaluates green transformation through pollutant emissions or emissions intensity (Fan et al., 2021; Qi et al., 2023). This approach may not work as well if

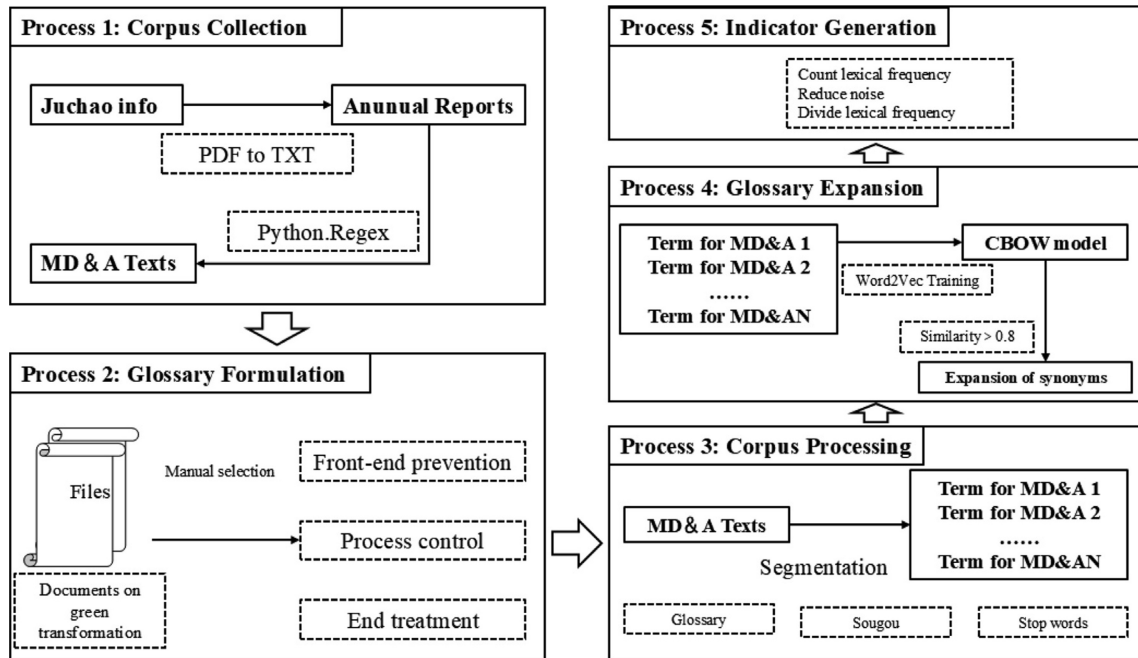


Fig. 3. Flowchart of corporate green transformation indicator generation.

the company grows or changes its strategic plan. Third, some researchers employ ESG indices for assessment (Liang et al., 2024). However, these indices are subject to subjectivity, a lack of transparency and wide rating variations. Fourth, green total factor productivity is employed (Kuosmanen and Maczulskij, 2024). However, this method may encounter difficulties in calculation due to its high data requirements. The present study is designed on the basis that the annual reports of publicly listed businesses contain more detailed information about factors connected to the green transition. The strategic direction and future planning of a company, as well as the business philosophy and development path advocated by the company, are all expressed through the use of vocabulary in annual reports. Consequently, the extent of firms' green transformation can be evaluated scientifically and equitably by calculating the frequency of terms associated with firms' green transformation in the annual reports of publicly traded companies (Wang et al., 2024).

This study employs machine learning-based textual analysis to quantify corporate green transition levels. Specifically, we measure the frequency of sustainability-related keywords in annual reports to construct a comprehensive green transformation score. The procedure is shown in Fig. 3. The methodology consists of the following steps: First is corpus collection. We obtain PDF versions of annual reports of listed companies from the Juchao website,² convert them into TXT format, and extract the Management Discussion & Analysis (MD&A) text. Second is glossary development. Based on environmental policy documents and academic research, we manually construct a glossary related to corporate green transformation by combining relevant documents.³ Third is corpus processing. The MD&A texts are segmented into discrete terms using the Jieba toolkit in Python. To improve accuracy, a custom dictionary is developed incorporating economic and management terminology from the cellular dictionary of Sogou.⁴ Additionally, to minimize the effect of terminological differences, we also refer to the stop word dictionaries from Baidu and Sichuan University's Intelligent

² URL: <https://www.cninfo.com.cn/new/index>.

³ Environment-related policy documents include the "Guiding Opinions of the State Council on Accelerating the Establishment of a Sound Green, Low-Carbon and Circular Economic System" ([2021] No. 4), the "13th Five-Year Plan for the Development of National Environmental Protection Standards," the "Guidelines for Green Investments (Trial)," the "Guidelines for Implementation of Green Manufacturing Projects (2016–2020)" and the "China Green Transformation and Sustainable Development Report" (2020). This paper also draws on the research of Eyraud et al. (2013).

⁴ URL: <https://shurufa.sogou.com/>.

Laboratory. Fourth is vocabulary enhancement. Given potential terminological variations in Chinese corporate reports, we systematically identify synonymous expressions within the corpus to expand the lexical coverage. To this end, we employ a Word2Vec-based machine learning approach for vocabulary augmentation, specifically utilizing the continuous bag-of-words model to process and optimize the acquired thesaurus data. Then, synonymous terms for each corporate green transformation concept are identified using a similarity threshold of 0.8. After manual review, 43 synonyms are retained (see Appendix C, Table 1). Fifth is indicator construction. We perform fuzzy matching between annual reports and the keyword lexicon, assigning one point for each match. The total score indicates the corporate green transformation intensity. To mitigate right-skewness in word frequency distribution, we apply a logarithmic transformation (after adding 1 to the total count) to derive the *UGreenTrans* metric for assessing corporate green transformation levels.

4.3.2. Independent variables

The key independent variable is downstream firms' green transformation level (*DGreenTrans*), which is measured in a manner consistent with that of the dependent variable. The dataset exhibits a many-to-one relationship, where multiple downstream firms' green transition levels may correspond to a single upstream firm's metrics. The econometric model must carefully address this dimensional mismatch between the independent and dependent variables to ensure the accurate estimation of supply chain spillovers from green transformation. To address this issue, we use firms' sales revenue to weight the green transformation level of downstream firms in obtaining their average green transformation level. The formula is

$$DGreenTrans_{it} = 1 - \sum_j \frac{SaleIncome_{ijt}}{\sum_j SaleIncome_{ijt}} DGreenTrans_{ijt} \quad (13)$$

where $SaleIncome_{ijt}$ is the sales revenue from upstream supplier i to downstream customer j and $DGreenTrans_{ijt}$ is the level of green transition of downstream customer j .

4.3.3. Control variables

Drawing on Amore and Bennedsen (2016) and Qi et al. (2023), this paper selects firm size (*Size*), firm age (*Lnage*), return on total assets (*Roa*), asset cash flow ratio (*Cflow*), whether the chairman and general manager are identical individuals (*Dual*), capital intensity (*CapLabor*), asset-liability ratio (*Finlev*) and market concentration (*HHI*) as control variables. Appendix C Table 2 presents the descriptive statistics and calculations of the control variables.

5. Empirical results analysis

5.1. Baseline regression analysis

This study examines how green transition among downstream firms influences upstream suppliers' sustainability transformation. As shown in Appendix C, Fig. A.1, a positive correlation is observed between the green transformation levels of downstream customers and those of their corresponding upstream suppliers. Although the fitted plot offers a preliminary visual assessment of this relationship, it ignores potential endogeneity between upstream and downstream green transformation or the influence of other confounding factors. Thus, it merely suggests a correlational link. To address this, we conduct regression analyses using a baseline model. Table 3 presents the regression results of supply chain green spillovers. Column (1) presents an OLS regression that includes only the downstream green transformation variable. Columns (2) and (3) sequentially incorporate firm and year fixed effects, together with control variables. Moreover, to mitigate potential biases stemming from clustered data structures, columns (4) and (5) present cluster-robust standard errors at the industry and regional levels, respectively. The results consistently show a statistically significant positive coefficient on the independent variable (*DGreenTrans*), indicating that downstream eco-friendly transitions significantly enhance upstream sustainability practices, demonstrating positive green spillovers across supply chains. In addition, the analysis in Appendix D examines upstream-to-downstream green spillovers, which are found to be statistically nonsignificant.

Table 3
Baseline regression results.

	<i>UGreenTrans</i>				
	(1)	(2)	(3)	(4)	(5)
<i>DGreenTrans</i>	0.530*** (0.043)	0.225*** (0.084)	0.224*** (0.085)	0.224** (0.091)	0.215** (0.082)
<i>Size</i>			0.041 (0.053)	0.041 (0.064)	0.030 (0.055)
<i>Lnage</i>			−0.111* (0.067)	−0.111 (0.072)	−0.104 (0.112)
<i>Roa</i>			1.862** (0.904)	1.862* (0.940)	1.407 (0.944)
<i>Cflow</i>			0.824* (0.438)	0.824 (0.553)	0.845* (0.418)
<i>Dual</i>			0.051 (0.074)	0.051 (0.106)	0.040 (0.075)
<i>CapLabor</i>			−0.004 (0.066)	−0.004 (0.061)	0.000 (0.062)
<i>Finlev</i>			0.181 (0.315)	0.181 (0.317)	0.143 (0.303)
<i>HHI</i>			−0.023 (0.157)	−0.023 (0.180)	−0.009 (0.197)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes
_cons	1.710*** (0.168)	2.899*** (0.331)	2.036* (1.105)	2.036 (1.235)	2.269* (1.224)
<i>N</i>	1570	1259	1259	1259	1209
<i>R</i> ²	0.166	0.637	0.644	0.644	0.648

Notes: *, **, *** represent fixed effects regression coefficients that are significant at the 10%, 5% and 1% levels, respectively. The notation for the following tables is identical and will not be repeated. Unless otherwise noted, regressions use firm-level clustered robust standard error values. Columns (4) and (5) display the cluster-robust standard errors, with clustering applied at the industry and regional levels, respectively, in parentheses.

5.2. Robustness tests

The results of the robustness tests in Appendix E support the baseline regression conclusions.

6. Endogeneity

6.1. Two-stage least-squares

We employ an instrumental variable (IV) approach, using whether a downstream firm is affected by green credit policies as our instrument, and estimate the model using two-stage least squares (2SLS). This choice is justified on two grounds. First, as established in the literature, green credit policies significantly promote corporate green transformation (Zhou et al., 2024a, 2024b; Nguyen et al., 2025; Xu and Lin, 2025), thus satisfying the relevance condition. Second, since our instrument is defined at the downstream level, it is unlikely to directly affect upstream firms' green transformation, thereby theoretically satisfying the exclusion restriction.

Following Nguyen et al. (2025) and Xu and Lin (2025), we identify firms affected by the green credit policy based on the Green Credit Guidelines issued by the China Banking Regulatory Commission. A firm is considered subject to the policy—and thus assigned an *IV* value of 1—if it operates in any of the nine high environmental-risk industries classified under “Category A” in the guidelines. These nine sectors are nuclear power generation, hydroelectric power generation, water conservancy and inland waterway port engineering and construction, coal mining and washing, petroleum and natural gas extraction, ferrous metal mining and

Table 4
Two-stage least-squares regression results.

	First	Second	First	Second
	<i>DGreenTrans</i>	<i>UGreenTrans</i>	<i>DGreenTrans</i>	<i>UGreenTrans</i>
	(1)	(2)	(3)	(4)
<i>IV</i>	0.081*** (0.019)		0.081*** (0.020)	
<i>DGreenTrans</i>		0.696*** (0.269)		0.730*** (0.272)
Control	Yes	Yes	Yes	Yes
Kleibergen–Paap rk LM	17.308***		16.359***	
Cragg–Donald Wald F	18.753		17.759	
<i>N</i>	1570	1570	1491	1491

Notes: First and Second denote the first- and second-stage regression results of the two-stage least-squares method, respectively.

processing, non-ferrous metal mining and processing, non-metallic ore mining and processing, and other mining sectors. Firms belonging to all remaining industries are coded with a value of 0. Table 4 presents the 2SLS estimates of how downstream green transformation affects upstream suppliers. To alleviate the issues arising from the effects of green credit rules on upstream firms, columns (3) and (4) exclude observations where both upstream and downstream firms are in green credit-restricted industries. The first-stage results in columns (1) and (3) show that the IV coefficients are significant and positive, confirming that the green credit policy significantly increases the probability of downstream green transformation. The second-stage results in columns (2) and (4) show significant and positive coefficients for IV, indicating that our baseline findings are robust. The Kleibergen–Paap rk LM statistic (16.359–17.308) rejects the null hypothesis of underidentification at the 1% level. The Cragg–Donald Wald F statistic (17.759–18.753) exceeds the Stock–Yogo critical value at the 10% level, allowing us to reject the hypothesis of a weak instrument. Overall, the IV strategy is valid, and the main results hold.

6.2. Difference-in-differences method

China has witnessed a significant rise in environmental litigation, driven by rapid industrialization, urbanization and worsening pollution. However, the conventional environmental legal framework and mechanisms encounter challenges in terms of gathering evidence, making judgments and enforcing actions in relation to environmental issues (He and Wang, 2024). To address these issues, a more specialized judiciary has become necessary. In 2007, China's inaugural environmental tribunal was officially formed in the Intermediate People's Court of Guiyang City. Subsequently, the pilot programs of China's environmental tribunals have expanded, becoming a substantial influence in advancing the rule of law in the nation's initiatives to mitigate environmental pollution. The Environmental Resources Trial Court was officially established by the Supreme People's Court in July 2014, marking the inception of China's environmental tribunal system. More than 160 environmental tribunals had been established by Chinese courts at all levels by 2023. These tribunals focus on regional environmental issues and are dispersed among different regions.

Extensive literature documents a positive association between specialized environmental justice systems and corporate green practices (Zhang et al., 2019; Zhao et al., 2022; Qi et al., 2023; Gao et al., 2024; He and Wang, 2024; Lan et al., 2024; Wang and Zhang, 2024). Because of this, we implement a difference-in-differences (DID) model utilizing the development of environmental courts as an exogenous shock to enterprises' green transformation.

Four reasons support the use of this policy as a quasi-experiment. First, the policy is exogenous. The establishment of environmental tribunals was a government-led initiative aimed at strengthening environmental protection and advancing ecological civilization, representing an external shock for most firms. Second, the policy's impact is broad and regional rather than firm-specific. Environmental courts are established to over-

see entire jurisdictions, not individual enterprises. This wide scope facilitates the construction of reliable control and treatment groups, enabling a precise estimation of the policy’s effects through the DID design.

Third, the policy provides a clear channel for a causal effect. The establishment of environmental courts aims to strengthen environmental protection through judicial means. Firms, in turn, may pursue green transformation to comply with stricter enforcement, mitigate regulatory risks and improve profitability. Thus, the establishment of environmental tribunals can be regarded as an external shock, facilitating a clearer examination of the causal relationship between policies and the green transformation of firms.

Fourth, our sample selection and empirical strategy are guided by data availability. Our study period serendipitously overlaps with the implementation of the environmental court policy, allowing us to exploit this exogenous shock. We define our treatment group as upstream firms whose major downstream customers are located in a city that establishes an environmental court. The rationale is that these upstream firms are exposed to green transformation demands cascading from their affected downstream clients. To ensure that the estimated effect is driven by downstream exposure rather than the firm’s own direct institutional environment, we exclude all upstream firms located in cities with an environmental court. For our model specification, we follow the approach established by Zhang et al. (2019).

$$UGreenTrans_{ipj} = \beta_0 + \beta_1 Policy_{it} + \gamma X + \delta_i + \mu_t + \varepsilon_{ipj}$$

(14)

$Policy_{it}$ is the core variable of interest in this section, and is the interaction term between $Treated_{it}$ and $Post_{it}$, which indicates the spillover effect of downstream customers’ green transformation on upstream suppliers’ green transformation. $Post_{it}$ is a temporal dummy variable that takes the value of 1 in the year of establishment of the regional environmental protection tribunals and the years after that, and 0 otherwise. $Treated_{it}$ is a subgroup dummy variable that takes the value of 1 for firms in the region where an environmental court is established, and 0 otherwise. The rest of the variables are set in the same way as in the baseline regression. Columns (1)–(3) of Table 5 show the DID regressions. The results show that the coefficient of $Policy_{it}$ is significantly positive, indicating that downstream customers’ green transformation can significantly promote upstream firms’ green transformation, and the benchmark regression results are robust.

This study evaluates the fundamental assumptions of the DID approach and analyzes the differing trends of the experimental and control groups in the time series data prior to and following the policy shocks, employing the parallel trend test. This analysis utilizes the year prior to the policy implementation as the reference

Table 5
Regression results of difference-in-differences and Heckman two-stage methods.

	DID			Heckman	
	<i>UGreenTrans</i>	<i>UGreenTrans</i>	<i>UGreenTrans</i>	<i>Disclosure</i>	<i>UGreenTrans</i>
	(1)	(2)	(3)	(4)	(5)
<i>DGreenTrans</i>	0.457*** (0.139)	0.457*** (0.126)	0.457** (0.218)	0.025*** (0.007)	0.334*** (0.113)
<i>IMR</i>					0.003 (2.296)
Control	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
_cons	1.294 (1.468)	1.294 (1.830)	1.448 (2.250)	1.014*** (0.126)	1.060 (3.899)
<i>N</i>	736	736	736	39,380	1048
Pseudo <i>R</i> ² / <i>R</i> ²	0.702	0.702	0.702	0.090	0.641

Notes: Columns (1)–(3) present the results of the difference-in-differences regressions. The values in parentheses in columns (2) and (3) are the clustering-robust standard errors of clustering for the industry and regional levels, respectively. Columns (4) and (5) present the first- and second-stage regression results of the Heckman two-stage method, respectively.

period. Companies situated in areas with established environmental protection courts comprise the experimental group, while those in other locations function as the control group. The interaction of the experimental group with the dummy variables for years beyond the baseline period is included as an independent variable in the regression model. To address the problem of multicollinearity, this research consolidates the data for the preceding 5 years into *pre5*, and the samples for the following 5 years into *post5*. We calculate the difference in mean values of the interaction term coefficients between the experimental and control groups before and after policy implementation to eliminate the initial disparity in the dependent variable; the resulting parallelism trend graph is shown in Appendix E Fig. A.2. The findings demonstrate that none of the coefficients for the interaction factors are statistically significant before the policy shock, indicating no meaningful disparity in the extent of green transformation between the treatment and control groups prior to the policy intervention. Following the policy shock, the coefficients of the interaction terms demonstrate significant changes, particularly an increase between the current period and the second period after the policy's implementation. This indicates that the green transformation of downstream customers substantially improves the green transformation of upstream enterprises, hence confirming the validity of the DID methodology.

Separately, we exclude interference by other contemporaneous policy shocks through a placebo test. First, samples are randomly selected from the matched data based on the quantity of actual experimental groups for each year, with the remaining firms in that year being the control group. Second, the randomly produced pseudo-policy shock variables undergo the multiplicative difference technique test. This is conducted for 2000 replicates. The findings of the placebo test in Appendix E Fig. A.3 indicate that the actual coefficients of green transformation for downstream customers significantly diverge from the center of the kernel density curve of the coefficients under pseudo-policy shocks, implying that this deviation was not coincidental, consequently reinforcing the reliability of the baseline regression findings.

6.3. Considering sample selection bias

The CSRC requires listed companies to disclose the proportion of transaction value from their top five suppliers and customers. However, they are not required to disclose the specific identities of these suppliers and customers, nor the exact amount of transactions. It is essential to tackle the problem of sample selection bias resulting from insufficient information disclosure by listed companies in the study. To mitigate the potential influence of this bias on the study's results, the Heckman two-step technique is used. We establish a selection equation in the first stage, in which the independent variable *Disclosure* is utilized to determine whether the names of significant customers are disclosed in detail by upstream firms. If the information is thoroughly disclosed, the variable receives a value of 1; if not, it receives a value of 0. To comprehensively evaluate disclosure, this paper applies the probit model to the regression analyses and incorporates the level of downstream firms' green transformation, firm scale, enterprise age, return on total assets, asset cash flow ratio, whether the chairman and general manager are identical individuals, capital intensity, gearing ratio and market concentration as independent variables. The findings are displayed in column (4) of Table 5. The inverse Mills ratio (*IMR*) is then included in the baseline regression model in the second stage to facilitate further regression analysis. This ratio is obtained through estimation in the initial phase. The coefficient of *DGreenTrans* remains significant and positive, as shown in column (5) of Table 5.

7. Heterogeneity tests

7.1. Heterogeneous effect across supplier absorptive capacity

The absorptive capacity of a provider, which dictates its capability to recognize, assimilate and implement new external knowledge, is crucial in supply chain collaboration. With high absorptive capacity, suppliers are better able not only to understand and utilize advanced green technologies and green management experience from partners but also to integrate this knowledge with their own technologies and knowledge to enhance their own green technologies.

This study examines variations in supply chain green spillovers by differentiating provider absorptive ability. We use the ratio of technical personnel to total personnel to assess the absorptive capacity of suppliers,

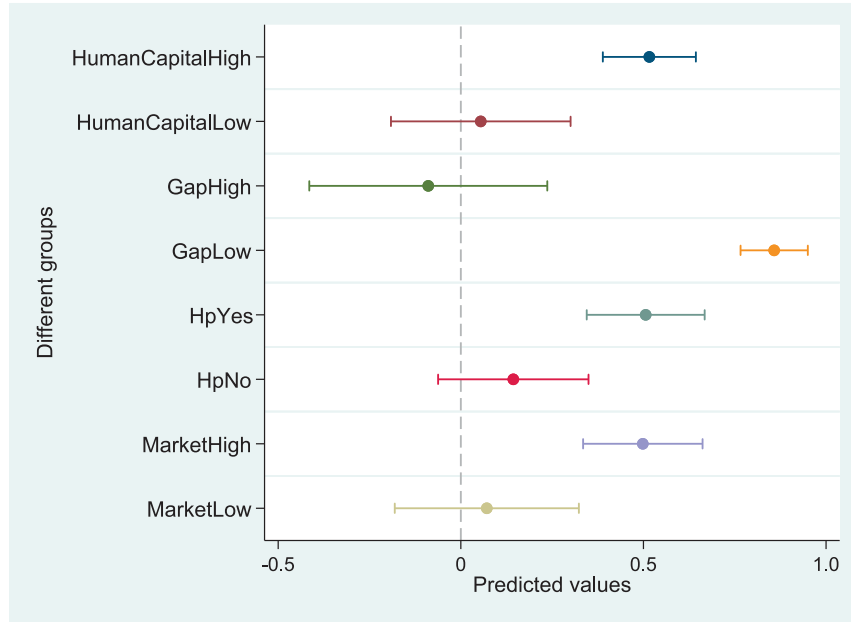


Fig. 4. Heterogeneity test results. Notes: The regression results of the heterogeneity analysis are displayed in Appendix E Table 3. The horizontal axis represents the coefficients of green spillovers in the supply chain, and the vertical axis represents the groupings of different heterogeneity tests.

following the methodology of Xu and Hu (2024) in the domain of indicator measurement. Enterprises can assimilate information more effectively if this ratio is increased. Group regression is performed by classifying the sample into two provider categories—those with high absorptive capacity (*HumanCapitalHigh*) and those with low capacity (*HumanCapitalLow*)—based on the mean of this metric. The green spillover effect in the supply chain from downstream customers to upstream suppliers is more pronounced when supplier absorption capacity is high, as evidenced by Fig. 4, where the coefficients of the independent variables in the high absorptive capacity group are significantly greater than those in the low absorptive capacity group.

7.2. Heterogeneous effect across the green-technology gap between customers and suppliers

The disparity in green technology between consumers and providers crucially influences the effects of supply chain partnerships and creativity spillovers. This technology gap can have a direct impact on the effectiveness of cooperation and the level of innovation between the two parties, thus affecting the sustainability and green transformation of the entire supply chain.

This study utilizes the absolute value of the variance in green transformation levels between suppliers and customers to measure the gap in green technology between the two parties. Specifically, we first calculate the green-technology gap at the supplier–customer level, which is calculated as $Gap_{ijt} = |N_{it} - N_{jt}|$. Here, N_{it} and N_{jt} indicate the quantity of green patents held by suppliers and customers, respectively. Then, similar to the construction of the independent variables, we calculate the weighted average of the green-technology gap at the supplier level, which is calculated as $Gap_{it} = \sum_j \frac{SaleIncome_{ijt}}{\sum_j SaleIncome_{ijt}} Gap_{ijt}$. Here, $SaleIncome_{ijt}$ is the sales of the upstream supplier i to the downstream customer j . The sample is separated into two groups based on the mean value—one with a significant green-technology gap (*GapHigh*) and the other with a minimal green-technology gap (*GapLow*)—followed by group regression analysis. As can be observed in Fig. 4, the coefficients of *DGreenTrans* in the group with a large green-technology gap are significantly smaller than the coefficients in the group with a small green-technology gap, indicating that the supply chain green spillover effect from downstream customers to upstream suppliers is stronger when the green-technology gap between customers and suppliers is small.

7.3. Heterogeneous effect across the market size of the customer's region

Heightened market demand allows businesses to alleviate the uncertainties linked to R&D initiatives and safeguard the potential benefits of innovation, hence achieving economies of scale and lowering the per-unit manufacturing cost. For green supply chains, this means that firms can reduce the costs of R&D and production and diffusion of green technologies through the economies-of-scale effect, thus making it easier to realize green transformation.

This study employs population density to evaluate the market size of the customer's city, splitting the dataset into two categories according to the mean value—high market size (*MarketHigh*) and low market size (*MarketLow*)—and thereafter performing group regression analysis. Fig. 4 demonstrates that the coefficients of *DGreenTrans* in the category with a large market size in the client's city are markedly larger than those in the group with a small market size, indicating that a larger market size correlates with a heightened green spillover effect from customer firms to their suppliers.

8. Extensions

8.1. Mechanisms for green supply chain spillovers

The green transformation of firms significantly influences their competitiveness and sustainable development, while also generating beneficial spillover effects throughout the supply chain. This paper's empirical analysis reveals that the knowledge and technology spillover effect, along with the spillover effect of environmental standards and norms, facilitates the green transformation successes of downstream organizations to permeate the whole supply chain, ultimately impacting and facilitating the green transformation of upstream firms. We employ the regression models of Guo et al. (2024), which are presented as follows:

$$UGreenTrans_{itpj} = \beta_0 + \beta_1 DGreenTrans_{it} + \gamma X + \delta_i + \mu_t + \varepsilon_{itpj} \quad (15)$$

$$M_{itpj} = \beta_0 + \beta_1 DGreenTrans_{it} + \gamma X + \delta_i + \mu_t + \varepsilon_{itpj} \quad (16)$$

where M_{itpj} is the mechanism variable. Eq. (15) represents the baseline regression and Eq. (16) represents the mechanism test regression model.

8.1.1. Knowledge and technology spillover effect

The similarity in green technology (*GreenSim*) between suppliers and customers is designated as a proxy variable for knowledge and technology spillover, based on the logic that when downstream customers spill over green knowledge and technology to upstream suppliers, information transfer and knowledge sharing between the two parties increases, and this sharing promotes a more consistent understanding and application of green technology between the two parties, which in turn improves suppliers' and customers' green technology similarity. The formula for assessing the green technology similarity between suppliers and customers is based on Bloom et al. (2013):

$$GreenSim_{it} = \frac{V_{it} V_{jt}^T}{\left(V_{it} V_{it}^T\right)^{1/2} \left(V_{jt} V_{jt}^T\right)^{1/2}} \quad (17)$$

where V_{it} is a vector measuring the green technology structure of upstream supplier i in year t ; $V_i = (X_{i1}, X_{i2}, X_{i3}, \dots, X_{in})$, with X_{in} capturing the incidence of green patent applications among upstream supplier i 's n th category in its total green patent applications; V_{it} is a vector measuring the green technology structure of upstream supplier i in year t , $V_j = (X_{j1}, X_{j2}, X_{j3}, \dots, X_{jn})$, with X_{jn} representing the ratio of green patent applications submitted by downstream customers j in the n th category to their aggregate quantity of green patent applications; T denotes the transpose of the vector. $GreenSim_{it}$ measures the degree of similarity between a supplier's and a customer's green technologies, with larger values indicating that the two are more similar in terms of green technologies. The results in column (1) of Table 6 indicate that the coefficients of the independent variables are significant and positive, suggesting that the green transformation of downstream firms produces knowledge and technology spillover effects.

Table 6
Mechanism tests.

	<i>GreenSim</i>	<i>IfISO</i>	<i>Standard</i>
	(1)	(2)	(3)
<i>DGreenTrans</i>	0.102** (0.051)	0.108** (0.050)	0.039* (0.022)
Control	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
_cons	0.160 (1.231)	2.586 (1.750)	0.453 (0.724)
<i>N</i>	656	654	654
<i>R</i> ²	0.322	0.538	0.623

Notes: Column (1) examines the knowledge and technology spillover effect of downstream firms' green transformation, while columns (2) and (3) examine the environmental standards and norms spillover effect of downstream firms' green transformation.

8.1.2. Environmental standards and norms spillover effect

Two indicators are chosen to quantify the spillovers of environmental standards and norms. First, the dummy variable *IfISO* is chosen as a proxy for environmental standards and norms spillovers, drawing on Wang et al. (2024). If firms have passed ISO 14001 certification, *IfISO* is 1, and if they have not, it is 0. The justification for this is that ISO 14001 is a standard for environmental management systems created by the International Organization for Standardization, an entity with significant global reputation and authority. If an enterprise has successfully completed the ISO 14001 certification process, this indicates that it has adhered to international environmental management standards. Consequently, using ISO 14001 as a proxy variable can approximate the environmental protection level of an enterprise and the environmental protection standards it adheres to. Second, utilizing the initial measurement approach, this study further evaluates the environmental standards and norms of upstream suppliers through the synthesis of indicators. Specifically, eight indicators, namely, whether a firm develops environmentally beneficial products (*BeneProd*), whether it takes measures to reduce waste (*Waste*), whether it uses renewable energy (*Renewa*), whether it uses energy conservation (*Conserva*), whether it adopts green office policies (*OffiPoli*), whether it passes ISO 14001 certification (*IfISO*), whether it receives environmental recognition (*Recog*) and whether it has other environmental advantages (*OtherAdvan*), are combined using the entropy weighting method to synthesize an indicator of environmental standards and norms (*Standard*).⁵ A greater value corresponds to higher environmental standards and norms among upstream suppliers. The coefficients of *DGreenTrans* in columns (2) and (3) of Table 6 are significant and positive, suggesting that the ecological transformation of clients facilitates the ecological transformation of suppliers via the spillover impact of environmental standards and norms.

8.2. Reducing disruption by greenwashing issues

The use of machine learning to process unstructured data to generate proxy variables has become a mainstream approach in economic and management research (Gamache et al., 2015; Eklund and Mannor, 2021). Machine learning-based variable measurement relies on NLP technology, which is able to transform large amounts of unstructured textual data into structured information for enterprise strategy analysis, thus providing an innovative quantitative methodology and perspective for strategic management research (Haans, 2019). This helps to mitigate cross-sectional error (Battistoni et al., 2023; Shao et al., 2024), measurement error (Ning

⁵ The measurement methods for environmental standards and norms are reported in Appendix A Table 4.

Table 7
Reducing disruption by greenwashing issues.

	<i>UGreenTrans</i>				
	90th	80th	70th	60th	50th
	(1)	(2)	(3)	(4)	(5)
<i>DGreenTrans</i>	0.299*** (0.091)	0.283*** (0.098)	0.294** (0.116)	0.306** (0.123)	0.304** (0.153)
Control	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
_cons	2.323 (1.540)	2.902* (1.610)	3.255* (1.761)	3.192* (1.788)	−3.706 (4.655)
<i>N</i>	873	755	651	536	402
<i>R</i> ²	0.690	0.703	0.694	0.685	0.670

Notes: Columns (1)–(5) present the regression results for *Greenwash* with different quartiles retained.

et al., 2023) and reverse causation (Shao et al., 2024) issues that interfere in empirical research. Compared with other methods, the variable measurement method based on machine learning through text analysis is a more reliable method to measure business transformation (Geng et al., 2024).

However, the accuracy of variable measurement methods based on machine learning through textual analysis relies to some extent on the authenticity of textual disclosures (Baden et al., 2022). Therefore, the greenwashing behavior of firms may skew this study's conclusions (Darendeli et al., 2022). To mitigate this effect, this paper first measures the level of greenwashing (*Greenwash*) at the firm level, drawing on Zhang (2022). The calculation formula is given in Eq. (18):

$$Greenwash_{it} = \left(\frac{esg_{it}^{disclose} - \overline{esg_{it}^{disclose}}}{\sigma^{disclose}} \right) - \left(\frac{esg_{it}^{rating} - \overline{esg_{it}^{rating}}}{\sigma^{rating}} \right) \quad (18)$$

where $esg_{it}^{disclose}$ and esg_{it}^{rating} represent the company's ESG disclosure and ESG actual performance respectively, $\overline{esg_{it}^{disclose}}$ and $\overline{esg_{it}^{rating}}$ represent the mean of the company's ESG disclosure and ESG actual performance respectively, and $\sigma^{disclose}$ and σ^{rating} represent the standard deviation of the company's ESG disclosure and ESG actual performance respectively. A greater *Greenwash* value indicates a higher degree of corporate greenwashing. Second, we systematically remove samples with higher levels of greenwashing (based on the baseline regression) according to different quartiles, and conduct the regression. The outcomes in columns (1)–(5) of Table 7 reveal that the coefficients of the independent variables are significant and positive, suggesting that the baseline regression results remain robust when considering firms' greenwashing behavior.

8.3. Considering non-listed companies

8.3.1. Spillover effects from green innovation in downstream industries

We use listed company data in the baseline regression and tax survey data in the robustness test. This is because listed companies can accurately identify upstream and downstream relationships at the enterprise level through supply chain disclosure (such as major customers and purchase amounts), while tax survey data lack such supply chain-level information and can only measure industry spillover effects at the industry level, which does not reflect the significant heterogeneity within an industry in terms of input quality and composition (De Loecker et al., 2016). It is also useful to examine the green supply chain spillover effects among non-listed companies to bolster our conclusions. First, doing so can correct sample selection bias to a certain extent. Listed companies are mostly large enterprises with strong financing capabilities, which may result in overestimation of green transformation transmission among leading companies. Introducing non-listed company samples

from tax surveys (which account for the majority of the real economy) can verify whether the conclusions are applicable to a broader group of small and medium-sized enterprises. Second, using listed company data can complement the data dimension of the study. We refer to previous studies on industrial chains and supply chains to measure the indirect effects of green transformation from an industry perspective (Linarello, 2018). We use the National Tax Survey Database (NTSD) of China and green patent data on Chinese enterprises from 2007 to 2016 to examine the green spillover effects of green transformation in downstream industries on upstream industries. The NTSD is sourced from the China National Bureau of Statistics and has the characteristics of census data, which is conducive to our examination of the economic activities of non-listed enterprises (Chen et al., 2021). Green patent data on Chinese enterprises are sourced from the China National Intellectual Property Administration, which records green patent application information at the enterprise level. In terms of variable measurement, we use the number of green patents to measure the green transformation of enterprises, and we denote the green transformation of downstream industries as $DownGreenInnovation_{kt} = \ln(1 + \sum_{k \neq l} \omega_{kl}^{2005} GreenInnovation_{lt})$. Here, ω_{kl}^{2005} is the ratio of input from industry k to the total output of industry k , calculated based on the input–output table for 42 sectors in 2005; $GreenInnovation_{lt}$ is the total number of green patents in downstream industry l in year t . Table 8 (column 1) shows that the coefficient of $DownGreenInnovation_{kt}$ is significant and positive, indicating that the core conclusion remains robust even when considering a sample of non-listed firms.

8.3.2. Pressure on corporate survival

Additionally, the logics of transformation for non-listed enterprises may be unique. Such firms rely more heavily on customer orders for survival, meaning their transformation motivations stem primarily from market survival needs. Given this, we examine the roles of two survival pressures—market competition pressure and funding shortage pressure. We employ market concentration (HHI) to measure market competition pressure, consistent with the baseline regression methodology, where higher values indicate lower market competition pressure. Simultaneously, drawing on Shi et al. (2023), we utilize the SA index to characterize funding shortage pressure. Higher values of this indicator signify more severe financing constraints faced by firms. The regression results in Table 8 (column 2) reveal that the interaction term between downstream firms' green transformation and market competition pressure ($DownGreenInnovation \times HHI$) has a significant and positive coefficient. This indicates that lower market competition pressure is more conducive to amplifying green spillover effects from downstream industries; in other words, market competition pressure is detrimental to green spillover effects. The regression results in Table 8 (column 3) show that the coefficient of the interaction term between down-

Table 8
Considering non-listed companies.

	<i>UGreenInnovation</i>		
	(1)	(2)	(3)
<i>DownGreenInnovation</i>	0.0386** (0.0155)	0.0134 (0.0103)	0.0432*** (0.0168)
<i>DownGreenInnovation</i> $\times$ <i>HHI</i>		0.0974*** (0.0178)	
<i>DownGreenInnovation</i> $\times$ <i>SA</i>			−0.0133* (0.0078)
Control	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
_cons	6.3131*** (0.0925)	−2.0815*** (0.0425)	4.1035*** (0.1225)
<i>N</i>	406,618	406,618	406,618
<i>R</i> ²	0.096	0.079	0.102

stream enterprises' green transformation and capital shortage pressure ($DownGreenInnovation \times SA$) is significant and negative, indicating that capital shortage pressure is detrimental to green spillover effects.

We offer an interpretation for this phenomenon. First, when market competition pressure is weak, non-listed enterprises operate in a relatively liberal market environment with minimal competitive threats from peers. Under such circumstances, companies need not expend excessive energy countering industry rivals, enabling them to focus more intently on receiving and absorbing green transformation signals and technological spillovers from downstream enterprises. Second, from the perspective of fund shortage pressure, green transformation by non-listed companies often requires substantial capital investment in technological R&D, equipment upgrades and environmental facility construction. When enterprises face severe funding shortage pressure, their available capital for green transformation becomes severely constrained. Even when downstream enterprises signal strong demand for green transformation, upstream enterprises struggle to undertake effective green transformation activities.

9. Conclusions and policy implications

9.1. Conclusion

This paper quantifies green transformation using NLP analysis, and examines the spillover impact of clients' green transformation on suppliers' green transformation from a supply chain perspective, along with the underlying mechanisms. The main findings are as follows. First, a significant spillover effect of customer green transformation is identified. This result remains robust after addressing endogeneity through an IV approach, applying a DID method, controlling for other types of spillover effects as interference, replacing the research window period, accounting for the lag of green spillovers and adopting quantile regression. Second, heterogeneity analysis reveals that green spillover effects within the supply chain are asymmetric. Specifically, clients' green transformation more effectively promotes that of suppliers when the suppliers exhibit strong absorptive capacity, when the green-technology gap between clients and suppliers is narrow and when the client operates in a region with a large market size. Third, mechanism tests indicate that the green transformation of downstream customers can facilitate knowledge and technology spillover effects, as well as environmental standards and norms spillover effects, thereby driving the green transformation of upstream suppliers.

9.2. Marginal contributions

There are three main possible marginal contributions of this paper. First, it examines the external drivers of corporate green transformation by focusing on the diffusion of green transformation from customer firms along the supply chain, offering a novel perspective to address the challenge of insufficient internal resources and capabilities that constrain firms' green transformation efforts. Existing literature on the catalysts of corporate green transformation predominantly frames its analysis around firms' internal attributes and the external policy landscape (Amore and Bennedsen, 2016; Fan et al., 2021; Gao et al., 2024). In contrast, this study conceptualizes green transformation as a comprehensive innovation process within supply chains, emphasizing the role of customer firms. It demonstrates that the experiences and knowledge derived from customer firms' green transformation practices facilitate the ecological transformation among suppliers through supply chain diffusion, thereby expanding the research on the determinants of enterprise green transformation.

Second, this research examines the mechanism through which environmental transformation diffuses from client companies to upstream companies along the supply chain. It elucidates how upstream firms gain access to green transformation resources and enhance their capabilities through such diffusion. Existing literature on supply chain diffusion primarily focuses on technological innovation and knowledge dissemination (Isaksson et al., 2016), as well as intrinsic motivations, feedback mechanisms and managerial social ties within business relationships among supply chain entities (Chu et al., 2019). However, it pays insufficient attention to the pathways through which green transformation resources are disseminated via direct corporate linkages. This paper reveals that upstream firms can acquire resources and enhanced capabilities from client firms' green transformation diffusion through supply chain learning mechanisms, thereby contributing to a deeper understanding of corporate diffusion processes within supply chains.

Third, this study introduces a novel approach for measuring corporate green transformation. By employing machine learning methods and textual analysis, we develop a green transformation dictionary and construct corresponding corporate green transformation indicators. This methodology helps mitigate the influence of cross-sectional error (Battistoni et al., 2023; Shao et al., 2024), measurement error (Ning et al., 2023) and reverse causation (Shao et al., 2024) that often complicate empirical research. Furthermore, the findings of this paper have valuable managerial implications for firms in business process optimization, supply chain management and organizational governance.

9.3. Policy implications

This study offers several implications for public policy and management. In terms of public policy, policymakers should adopt a more nuanced perspective and recognize the vertical spillover effects of corporate green transformation in a scientific and objective manner. Consistent with prior research (Hsieh and Lathifah, 2024), our study demonstrates that customer-driven green transformation can substantially enhance the ecological transition of suppliers. Therefore, government authorities should leverage the vertical spillover effects generated by downstream firms' environmental initiatives and judiciously adapt industrial policies to promote green transformation among upstream supply chain participants. Such measures would help ensure that policy benefits reach a broader range of enterprises. At the same time, policymakers should also focus on the implementation of industrial policies to promote green transformation. This study finds that the green spillover impact of the supply chain exhibits asymmetry across various areas. Therefore, policy measures could be refined through region-specific incentive structures to more effectively and targeted facilitate corporate ecological transformation.

Regarding management implications, this study offers insights from two perspectives. First, managers should strengthen supply chain cooperation and communication by actively building close cooperative relationships with supply chain partners. Firms across the supply chain possess distinct resources and advantages. Through enhanced cooperation, enterprises can share green technologies, environmentally friendly materials and energy-saving equipment, thereby achieving resource complementarity and collectively elevating environmental standards throughout the supply chain (Yang et al., 2024a, 2024b). This paper finds that green transformation of customers can effectively facilitate ecological change by suppliers. Therefore, managers should establish regular communication mechanisms across supply chain entities to share the progress, experience and challenges of green transformation. Employing diverse communication channels—such as email, video conferencing and social media—can improve communication efficiency and convenience. Second, managers should enhance corporate absorptive capacity to maximize green spillovers. Absorptive capacity plays an important role in fostering innovation, influencing firm strategy and scope of operations, facilitating knowledge transfer and application and shaping competitive advantage. This paper finds that suppliers benefit more efficiently from green spillovers from downstream customers when they exhibit strong absorptive capacity and operate with a narrow green-technology gap. Therefore, management should increase R&D investment within financial constraints, improve the perception and responsiveness to green transformation information and strengthen firms' ability to acquire, assimilate, transform and apply knowledge—ultimately facilitating the commercialization of green innovation outcomes.

9.4. Limitations and future research

This study has several limitations. First, its context is inherently limited. Since the findings of this study are derived from a single-country setting (China), their generalizability to other nations may be constrained. Although China provides a suitable context for testing our theoretical framework, unique institutional, cultural and geographic factors may cause firms' green transformation decisions to vary across borders (Gao et al., 2024). Future research could enhance the generalizability of the findings by replicating this study in other emerging economies, such as Brazil, India and South Africa.

A further limitation stems from the mathematical model's assumptions. The model presupposes that upstream firms hold a dominant position, allowing them to observe downstream actions and subsequently make optimal decisions for their own profit. However, because supply chains are complex (Katsaliaki

et al., 2024), the findings of this study may lack generalizability. Moreover, previous research documents the existence of green technology and norms spillovers between supply chain partners (Wang et al., 2024; Yang et al., 2024a, 2024b). Nevertheless, similar to earlier modeling studies (De Bettignies et al., 2018; Aghion et al., 2024), our model omits these spillover effects. Future studies should therefore explore this area further, particularly by investigating spillovers within multi-level supply chains and how they interact with supply chain complexity.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Cost-benefit analysis

In the discussion of real-world issues, existing literature generally agrees that downstream firms' green behavior promotes green transformation in upstream firms within the supply chain (Gonzalez-Loureiro et al., 2015; Tang et al., 2023; Sun et al., 2024; Yang et al., 2024a, 2024b; Qian, 2025). Therefore, we assume $\frac{\partial g_{uk}^*}{\partial g_{di}} > 0$. The situation for $\frac{\partial g_{uk}^*}{\partial g_{di}} < 0$ is similar to the following, so we will not elaborate further. Substituting (10) into (9) yields:

$$q_{uk} = \frac{\mu}{d - t_u} g_{uk} \quad (19)$$

First is cost analysis. Cost analysis of upstream enterprises shows that:

$$C_{ukq_{uk},g_{uk}} = cq_{uk} - dg_{uk}q_{uk} + \frac{\mu g_{uk}^2}{2} + (1 - g_{uk})t_u q_{uk} \quad (20)$$

Taking the partial derivative of the above equation on g_{uk} , we obtain:

$$\frac{\partial C_{uk}}{\partial g_{uk}} = -dq_{uk} + \mu g_{uk} - t_u q_{uk} = \frac{2t_u \mu}{t_u - d} g_{uk} \quad (21)$$

Generally speaking, due to $d > t_u$, therefore, $\frac{\partial C_{uk}}{\partial g_{di}} = \frac{2t_u \mu}{t_u - d} \frac{\partial g_{uk}^*}{\partial g_{di}} < 0$. This indicates that the green transformation of downstream industry enterprises can effectively reduce the costs of upstream industry enterprises. The economic explanation is as follows: Upstream enterprises are subject to environmental regulations and must bear costs such as environmental protection equipment investment, pollution detection, and compliance certification. If downstream firms have not transitioned, upstream firms must produce both green and non-

green products simultaneously, meeting regulatory requirements for green products while also addressing potential compliance risks associated with non-green products. As a result, equipment utilization rates are low and testing costs are high. Once downstream firms have transitioned to green production and only demand green products, upstream firms can focus on compliant production without the need to maintain redundant investments in non-green production capacity. This improves the utilization rate of environmental protection equipment and indirectly reduces costs.

Second is benefit analysis. Similarly, the benefit analysis of upstream enterprises shows that:

$$B_{uk}q_{uk}g_{uk} = P_u q_{uk} = \left[a + bg_{di} - (1 - g_{di})t_d - \frac{n+1}{n} \sum_{k=1}^m q_{uk} \right] q_{uk} \quad (22)$$

Taking the partial derivative of the above equation with respect to g_{uk} , we obtain $\frac{\partial B_{uk}}{\partial g_{uk}} = \left(\frac{\mu}{d-t_u} \right)^2 \left(P_u + \frac{\mu}{d-t_u} g_{uk} \right) g_{uk} > 0$. Therefore, we obtain:

$$\frac{\partial B_{uk}}{\partial g_{di}} = \left(\frac{\mu}{d-t_u} \right)^2 \left(\frac{\partial P_u}{\partial g_{di}} g_{uk} + P_u \frac{\partial g_{uk}}{\partial g_{di}} + \frac{2\mu}{d-t_u} g_{uk} \frac{\partial g_{uk}}{\partial g_{di}} \right) > 0 \quad (23)$$

This indicates that the green transformation of downstream industry enterprises can effectively increase the profits of upstream industry enterprises. The economic explanation is as follows: The green transformation of downstream enterprises requires the use of green inputs such as environmentally friendly raw materials and energy-saving equipment, which directly expands the demand for green products from upstream enterprises. At the same time, after the transformation, downstream products are more compliant with environmental protection standards, their premium pricing ability and market competitiveness are enhanced, and their profit margins are expanded, ultimately driving profit growth.

Appendix B. Case study

B.1. Case study on knowledge and technology spillovers

The case of green transformation between Tex Year Group and its upstream suppliers is a concrete example of green transformation of a downstream customer company facilitating the green transformation of an upstream supplier company through the knowledge and technology spillover pathway.

Background: Tex Year Group is one of Taiwan's largest manufacturers of hot melt adhesives and is committed to the production and sale of environmentally friendly and non-toxic products. With the implementation of the dual-carbon policy and increased awareness of environmental protection, Tex Year Group has actively promoted green transformation and successfully developed innovative products such as bio-based and biodegradable hot melt adhesives. Tex Year Group, as a downstream customer enterprise facing the dual pressure of dual-carbon policy and market demand, requires suppliers to provide environmentally friendly and biodegradable materials to reduce environmental pollution and carbon emissions in the production process.

Spreading of green technology: Tex Year Group has accumulated rich experience in green technology in the process of developing and producing environmentally friendly hot melt adhesives. These technologies not only improve the environmental performance of products, but also reduce production costs. Tex Year Group spreads these green technologies to upstream supplier companies through technical exchanges and training, helping them to improve their environmental production capacity and technology.

Sharing of Green Knowledge: Tex Year Group has developed a sound environmental management system and green production process during the green transformation process. These experiences and knowledge are important references for upstream supplier companies. By sharing this green knowledge, Tex Year Group helps upstream supplier companies to establish environmental awareness, optimise production processes and reduce environmental pollution.

Driven by Tex Year Group's green transformation and knowledge and technology overflow, its upstream supplier enterprises have also begun to actively carry out green transformation. They have adopted environ-

mentally friendly materials and production processes to improve the environmental performance and quality of their products. At the same time, these supplier companies have also strengthened their cooperation and communication with Tex Year Group to jointly promote the green transformation of the entire supply chain.

Result: Through the joint efforts and cooperation between Tex Year Group and its upstream supplier companies, the entire supply chain has achieved green transformation. This not only improves the environmental performance and market competitiveness of products, but also reduces production costs and environmental pollution. At the same time, this green transformation is also in line with the country's dual-carbon policy and environmental protection requirements, making a positive contribution to sustainable development. This example fully illustrates the facilitating effect of green transformation of downstream customer enterprises on the green transformation of upstream supplier enterprises through the path of knowledge and technology spillovers. In practice, such transformation requires close cooperation and communication between upstream and downstream enterprises, as well as support and guidance from the government, industry associations and other institutions.

B.2. Case study on the overflow of environmental standards and norms

The case of the green transformation of the BMW Group and its upstream suppliers is a concrete example of how the green transformation of a downstream customer company can contribute to the green transformation of an upstream supplier company through the spillover of environmental standards and norms.

Background: The BMW Group, as the world's leading luxury automotive company, has always been committed to sustainable development. With the growing global concern for environmental protection and climate change, the BMW Group has decided to accelerate its own green transformation and set higher environmental standards and norms for its upstream supplier companies. The BMW Group has set up strict environmental standards, requiring upstream suppliers to provide products or services that meet these standards. These standards cover a wide range of aspects such as raw material procurement, production processes, energy use, and waste treatment. At the same time, the BMW Group strengthens environmental management in the production process to ensure that production activities comply with environmental standards. For example, the BMW Shenyang production site already uses 100% renewable electricity and has solar panels covering 290,000 square metres, generating 60,000 megawatt-hours of electricity annually and reducing carbon dioxide emissions by nearly 45,000 tonnes per year.

Spillover of environmental standards and norms: The BMW Group transmits its environmental standards and norms to upstream supplier companies, requiring them to provide products or services that meet environmental requirements. For example, BMW's Tier 1 power battery supplier, Ningde Times, has already achieved production using 100 per cent renewable electricity. Driven by the BMW Group, its upstream supplier enterprises have undertaken green transformation. These supplier companies have had to strengthen their own environmental management and raise their environmental standards in order to meet BMW's environmental requirements. For example, BMW Brilliance purchased 20,000 tonnes of aluminium ingots produced using 100% renewable electricity for the production of cylinder blocks, among other things. The BMW Group and its upstream suppliers have jointly established a green supply chain, realising green management of the entire chain from raw material procurement to product sales. The establishment of this green supply chain not only improves the environmental performance of BMW products, but also promotes the sustainable development of the entire supply chain.

Result: Through the BMW Group's green transformation and the spillover of environmental standards and norms, its upstream supplier enterprises have also realised green transformation. This transformation not only improves the environmental performance and quality of products, but also reduces production costs and environmental pollution. At the same time, this green transformation is also in line with national environmental policies and regulatory requirements, making a positive contribution to sustainable development. In summary, the BMW Group, as a downstream customer enterprise, has realised its own green transformation by formulating strict environmental protection standards, promoting green technology innovation and strengthening environmental protection management. This transformation not only improves the environmental performance and market competitiveness of BMW products, but also promotes the green transformation of its upstream supplier enterprises through the spillover of environmental standards and norms.

Appendix C. Tables and figures

Table A1

Keywords for firms' green transformation.

Level 1 indicators	Level 2 indicators	Keywords
Green concerns for business executives	Front-end prevention	Waste heat power generation, heat recovery, rain and pollution diversion, cleaner production, process innovation, upgrading technical innovation, emission limits, emission standards, three simultaneous, environmental protection, low-carbon, green, environmental protection, environmental protection publicity
	Process control	Frequency conversion, low energy consumption, energy saving, consumption reduction, automatic regulation, energy saving and emission reduction, environmental monitoring, online monitoring, automatic monitoring, environmental training
	End treatment	Pollution control, waste treatment, waste residue treatment, solid waste treatment, desulfurization, denitrification, deodorization, low nitrogen, sewage treatment, waste gas treatment, acid fog absorption, treatment and reuse, recycling, classification and collection, noise control, dust control, harmless

Table A2

Descriptive statistics for variables.

Variables	N	Mean	Std. Dev.	Min	Max
<i>UGreenTrans</i>	1209	3.799	0.954	0	6.702
<i>DGreenTrans</i>	1209	3.937	0.734	2.197	6.678
<i>Size</i>	1209	24.071	2.149	20.459	30.541
<i>Lnage</i>	1209	2.256	0.782	0	3.332
<i>Roa</i>	1209	0.045	0.052	−0.117	0.220
<i>Cflow</i>	1209	0.056	0.065	−0.129	0.254
<i>Dual</i>	1209	0.168	0.374	0	1
<i>CapLabor</i>	1209	14.888	1.095	12.849	18.461
<i>Finlev</i>	1209	0.385	0.252	0	0.874
<i>HHI</i>	1209	0.147	0.178	0.014	0.934

Notes: *N* denotes the sample size, Mean denotes the mean of the variable, *Std. Dev.* denotes the standard deviation of the variable, and *Min* and *Max* denote the minimum and maximum values of the variable, respectively. The indicators are measured in the following ways: enterprise size (*Size*), expressed as the natural logarithm of the total assets of the enterprise; age of the enterprise (*Lnage*), calculated as the logarithm of the number of years of the enterprise's existence plus one; return on total assets (*Roa*), expressed as the ratio of the enterprise's net profit to the enterprise's total assets; and the cash flow ratio of assets (*Cflow*), measured as the ratio of the enterprise's cash flow from operating activities to the enterprise's total assets; Whether the two positions for the same person (*Dual*), expressed through a dummy variable, if the chairman and general manager of the same person is 1, otherwise 0; Capital Intensity (*CapLabor*), expressed as the natural logarithm of the ratio of the total assets of the enterprise to the number of employees; asset-liability ratio (*Finlev*), expressed as the ratio of the enterprise's total liabilities to the total assets; market concentration, measured by the Herfindahl Index (*HHI*), the higher the *HHI*, the higher the market concentration.

Table A3
Heterogeneity analysis results.

	<i>UGreenTrans</i>					
	(1)	(2)	(3)	(4)	(7)	(8)
	<i>HumanCapitalHigh</i>	<i>HumanCapitalLow</i>	<i>GapHigh</i>	<i>GapLow</i>	<i>MarketHigh</i>	<i>MarketLow</i>
<i>DGreenTrans</i>	0.516*** (0.065)	0.055 (0.125)	−0.089 (0.166)	0.858*** (0.047)	0.498*** (0.083)	0.071 (0.128)
<i>Control</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm Fixed Effects</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Time-fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Difference in coefficients</i>	−0.462***		0.947***		−0.427**	
<i>P value</i>	[0.000]		[0.000]		[0.030]	
<i>_cons</i>	0.180 (1.962)	0.161 (1.261)	3.857** (1.703)	−1.566** (0.739)	−0.034 (1.703)	0.526 (1.496)
<i>N</i>	632	938	749	821	656	914
<i>R²</i>	0.360	0.252	0.251	0.704	0.242	0.294

Notes: P-values were obtained by autosampling (Bootstrap) 1000 times using Fisher's combined test.

Table A4
Measurement methods for environmental standards and norms.

Variables	Definition	Measurement
<i>BeneProd</i>	Whether to develop environmentally beneficial products	The firm has developed innovative products, equipment, or technologies that are beneficial to the environment, with a variable of 1 if they have, and 0 if they have not.
<i>Waste</i>	Whether to take measures to reduce the three wastes	Policies, measures or technologies adopted by the company to reduce emissions of waste gases, waste water, waste residues and greenhouse gases, with variable 1 if available and 0 if not available.
<i>Renewa</i>	Adoption of renewable energy sources	Whether the company uses renewable energy or adopts policies and measures for a circular economy, the variable is 1 if it does and 0 if it does not.
<i>Conserva</i>	Adoption of energy savings	Whether the company has policy measures or technologies to conserve energy, the variable is 1 if it does and 0 if it does not.
<i>OffiPoli</i>	Adoption of green office policies	Whether or not the company has a green office policy or initiative, the variable is 1 if it does and 0 if it does not.
<i>IfISO</i>	ISO 14001 certified or not	The company's environmental management system is ISO 14001 certified, which is 1 if it is and 0 if it is not.
<i>Recog</i>	Whether or not they have received environmental recognition	The variable is 1 if the company has received environmental recognition or other positive comments, and 0 if it has not.
<i>OtherAdvan</i>	Availability of other environmental advantages	The presence of other strengths in the firm's environment not covered by the above indicators, with a variable of 1 if there is one and 0 if there is none.

Notes: The data are all from the CNRDS database. Measures of environmental standards and norms are synthesized from the above indicators using the entropy weighting method.

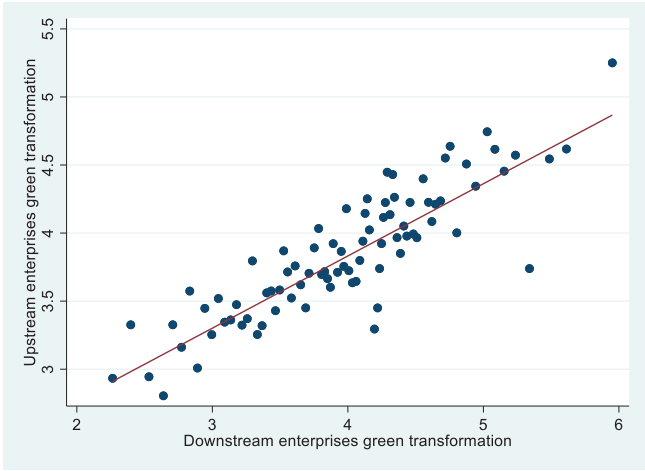


Fig. A.1 Downstream enterprises green transformation and upstream enterprises green transformation fitting chart.

Notes: In this paper, we first equalize the sample into 100 sample intervals based on the downstream firms’ green transformation, and find the mean value of the upstream firms’ green transformation in each interval, and plot it in the graph. The horizontal axis indicates the mean value of downstream firms’ green transformation, and the vertical axis indicates the mean value of upstream firms’ green transformation.

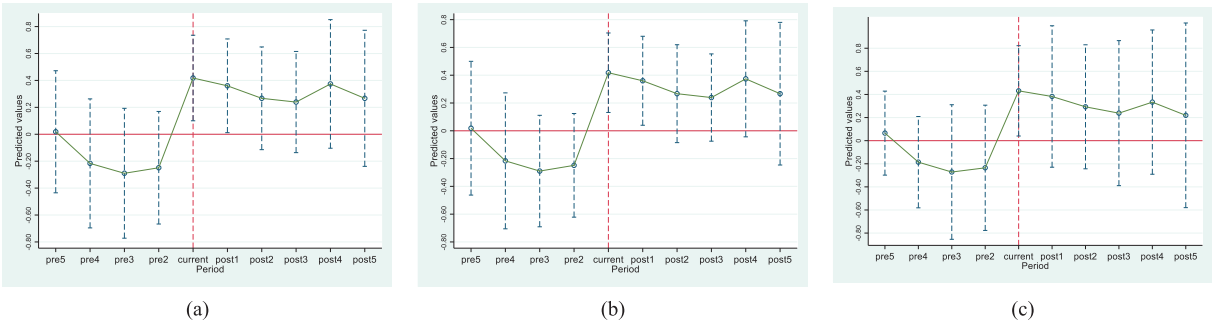


Fig. A.2. Parallelism trend test chart.

Notes: (a), (b), and (c) denote the results of the parallelism trend test of the difference-in-differences (DID) method in the case of robust standard error clustering to the individual, industry, and regional levels, respectively. The horizontal axis denotes the time away from the policy shock, and the vertical axis denotes the coefficients of the supply chain green spillovers.

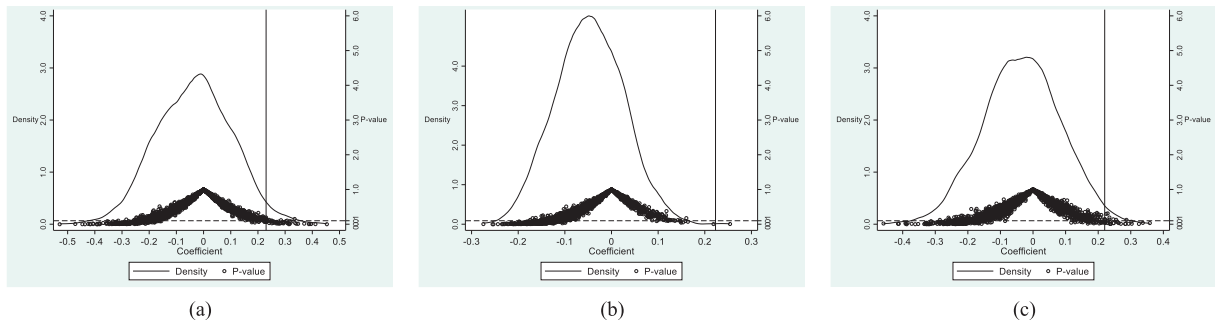


Fig. A.3. Placebo test chart.

Notes: (a), (b), and (c) denote the results of the placebo test of the difference-in-differences (DID) method in the case of robust standard error clustering to the individual, industry, and region levels, respectively. The horizontal axis denotes time away from the policy shock and the vertical axis denotes the coefficients of green spillovers in the supply chain.

Appendix D. Green spillovers from upstream firms to downstream firms

The previous section analysed the green spillover effects of the green transformation of downstream enterprises on upstream enterprises. However, the analytical framework has not yet considered the potential spillover effects of the green transformation of upstream firms on the green transformation of downstream firms. Given the key position of upstream enterprises in the supply chain, this subsection explores how the green transformation of upstream enterprises affects the green transformation of downstream enterprises.

The research in this section focuses on the dataset of listed companies and their upstream suppliers, and constructs the sample data through exact matching. To measure the green transformation of upstream firms (SGreenTrans), we use the methodology of measuring the green transformation of downstream firms in the baseline regression by using the weighted average measure of green transformation of upstream firms while maintaining consistency of other control variables. The results in column (1) of Table D.1 show that green transformation of upstream firms does not contribute significantly to green transformation of downstream firms. For this reason, we further explore the reasons behind this, and this paper argues that the high technological barriers of upstream firms may be the main reason why the green transformation of upstream firms does not significantly contribute to the green transformation of downstream firms.

From the perspective of technological barriers, upstream enterprises may possess core technologies or patents that are often strictly protected by intellectual property rights, and even when upstream enterprises engage in business dealings with downstream enterprises, they may be reluctant to easily transfer key technologies or innovations to downstream enterprises. Upstream firms tend to set higher technological barriers and achieve technological monopoly, thus weakening the green technology spillover effect from upstream firms to downstream firms. To test this hypothesis, we introduce an interaction term between the green transformation of upstream firms and the technology protection of upstream firms ($SGreenTrans \times TechProt$). The logic is that in the process of implementing a patent strategy, an enterprise will make strategic innovations by increasing the number of patents and constructing patent barriers, so as to occupy a place in the relevant technological field and achieve a technological monopoly to prevent other competitors (Somaya, 2012). In view of this, this paper uses upstream enterprise strategic innovation to replace upstream enterprise technology protection ($TechProt$). Drawing on Li and Zheng (2016) and Hu et al. (2020), the number of utility model and design patent applications is used to measure enterprise strategic innovation. The results are shown in column (2) of Table D.1, where the coefficient of the interaction term is significantly negative, proving that the technology protection behaviour of upstream firms weakens the green spillover effect of upstream firms on downstream firms.

Table D1

Results of spillovers from upstream firms to downstream firms.

	<i>UGreenTrans</i>	<i>UGreenTrans</i>
	(1)	(2)
<i>SGreenTrans</i>	0.066	0.174**
	(0.059)	(0.075)
<i>SGreenTrans</i> × <i>TechProt</i>		−0.010**
		(0.005)
<i>Control</i>	Yes	Yes
<i>Firm FE</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes
<i>_cons</i>	1.945	1.370
	(3.936)	(3.893)
<i>N</i>	401	401
<i>R</i> ²	0.730	0.733

Appendix E. Robustness test

E.1. Replacing the measurement of firms' green transformation

To enhance the dependability of the baseline regression results, this study re-executes the regression after substituting the metric for firms' green transformation. First, firms' green transformation is proxied by enterprise innovation. Drawing on Liu and Qiu (2016) and Amore and Bennedsen (2016), the enterprise green innovation measure in this paper is $GreInnov_{it} = \ln \left(N_{it} + \sqrt{N_{it}^2 + 1} \right)$, where N_{it} is the total number of patents applied for green inventions by enterprises. The results in column (1) of Table C.1 show that the coefficient of the independent variable (*DGreenInnov*) is significantly positive, indicating that downstream customers' green innovations can promote green innovations by upstream suppliers. Second, firms' green transformation is proxied by firms' ESG scores. This paper utilizes the CSI ESG rating based on the technique of Lin et al. (2021). The EGS rating system assigns ESG levels ranging from 1 to 9 for publicly traded corporations, and this study utilizes the mean value method to calculate the composite ESG rating assessments of companies. The findings in Column (2) of Table C.1 indicate that the coefficient of *DESG* is significantly positive, suggesting that enhancements in the ESG ratings of downstream consumers can facilitate improvements in the ESG ratings of upstream suppliers. The baseline regression results are robust when considered collectively.

E.2. Reducing interference from potential factors

In addition to the vertical transmission of inter-firm spillovers along the supply chain, there are also other possible transmission channels, such as transmission from within firms (Fernandes and Paunov, 2015; Kim and Lui, 2015; Lee et al., 2024), and spatial spillovers from geographic proximity of downstream customers and upstream suppliers (Chu et al., 2019). To mitigate the impact of possible additional spillovers, this work re-executes the regressions after omitting samples when the upstream and downstream enterprises are part of the same corporate group and situated in the same city. The results in column (3) of Table C.1 demonstrate that the coefficient of *DGreenTrans* is significantly positive, indicating that the baseline regression outcomes are resilient when considering the impact of other spillover effects.

E.3. Replacing the research window

The existence of green spillover effects throughout the supply chain necessitates a stable network between upstream and downstream enterprises; therefore, a comprehensive examination of these effects must account for the potential influence of various external factors on the interrelations within the production chain. The baseline regression period for this study is 2008–2022, coinciding with the global commencement of the COVID-19 pandemic in 2019. During the COVID-19 pandemic, a global public health catastrophe, the influence of local control policies on supply chain stability is notably substantial. The COVID-19 pandemic directly disrupted the normal operations of enterprises and indirectly caused a breakdown in the production chain relationships among them (Bonadio et al., 2021), significantly affecting the green spillover effects of the supply chain. This paper narrows the sample's temporal frame to more precisely assess the green spillovers of the supply chain, hence eliminating any disruptions caused by the COVID-19 epidemic. This research delineates the sample's temporal scope as 2008–2019, corresponding to the interval preceding the COVID-19 pandemic disruption. This investigation effectively assesses the green spillovers of enterprises' supply chains under standard market settings, mitigating potential biases introduced by epidemic factors on the research outcomes through this framework. The coefficients of *DGreenTrans* are markedly positive, as demonstrated according to the outcomes shown in column (4) of Table C.1. This indicates that the baseline regression outcomes remain robust when considering the impacts of disruptions in enterprises' supply chain relationships.

E.4. Considering lags in green spillovers

When analyzing the environmental impacts of supply chains, it is crucial to account for the possible latency in the manifestation of these consequences. The principal reason for this delay can be ascribed to two causes. One factor to examine is the research and development process of sustainable technology, together with the application cycle. Green innovations, including new energy technologies and energy-saving technologies, undergo a lengthy process from research and development, testing, to actual implementation (Amore and Bennesen, 2016; Lin et al., 2021). The spillover effect of this process is not immediately visible due to various reasons, including the maturity of the technology, economy, and compatibility with existing systems. Subsequently, there is a noticeable delay in its impact. Another reason is that supply chains are intricate and multifaceted. The coordination and cooperation among these participants necessitate time and effort, as supply chains typically consist of multiple links and participants (Chu et al., 2019; Wang et al., 2024). The implementation and utilization of green technologies require the cooperative engagement of the entire supply chain. This process is frequently not immediate, but rather necessitates gradual advancement. Given this, this paper addresses the green transition of primary suppliers in the benchmark regression with one lag period. The coefficient of *DGreenTrans* is significantly positive, as indicated by the findings in column (5) of Table C.1.

Table E1
Robustness testing.

	<i>UGreenInnov</i>	<i>UESG</i>	<i>UGreenTrans</i>	<i>UGreenTrans</i>	<i>LUGreenTrans</i>
	(1)	(2)	(3)	(4)	(5)
<i>DGreenInnov</i>	0.378*** (0.075)				
<i>DESG</i>		0.105** (0.051)			
<i>DGreenTrans</i>			0.252*** (0.089)	0.181* (0.106)	0.183** (0.084)
<i>Control</i>	Yes	Yes	Yes	Yes	Yes
<i>Firm fixed effects</i>	Yes	Yes	Yes	Yes	Yes
<i>Time fixed effects</i>	Yes	Yes	Yes	Yes	Yes
<i>_cons</i>	−4.192 (3.861)	1.008 (3.107)	2.353* (1.307)	2.401 (1.603)	1.366 (2.707)
<i>N</i>	926	907	922	953	425
<i>R</i> ²	0.514	0.560	0.686	0.667	0.802

Notes: *Control* comprises a set of control variables, the same as in the table below, and will not be repeated. (1) and (2) are the regression results of replacing the firms' green transformation measurement, (3) is the regression result of reducing the interference of potential factors, (4) presents the regression outcome of altering the study window duration, whereas (5) displays the regression result that accounts for the lag of green spillover.

E.5. Changing the regression methodology

The mean regression model utilized in the aforementioned benchmark regression aims to examine the average association between the green transformation of upstream and downstream businesses. This subsection is focused on analyzing the influence of heterogeneity on supply chain green spillovers resulting from varying distributions of upstream firms' green transformation characteristics. To achieve this, this section employs panel quantile regression for robustness testing. The validity of the baseline regression conclusions can be further examined by panel quantile regression, which has the advantages of a low impact of data bias and outliers on the results and a small model error term requirement (You et al., 2015). In Fig. E.1, we exhibit the quantile regression results for five representative quartiles of firms' green transformation: 15%, 25%, 50%, 75%, and 85%. This research can make two important conclusions following a comprehensive analysis of the distribution characteristics of the coefficients of *DGreenTrans*. Firstly, the coefficients of supply chain green spillovers consistently demonstrate a positive trend in regressions across many quartiles. This fact undoubtedly strengthens the reliability of the baseline regression results. The green transformation of downstream consumers somewhat facilitates the green transformation of providers, regardless of the distribution of green transformation among upstream suppliers.

Secondly, the coefficients of supply chain green spillover effects exhibit substantial variations across various quartiles. Specifically, the supply chain's green spillover effect initially rises and subsequently declines as the degree of environmentally friendly transformation among upstream providers escalates. This implies that the extent of the supply chain's green spillover effect will be influenced by the extent of green transformation among upstream suppliers. Specifically, in the first place, when the level of green transformation of upstream suppliers is low, supply chain green spillovers are likely to be lower. This may be a result of the fact that upstream suppliers lack the necessary capacity or resources to implement additional green transformation measures, thereby restricting the scope of spillover effects. In the second place, the magnitude of green spillovers in the supply chain will incrementally rise as the degree of green transformation among upstream sup-

pliers escalates. This is due to the fact that the green transformation initiatives of upstream suppliers can have a positive impact on downstream segments by enhancing the efficiency of resource utilization, production processes, and product design. Consequently, the entire supply chain's green factor can be increased. Ultimately, once upstream suppliers attain a particular degree of green transformation, supply chain green spillovers can start to decrease. This can be because upstream suppliers that have already adopted a higher degree of green transformation strategies will see a decline in the marginal advantages of further improving their green status.

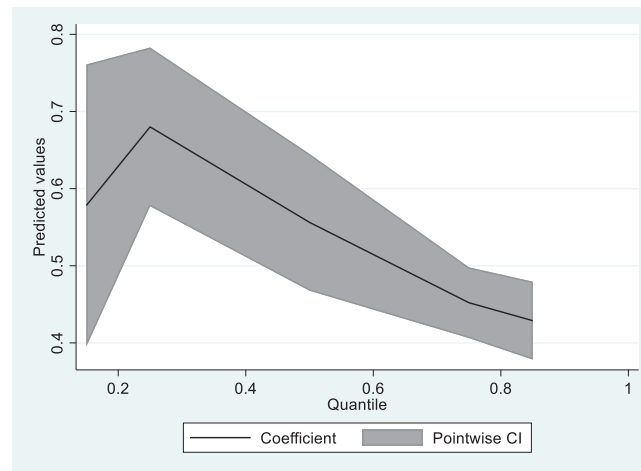


Fig. E.1. Quartile regression results.

Notes: The horizontal axis indicates the different quartiles of green transformation of upstream suppliers, and the vertical axis indicates the coefficients of the green spillover effect of the supply chain.

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The flow of textual risk information along the supply chain: Evidence from supplier analysts' forecasts

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ABSTRACT

This paper investigates how customers' textual risk information flows along the supply chain and affects supplier analysts' behavior. We find that the greater the disclosure of customers' textual risk, the lower the analysts' forecast errors. Further distinguishing customers' risk disclosures into current and future risk, we find that the informativeness of risk information mainly comes from the disclosure of future risk. This inverse association is stronger when customers have strong bargaining power, when the customer–supplier relationship is stable, when customers' earnings quality is high, when customers disclose risk information promptly, when the risk information is credible and when suppliers' information environment is poor. Customers' textual risk disclosure reduces the need for analyst site visits. Overall, the results suggest that supplier analysts benefit from customers' textual risk disclosure.

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1. Introduction

Information spillovers within the supply chain represent an important research area in corporate finance (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010). Research focuses on the spillover effects of quantitative information, such as earnings announcements and bankruptcy signals, along the supply chain and finds that investors use such information to assess the risks of firms within the chain (Hertzel et al., 2008; Pandit et al., 2011; Li et al., 2024). In addition to quantitative information, mandatorily disclosed textual risk information also carries important informational value. Unlike structured financial data, the forward-looking and quali-

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tative nature of textual risk information introduces a paradox for capital markets. While management's discussion of future uncertainties can heighten market risk perceptions, the very same disclosures can also resolve information asymmetry by clarifying the firm's prospects and strategies (Kravet and Muslu, 2013; Campbell et al., 2014; Hope et al., 2016). Therefore, the spillover effects of textual risk information may be more complex than those of quantitative information. However, little is known about how textual risk information propagates through the supply chain.

This paper addresses this gap by examining how textual risk information spills over the supply chain and is subsequently processed by sell-side analysts, a sophisticated group of information intermediaries. The spillover of textual risk information along the supply chain can be attributed to two primary factors. First, the substantial economic interdependence between supplier firms and their principal customers implies that suppliers are highly exposed to the idiosyncratic shocks affecting their customers (Chen et al., 2024; Yang et al., 2024; Liu et al., 2025). Second, unlike general information, risk information is often regarded as "bad news," which gives firms a stronger incentive to withhold such information (Piotroski et al., 2015). Consequently, textual risk information disclosed by a customer, however limited, becomes an indispensable resource for sell-side analysts in assessing the prospects and risks of the supplier firm.

This study is conducted in the Chinese context for three primary reasons. First, the Chinese context provides a powerful setting to observe supply chain information spillovers due to the strong economic links between firms. Specifically, firms in China are relatively dependent on their principal customers compared with firms in other contexts. For instance, nearly 50% of the firms in our sample have a major customer that accounts for more than 10% of their annual sales, whereas this percentage is only 26% in U.S. samples (Dhaliwal et al., 2016). This high degree of customer concentration strengthens the potential for, and the detectability of, risk information spillovers along the supply chain. Second, the information environment in emerging markets, like China, is relatively poor. This information opacity compels market intermediaries, notably financial analysts, to more actively seek alternative sources of information, including those from the supply chain. Chinese analysts, in particular, are often characterized as "embedded information intermediaries," who are highly sensitive to such alternative information (Li et al., 2020). This information environment offers an ideal setting for examining how analysts acquire and process risk information originating from the supply chain. Third, China's regulatory framework offers a unique setting for disentangling the distinct impacts of present versus future risk disclosures. Unlike in the U.S., where firms are encouraged by the Securities and Exchange Commission (SEC) to disclose forward-looking risks, the China Securities Regulatory Commission (CSRC) requires listed firms to first summarize known, realized risks before providing an outlook on future risks.

We primarily focus on the textual risk information in a customer firm's annual report, which is identified by extracting risk-related words (or sentences). Using a paired sample comprising both listed supplier firms and listed customer firms of Chinese A-share firms from 2007 to 2019, we empirically investigate the impact of customers' textual risk disclosure on supplier analysts' forecast errors. Our findings are as follows. (1) The forecast error of supplier analysts is negatively correlated with the amount of textual risk disclosure in customers' annual reports. Notably, the customers' future risk disclosure has a more pronounced effect than current risk disclosure. The results remain robust after controlling for potential biases arising from self-selection. (2) The negative impact is more pronounced when the customer has more bargaining power, when the customer-supplier relationship is stable, when customers' earnings quality is high, when customers disclose risk information promptly, when the risk information is more credible and when suppliers' information environment is poor. (3) Customers' textual risk disclosure may reduce analysts' reliance on other sources of information, such as site visits.

Our study contributes to several streams of research. First, we expand the literature on the usefulness of textual risk information by investigating its spillover effects to market participants outside the disclosing firm's immediate sphere. A large body of literature documents the usefulness of a firm's risk disclosures for its own stakeholders—including managers (Kim et al., 2023; Zhao, 2025), analysts (Wang et al., 2017; Zhao et al., 2022) and investors (Campbell et al., 2014)—and its direct supply chain partners (Chiu et al., 2019; Liu et al., 2025). We extend this research by demonstrating that such information also spills over to market participants one step removed: analysts covering the supplier firm.

Second, and more importantly, we decompose risk disclosures and show that their informativeness is not uniform. We categorize a customer's risk disclosures into present risk disclosures and future risk disclosures and find that the spillover effect is primarily driven by the forward-looking component. This result deepens our understanding of what specific attributes of risk disclosure are most salient and extends the findings of Li et al. (2023), who document that forward-looking risk discussions are associated with lower SEO discounts.

Third, our work extends the literature on supply chain information spillovers by shifting the focus from quantitative signals to qualitative textual disclosures. Research extensively documents the spillover effects of customers' numerical information, such as earnings forecasts, accounting quality and analyst or credit ratings (Radhakrishnan et al., 2014), as well as the market reaction to specific quantitative events like customer earnings announcements (Guan et al., 2015; Cho et al., 2020). We contribute to this body of work by providing novel evidence that customers' textual risk disclosures also exhibit a powerful and discernible spillover effect, thereby broadening the scope of what constitutes "transmittable" information in a supply chain context.

Fourth, our study contributes to the literature on analysts' information sources by offering a more granular understanding of how they use supply chain information. While prior work notes that analysts may use supply chain information (Guan et al., 2015; Luo and Nagarajan, 2015), our findings move beyond this general observation. We specifically demonstrate that analysts are sophisticated enough to distinguish the high-value, forward-looking components of textual risk disclosures originating from their target firm's customers.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature and presents testable hypotheses. Section 3 describes the research design and sample. Section 4 presents the empirical results and Section 5 provides further analysis. Section 6 concludes the paper.

2. Related literature and hypothesis development

2.1. Information content of annual report risk information

In 2007, the CSRC revised its Guideline No. 2 on the content and format of information disclosure by listed firms and made it mandatory for listed firms to disclose risk factors that may adversely affect their development strategies and business objectives and any corresponding countermeasures. Subsequently, in 2012, the CSRC proposed the principles of relevance and materiality for risk disclosure by listed firms and further clarified the specific requirements for risk disclosure. Specific requirements include the following: the separate disclosure of material risk warnings after the annual report table of contents; clear risk categorization; discussion of the impact of risk factors on current and future performance; explanation of the risk response measures taken or planned; and comparative analysis of current risk versus prior year. Therefore, the textual risks disclosed in annual reports include both the current and future risks faced by a firm, providing incremental value in terms of information content and information quality. In terms of information content, textual risk information contains a description of the current status and future development of a firm's operations and may provide information about potential operational and financial risks at the customer level that are useful to the supplier's stakeholders. In terms of information quality, the CSRC's mandatory disclosure requirements for Management's Discussion and Analysis (MD&A) sections may prompt firms to release new risk information to the public.

Textual risk information has both risk and information properties: the former amplifies the dispersion of risk among stakeholders, while the latter conveys information content, thereby reducing information asymmetry. Thus, external stakeholders interpret textual risk disclosure in two ways, which can trigger the "risk effect" or the "information effect." There are two dominant perspectives in the literature on the impact of textual risk information on direct stakeholders: the "risk perspective" and the "information perspective." The risk perspective stresses the risk attributes of annual report risk information, arguing that risk disclosures in annual reports increase investors' awareness of risk, which in turn leads to greater volatility in stock returns and more dispersion in analysts' forecasts. Li (2006), one of the first to study the impact of textual risk disclosure, confirms that firms disclosing more risk-related keywords in their annual reports tend to perform worse, have lower stock returns and are more likely to be targeted by hedge funds for short selling than their counterparts. Similarly, Kravet and Muslu (2013) find that risk information disclosure leads to an increase in stock returns,

trading volume and analyst forecast dispersion. The information view places more emphasis on the informational attributes of annual report risk information, arguing that risk disclosure can reduce information asymmetry and alleviate financing constraints (Campbell et al., 2014; Chiu et al., 2019). Wang et al. (2017) and Zhao et al. (2022) show that textual risk disclosure positively affects analysts' forecast accuracy.

In summary, risk information disclosed by listed firms exerts an influence on the decision-making processes of their stakeholders, and this influence manifests through the dual nature inherent in such risk information—specifically, its risk effect and information effect. The relative dominance of these two effects is contingent on the research context. Within the supply chain context, this paper is concerned with the effect of risk disclosure in customer annual reports on analysts' forecasts. Risk information includes both current risk and potential future risk, which produce different signals. Accordingly, we divide risk information into two categories: current and future risk. However, we have limited knowledge about the spillover effects of risk information on other investors in the supply chain.

2.2. Customers' textual risk disclosure and analyst forecast accuracy

Due to their intimate economic connections, the shared interests of suppliers and customers are inherently intertwined (Dong et al., 2021). Customers' risk information not only mirrors their own financial and operational circumstances but also conveys insights into the prospective trajectory of upstream firms within the supply chain (Pandit et al., 2011). The stock price of suppliers may decline due to increasing financial risk or insolvency risk among their customers (Hertzel et al., 2008), resulting in higher financing costs (Houston et al., 2016; Files and Gurun, 2018). Supplier firms also use the risk information disclosed by their customers to guide investment decisions (Chiu et al., 2019; Liu et al., 2025). Especially for Chinese firms that rely heavily on relationship-based transactions (Li et al., 2020), the spillover effects of customer risk information may be very pronounced and valuable to external stakeholders.

Analysts strive to expand their information channels to improve the accuracy of their earnings forecasts, which can significantly impact their careers (Brown et al., 2015). However, due to their dual attributes of risk and information, customer risk disclosures can have two possible effects on supplier analysts' forecasts. A customer's risk disclosure may create a risk effect, enhance supplier analysts' risk perception and subsequently increasing their earnings forecast bias. The risk information disclosed in a customer's annual report highlights the customer's risks and uncertainties, conveying certain heterogeneous information to the market and increasing the difficulty for external stakeholders to understand this information. First, the increase in information uncertainty and comprehension difficulty can complicate analysts' predictions and lead to heterogeneous beliefs, potentially reducing the accuracy of supplier analysts' forecasts and increasing the divergence among analysts (Campbell et al., 2014).

Second, disclosing a large amount of complex risk information can easily trigger market panic and undermine investor confidence (Kravet and Muslu, 2013), leading to the firm being labeled as "high risk." The market tends to be fearful of and averse to unknown risks, often resulting in distorted or exaggerated perceptions of a firm's actual risk situation. In such cases, supplier analysts' misinterpretation of customers' high-risk status can lead to forecast biases.

However, the disclosure of customer risk information also generates an information effect, providing suppliers' analysts with supplementary information that helps improve their forecast accuracy. First, the risk described in a customer's annual report provides insight into the potential risks to the supplier. For example, customers who lose their competitive advantage may reduce raw material purchases, thereby increasing the uncertainty of suppliers' sales and future cash flows. Customers exposed to financial risk often use their dominant market position to exert pressure on product prices, seek additional commercial credit or extend payment terms, ultimately straining suppliers' liquidity and increasing the risk of cash flow shortages (Alldredge et al., 2021). As a result, by analyzing the textual risk of customers, analysts can obtain a more comprehensive view of the potential risks faced by suppliers.

Second, analysts can cross-reference textual risks from customers with risk disclosures from suppliers. Research indicates that managers are incentivized to withhold unfavorable information (Baginski et al., 2018; Fu et al., 2021). This incentive can lead to the use of boilerplate disclosures in financial reporting, which consequently makes risk information less useful (Miao et al., 2025). Thus, cross-validation helps to identify

opportunistic behavior of supplier managers in disclosing risk information, which ultimately improves the accuracy of analysts' forecasts.

Hence, we posit the following competing hypotheses.

H1a. Disclosing more risk information in customers' annual reports improves the accuracy of analysts' forecasts for suppliers.

H1b. Disclosing more risk information in customers' annual reports reduces the accuracy of analysts' forecasts for suppliers.

3. Research design

3.1. Data and sample selection

Using a sample of A-share listed firms that disclosed the names of their top five customers and suppliers from the 2007–2019 period, this paper manually collects a paired sample comprising both listed supplier firms and listed customer firms. After removing the observations with missing values for control variables and excluding listed firms with the Special Treatment labels ST and *ST¹ and listed firms in financial and insurance industries, a final sample of 24,025 observations is obtained. The data on customer textual risk disclosure are obtained through text analysis; other financial data are obtained from the CSMAR database. In addition, all of the continuous variables are winsorized at 1% to eliminate the effects of extreme values.

3.2. Regression model

To test H1a and H1b, we use the following regression model:

$$Error_{i,j,t} = a_0 + a_1 Cus_Risk_{j,t-1} + Controls + Ind + Year + e \quad (1)$$

where $Error_{i,j,t}$ is the dependent variable, representing the earnings forecast error of analyst i for firm j in year t . We calculate the analyst earnings forecast error as follows:

$$Error_{i,j,t} = \frac{|FEPS_{i,j,t} - EPS_{j,t}|}{|EPS_{j,t}|}$$

where $FEPS_{i,j,t}$ is the latest earnings forecast of analyst i for firm j in year t , and $EPS_{j,t}$ is the actual earnings of firm j in year t . We use its absolute value as the denominator. A higher value of $Error_{i,j,t}$ implies a less accurate forecast by the analyst.

The main variable of interest, $Cus_Risk_{j,t-1}$, indicates the level of customer risk in year $t-1$ for supplier firm j . It equals the firm-size-weighted average of the risk disclosure levels of listed customers owned by supplier firm j in year $t-1$. From this, we obtain one-to-one pairs of suppliers and their major customer in each year. Listed firms typically include major risk warnings immediately following the annual report's table of contents and discuss risks relevant to achieving future strategies and business objectives in the MD&A section. To avoid collecting duplicating risk information from the major risk warnings and MD&As (Campbell et al., 2014), we construct $Cus_Risk_{j,t-1}$ based on the text from the MD&A sections. In cases where firms may have multiple listed customers (with the multiple listed customers accounting for 13.86%), we take the firm-size-weighted average of the risk information of the set of customers.

In line with prior research (Kravet and Muslu, 2013; Campbell et al., 2014), we obtain $Cus_Risk_{j,t-1}$ by the following steps. First, we break down the textual content of the MD&A section into individual words. Words that evidently hold no relevance to risk are excluded. This initial step generates a compilation of risk-related keywords (see Appendix 2 for details). Second, we count the frequency of occurrence of the risk-related key-

¹ Special Treatment (ST and *ST) firms in China are publicly listed firms facing financial distress that are at risk of being delisted unless they return to profitability.

words. Notably, risk-related words with preceding negative words are omitted from this count. The rationale for this practice is that one of the objectives of this paper is to identify corporate risk information through risk vocabulary. If the keywords are preceded by negative words, the text may convey the exact opposite meaning, that is, that there is no risk (Li, 2010; Wu et al., 2021). For instance, phrases like “no risk” and “no barrier” are cases in point. Finally, we measure the total customer risk disclosure as follows:

$$Cus_RiskT_{j,t-1} = \frac{RiskT_Words_{j,t-1}}{MD\&A_Words_{j,t-1}} \times 100$$

We control for a range of factors known to influence the supply chain information spillover effects of customers and the accuracy of analyst forecasts, drawing from previous research (Guan et al., 2015). *Size* is measured as the natural logarithm of total assets. *Lev* is measured as the ratio of total liabilities over total assets. *ROE* is the return on net assets. *Big4* is an indicator variable that equals 1 if the firm is audited by a Big 4 accounting firm, and 0 otherwise. *Top1* is measured as the ratio of the shares held by the largest shareholder to total shares. *Director* is measured as the proportion of independent directors on the board. *RiskD* is measured as the risk disclosure by the supplier firm itself. *Cus_ROE* represents the return on net assets of the customer firm. *Cus_Big4* is an indicator variable that equals 1 if the customer firm is audited by a Big 4 accounting firm, and 0 otherwise. *Cus_Volatility* is measured as the profit volatility of the customer firm over the past 3 years. *Cus_Lev* is measured as the ratio of total liabilities over total assets of the customer firm. *Number* is measured as the natural logarithm of the number of analyst reports about the firm. *Forecasthorizon* is measured as the analyst’s forecast horizon for the supplier firm. *Star* is an indicator variable that equals 1 if the analyst was awarded a star analyst rating by New Fortune Magazine in the previous year, and 0 otherwise. *Experience* is measured as the analyst’s experience. *Firmexp* is measured as the analyst’s firm-specific experience. *Brokerage_size* is measured as the total number of analysts employed by the analyst’s brokerage firm at the end of the year. *Retstd* is measured as the annual standard deviation of the firm’s daily stock returns. *Trading_vol* is measured as the stock turnover rate of the firm. *Volatility* is measured as the profit volatility of the firm over the past 3 years. In addition, we include industry (*Ind*) and year (*Year*) fixed effects. Detailed definitions of all of the variables are provided in Appendix 1.

4. Results

4.1. Descriptive statistics

Table 1 provides a snapshot of the descriptive statistics for our main variables. Additional variables used in the tests are listed in Appendix Table A2. The mean and standard deviation of the analyst forecast errors are 0.449 and 1.124, respectively. The average total customer textual risk disclosure is 1.647, denoting that on average, 1.65% of the words in a customer’s MD&A section are risk-related keywords. Furthermore, the standard deviation of total customer risk disclosure is 0.760, suggesting that the extent of risk disclosure varies considerably in our sample.

4.2. Baseline regression results

Table 2 presents the results of the regression analysis of customers’ textual risk disclosures on analyst forecast accuracy. In column (1), the regression coefficient on *Cus_RiskT* is negative and significant at the 1% level, indicating that as the extent of customers’ textual risk disclosure increases, there is a substantial decrease in analyst forecast error. Specifically, the coefficients indicate that with a one-standard-deviation increase in customers’ textual risk disclosure, the analyst forecast error drops by 13.51% ($0.08 \times 0.76/0.45$).

Forward-looking disclosures convey substantial incremental information, complementing and explaining corporate information beyond financial reports (Davis and Tama-Sweet, 2012), and serve as a critical basis for forecasting future firm performance (Li, 2010). As customers constitute the primary source of revenue for supplier firms, their disclosures of forward-looking risk information provide critical information for analysts assessing the expected returns of supplier firms’ investment projects. Consequently, based on the preceding empirical findings, we posit that customer forward-looking risk disclosures primarily exhibit an infor-

Table 1
Summary statistics.

Variables	Observation	Mean	STD	Median	Minimum	Maximum
<i>Error</i>	24,025	0.449	1.124	0.121	0	9.405
<i>Cus_RiskT</i>	24,025	1.647	0.760	1.545	0.384	4.776
<i>Size</i>	24,025	22.570	1.271	22.450	19.900	25.770
<i>Lev</i>	24,025	0.450	0.191	0.475	0.042	0.833
<i>ROE</i>	24,025	0.123	0.074	0.119	−0.235	0.371
<i>Big4</i>	24,025	0.066	0.248	0	0	1
<i>Top1</i>	24,025	9.895	18.140	0.482	0.122	72.880
<i>Director</i>	24,025	9.474	15.710	0.364	0.333	57.140
<i>RiskD</i>	24,025	1.633	0.846	1.446	0.428	4.724
<i>Cus_ROE</i>	24,025	0.107	0.080	0.098	−0.103	0.360
<i>Cus_Big4</i>	24,025	0.234	0.404	0	0	1
<i>Cus_Volatility</i>	24,025	18.230	1.363	18.130	14.320	21.610
<i>Cus_Lev</i>	24,025	0.449	0.194	0.482	0.042	0.833
<i>Number</i>	24,025	0.558	0.693	0	0	2.773
<i>Forecasthorizon</i>	24,025	4.446	1.214	4.753	0.693	5.968
<i>Star</i>	24,025	0.176	0.380	0	0	1
<i>Experience</i>	24,025	1.022	0.678	1.099	0	2.398
<i>Firmexp</i>	24,025	0.487	0.590	0	0	2.079
<i>Brokerage_size</i>	24,025	3.924	0.659	4.025	2.079	5.004
<i>Retstd</i>	24,025	0.031	0.017	0.028	0.011	0.154
<i>Trading_vol</i>	24,025	23.850	0.952	23.870	21.460	25.970
<i>Volatility</i>	24,025	18.310	1.379	18.220	14.320	21.610

mation effect, enhancing supplier analyst forecast accuracy. Therefore, we further identify the forward-looking customer risk information in the subsequent analysis, constructing $Cus_RiskF_{j,t-1}$. We create a vocabulary list composed of forward-looking keywords and identify risk keywords situated within a distance of less than 10 words from the identified forward-looking keywords (see Appendix 3 for details). This proximity signifies that these risk keywords are indicative of the firm's future risks. Then, we count the frequency of occurrence for these future risk keywords as follows.

$$Cus_RiskF_{j,t-1} = \frac{RiskF_Words_{j,t-1}}{MD\&A_Words_{j,t-1}} \times 100$$

To test the effect of customers' future risk disclosure on analyst forecast accuracy, we also control the effect of customers' non-future risk disclosures (Cus_RiskP), which is equal to the value of total customer risk disclosure (Cus_RiskT) minus customers' future risk disclosure (Cus_RiskF). In column (4), the regression coefficient on Cus_RiskF is negative and significant at the 1% level, while the coefficient on Cus_RiskP is positive and not significant. Specifically, the coefficient on Cus_RiskF indicates that with a one-standard-deviation increase in customers' future risk disclosure, the analyst forecast error drops by 22.86% ($0.16 \times 0.66/0.45$). This demonstrates that customers' future risk disclosure has a more pronounced effect on enhancing analyst forecast accuracy than does current risk disclosure. These outcomes align with H1a, suggesting that customers' textual risk disclosure is valuable for suppliers' analysts. These findings also support the information view regarding the usefulness of textual risk disclosure.

4.3. Endogeneity corrections

4.3.1. Instrumental variable regressions

We use the instrumental variable (IV) approach to mitigate the endogeneity issue arising from self-selection between customer and supplier firms. Drawing on the methodology of Chiu et al. (2019), we use the industry-average annual report risk disclosure levels of peer customer firms in the same year and industry ($Risk_indu$) as the IV.

Table 2

Regressions of analyst forecast accuracy on customers' textual risk disclosure.

	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>
<i>Cus_RiskT</i>	-0.080*** (-4.659)			
<i>Cus_RiskF</i>		-0.155*** (-6.929)		-0.156*** (-6.954)
<i>Cus_RiskP</i>			0.028 (1.019)	0.032 (1.178)
<i>Size</i>	-0.310*** (-23.105)	-0.310*** (-23.122)	-0.308*** (-22.974)	-0.310*** (-23.098)
<i>Lev</i>	1.137*** (13.186)	1.119*** (13.024)	1.097*** (12.692)	1.110*** (12.849)
<i>ROE</i>	-4.319*** (-33.238)	-4.358*** (-33.500)	-4.283*** (-33.007)	-4.359*** (-33.509)
<i>Big4</i>	-0.069** (-2.229)	-0.075** (-2.420)	-0.065** (-2.082)	-0.076** (-2.431)
<i>Top1</i>	-0.002** (-2.433)	-0.002** (-2.415)	-0.002** (-2.407)	-0.002** (-2.407)
<i>Director</i>	0.003 (0.827)	0.002 (0.813)	0.002 (0.629)	0.002 (0.778)
<i>RiskD</i>	0.046*** (3.814)	0.048*** (3.987)	0.041*** (3.381)	0.048*** (3.943)
<i>Cus_ROE</i>	-0.390*** (-3.713)	-0.372*** (-3.574)	-0.311*** (-2.966)	-0.356*** (-3.392)
<i>Cus_Big4</i>	-0.060*** (-3.121)	-0.058*** (-3.006)	-0.068*** (-3.539)	-0.059*** (-3.050)
<i>Cus_Volatility</i>	0.081*** (6.621)	0.075*** (6.145)	0.082*** (6.716)	0.075*** (6.070)
<i>Cus_Lev</i>	-0.181** (-2.277)	-0.159** (-2.010)	-0.160** (-2.009)	-0.152* (-1.912)
<i>Number</i>	-0.011 (-1.056)	-0.011 (-1.007)	-0.012 (-1.132)	-0.011 (-1.010)
<i>Forecasthorizon</i>	0.001*** (6.190)	0.001*** (6.286)	0.001*** (6.253)	0.001*** (6.312)
<i>Star</i>	-0.063*** (-3.361)	-0.064*** (-3.393)	-0.064*** (-3.386)	-0.064*** (-3.403)
<i>Experience</i>	0.003 (0.234)	0.003 (0.252)	0.002 (0.178)	0.003 (0.245)
<i>Firmexp</i>	-0.068*** (-4.692)	-0.067*** (-4.627)	-0.069*** (-4.722)	-0.067*** (-4.619)
<i>Brokerage_size</i>	0.009 (0.783)	0.008 (0.731)	0.009 (0.784)	0.008 (0.722)
<i>Retstd</i>	-2.478*** (-4.657)	-2.499*** (-4.698)	-2.477*** (-4.653)	-2.502*** (-4.705)
<i>Trading_vol</i>	0.121*** (9.525)	0.122*** (9.582)	0.119*** (9.347)	0.122*** (9.561)
<i>Volatility</i>	0.064*** (4.499)	0.071*** (4.925)	0.065*** (4.546)	0.072*** (5.000)
<i>Ind</i>	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	1.590*** (4.659)	1.590*** (4.660)	1.585*** (4.641)	1.589*** (4.657)
<i>Observations</i>	24,025	24,025	24,025	24,025
<i>F value</i>	61.27	61.73	60.91	60.85
<i>Adjusted-R²</i>	0.147	0.147	0.146	0.147

Note: This table reports the estimated results of the OLS regression. Appendix 1 provides details of all of the main variables. The t-values are reported in parentheses.

* Statistical significance at the 10% level.

** Statistical significance at the 5% level.

*** Statistical significance at the 1% level.

This IV meets both the relevance and exogeneity requirements. In terms of relevance, firms operating in the same industry face similar industry characteristics and external environments, resulting in correlated annual report risk disclosures. Regarding exogeneity, there is no evidence suggesting that risk disclosures from peer firms in the same industry as customers affect suppliers' information environment, thus satisfying the exogeneity condition.

Table 3 presents the IV regression results based on *Risk_indu*. Columns (1), (3) and (5) report the first-stage results of the two-stage least squares (2SLS) regression, while columns (2), (4) and (6) present the second-stage results. The main findings of the study remain robust.

4.3.2. Fixed effects

To control for the effects of unobservable and time-invariant characteristics of firms, analyst and customer–supplier relationships on the baseline results, we include firm (*Firm*), analyst (*Analyst*) and customer–supplier pair (*Pair*) fixed effects to the model. The results are presented in Table 4. The coefficients on *Cus_RiskT* and *Cus_RiskF* remain significant and negative.

4.4. Robustness checks

4.4.1. Alternative measures of textual risk disclosure

Business models and risk profiles vary across industries, which may lead to differences in textual risk disclosures across industries. We construct enhanced textual risk disclosure measures (*Cus_RiskT2* and *Cus_RiskF2*) by deducting industry-average risk levels from the original measures (*Cus_RiskT* and *Cus_RiskF*). This adjustment isolates firm-specific risk components, as suggested by Hope et al. (2016). The results are presented in columns (1) and (2) of Table 5, where the coefficients on *Cus_RiskT2* and *Cus_RiskF2* remain significant and negative and the conclusions are unchanged.

In the baseline regression, we use the proportion of risk-related keywords to measure the extent of textual risk disclosure. For robustness, we re-estimate our measure of textual risk disclosure. Following Campbell et al. (2014), we use the proportion of sentences that incorporate risk-related keywords as follows:

$$Cus_RiskT3_{j,t-1} = \frac{RiskT_Sentences_{j,t-1}}{MD\&A_Sentences_{j,t-1}} \times 100$$

$$Cus_RiskF3_{j,t-1} = \frac{RiskF_Sentences_{j,t-1}}{MD\&A_Sentences_{j,t-1}} \times 100$$

where *RiskT_Sentences* denotes the frequency of sentences containing risk-related keywords in the MD&A and *RiskF_Sentences* denotes the frequency of sentences containing both risk-related and future keywords. *MD&A_Sentences* denotes the number of sentences in the MD&A. *Cus_RiskT3* and *Cus_RiskF3* measure the proportion of sentences containing total risk and future risk information, respectively. The results are presented in columns (3) and (4) of Table 5 and the findings remain consistent with the baseline results.

4.4.2. Alternative measures of analyst forecast

Analysts, especially those with information disadvantages, tend to issue optimistic earnings forecasts to gain favor with firm management (Das et al., 1998). Thus, if customers' textual risk disclosure is indeed an important source of information for supplier analysts, it should be effective in reducing their optimistic forecast bias. We calculate analysts' optimistic forecast bias as follows:

$Fbias_{i,j,t} = \frac{FEPS_{i,j,t} - EPS_{j,t}}{|EPS_{j,t}|}$ where *FEPS_{i,j,t}* is the latest earnings forecast of analyst *i* for firm *j* in year *t*, and *EPS_{j,t}* is the actual earnings of firm *i* in year *t*. The results are shown in columns (1) and (2) of Table 6. The coefficients on *Cus_RiskT* and *Cus_RiskF* are significant and negative at the 1% level, consistent with the baseline conclusions.

To directly test the risk perspective, we estimate regressions for analysts' forecast dispersion (Kravet and Muslu, 2013). Specifically, we regress the properties of analysts' forecasts, namely consensus forecast errors (*Consensusfe*) and forecast dispersion (*Dispersion*), on the customer's risk disclosure. *Consensusfe_{j,t}* is defined as the average absolute forecast error of the latest earnings forecast issued by each analyst for firm *j* in year *t*.

Table 3
IV regressions.

	First (1) <i>Cus_RiskT</i>	Second (2) <i>Error</i>	First (3) <i>Cus_RiskF</i>	Second (4) <i>Error</i>	First (5) <i>Cus_RiskP</i>	Second (6) <i>Error</i>
<i>Cus_RiskT</i>		−0.050* (−1.837)				
<i>Cus_RiskF</i>				−0.086* (−1.841)		
<i>Cus_RiskP</i>						−0.120* (−1.831)
<i>Size</i>	−0.027*** (−5.861)	−0.310*** (−14.809)	−0.015*** (−3.903)	−0.309*** (−14.815)	−0.013*** (−4.097)	−0.310*** (−14.798)
<i>Lev</i>	0.224*** (8.818)	1.125*** (14.018)	−0.011 (−0.608)	1.113*** (13.974)	0.235*** (13.318)	1.142*** (13.919)
<i>ROE</i>	0.208*** (5.103)	−4.305*** (−22.753)	−0.101*** (−2.896)	−4.324*** (−22.737)	0.310*** (10.807)	−4.278*** (−22.648)
<i>Big4</i>	−0.004 (−0.469)	−0.068*** (−3.401)	−0.037*** (−4.434)	−0.071*** (−3.495)	0.033*** (5.824)	−0.064*** (−3.227)
<i>Top1</i>	0.000*** (3.237)	−0.002*** (−2.993)	0.000*** (3.427)	−0.002*** (−2.981)	0.000 (0.609)	−0.002*** (−3.008)
<i>Director</i>	0.004*** (9.729)	0.002 (0.986)	0.002*** (5.045)	0.002 (0.962)	0.003*** (9.528)	0.002 (1.020)
<i>RiskD</i>	0.052*** (15.262)	0.044*** (3.184)	0.039*** (13.689)	0.045*** (3.224)	0.012*** (5.184)	0.043*** (3.122)
<i>Cus_ROE</i>	−0.670*** (−19.019)	−0.366*** (−3.330)	−0.224*** (−7.031)	−0.351*** (−3.282)	−0.446*** (−19.757)	−0.386*** (−3.367)
<i>Cus_Big4</i>	0.063*** (10.540)	−0.063*** (−3.791)	0.046*** (8.703)	−0.062*** (−3.733)	0.018*** (3.832)	−0.064*** (−3.864)
<i>Cus_Volatility</i>	−0.043*** (−11.333)	0.082*** (7.638)	−0.060*** (−20.180)	0.079*** (7.166)	0.016*** (6.678)	0.086*** (8.020)
<i>Cus_Lev</i>	0.006 (0.258)	−0.175** (−2.277)	0.154*** (8.918)	−0.162** (−2.113)	−0.148*** (−9.154)	−0.193** (−2.467)
<i>Number</i>	0.003 (0.903)	−0.012 (−1.133)	0.004* (1.700)	−0.011 (−1.108)	−0.002 (−0.785)	−0.012 (−1.168)
<i>Forecasthorizon</i>	−0.000** (−2.442)	0.001*** (5.618)	0.000* (1.912)	0.001*** (5.657)	−0.000*** (−5.710)	0.001*** (5.557)
<i>Star</i>	0.000 (0.009)	−0.063*** (−3.649)	−0.004 (−0.792)	−0.064*** (−3.673)	0.004 (0.931)	−0.063*** (−3.614)
<i>Experience</i>	0.009** (2.415)	0.003 (0.212)	0.006* (1.917)	0.003 (0.218)	0.003 (1.087)	0.003 (0.204)
<i>Firmexp</i>	−0.006 (−1.209)	−0.069*** (−4.739)	0.003 (0.678)	−0.068*** (−4.709)	−0.008** (−2.558)	−0.069*** (−4.774)
<i>Brokerage_size</i>	−0.006* (−1.673)	0.009 (0.777)	−0.007** (−2.392)	0.008 (0.749)	0.001 (0.525)	0.009 (0.815)
<i>Retstd</i>	−0.177** (−2.363)	−2.477*** (−6.959)	−0.233*** (−3.592)	−2.488*** (−6.969)	0.056 (1.011)	−2.461*** (−6.941)
<i>Trading_vol</i>	0.003 (0.768)	0.120*** (8.887)	0.004 (1.186)	0.121*** (8.906)	−0.001 (−0.344)	0.120*** (8.858)
<i>Volatility</i>	0.028*** (6.207)	0.064*** (3.758)	0.056*** (15.409)	0.068*** (3.964)	−0.028*** (−9.883)	0.060*** (3.401)
<i>Risk_indu</i>	0.887*** (105.354)		0.516*** (61.559)		0.371*** (50.076)	
<i>Ind</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	0.583*** (6.193)	1.589*** (5.268)	0.333*** (4.312)	1.588*** (5.270)	0.250*** (4.091)	1.589*** (5.264)
<i>Observations</i>	24,025	24,025	24,025	24,025	24,025	24,025
<i>F value</i>	7077	.	3633	.	3881	.
<i>Adjusted-R²</i>	0.839	0.146	0.738	0.147	0.675	0.145

Table 4
Regressions with fixed effects.

	Firm fixed		Analyst fixed		Firm and analyst fixed		Pair fixed	
	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>	(5) <i>Error</i>	(6) <i>Error</i>	(7) <i>Error</i>	(8) <i>Error</i>
<i>Cus_RiskT</i>	-0.126*** (-4.962)		-0.088*** (-4.580)		-0.135*** (-4.411)		-0.255*** (-6.941)	
<i>Cus_RiskF</i>		-0.186*** (-6.954)		-0.155*** (-6.223)		-0.209*** (-5.224)		-0.432*** (-9.358)
<i>Cus_RiskP</i>		0.117*** (2.950)		0.010 (0.335)		-0.039 (-0.845)		-0.040 (-0.797)
<i>Size</i>	-0.541*** (-9.484)	-0.524*** (-8.487)	-0.305*** (-20.690)	-0.305*** (-20.659)	-0.276*** (-3.317)	-0.302*** (-3.601)	0.182** (2.334)	0.060 (0.742)
<i>Lev</i>	1.228*** (6.404)	2.160*** (10.792)	1.191*** (12.851)	1.170*** (12.612)	1.382*** (5.659)	1.322*** (5.399)	1.733*** (7.354)	1.824*** (7.732)
<i>ROE</i>	-4.032*** (-16.906)	-4.506*** (-17.593)	-4.253*** (-29.646)	-4.283*** (-29.834)	-3.095*** (-9.677)	-3.210*** (-9.965)	-3.202*** (-10.661)	-3.445*** (-11.385)
<i>Big4</i>	-2.919*** (-16.461)	-2.822*** (-15.814)	-0.029 (-0.837)	-0.036 (-1.034)	-3.286*** (-9.112)	-3.279*** (-9.099)	-5.408*** (-17.209)	-5.304*** (-16.868)
<i>Top1</i>	-0.005*** (-3.339)	0.001 (0.385)	-0.002* (-1.814)	-0.002* (-1.779)	-0.003 (-1.294)	-0.003 (-1.351)	-0.008*** (-4.343)	-0.008*** (-4.326)
<i>Director</i>	-0.001 (-0.130)	0.009 (1.503)	0.001 (0.324)	0.001 (0.265)	-0.007 (-0.889)	-0.008 (-1.006)	0.006 (0.902)	0.003 (0.462)
<i>RiskD</i>	0.158*** (7.633)	0.171*** (7.812)	0.042*** (3.195)	0.044*** (3.332)	0.138*** (5.337)	0.141*** (5.467)	0.086*** (3.346)	0.101*** (3.914)
<i>Cus_ROE</i>	-0.916*** (-5.916)	-0.018 (-0.101)	-0.392*** (-3.406)	-0.362*** (-3.144)	0.156 (0.815)	0.232 (1.201)	-2.054*** (-7.901)	-2.037*** (-7.840)
<i>Cus_Big4</i>	-0.244*** (-7.352)	-0.249*** (-6.082)	-0.045** (-2.116)	-0.045** (-2.127)	-0.153*** (-3.555)	-0.163*** (-3.789)	-0.337*** (-5.784)	-0.374*** (-6.392)
<i>Cus_Volatility</i>	0.069*** (4.694)	0.098*** (6.322)	0.081*** (6.234)	0.075*** (5.736)	0.070*** (4.292)	0.067*** (4.104)	0.122*** (7.447)	0.123*** (7.500)
<i>Cus_Lev</i>	-0.552*** (-5.059)	-1.036*** (-8.809)	-0.201** (-2.372)	-0.179** (-2.109)	-0.514*** (-4.200)	-0.503*** (-4.109)	-1.036*** (-7.784)	-1.035*** (-7.782)
<i>Number</i>	-0.007 (-0.759)	-0.005 (-0.552)	-0.016 (-1.311)	-0.016 (-1.258)	0.007 (0.381)	0.006 (0.349)	-0.001 (-0.104)	-0.002 (-0.183)
<i>Forecasthorizon</i>	0.001*** (7.807)	0.001*** (9.010)	0.001*** (4.215)	0.001*** (4.323)	0.000 (1.568)	0.000 (1.390)	0.001*** (9.017)	0.001*** (8.834)
<i>Star</i>	-0.069*** (-4.239)	-0.062*** (-3.820)	-0.020 (-0.714)	-0.019 (-0.691)	-0.021 (-0.660)	-0.022 (-0.694)	-0.059*** (-3.792)	-0.059*** (-3.790)
<i>Experience</i>	-0.010 (-0.964)	-0.009 (-0.872)	0.014 (0.627)	0.014 (0.628)	-0.044 (-0.992)	-0.043 (-0.957)	-0.003 (-0.328)	-0.003 (-0.247)
<i>Firmexp</i>	-0.059*** (-4.608)	-0.059*** (-4.583)	-0.037** (-2.136)	-0.036** (-2.077)	0.020 (0.445)	0.018 (0.401)	-0.068*** (-5.516)	-0.070*** (-5.642)
<i>Brokerage_size</i>	-0.001 (-0.135)	-0.002 (-0.258)	0.059** (2.142)	0.057** (2.079)	0.082** (1.970)	0.082** (1.971)	-0.006 (-0.706)	-0.007 (-0.736)
<i>Retstd</i>	-2.808*** (-3.560)	-3.966*** (-4.906)	-3.104*** (-5.415)	-3.128*** (-5.459)	-2.961** (-2.467)	-2.971** (-2.477)	-2.376*** (-2.751)	-2.560*** (-2.964)
<i>Trading_vol</i>	0.108*** (5.202)	0.058** (2.552)	0.122*** (8.464)	0.121*** (8.434)	0.084*** (2.933)	0.083*** (2.909)	-0.046* (-1.699)	-0.049* (-1.807)
<i>Volatility</i>	-0.051** (-2.523)	-0.087*** (-4.167)	0.047*** (3.068)	0.054*** (3.507)	-0.061*** (-2.619)	-0.057** (-2.436)	-0.112*** (-4.697)	-0.116*** (-4.865)
<i>Firm</i>	Yes	Yes	No	No	Yes	Yes	No	No
<i>Analyst</i>	No	No	Yes	Yes	Yes	Yes	No	No
<i>Pair</i>	No	No	No	No	No	No	Yes	Yes
<i>Ind</i>	No	No	Yes	Yes	No	No	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	9.643*** (7.960)	9.436*** (7.006)	1.609*** (3.982)	1.616*** (4.000)	3.934** (2.264)	4.553*** (2.602)	-2.958* (-1.855)	-0.108 (-0.065)
<i>Observations</i>	24,025	24,025	24,025	24,025	24,025	24,025	24,025	24,025
<i>F value</i>	43.08	36.02	41.67	41.36	14.75	14.57	45.01	44.93
<i>Adjusted-R²</i>	0.371	0.385	0.162	0.163	0.577	0.577	0.431	0.432

Table 5
Alternative measure of the explanatory variable.

	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>
<i>Cus_RiskT2</i>	−0.092*** (−4.314)			
<i>Cus_RiskF2</i>		−0.132*** (−5.772)		
<i>Cus_RiskP2</i>		0.078*** (3.219)		
<i>Cus_RiskT3</i>			−0.140*** (−6.256)	
<i>Cus_RiskF3</i>				−0.736*** (−5.336)
<i>Cus_RiskP3</i>				−0.071*** (−2.595)
<i>Size</i>	−0.311*** (−23.175)	−0.310*** (−23.074)	−0.254*** (−12.843)	−0.257*** (−12.979)
<i>Lev</i>	1.124*** (13.057)	1.083*** (12.587)	0.969*** (10.224)	0.981*** (10.359)
<i>ROE</i>	−4.255*** (−32.767)	−4.308*** (−32.872)	−3.980*** (−24.878)	−4.055*** (−25.216)
<i>Big4</i>	−0.064** (−2.066)	−0.071** (−2.279)	−0.147*** (−4.011)	−0.158*** (−4.311)
<i>Top1</i>	−0.002** (−2.361)	−0.002** (−2.351)	−0.272*** (−3.694)	−0.245*** (−3.313)
<i>Director</i>	0.002 (0.780)	0.002 (0.661)	0.883*** (4.695)	0.829*** (4.398)
<i>RiskD</i>	0.046*** (3.792)	0.045*** (3.751)	0.102*** (5.533)	0.106*** (5.752)
<i>Cus_ROE</i>	−0.385*** (−3.671)	−0.318*** (−3.047)	−0.273** (−2.275)	−0.230* (−1.907)
<i>Cus_Big4</i>	−0.061*** (−3.205)	−0.063*** (−3.281)	−0.085*** (−4.149)	−0.088*** (−4.271)
<i>Cus_Volatility</i>	0.079*** (6.419)	0.074*** (5.962)	0.071*** (5.617)	0.070*** (5.541)
<i>Cus_Lev</i>	−0.163** (−2.061)	−0.131* (−1.651)	−0.239*** (−2.982)	−0.230*** (−2.867)
<i>Number</i>	−0.012 (−1.113)	−0.011 (−1.074)	−0.005 (−0.396)	−0.006 (−0.454)
<i>Forecasthorizon</i>	0.001*** (6.189)	0.001*** (6.346)	−0.001*** (−5.378)	−0.001*** (−5.332)
<i>Star</i>	−0.064*** (−3.381)	−0.064*** (−3.428)	−0.077*** (−3.740)	−0.078*** (−3.790)
<i>Experience</i>	0.003 (0.253)	0.003 (0.232)	−0.009 (−0.656)	−0.010 (−0.722)
<i>Firmexp</i>	−0.070*** (−4.775)	−0.068*** (−4.676)	−0.066*** (−4.062)	−0.063*** (−3.854)
<i>Brokerage_size</i>	0.008 (0.741)	0.008 (0.696)	0.000 (0.020)	−0.000 (−0.033)
<i>Retstd</i>	−2.492*** (−4.683)	−2.511*** (−4.721)	−6.661** (−2.460)	−6.801** (−2.513)
<i>Trading_vol</i>	0.119*** (9.375)	0.119*** (9.392)	0.148*** (7.702)	0.151*** (7.873)
<i>Volatility</i>	0.067*** (4.679)	0.074*** (5.152)	0.033** (2.150)	0.036** (2.338)
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Ind</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	1.646*** (4.816)	1.619*** (4.737)	0.863** (2.352)	0.897** (2.445)

Table 5 (continued)

	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>
<i>Observations</i>	24,025	24,025	24,025	24,025
<i>F value</i>	61.22	60.69	45.79	45.43
<i>Adjusted-R²</i>	0.146	0.147	0.139	0.140

$Dispersion_{j,t}$ is defined as the standard deviation of the latest earnings forecast issued by all analysts following the firm. We only select samples where the number of analyst followers is greater than two.

The results are shown in columns (3) to (6) of Table 6. With *Consensusfe* and *Dispersion* as the dependent variables, the estimated coefficients on *Cus_RiskF* are both negative and statistically significant. The estimated coefficient on *Cus_RiskT* is significant and negative in column (3) but is not significant in column (5). These results further support the information perspective.

4.4.3. Small sample test for suppliers who have lost their only major customer

In addition, we conduct robustness tests on the main results based on a small subsample of the supplier firms who lost their only major listed customer companies (OMCs). Specifically, we limit the sample to such supplier firms and retain the data of the last year before losing their OMC and the 3 years after losing their OMC. When a supplier firm loses its OMC, the analysts of the supplier lose an open channel to obtain customers' risk information. Through this research design, we aim to more directly analyze the impact of changes in customer risk information disclosure on the analyst forecasts of suppliers. The results are presented in Table 7. The results support our baseline conclusions.

5. Additional analyses

5.1. Impacts of supplier–customer relationships

5.1.1. Dependence on customers

Firms that heavily depend on major customers are naturally more exposed to the business uncertainties and financial conditions of these customers, resulting in more complementarities between these firms (Luo and Nagarajan, 2015). Moreover, firms with a heavy reliance on major customers often adopt a disclosure strategy marked by a tendency to reveal positive news in advance while delaying the disclosure of negative news, particularly news concerning litigation outcomes (Cen et al., 2018). This strategic disclosure behavior can prevent analysts from obtaining comprehensive risk-related information directly from the firm in a timely manner, which amplifies the value of customer textual risk information for analysts.

As some firms have multiple listed customers, we use customer concentration (*Cus_HHI*), as defined by Zhao et al. (2022), to measure a firm's dependence on major customers and split the sample into two subsamples based on the median value. Table 8 presents the results. Columns (1) and (2) list the results of the subsample with a high percentage of customer sales among total annual sales. The coefficients on *Cus_RiskT* and *Cus_RiskF* are significant and negative. Columns (3) and (4) present the results for the subsample with a low customer concentration. The coefficient on *Cus_RiskT* is significant and negative and the coefficient on *Cus_RiskF* is not significant. Their absolute values are smaller than those of the subsample with a high customer concentration. The p-values of the coefficient difference tests between the two subsamples are less than 0.01. These findings collectively suggest that the impact of customers' textual risk disclosure is more pronounced for major customers than for other customers.

5.1.2. Stable customers

Stable customer relationships can result in more interdependence between the firm's development and the survival of the customer. Specifically, firms with stable customers often establish relationship-based transactions and invest in proprietary assets, leading to high sunk costs associated with losing those customers

Table 6
Alternative measures of the dependent variable.

	(1) <i>Fbias</i>	(2) <i>Fbias</i>	(3) <i>Dispersion</i>	(4) <i>Dispersion</i>	(5) <i>Consensusfe</i>	(6) <i>Consensusfe</i>
<i>Cus_RiskT</i>	−0.082*** (−4.816)		−0.004** (−2.569)		0.000 (1.509)	
<i>Cus_RiskF</i>		−0.162*** (−7.316)		−0.015*** (−7.225)		−0.002*** (−12.153)
<i>Cus_RiskP</i>		0.037 (1.371)		0.012*** (4.748)		0.003*** (17.063)
<i>Size</i>	−0.274*** (−20.577)	−0.274*** (−20.569)	−0.009*** (−7.126)	−0.009*** (−7.105)	−0.002*** (−18.747)	−0.002*** (−18.836)
<i>Lev</i>	1.003*** (11.708)	0.973*** (11.352)	0.013* (1.652)	0.009 (1.155)	0.009*** (15.007)	0.009*** (13.856)
<i>ROE</i>	−3.945*** (−30.581)	−3.988*** (−30.881)	0.164*** (13.772)	0.158*** (13.285)	−0.022*** (−23.204)	−0.023*** (−24.592)
<i>Big4</i>	−0.055* (−1.789)	−0.062** (−2.006)	−0.027*** (−9.590)	−0.028*** (−9.911)	−0.001*** (−4.873)	−0.001*** (−5.708)
<i>Top1</i>	−0.000 (−0.419)	−0.000 (−0.389)	0.001*** (16.267)	0.001*** (16.332)	−0.000 (−0.951)	−0.000 (−0.849)
<i>Director</i>	0.002 (0.646)	0.002 (0.594)	−0.002*** (−6.215)	−0.002*** (−6.299)	0.000*** (6.022)	0.000*** (5.882)
<i>RiskD</i>	0.021* (1.721)	0.022* (1.859)	0.015*** (13.097)	0.015*** (13.311)	0.000*** (3.858)	0.000*** (4.397)
<i>Cus_ROE</i>	−0.589*** (−5.654)	−0.554*** (−5.308)	0.073*** (7.638)	0.078*** (8.126)	0.003*** (3.956)	0.004*** (5.228)
<i>Cus_Big4</i>	−0.059*** (−3.076)	−0.057*** (−3.000)	0.001 (0.586)	0.001 (0.699)	−0.001*** (−6.310)	−0.001*** (−6.080)
<i>Cus_Volatility</i>	0.095*** (7.827)	0.088*** (7.234)	0.017*** (14.809)	0.016*** (13.946)	0.001*** (12.355)	0.001*** (10.351)
<i>Cus_Lev</i>	−0.161** (−2.045)	−0.131* (−1.655)	0.014* (1.904)	0.018** (2.463)	0.001* (1.690)	0.002*** (3.121)
<i>Number</i>	−0.005 (−0.509)	−0.005 (−0.459)	0.004*** (4.469)	0.004*** (4.548)	−0.000** (−2.470)	−0.000** (−2.308)
<i>Forecasthorizon</i>	0.001*** (7.783)	0.001*** (7.914)	0.000*** (7.240)	0.000*** (7.435)	−0.000*** (−3.936)	−0.000*** (−3.496)
<i>Star</i>	−0.061*** (−3.282)	−0.062*** (−3.327)	−0.001 (−0.304)	−0.001 (−0.367)	0.000*** (3.041)	0.000*** (2.910)
<i>Experience</i>	−0.003 (−0.267)	−0.003 (−0.255)	−0.003*** (−2.803)	−0.003*** (−2.790)	0.000 (0.979)	0.000 (1.032)
<i>Firmexp</i>	−0.067*** (−4.642)	−0.066*** (−4.564)	0.004*** (2.984)	0.004*** (3.104)	−0.000** (−2.425)	−0.000** (−2.151)
<i>Brokerage_size</i>	0.016 (1.432)	0.015 (1.368)	−0.000 (−0.220)	−0.000 (−0.315)	0.000*** (3.669)	0.000*** (3.462)
<i>Retstd</i>	−2.684*** (−5.080)	−2.710*** (−5.132)	0.364*** (7.469)	0.360*** (7.407)	−0.013*** (−3.253)	−0.013*** (−3.462)
<i>Trading_vol</i>	0.139*** (11.005)	0.139*** (11.045)	−0.006*** (−5.192)	−0.006*** (−5.151)	−0.000 (−0.906)	−0.000 (−0.795)
<i>Volatility</i>	0.013 (0.927)	0.021 (1.482)	0.012*** (9.514)	0.014*** (10.289)	0.001*** (9.774)	0.001*** (11.860)
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Ind</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	0.901*** (2.658)	0.899*** (2.655)	0.042 (1.334)	0.042 (1.329)	0.012*** (4.832)	0.012*** (4.859)
<i>Observations</i>	24,025	24,025	24,018	24,018	24,018	24,018
<i>F value</i>	55.17	54.90	146.4	145.6	142.8	149.4
<i>Adjusted-R²</i>	0.134	0.135	0.293	0.295	0.288	0.300

Table 7
Regression using supplier firms that lose their major listed customers.

	(1) <i>Error</i>	(2) <i>Error</i>
<i>Cus_RiskT</i>	−0.318*** (−5.038)	
<i>Cus_RiskF</i>		−0.320*** (−4.025)
<i>Cus_RiskP</i>		−0.315*** (−3.105)
<i>Size</i>	−0.165*** (−5.957)	−0.165*** (−5.710)
<i>Lev</i>	1.305*** (7.049)	1.305*** (7.034)
<i>ROE</i>	−2.210*** (−7.646)	−2.214*** (−7.223)
<i>Big4</i>	0.004 (0.066)	0.004 (0.057)
<i>Top1</i>	−0.003* (−1.754)	−0.003* (−1.711)
<i>Director</i>	0.001 (0.152)	0.001 (0.146)
<i>RiskD</i>	−0.002 (−0.100)	−0.002 (−0.100)
<i>Cus_ROE</i>	−1.246*** (−3.832)	−1.240*** (−3.467)
<i>Cus_Big4</i>	−0.187*** (−3.829)	−0.186*** (−3.664)
<i>Cus_Volatility</i>	0.089*** (3.099)	0.089*** (3.069)
<i>Cus_Lev</i>	−0.206 (−1.060)	−0.205 (−1.054)
<i>Number</i>	−0.029* (−1.715)	−0.029* (−1.714)
<i>Forecasthorizon</i>	0.001*** (3.277)	0.001*** (3.276)
<i>Star</i>	−0.020 (−0.615)	−0.020 (−0.616)
<i>Experience</i>	0.006 (0.301)	0.006 (0.302)
<i>Firmexp</i>	−0.041 (−1.587)	−0.041 (−1.586)
<i>Brokerage_size</i>	0.022 (1.171)	0.022 (1.171)
<i>Retstd</i>	0.118 (0.141)	0.120 (0.143)
<i>Trading_vol</i>	−0.042 (−1.443)	−0.042 (−1.416)
<i>Volatility</i>	−0.002 (−0.051)	−0.001 (−0.042)
<i>Ind</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>Constant</i>	−0.013 (−0.018)	−0.009 (−0.012)
<i>Observations</i>	4,691	4,691
<i>F value</i>	34.74	34.17
<i>Adjusted-R²</i>	0.305	0.305

Table 8
Impact of dependence on customers.

	High dependence on customers		Low dependence on customers	
	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>
<i>Cus_RiskT</i>	−0.208*** (−7.978)		−0.001 (−0.038)	
<i>Cus_RiskF</i>		−0.330*** (−10.196)		0.040 (1.206)
<i>Cus_RiskP</i>		−0.019 (−0.472)		−0.051 (−1.366)
<i>Size</i>	−0.247*** (−11.733)	−0.248*** (−11.784)	−0.387*** (−22.138)	−0.388*** (−22.185)
<i>Lev</i>	0.890*** (7.032)	0.851*** (6.727)	1.347*** (10.847)	1.374*** (10.977)
<i>ROE</i>	−4.240*** (−22.053)	−4.331*** (−22.493)	−4.610*** (−23.709)	−4.618*** (−23.747)
<i>Big4</i>	−0.176*** (−3.421)	−0.185*** (−3.602)	0.034 (0.802)	0.034 (0.790)
<i>Top1</i>	−0.012*** (−7.446)	−0.012*** (−7.369)	0.005*** (4.015)	0.005*** (4.080)
<i>Director</i>	0.005 (0.913)	0.005 (0.961)	−0.005 (−1.428)	−0.005 (−1.449)
<i>RiskD</i>	0.048** (2.390)	0.053*** (2.619)	0.070*** (4.645)	0.070*** (4.678)
<i>Cus_ROE</i>	−0.007 (−0.044)	0.050 (0.329)	−0.775*** (−4.977)	−0.766*** (−4.919)
<i>Cus_Big4</i>	−0.103*** (−3.631)	−0.102*** (−3.581)	−0.130*** (−4.570)	−0.128*** (−4.504)
<i>Cus_Volatility</i>	0.140*** (7.179)	0.138*** (7.095)	0.045*** (2.759)	0.051*** (3.063)
<i>Cus_Lev</i>	−0.223* (−1.955)	−0.169 (−1.484)	0.127 (1.103)	0.105 (0.905)
<i>Number</i>	0.013 (0.806)	0.015 (0.915)	−0.036*** (−2.863)	−0.036*** (−2.854)
<i>Forecasthorizon</i>	0.001*** (4.943)	0.001*** (5.175)	0.001*** (4.560)	0.001*** (4.557)
<i>Star</i>	−0.070** (−2.538)	−0.072*** (−2.622)	−0.049** (−2.123)	−0.049** (−2.129)
<i>Experience</i>	−0.007 (−0.377)	−0.006 (−0.340)	0.017 (1.107)	0.017 (1.114)
<i>Firmexp</i>	−0.089*** (−4.152)	−0.087*** (−4.069)	−0.034* (−1.889)	−0.034* (−1.895)
<i>Brokerage_size</i>	0.016 (1.007)	0.015 (0.914)	−0.005 (−0.343)	−0.005 (−0.332)
<i>Retstd</i>	−4.777*** (−5.418)	−4.959*** (−5.629)	−1.755*** (−2.793)	−1.788*** (−2.845)
<i>Trading_vol</i>	0.102*** (5.269)	0.099*** (5.104)	0.141*** (8.019)	0.141*** (7.989)
<i>Volatility</i>	−0.013 (−0.582)	−0.010 (−0.449)	0.128*** (6.993)	0.121*** (6.462)
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Ind</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	1.557*** (3.054)	1.656*** (3.252)	1.857*** (3.000)	1.911*** (3.083)
<i>Observations</i>	13,711	13,711	10,314	10,314
<i>F value</i>	39.32	39.44	40.82	40.24
<i>Adjusted-R²</i>	0.159	0.161	0.196	0.197

Coefficient difference test between subsamples

(1), (3) $\chi^2(1) = 24.52$ Prob > $\chi^2 = 0.000$
 (2), (4) $\chi^2(1) = 53.02$ Prob > $\chi^2 = 0.000$

(Patatoukas, 2012; Geng et al., 2025). Thus, stable customers' textual risk information provides analysts with a more accurate reflection of the firm's actual risk exposure.

The grouping variable *Cus_Stable* is a dummy variable. It equals 1 when the firm has been a top five customer for at least 2 consecutive years, and 0 otherwise. Table 9 presents the results. In the stable customer subsample, the coefficients on *Cus_RiskT* and *Cus_RiskF* are negative and significant at the 1% level. In the non-stable customer subsample, the coefficient on *Cus_RiskT* is not statistically significant, while the coefficient on *Cus_RiskF* is significant and negative, but its magnitude is smaller than that in the stable customer subsample ($p < 0.01$). The above results suggest that textual risk information from stable customers is more useful to supplier analysts than such information from non-stable customers.

5.2. Impacts of customers' risk disclosure characteristics

5.2.1. Customers' information quality

Earnings management exacerbates information asymmetry and investor uncertainty (Abad et al., 2018; Beyer et al., 2019). In addition, firms may manage the tone of the words to complement earnings management efforts to disinform investors (Huang et al., 2014). Customers engaged in earnings management may manipulate their risk disclosures, thereby reducing their informativeness. Hence, textual risk information from customers with low earnings management is expected to be more useful for supplier analysts than such information from customers with high earnings management.

We use the accruals earnings management (AEM) of customer firms as a proxy for customers' information quality, which is calculated based on the non-linear Jones model (Banker et al., 2020). We split the sample into two subsamples based on the median of customers' AEM (*Cus_AEM*). The results are shown in Table 10. The absolute values of the coefficients on *Cus_RiskT* and *Cus_RiskF* are higher in the low *Cus_AEM* subsample than in the high *Cus_AEM* subsample. The p-values of the coefficient difference tests between the two subsamples are less than 0.05. The above results suggest that textual risk disclosures from low information quality customers are less informative to supplier analysts than such information from high information quality customers.

5.2.2. Customers' information timeliness

According to the theory of information economics, timely disclosure of information can reduce the time for insiders to take advantage of information to gain benefits, lower transaction costs and alleviate the problem of information asymmetry. Therefore, the timing of disclosure conveys different signals than those conveyed by annual reports (Chambers and Penman, 1984). Timely disclosure of information in annual reports can send a positive signal to the outside world about the quality of the firm's information (Wang et al., 2008). Thus, customers with timely annual report disclosures possess high information quality and their textual risk information is expected to be more useful for supplier analysts than such information from firms with less timely disclosures.

We measure customers' information timeliness as the number of days between the actual disclosure date and the fiscal year-end date. We split the sample into two subsamples based on the median of customers' information timeliness (*Cus_Timeliness*). The results are shown in Table 11. In the subsample with timely customer information, the absolute values of the coefficients on the risk information measurement indicators *Cus_RiskT* and *Cus_RiskF* are significantly higher than those in the subsample with less timely customer information. The p-values of the coefficient difference tests between the two subsamples are less than 0.01. The above results suggest that more timely textual risk disclosures from customers are more useful to supplier analysts than less timely disclosures.

5.2.3. Customers' information credibility

Information credibility is an important prerequisite for improving information utilization and reducing information asymmetry. Therefore, when customers' information is more credible, their textual risk information is expected to contain more information content and be more useful to supplier analysts than such information from customers with low information credibility.

Table 9
Impact of customer stability.

	Stable customers		Non-stable customers	
	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>
<i>Cus_RiskT</i>	−0.062*** (−2.831)		−0.002 (−0.074)	
<i>Cus_RiskF</i>		−0.211*** (−7.902)		−0.058** (−2.293)
<i>Cus_RiskP</i>		0.202*** (5.769)		0.121*** (3.276)
<i>Size</i>	−0.232*** (−12.208)	−0.230*** (−12.139)	−0.308*** (−19.356)	−0.308*** (−19.390)
<i>Lev</i>	1.073*** (9.359)	1.070*** (9.365)	0.998*** (8.017)	0.952*** (7.622)
<i>ROE</i>	−3.082*** (−17.600)	−3.129*** (−17.938)	−4.800*** (−29.100)	−4.885*** (−29.397)
<i>Big4</i>	−0.193*** (−4.490)	−0.188*** (−4.383)	−0.100** (−2.316)	−0.101** (−2.324)
<i>Top1</i>	−0.001 (−0.592)	−0.001 (−0.661)	0.000 (0.189)	0.000 (0.292)
<i>Director</i>	0.001 (0.265)	0.002 (0.976)	−0.005*** (−3.431)	−0.005*** (−2.904)
<i>RiskD</i>	0.033* (1.654)	0.061*** (3.018)	0.093*** (6.924)	0.093*** (6.954)
<i>Cus_ROE</i>	−1.194*** (−7.593)	−1.250*** (−7.981)	−0.173 (−1.265)	−0.068 (−0.487)
<i>Cus_Big4</i>	−0.063** (−2.356)	−0.053** (−2.008)	0.012 (0.453)	0.006 (0.230)
<i>Cus_Volatility</i>	0.112*** (6.762)	0.107*** (6.506)	0.088*** (4.801)	0.073*** (3.875)
<i>Cus_Lev</i>	−0.315*** (−2.987)	−0.357*** (−3.396)	0.289** (2.424)	0.348*** (2.901)
<i>Number</i>	−0.027 (−1.634)	−0.024 (−1.449)	−0.016 (−1.124)	−0.017 (−1.194)
<i>Forecasthorizon</i>	−0.000 (−1.144)	−0.000 (−0.947)	0.001*** (10.047)	0.001*** (9.971)
<i>Star</i>	−0.054* (−1.958)	−0.060** (−2.177)	−0.079*** (−3.087)	−0.079*** (−3.088)
<i>Experience</i>	−0.015 (−0.798)	−0.014 (−0.749)	0.013 (0.761)	0.013 (0.781)
<i>Firmexp</i>	−0.087*** (−3.991)	−0.083*** (−3.826)	−0.038* (−1.893)	−0.037* (−1.847)
<i>Brokerage_size</i>	0.001 (0.035)	−0.000 (−0.020)	−0.006 (−0.379)	−0.005 (−0.364)
<i>Retstd</i>	−4.608*** (−4.102)	−5.137*** (−4.587)	−0.308 (−0.549)	−0.303 (−0.541)
<i>Trading_vol</i>	0.056*** (3.649)	0.045*** (2.958)	0.146*** (12.010)	0.142*** (11.682)
<i>Volatility</i>	0.072*** (3.598)	0.079*** (3.946)	0.047** (2.259)	0.062*** (2.920)
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Ind</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	1.421*** (4.292)	1.522*** (4.616)	1.396*** (4.893)	1.465*** (5.126)
<i>Observations</i>	10,840	10,840	13,185	13,185
<i>F value</i>	36.42	39.25	115.0	110.7
<i>Adjusted-R²</i>	0.0647	0.0725	0.154	0.155

Coefficient difference test between subsamples

(1), (3) $\chi^2(1) = 3.67$ Prob > $\chi^2 = 0.055$

(2), (4) $\chi^2(1) = 16.18$ Prob > $\chi^2 = 0.000$

Table 10
Impact of customers' information quality.

	High <i>Cus_AEM</i>		Low <i>Cus_AEM</i>	
	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>
<i>Cus_RiskT</i>	0.044* (1.824)		−0.110*** (−3.795)	
<i>Cus_RiskF</i>		−0.033 (−0.999)		−0.143*** (−3.839)
<i>Cus_RiskP</i>		0.148*** (3.805)		−0.063 (−1.419)
<i>Size</i>	−0.410*** (−22.583)	−0.411*** (−22.670)	−0.207*** (−9.791)	−0.206*** (−9.717)
<i>Lev</i>	0.692*** (6.728)	0.658*** (6.361)	1.525*** (9.694)	1.524*** (9.690)
<i>ROE</i>	−4.472*** (−25.662)	−4.498*** (−25.800)	−4.557*** (−21.941)	−4.595*** (−21.940)
<i>Big4</i>	0.133*** (2.814)	0.125*** (2.643)	−0.171*** (−3.624)	−0.178*** (−3.752)
<i>Top1</i>	0.002 (1.226)	0.002 (1.307)	−0.005*** (−3.336)	−0.005*** (−3.366)
<i>Director</i>	−0.008* (−1.891)	−0.008* (−1.893)	0.016*** (3.488)	0.016*** (3.496)
<i>RiskD</i>	0.089*** (5.462)	0.091*** (5.565)	0.015 (0.800)	0.015 (0.793)
<i>Cus_ROE</i>	−0.502*** (−3.636)	−0.458*** (−3.306)	0.792*** (4.338)	0.818*** (4.460)
<i>Cus_Big4</i>	−0.055** (−2.170)	−0.057** (−2.244)	−0.114*** (−3.394)	−0.109*** (−3.249)
<i>Cus_Volatility</i>	0.040** (2.007)	0.032 (1.555)	0.103*** (5.992)	0.101*** (5.856)
<i>Cus_Lev</i>	0.259*** (2.605)	0.283*** (2.840)	−0.599*** (−4.226)	−0.586*** (−4.121)
<i>Number</i>	−0.012 (−0.857)	−0.011 (−0.827)	−0.012 (−0.767)	−0.012 (−0.735)
<i>Forecasthorizon</i>	0.001*** (9.110)	0.001*** (9.147)	0.000 (1.500)	0.000 (1.577)
<i>Star</i>	−0.019 (−0.776)	−0.019 (−0.782)	−0.096*** (−3.443)	−0.096*** (−3.450)
<i>Experience</i>	−0.011 (−0.678)	−0.010 (−0.652)	0.011 (0.592)	0.011 (0.595)
<i>Firmexp</i>	−0.038** (−1.987)	−0.037* (−1.930)	−0.094*** (−4.394)	−0.094*** (−4.400)
<i>Brokerage_size</i>	−0.011 (−0.759)	−0.012 (−0.847)	0.023 (1.410)	0.023 (1.417)
<i>Retstd</i>	−6.269*** (−6.504)	−6.173*** (−6.403)	−1.003 (−1.434)	−1.064 (−1.518)
<i>Trading_vol</i>	0.145*** (8.167)	0.149*** (8.405)	0.129*** (6.599)	0.126*** (6.381)
<i>Volatility</i>	0.168*** (7.601)	0.176*** (7.921)	−0.057*** (−2.674)	−0.054** (−2.534)
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Ind</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	2.733*** (5.419)	2.666*** (5.286)	0.248 (0.489)	0.288 (0.568)
<i>Observations</i>	11,926	11,926	12,099	12,099
<i>F value</i>	51.20	50.67	32.18	31.73
<i>Adjusted-R²</i>	0.224	0.225	0.146	0.146

Coefficient difference test between subsamples
 (1), (3) $\chi^2(1) = 11.30$ Prob > $\chi^2 = 0.000$
 (2), (4) $\chi^2(1) = 4.91$ Prob > $\chi^2 = 0.027$

Table 11
Impact of customers' information timeliness.

	More timely customer information		Less timely customer information	
	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>
<i>Cus_RiskT</i>	−0.152*** (−6.440)		0.037 (1.311)	
<i>Cus_RiskF</i>		−0.226*** (−7.353)		−0.043 (−1.202)
<i>Cus_RiskP</i>		−0.038 (−1.003)		0.147*** (3.538)
<i>Size</i>	−0.347*** (−20.161)	−0.346*** (−20.066)	−0.235*** (−8.285)	−0.249*** (−8.699)
<i>Lev</i>	1.244*** (12.019)	1.212*** (11.674)	0.781*** (4.221)	0.811*** (4.383)
<i>ROE</i>	−4.813*** (−26.960)	−4.851*** (−27.140)	−3.370*** (−14.999)	−3.457*** (−15.308)
<i>Big4</i>	−0.148*** (−3.768)	−0.156*** (−3.972)	−0.187*** (−2.787)	−0.193*** (−2.882)
<i>Top1</i>	−0.002** (−2.378)	−0.002** (−2.244)	−0.235** (−2.257)	−0.208** (−1.990)
<i>Director</i>	−0.003 (−1.009)	−0.003 (−1.018)	1.149*** (4.528)	1.201*** (4.727)
<i>RiskD</i>	0.011 (0.756)	0.010 (0.710)	0.149*** (5.601)	0.163*** (6.076)
<i>Cus_ROE</i>	−0.298** (−2.009)	−0.258* (−1.734)	−0.349** (−2.048)	−0.335** (−1.972)
<i>Cus_Big4</i>	−0.071*** (−2.739)	−0.061** (−2.366)	−0.180*** (−4.920)	−0.186*** (−5.091)
<i>Cus_Volatility</i>	0.116*** (6.739)	0.110*** (6.383)	−0.029 (−1.548)	−0.039** (−2.049)
<i>Cus_Lev</i>	−0.513*** (−5.202)	−0.489*** (−4.948)	0.870*** (5.476)	0.908*** (5.709)
<i>Number</i>	−0.012 (−0.948)	−0.012 (−0.962)	0.009 (0.473)	0.011 (0.567)
<i>Forecasthorizon</i>	0.001*** (6.975)	0.001*** (6.988)	−0.000 (−1.143)	−0.000 (−0.988)
<i>Star</i>	−0.084*** (−3.483)	−0.085*** (−3.545)	−0.043 (−1.558)	−0.042 (−1.519)
<i>Experience</i>	0.015 (0.954)	0.015 (0.955)	−0.026 (−1.346)	−0.025 (−1.301)
<i>Firmexp</i>	−0.073*** (−3.937)	−0.072*** (−3.883)	−0.031 (−1.388)	−0.031 (−1.389)
<i>Brokerage_size</i>	0.011 (0.817)	0.011 (0.783)	0.003 (0.186)	0.002 (0.099)
<i>Retstd</i>	−2.347*** (−4.122)	−2.363*** (−4.151)	0.843 (0.219)	−0.365 (−0.094)
<i>Trading_vol</i>	0.111*** (6.603)	0.111*** (6.597)	0.112*** (4.046)	0.118*** (4.266)
<i>Volatility</i>	0.093*** (4.703)	0.100*** (5.017)	0.084*** (3.779)	0.097*** (4.302)
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Ind</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	1.791*** (4.345)	1.787*** (4.338)	0.820 (1.524)	0.917* (1.704)
<i>Observations</i>	10,657	10,657	13,368	13,368
<i>F value</i>	51.75	51.25	25.25	25.09
<i>Adjusted-R²</i>	0.176	0.176	0.159	0.161
Coefficient difference test between subsamples	(1), (3) $\chi^2(1) = 21.72$ Prob > $\chi^2 = 0.000$ (2), (4) $\chi^2(1) = 14.64$ Prob > $\chi^2 = 0.000$			

Table 12
Impact of customers' information credibility.

	High-credibility customers		Low-credibility customers	
	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>
<i>Cus_RiskT</i>	−0.178*** (−9.758)		0.255*** (5.283)	
<i>Cus_RiskF</i>		−0.179*** (−7.646)		0.018 (0.262)
<i>Cus_RiskP</i>		−0.177*** (−6.016)		0.571*** (7.107)
<i>Size</i>	−0.198*** (−13.397)	−0.198*** (−13.394)	−0.483*** (−14.238)	−0.490*** (−14.476)
<i>Lev</i>	0.766*** (8.359)	0.766*** (8.343)	2.451*** (10.697)	2.354*** (10.256)
<i>ROE</i>	−3.216*** (−23.006)	−3.217*** (−22.974)	−8.697*** (−21.935)	−8.863*** (−22.319)
<i>Big4</i>	−0.055* (−1.706)	−0.055* (−1.707)	−0.078 (−0.750)	−0.078 (−0.752)
<i>Top1</i>	−0.002** (−2.069)	−0.002** (−2.068)	0.005*** (2.711)	0.005*** (2.687)
<i>Director</i>	0.016*** (4.086)	0.016*** (4.086)	−0.023*** (−4.146)	−0.024*** (−4.269)
<i>RiskD</i>	0.096*** (7.051)	0.096*** (7.049)	−0.045 (−1.558)	−0.045 (−1.555)
<i>Cus_ROE</i>	−0.539*** (−4.908)	−0.538*** (−4.895)	1.203*** (3.509)	1.375*** (3.998)
<i>Cus_Big4</i>	−0.078*** (−3.864)	−0.078*** (−3.856)	−0.074 (−1.198)	−0.100 (−1.614)
<i>Cus_Volatility</i>	0.063*** (4.675)	0.063*** (4.627)	0.189*** (5.521)	0.182*** (5.320)
<i>Cus_Lev</i>	−0.177** (−2.139)	−0.176** (−2.131)	−0.614*** (−2.601)	−0.510** (−2.158)
<i>Number</i>	−0.017 (−1.424)	−0.017 (−1.423)	−0.002 (−0.071)	0.000 (0.016)
<i>Forecasthorizon</i>	0.000** (2.195)	0.000** (2.196)	0.001*** (6.147)	0.001*** (6.366)
<i>Star</i>	−0.031 (−1.601)	−0.031 (−1.601)	−0.137*** (−3.126)	−0.139*** (−3.175)
<i>Experience</i>	0.001 (0.108)	0.001 (0.108)	0.000 (0.007)	0.001 (0.031)
<i>Firmexp</i>	−0.069*** (−4.540)	−0.069*** (−4.538)	−0.047 (−1.375)	−0.045 (−1.343)
<i>Brokerage_size</i>	−0.012 (−1.038)	−0.012 (−1.038)	0.066*** (2.607)	0.063** (2.503)
<i>Retstd</i>	−2.528*** (−3.891)	−2.529*** (−3.891)	−0.629 (−0.638)	−0.389 (−0.395)
<i>Trading_vol</i>	0.102*** (7.346)	0.102*** (7.344)	0.126*** (4.012)	0.132*** (4.191)
<i>Volatility</i>	−0.013 (−0.823)	−0.013 (−0.807)	0.142*** (3.746)	0.149*** (3.955)
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Ind</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	0.745** (1.984)	0.745** (1.983)	2.640** (2.449)	2.698** (2.508)
<i>Observations</i>	14,050	14,050	9,975	9,975
<i>F value</i>	38.87	38.31	47.85	47.67
<i>Adjusted-R²</i>	0.124	0.124	0.334	0.337

Coefficients differences test between subsamples

(1), (3) $\chi^2(1) = 33.26$ Prob > $\chi^2 = 0.000$ (2), (4) $\chi^2(1) = 15.61$ Prob > $\chi^2 = 0.000$

Following Wei et al. (2017), we adopt customer reputation as a proxy for customers' information credibility and measure customer reputation based on the proportion of positive news reports about the customer firm in the financial news reports from the CNRDS database. This database can accurately determine the sentiment of firms' news coverage through data cleansing, expert judgment and the combination of artificial intelligence algorithms. We split the sample into two subsamples based on the median score of customers' information credibility (*Cus_Credibility*). The results are shown in Table 12. The results indicate that in the high-credibility customer subsample, the coefficients on *Cus_RiskT* and *Cus_RiskF* are significant and negative ($p < 0.01$), whereas they are positive in the low-credibility customer subsample. Furthermore, there exists a statistically significant difference between the coefficients of these two subsamples ($p < 0.01$).

5.3. Impacts of firms' information environment

The accuracy of analysts' forecasts is closely related to firms' information environment. When a firm's information environment is poor, analysts will seek alternative sources of information, and the effects of customers' textual risk disclosure will be more pronounced.

We use *AEM*, calculated using the non-linear Jones model (Banker et al., 2020), to measure firms' information environment and split the sample into two subsamples based on its median. The results are presented in Table 13. The coefficients on *Cus_RiskT* and *Cus_RiskF* are significant and negative in the subsample of firms with poor information environments, while in the subsample of firms with good information environments, the coefficients are not significant. The *p*-values of the coefficient difference tests between the two subsamples are less than 0.05.

5.4. Impact on information access behavior

Site visits are an important type of information acquisition activity for analysts (Cheng et al., 2016), although they are also costly due to the travel expenses (Chen et al., 2022). If customers' textual risk disclosure is an effective information source for analysts, it will reduce analysts' use of other high-cost information acquisition channels. To test the above conjecture, we use the following regression model:

$$SV_{i,j,t} = a_0 + a_1 Cus_Risk_{j,t-1} + Controls + Ind + Year + e \quad (3)$$

where the explanatory variable $SV_{i,j,t}$ is the frequency of analyst *i*'s site visits to firm *j* in year *t*. Following Chen et al. (2021) and Han et al. (2018), we control firms' risk disclosure (*RiskD*), institutional ownership ratio (*Inshold*), analyst attention (*Number*), earnings quality (*AEM*), Big 4 accounting firm indicator (*Big4*), earnings volatility (*Volatility*), return on equity (*ROE*), intangible asset (*Intang*), nature of equity (*SOE*) and firm size (*Size*).

The data of site visits is sourced from the CSMAR database. The Shenzhen Stock Exchange has required listed companies to disclose information about site visit activities since 2012. Therefore, this sample includes A-share companies listed on the Shenzhen Stock Exchange during the 2012 to 2019 period.

The results are shown in Table 14. The coefficients on *Cus_RiskT* and *Cus_RiskF* are significant and negative, indicating that the more textual risk disclosures there are in customers' annual reports, the lower the frequency of analysts' site visits to firms. These results suggest that customers' textual risk disclosure is an important substitute for analysts' site visits.

6. Conclusions

This paper's findings support the information view perspective on risk information disclosure and suggest that customers' textual risk disclosure helps suppliers' analysts make more accurate earnings forecasts.

Table 13
Impact of firms' information environment.

	High <i>AEM</i>		Low <i>AEM</i>	
	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>
<i>Cus_RiskT</i>	−0.125*** (−5.317)		−0.017 (−0.592)	
<i>Cus_RiskF</i>		−0.235*** (−7.522)		−0.047 (−1.298)
<i>Cus_RiskP</i>		0.017 (0.470)		0.034 (0.718)
<i>Size</i>	−0.329*** (−18.433)	−0.329*** (−18.491)	−0.283*** (−12.749)	−0.281*** (−12.678)
<i>Lev</i>	0.954*** (8.173)	0.904*** (7.737)	1.351*** (9.697)	1.347*** (9.666)
<i>ROE</i>	−4.152*** (−24.026)	−4.216*** (−24.362)	−4.330*** (−20.624)	−4.366*** (−20.634)
<i>Big4</i>	−0.113*** (−2.616)	−0.132*** (−3.040)	−0.129*** (−2.601)	−0.132*** (−2.654)
<i>Top1</i>	0.000 (0.024)	0.000 (0.042)	−0.003** (−2.089)	−0.003** (−2.005)
<i>Director</i>	−0.010** (−2.469)	−0.010** (−2.527)	0.013** (2.543)	0.013** (2.546)
<i>RiskD</i>	0.177*** (10.357)	0.178*** (10.425)	−0.043** (−2.339)	−0.043** (−2.325)
<i>Cus_ROE</i>	−0.595*** (−3.911)	−0.553*** (−3.632)	−0.190 (−1.162)	−0.159 (−0.961)
<i>Cus_Big4</i>	−0.049* (−1.803)	−0.041 (−1.510)	−0.009 (−0.298)	−0.011 (−0.367)
<i>Cus_Volatility</i>	0.014 (0.717)	−0.001 (−0.027)	0.135*** (7.566)	0.134*** (7.492)
<i>Cus_Lev</i>	0.190* (1.809)	0.234** (2.223)	−0.610*** (−4.769)	−0.603*** (−4.703)
<i>Number</i>	−0.000 (−0.019)	0.001 (0.072)	−0.013 (−0.840)	−0.014 (−0.865)
<i>Forecasthorizon</i>	0.000** (2.135)	0.000** (2.287)	0.001*** (6.804)	0.001*** (6.805)
<i>Star</i>	−0.038 (−1.531)	−0.039 (−1.575)	−0.090*** (−3.290)	−0.090*** (−3.303)
<i>Experience</i>	0.001 (0.042)	0.001 (0.036)	−0.002 (−0.119)	−0.002 (−0.109)
<i>Firmexp</i>	−0.039** (−2.030)	−0.038* (−1.948)	−0.093*** (−4.367)	−0.093*** (−4.353)
<i>Brokerage_size</i>	−0.004 (−0.268)	−0.005 (−0.317)	0.009 (0.563)	0.009 (0.545)
<i>Retstd</i>	−2.112*** (−3.459)	−2.116*** (−3.470)	−8.662*** (−7.139)	−8.583*** (−7.066)
<i>Trading_vol</i>	0.061*** (3.512)	0.067*** (3.850)	0.139*** (6.543)	0.137*** (6.449)
<i>Volatility</i>	0.156*** (7.276)	0.171*** (7.903)	−0.015 (−0.682)	−0.014 (−0.612)
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Ind</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	2.785*** (5.674)	2.734*** (5.574)	1.232** (2.261)	1.234** (2.266)
<i>Observations</i>	12,267	12,267	11,758	11,758
<i>F value</i>	41.18	41.09	36.54	36.03
<i>Adjusted-R²</i>	0.183	0.185	0.169	0.169

Coefficient difference test between subsamples

(1), (3) $\chi^2(1) = 5.26$ Prob > $\chi^2 = 0.021$

(2), (4) $\chi^2(1) = 12.80$ Prob > $\chi^2 = 0.000$

Table 14
Regressions of analysts' site visits on customers' textual risk disclosure.

	(1) <i>SV</i>	(2) <i>SV</i>
<i>Cus_RiskT</i>	−0.420*** (−2.921)	
<i>Cus_RiskF</i>		−1.492*** (−8.021)
<i>Cus_RiskP</i>		1.023*** (4.767)
<i>RiskD</i>	−1.268*** (−7.511)	−1.157*** (−6.865)
<i>Inshold</i>	−2.462*** (−6.745)	−2.821*** (−7.715)
<i>AEM</i>	0.942 (0.890)	0.685 (0.650)
<i>Big4</i>	−0.576 (−1.183)	−0.752 (−1.550)
<i>Volatility</i>	−0.651*** (−6.951)	−0.610*** (−6.534)
<i>ROE</i>	−3.692*** (−2.819)	−3.925*** (−3.009)
<i>Intang</i>	−9.814*** (−4.991)	−10.740*** (−5.478)
<i>SOE</i>	2.822*** (14.936)	2.969*** (15.725)
<i>Size</i>	−0.087 (−0.775)	−0.139 (−1.252)
<i>Number</i>	−0.009*** (−10.127)	−0.010*** (−11.191)
<i>Forecasthorizon</i>	0.001 (0.328)	0.002 (0.752)
<i>Star</i>	0.053 (0.335)	0.056 (0.359)
<i>Experience</i>	−0.115 (−1.134)	−0.119 (−1.176)
<i>Firmexp</i>	−0.134 (−1.060)	−0.110 (−0.875)
<i>Brokerage_size</i>	0.045 (0.467)	0.024 (0.252)
<i>Year</i>	Yes	Yes
<i>Ind</i>	Yes	Yes
<i>Constant</i>	13.958*** (6.532)	14.634*** (6.874)
<i>Observations</i>	9,601	9,601
<i>F value</i>	80.72	86.37
<i>Adjusted-R²</i>	0.338	0.344

Extending this hypothesis, we test whether both current and future risk disclosure contribute to the forecast accuracy of supplier analysts. We also conduct several cross-sectional tests based on different supplier–customer relationships and different levels of information access. As the first study to address the impact of customers' textual risk disclosure on analyst behavior, these results provide important initial evidence that a firm's textual risk disclosure matters not only to decisions within the supply chain but also to the behaviors of external stakeholders—particularly, supplier firms' analysts.

Our analyses of the behavior of supplier firms' analysts reveal the following. First, their forecast error is negatively associated with major customers' textual risk disclosure (measured by risk keywords) in the MD&A section, with this negative relationship primarily driven by customers' future risk disclosure rather than their current risk disclosure. Second, the negative relationship becomes more pronounced in scenarios involving close or stable supplier–customer relationships, high customer information quality and poor firm information environments. Finally, the channel test demonstrates that customer textual risk disclosure can reduce the necessity for analysts to conduct site visits to supplier firms. These results are robust to a battery of robustness checks.

Our findings indicate that customers' textual risk disclosure has a significant spillover effect across the supply chain, offering analysts additional information to better understand supplier firms' risk and formulate accurate earnings forecasts. This disclosure mechanism even serves as a partial substitute for other information sources that analysts typically rely on, such as site visits. Furthermore, supplier–customer relationship characteristics and customers' information quality exert substantial influence on the impacts of customer textual risk disclosure.

This study has important implications for both the theoretical understanding and practical application of risk disclosure. From a theoretical standpoint, our study provides important insights into the dynamics of information flow within supply chains and the role of customers' textual risk disclosure in shaping supplier analysts' behavior. On a practical level, this paper has policy implications, offering valuable insights for regulators in emerging markets as they formulate and refine disclosure requirements for textual risk information. Additionally, it identifies new information channels for capital market participants seeking to understand the risk information of listed firms.

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Declaration of competing interest

Authors declares that he/she has no conflict of interest.

Appendix 1. Variable definitions

Table A1. Variable definitions.

Variable Type	Variable	Definition
Dependent variable	<i>Error</i>	$ \text{Analyst forecast EPS} - \text{Firm actual EPS} / \text{Firm actual EPS} $
Explanatory variables	<i>Cus_RiskT</i>	(Frequency of risk keywords in customer's MD&A / Total number of words in customer's MD&A) $\times$ 100
	<i>Cus_RiskF</i>	(Frequency of risk keywords within 10 words from the forward-looking keywords in the customer's MD&A / Total number of words in the MD&A) $\times$ 100
	<i>Cus_RiskP</i>	$Cus_RiskT - Cus_RiskF$

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Table A1. (continued)

Variable Type	Variable	Definition
Grouping Variables	<i>Cus_HHI</i>	Herfindahl index of sales revenue share of top five customers
	<i>Cus_Stable</i>	A dummy variable that equals 1 when the firm has been a top five customers for at least 2 consecutive years, and 0 otherwise.
	<i>Cus_AEM</i>	Absolute value of the customer's accruals earnings management indicator, which is calculated based on the non-linear Jones model (Banker et al., 2020)
	<i>Cus_Timeliness</i>	The number of days between the actual disclosure date and the fiscal year-end date of the customer firms
	<i>Cus_Credibility</i>	The proportion of news reports about the customer firm that are positive among the financial news reports
	<i>AEM</i>	Absolute value of the supplier's accruals earnings management indicator, which is calculated based on the non-linear Jones model (Banker et al., 2020)
Control variables	<i>Size</i>	Natural logarithm of total assets
	<i>Lev</i>	Total liabilities / Total assets
	<i>ROE</i>	Net income / Net assets
	<i>Big4</i>	A dummy variable that is equal to 1 if the auditor is from a Big 4 accounting firm, and 0 otherwise
	<i>Top1</i>	Shareholding percentage of the largest shareholder $\times 100$
	<i>Director</i>	Number of independent directors / Total number of directors $\times 100$
	<i>RiskD</i>	Frequency of risk keywords in firm's MD&A / Total number of words in firm's MD&A) $\times 100$
	<i>Cus_ROE</i>	Customer net profit / Net assets
	<i>Cus_Big4</i>	A dummy variable that is equal to 1 if the auditor of the customer is a Big 4 accounting firm, and 0 otherwise
	<i>Cus_Volatility</i>	The natural logarithm of the standard deviation of a customer's net profit over the past 3 years.
	<i>Cus_Lev</i>	Customer total liabilities / Total assets
	<i>Number</i>	The natural logarithm of the number of analyst reports about the firm
	<i>Forecasthorizon</i>	The natural logarithm of the number of days spanning from the date when an analyst issues the latest earnings forecast to the end date of the annual report.
	<i>Star</i>	A dummy variable that is equal to 1 if the analyst was awarded a star analyst rating by New Fortune Magazine in the previous year, and 0 otherwise
	<i>Experience</i>	The natural logarithm of the number of years between the analyst's first forecast for any firm in the database and the date of the current forecast plus 1
	<i>Firmexp</i>	The natural logarithm of the number of years between the analyst's first forecast for the firm and the date of the current forecast plus 1
	<i>Brokerage_size</i>	The natural logarithm of total number of analysts employed by the brokerage firm at the end of the year
	<i>Retstd</i>	The annual standard deviation of the firm's daily stock returns
	<i>Trading_vol</i>	The stock turnover rate of the firm
	<i>Volatility</i>	The natural logarithm of the standard deviation of a firm's net profit over the past 3 years.
	<i>Ind</i>	Dummy variables of industry
	<i>Year</i>	Dummy variables of year

Table A1. (continued)

Variable Type	Variable	Definition
Other variables	<i>Risk_indu</i>	The industry-average annual report risk disclosure levels of peer customer firms in the same year and industry
	<i>Cus_RiskT2</i>	(Frequency of risk keywords in customer's MD&A / Total number of words in customer's MD&A) $\times$ 100 – Average <i>Cus_RiskT</i> for the customer's industry
	<i>Cus_RiskF2</i>	(Frequency of risk keywords within 10 words from the forward-looking keywords in the customer's MD&A / Total number of words in the MD&A) $\times$ 100 – Average <i>Cus_RiskF</i> for the customer's industry
	<i>Cus_RiskP2</i>	<i>Cus_RiskT2</i> – <i>Cus_RiskF2</i>
	<i>Cus_RiskT3</i>	(Frequency of sentences containing risk-related keywords in customer's MD&A / Total number of sentences in customer's MD&A) $\times$ 100
	<i>Cus_RiskF3</i>	(Frequency of sentences containing both risk-related and future keywords in the customer's MD&A / Total number of sentences in the MD&A) $\times$ 100
	<i>Cus_RiskP3</i>	<i>Cus_RiskT3</i> – <i>Cus_RiskF3</i>
	<i>Fbias</i>	(Analyst's latest earnings forecast – Firm's actual earnings) / Firm's actual earnings
	<i>Dispersion</i>	The standard deviation of the latest earnings forecast issued by all analysts following the firm.
	<i>Consensusfe</i>	The average absolute forecast error of the latest earnings forecast issued by each analyst for a firm
	<i>SV</i>	The frequency of analysts' site visits
	<i>Inshold</i>	Institutional holdings shares / Total shares
	<i>Intang</i>	Intangible asset / Total assets
	<i>SOE</i>	A dummy variable that is equal to 1 if the firm is a state-owned enterprise, and 0 otherwise

Table A2

Summary statistics for other variables.

Variables	Observations	Mean	STD	Median	Minimum	Maximum
<i>Cus_RiskF</i>	24,025	0.982	0.658	0.868	0	3.702
<i>Cus_RiskP</i>	24,025	0.665	0.325	0.588	0.108	2.427
<i>Cus_RiskT2</i>	24,025	–0.0673	0.512	–0.0261	–1.463	1.604
<i>Cus_RiskF2</i>	24,025	–0.0344	0.463	–0.0132	–1.947	1.604
<i>Cus_RiskP2</i>	24,025	–0.0328	0.168	0	–0.597	0.510
<i>Cus_RiskT3</i>	24,025	1.359	0.618	1.254	0.375	3.309
<i>Cus_RiskF3</i>	24,025	0.999	0.468	0.917	0.101	2.495

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Table A2 (continued)

Variables	Observations	Mean	STD	Median	Minimum	Maximum
<i>Cus_RiskP3</i>	24,025	0.360	0.671	0	0	2.482
<i>Fbias</i>	24,025	0.336	1.108	0.0476	−0.675	8.250
<i>Dispersion</i>	24,025	0.153	0.113	0.127	0.0165	0.609
<i>Consensusfe</i>	24,025	0.00914	0.00906	0.00663	0.00115	0.0616
<i>Cus_HHI</i>	24,025	0.0391	0.0709	0.0121	1.20e-05	0.454
<i>Cus_Stable</i>	24,025	0.451	0.498	0	0	1
<i>Cus_AEM</i>	24,025	0.129	0.113	0.101	0	0.642
<i>Cus_Timeliness</i>	24,025	69.95	43.68	87	0	120
<i>Cus_Credibility</i>	24,025	0.388	0.425	0.231	0	1.333
<i>AEM</i>	24,025	0.130	0.122	0.0962	0	0.668
<i>SV</i>	9601	2.328	7.488	0	0	41
<i>Inshold</i>	9601	0.501	0.247	0.568	0.018	0.860
<i>Intang</i>	9601	0.038	0.036	0.029	0	0.170
<i>SOE</i>	9601	0.399	0.490	0	0	1

Appendix 2. Process of identifying risk-related keywords

This paper adopts a method that combines “seed words” with “Word2Vec similar word expansion” to identify risk keywords. First, we translate the risk vocabularies in Campbell et al. (2014) and Kravet and Muslu (2013) into Chinese for the Chinese context. Second, we supplement this risk vocabulary by referring to the descriptions and classifications of risk events in the DIB Internal Control and Risk Management Database. We then conduct a manual review of the MD&A documents of 200 randomly selected company annual reports to semantically confirm the validity of the risk seed words identified in the previous steps. We remove any terms that clearly lack risk connotations, ultimately forming a set of 100 risk seed words. Third, we use the unsupervised Word2Vec statistical language model, a machine learning algorithm, to expand the list to include words similar to the identified risk seed words, ultimately obtaining 414 risk keywords through the Word2Vec algorithm.

Risk-related Keywords

Abnormal	Conflict	Disruption	Harsh	Lagging behind	Overdue	Revision	Technological backwardness
Absence	Confront	Distress	Harsh environment	Landslide	Overload	Rising costs	Tension
Accident	Confrontation	Divergence	Hazard	Lead to	Overproduction	Rising winds	Termination
Adding insult to injury	Constitute a threat	Downgrade	High difficulty	Leak of information	Oversight	Risk	Terrorism
Administrative penalties	Constraint	Downward trend	High energy consumption	Legacy issues	Over-supply	Riskiness	Thin
Adverse	Contain	Drop	High energy usage	Legal dispute	Panic	Safety hazard	Threat
Adverse impact	Continuous emergence	Economic backwardness	High pollution	Lethargy	Paralysis	Safety incident	Tight funding
Against the trend	Contract dispute	Economic burden	High pressure	Limit	Passive	Scarcity	Tightening
Aging	Contradiction	Economic crisis	Homogenization	Limitations	Penalty	Scarcity factor	Time-consuming
Ambiguous	Contradictory	Economic downturn	Human error	Limited	Plummet	Seasonality	Time-sensitive
Arduous	Controlled	Economic fluctuations	Illegal	Litigation	Political crisis	Sensitive	Tough problem
Arrears	Counterfeit	Economic losses	Illegal behavior	Loan limit	Poor	Serious	Trade barriers
Attack	Credit risk	Economic recession	Illegal infringement	Loan risk	Poor capability	Serious circumstances	Transformation
Backlog	Crisis	Economic sanctions	Imbalance	Loopholes	Poor condition	Serious consequences	Transition
Bad debts	Critical period	Elimination	Imminent	Loss	Poor management	Severe	Trap
Bankruptcy	Cultural differences	Emergency	Impact	Low level	Postponement	Severe blow	Trigger
Barrier	Currency depreciation	Encounter	Impairment	Low position	Potential	Severe situation	Turmoil
Blind development	Cutthroat competition	Endanger	Improper	Low speed	Powerless	Shock	Uncertainty

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Risk-related Keywords							
Blind investment	Damage	Energy consumption	Improper handling	Major event	Pressing need	Shortage	Unclear
Blocked	Danger	Environmental pollution	In conflict	Major loss	Pressure	Shrinkage	Uncontrollable
Bottleneck	Debt	Environmental pressure	Inaccurate	Malfunction	Prevent	Shutdown	Under-supply
Break below	Decelerate	Error	Increase	Malice	Price competition	Sink	Unexpected event
Burden	Decline	Escalating	Increasingly intense	Malignant	Price decrease	Slide	Unknown
Business losses	Decrease	Event	Increasingly severe	Mandatory	Price drop	Slow	Unlimited
Business rectification	Decrease in quantity	Exceeding budget	Increasingly strict	Market contraction	Price increase	Slow development	Unprecedented
Business suspension	Default	Exclusion	Indebtedness	Military conflict	Price limit	Slow progress	Unpredictable change
Cancellation	Default risk	Experience	Indifference	Minimal effect	Price undercutting	Slowdown	Unreasonable
Cannot be ignored	Defect	Expose	Ineffective	Misjudgment	Price war	Slump	Unrecoverable
Casualties	Deficiency	Extreme	Ineffective measures	Mismatch	Production cut	Spread	Unrest
Catastrophic Challenge	Delay	Face	Inevitable	Misoperation	Production halt	Squeeze	Unsold
	Delayed	Fade	Infectious	Missed opportunity	Production limit	Squeeze out	Unstable
Challenging tasks	Delisting	Failure	Inferior counterfeit products	Mistake	Property loss	Stagnation	Ups and downs
Chaos	Deny	Fall into	Inflation	Mixed quality	Protraction	Stimulus	Urgency
Chaotic management	Dependence	Falsification	Infringe	Mutation	Purchase limit	Storm	Urgent
Climate anomalies	Depreciation	Financial crisis	Infringing behavior	Narrowing	Quality incident	Strict control	Urgent need
Climate change	Destruction	Financial risk	Insolvency	Negative	Rapid changes	Strike	Urgently need to be resolved

(continued)

Risk-related Keywords						
Collapse	Deteriorate	Fire incident	Insufficient	Negative effect	Rebound	Stringent control
Compel	Deteriorating relations	Flood	Insufficient funds	Negative growth	Recession	Struggle
Compensate	Deviation	Fluctuation	Insufficient momentum	Negative impact	Rectification	Struggling to make progress
Compensation	Difference	Force	Insufficient personnel	Neglect	Reduce	Sudden outbreak
Compensation claim	Difficult	Force majeure	Intense	Negligence	Reduction	Suddenly
Compensation for losses	Difficult and tortuous	Forced	Intensify	Non-compliance	Reduction rate	Suffer
Competition	Difficult points	Fraud	International competition	Obstacle	Redundancy	Suffer losses
Competitor	Difficulties	Friction	International dispute	Obstruct	Regional conflict	Supply limit
Complaint	Difficulty	Funding shortage	Interruption	Occupy	Regression	Supply suspension
Complex	Difficulty in financing	Gap	Intervention	Off-season	Regulation	Supply-demand contradiction
Complex and diverse	Dilemma	Governance	Invalid	Operational error	Regulatory breach	Suppress
Complex and variable	Disadvantages	Growing pains	Irreversible	Operational risk	Remain high	Suppression
Complexity	Disaster	Growing seriousness	Lack	Operations suspension	Reorganization	Survival of the fittest
Compression	Disparity	Hard to	Lack of experience	Oppression	Resistance	Suspend operations
Compulsory	Dispute	Harm	Lack of vigor	Outbreak	Restricted	Suspension
Conceal	Disputes	Harmful	Lag	Overcapacity	Restriction	Talent drain
						Work error
						Withdrawal
						Withstand
						Work error

Appendix 3. Process for identifying future-related keywords

This paper adopts a method that combines the seed word method with the Word2Vec similar-word expansion method to identify future-related keywords. First, we translate the risk vocabulary disclosed by Li (2010) into Chinese for the Chinese context. Second, we manually review the MD&A documents from the annual reports of 200 randomly selected companies, semantically confirming the risk seed words obtained from the previous two steps. We then remove any terms that clearly lack future connotations and ultimately form a set of 20 future seed words. Third, we use the unsupervised Word2Vec statistical language model from machine learning algorithms to identify similar words based on the identified future seed words, ultimately deriving 61 future keywords using the Word2Vec algorithm.

Future-related Keywords						
Advance	Develop	Forward-looking	In the days to come	Might	Project	Sustainability
Anticipate	Development prospects	Further	In the future	New round	Recent	Tend to
Awaiting	Estimate	Future	In the short term	Objective	Second half of the year	Trend
Believe	Expect	Goal	Increasingly	Opportunity	Seek	Upcoming
Blueprint	Expectation	Going forward	Indicate	Outlook	Short time	Urgently needed
Can	Follow-up	Going to	Intend	Pending	Short-term	Will
Contingency plan	Forecast	Gradually	Long-term	Plan	Should	Year by year
Continue	Foreknowledge	Hope	Market prospects	Prefabricated	Strategic objectives	
Could	Foresee	Implementation plan	May	Progress	Strategic planning	

Appendix 4. Double cross-sectional analysis

Supplier firms with good disclosure quality tend to select customers with similarly strong disclosure practices. To address this self-selection bias and ensure the robustness of our findings, we conduct a double cross-sectional analysis based on both customer and supplier disclosure quality measures. We use real earnings management (*AEM*) as our proxy for disclosure quality, where higher *AEM* values indicate poorer disclosure practices. We divide the sample into quartiles based on whether both customer (*Cus_AEM*) and supplier (*AEM*) firms' earnings management levels are above or below their respective medians.

The results in Table A3, columns (5) – (8) demonstrate that *Cus_RiskT* exhibits statistically significant negative coefficients in both the Low *AEM* & Low *Cus_AEM* and High *AEM* & Low *Cus_AEM* subsamples, confirming that customers' risk information retains its value regardless of the suppliers' information environment when customer disclosure quality is high. Notably, even in the High *AEM* & High *Cus_AEM* subsample (poorest disclosure quality), future risk information (*Cus_RiskF*) remains significant at the 5% level. These findings indicate that our core conclusions are not driven by endogenous matching, as the informational effects of customer risk disclosures remain consistent across varying levels of supply chain disclosure quality.

Table A3

Cross-sectional tests based on customer and supplier information environments.

	High <i>AEM</i> & High <i>Cus_AEM</i>		Low <i>AEM</i> & High <i>Cus_AEM</i>		High <i>AEM</i> & Low <i>Cus_AEM</i>		Low <i>AEM</i> & Low <i>Cus_AEM</i>	
	(1) <i>Error</i>	(2) <i>Error</i>	(3) <i>Error</i>	(4) <i>Error</i>	(5) <i>Error</i>	(6) <i>Error</i>	(7) <i>Error</i>	(8) <i>Error</i>
<i>Cus_RiskT</i>	0.013 (0.351)		0.039 (0.914)		−0.168*** (−4.490)		−0.105** (−2.171)	
<i>Cus_RiskF</i>		−0.109** (−2.450)		0.070 (1.308)		−0.044 (−0.886)		−0.349*** (−5.864)
<i>Cus_RiskP</i>		0.202*** (3.740)		−0.009 (−0.139)		−0.325*** (−5.786)		0.351*** (4.331)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Ind</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	3.124*** (4.202)	3.047*** (4.104)	3.529*** (4.242)	3.555*** (4.271)	−1.974** (−2.515)	−1.919** (−2.448)	1.524** (1.962)	0.839 (1.077)
<i>Observations</i>	6,710	6,710	5,214	5,214	5,557	5,557	5,880	5,880
<i>F value</i>	34.58	34.50	34.28	33.76	36.62	36.35	36.94	37.46
<i>Adjusted-R²</i>	0.243	0.245	0.287	0.287	0.290	0.292	0.264	0.271

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The environmental externality of peer performance

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ABSTRACT

This paper investigates the impact of peer performance on firms' pollution emissions using establishment-level pollution emissions data of Chinese listed firms. The empirical results show that managers increase pollution emissions intensity to save costs in response to performance pressure from peer firms. We identify two underlying mechanisms, capital market pressure and compensation pressure, through which peer performance exacerbates pollution emissions. Heterogeneity analysis shows that CSR activity by focal or peer firms and regional environmental regulations help mitigate the environmental externalities of peer performance, while firms with state ownership and GDP importance are more likely to increase emissions in response to peer performance. This study sheds light on how peer performance exerts a negative environmental externality and provides implications for balancing the relationship between economic benefits and environmental sustainability.

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1. Introduction

Performance-based compensation schemes encourage managers' myopic behavior due to short-term performance pressures (Cremers et al., 2020; Edmans et al., 2022). Short-term pressures to meet earnings expectations may lead to decision-making that sacrifices potentially long-term economic value to obtain short-term benefits (Graham et al., 2005; Bhojraj et al., 2009) and bring about various negative consequences. Numerous studies discuss the determinants of managerial short-termism from the perspectives of capital market pressures (Graham et al., 2005; Cremers et al., 2020; Liu et al., 2021), product market competition (Lee et al., 2018) and performance target pressures (Cao et al., 2018). However, fewer studies focus on how performance pressure from peer firms affects managers' short-termism. Du and Shen (2018) examine the economic consequences

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of peer performance for earnings management. Unlike Du and Shen (2018), we investigate whether and how peer performance leads to a negative environmental externality, measured by sulfur dioxide (SO₂) emissions, which has effects beyond immediate firm stakeholders and results in welfare losses for residents.

We argue that peer performance influences managers' pollution emissions decisions mainly through capital market pressures and compensation pressures. First, as peer performance is used as a benchmark to evaluate earnings forecasts (De Franco et al., 2015), analysts will revise the earnings forecasts of target firms upwards when their peers perform well (Du and Shen, 2018). This increases capital market expectations and short-term performance pressure on managers (Du and Shen, 2018). Second, many managers' compensation contracts are based on peer performance (e.g., relative performance evaluation), and higher performances by peer firms raise the threshold for managers to meet their compensation contracts, increasing the likelihood of dismissal (Jenter and Kanaan, 2015). Consequently, we expect that managers have an incentive to engage in cost savings by increasing SO₂ emissions in response to the pressure from peer performance.

We investigate the relationship between peer performance and firms' pollution emissions based on the Chinese institutional background for three main reasons. First, the trade-off between economic development and environmental protection remains an essential issue for emerging markets. China, as the largest emerging country, is experiencing rapid economic development while facing the challenge of growing environmental pollution concerns. The discussion of the determinants of sustainable development based on the Chinese institutional setting has implications for other emerging markets. Second, China is one of the world's largest emitters of SO₂. As a major cause of air pollution, SO₂ emissions have become the focus of government environmental regulation and enforcement. Compared with other pollutants, SO₂ emissions data are of key interest to environmental enforcement authorities and are accurate and reliable (Liu et al., 2021). We can measure SO₂ emissions at the establishment level accurately. Third, China provides us with a rich heterogeneity in terms of property rights protection, environmental regulation and corporate social responsibility (CSR) performance, which helps us to explore which factors moderate the relationship between peer performance and corporate emissions.

We examine the impact of peer performance on firms' pollution emissions using 18,442 establishment-year observations of 1210 listed firms (4096 establishments) from 2003 to 2014. Considering that individual manufacturing establishments are the primary source of pollution emissions, rather than the listed firm's headquarters (Liu et al., 2021), we focus on SO₂ emissions at the establishment level. Following Leary and Roberts (2014), we use the average idiosyncratic equity return of all other firms in the same industry as a proxy for peer performance, instead of accounting performance, due to endogeneity concerns.

We find that managers increase pollution emissions intensity to save costs in response to performance pressure from peer firms. The effect is both statistically and economically significant. A one standard deviation increase in peer performance is associated with approximately a 12.64 percent increase in pollution emissions, equivalent to an increase in SO₂ emissions of 82.16 g/1000 CNY of industrial output, representing on average a 1.406 million CNY cost saving from additional pollution emissions. The conclusion remains robust after using the instrumental variable (IV) method and a series of robust tests.

Further, we show that the positive effect of peer performance on pollution emissions is more pronounced in firms where over half of analysts revise upward, whose performance just meets market expectations, and whose executive compensation is associated with relative performance evaluation. The above evidence supports capital market pressure and compensation pressure as the mechanisms through which peer performance affects pollution emissions. Finally, we perform four cross-sectional analyses. The results show that CSR activity by focal or peer firms and regional environmental regulations help mitigate the environmental externalities of peer performance, while firms with state ownership and GDP importance are more likely to increase emissions in response to peer performance.

This study contributes to several streams of the literature. First, this study contributes to the short-termism literature. Previous research mainly focuses on the economic consequences of short-term performance pressure (Graham et al., 2005; Bhojraj et al., 2009; Du and Shen, 2018; Cremers et al., 2020; Edmans et al., 2022). We provide additional evidence on the environmental externalities of short-term performance pressure. We complement the findings of Liu et al. (2021) by showing that capital market pressures stem partially from peer performance, although this is just one of the economic mechanisms through which peer performance generates environmental externalities.

Second, this study contributes to a better understanding of the determinants of environmental, social and governance (ESG) activities. We complement the findings of Lee et al. (2018) by showing that peer firms affect firms' ESG activities not only through competition mechanisms but also through pressure mechanisms from capital markets and compensation contracts.

Third, this study complements the literature on the consequences of peer effects. Existing studies mainly focus on the effects of peer firms on capital structure choices (Leary and Roberts, 2014), earnings management (Du and Shen, 2018), corporate innovation (Machokoto et al., 2021) and CSR (Cao et al., 2019a). We provide additional evidence on the actual environmental consequences of peer firms.

2. Literature review and hypothesis development

2.1. Literature review

In the standard economic treatment of the principal–agent problem, compensation systems maximize shareholder value and reward productive work (Holmstrom and Milgrom, 1991). However, the performance-based compensation framework results in a classic trade-off: performance incentives yield more effort, but possibly at the expense of distortions to the type of effort. Short-term pressures to meet or beat earnings expectations may lead to decision-making that sacrifices potentially long-term economic value to obtain short-term stock price benefits (Graham et al., 2005; Bhojraj et al., 2009) and bring about various negative consequences. For example, many studies find that short-term pressures increase manipulation (earnings management) (Healy and Wahlen, 1999; Du and Shen, 2018), pollution emissions (Liu et al., 2021; Thomas et al., 2022) and product pricing (Bisetti and Karolyi, 2024), reduce R&D investment (Cremers et al., 2020; Terry, 2023) and CSR activities (Lee et al., 2018), and distort lending institutions' monitoring behaviors (Bird et al., 2022) and investment portfolio management (Fan et al., 2024), resulting in significant welfare losses (Caskey and Ozel, 2017; Raghunandan, 2021; Terry, 2023).

The existing literature discusses the determinants of managers' performance pressure in two main ways. On the one hand, performance pressures may arise from external capital market pressures such as analysts' earnings forecasts (Graham et al., 2005; Liu et al., 2021), M&A activity (Bens et al., 2012), short-sighted investor shareholdings (Cremers et al., 2020) and production market competitive pressures (Lee et al., 2018). On the other hand, performance pressure may be driven by internal factors of firms, such as over-performance target setting (Cao et al., 2018). However, few studies document the causes of performance pressure from the perspective of peer performance.

In recent years, some literature has examined the economic consequences of performance pressure based on the perspective of peer firms. Lee et al. (2018) find that firms in more competitive product markets are less engaged in CSR activities. Cao et al. (2019a) argue that a firm's proposed CSR measures and their implementation are followed by the adoption of similar CSR practices by peer firms, indicating that the spillover effect of CSR is a strategic response to competitive threats. However, peer firms do not only influence other firms' policies through product market competition; performance from peer firms can also influence firms' short-term behavior through external capital markets and internal compensation pressures. Du and Shen (2018) examine the effect of peer performance on earnings management and find that higher peer performance leads to higher discretionary accruals through market pressure and compensation pressure mechanisms. Unlike Du and Shen (2018), we focus on the negative externalities of peer performance, such as firms' pollution emissions. Almeida et al. (2024) find that short-term earnings pressures can act through the free cash flow channel to incentivize firms to increase the efficiency of R&D expenditures.

Firms' pollution emissions are related to their ESG or CSR activities. ESG activities aim to internalize the externalities caused by the pursuit of profit maximization, redefining the boundary between the firm and the market. Research shows that listed firms with higher ESG activity face less litigation risk and regulatory penalties (Hong and Kacperczyk, 2009; Hong and Liskovich, 2015), reduce their financing costs (El Ghouli et al., 2011; Shi et al., 2024) and increase their sustainability and corporate value (Fatemi et al., 2015; Albuquerque et al., 2019). In contrast, agency theory argues that ESG activities may not directly increase shareholder value, as managers may seek to over-invest in CSR for their private benefit (Barnea and Rubin, 2010; Lee et al., 2018).

Literature exploring the impact of product market competition on firms' ESG activities obtains contradictory conclusions. For example, Flammer (2015) finds that product market competition in developed markets helps firms to increase CSR activities, while Lee et al. (2018) find the opposite in an emerging market background. Another strand of the literature examines the peer effect of CSR or ESG (Cao et al., 2019a; Li and Wang, 2022; Zhao and Wang, 2024). Unlike existing studies, we explore the determinants of firms' ESG activities from the perspective of peer performance, which can influence firm behavior not only from product market competition but also through capital market pressures or compensation pressures.

2.2. Peer performance and firm pollution emissions

Standard agency theory argues that aggregate measures like peer performance often provide sufficient information about common industry shocks; thus, relative performance evaluation is efficient in evaluating the talent and effort of managers (Diamond and Verrecchia, 1982; Holmstrom, 1982). In practice, peer performance plays an important role as a performance benchmark for market participants in evaluating a firm's performance. Investors employ peer performance to evaluate a firm's value and make investment decisions (Bhojraj and Lee, 2002; Kaustia and Knüpfer, 2012), while analysts apply peer performance as a benchmark to provide earnings forecasts and recommendations (De Franco et al., 2015). In addition, corporate boards use relative performance evaluation techniques to link managerial compensation to peer performance (Aggarwal and Samwick, 1999; Gong et al., 2011; Jenter and Kanaan, 2015). In other words, peer performance affects both capital market expectations of a firm's performance and the board's evaluation of the manager's efforts. Accordingly, managers face short-term performance pressures when peer firms outperform under standard performance-based compensation schemes. Previous literature argues that short-term performance pressures incentivize managers to engage in short-termism (Graham et al., 2005; Bhojraj et al., 2009; Cohen and Zarowin, 2010; Caskey and Ozel, 2017), such as increasing SO₂ emissions, which as an externality is conducive to cost savings for managers (Liu et al., 2021; Thomas et al., 2022).

From the perspective of firms, the cost of reducing pollution is high, and cost savings through increased pollution emissions are economically feasible. Strict implementation of environmental protection policies by firms requires increased investment in pollution abatement, which contributes heavily to firms' private costs (Liu et al., 2021). Greenstone et al. (2012) find that stricter air quality regulations reduce total factor productivity by around 2.6%, representing approximately 8.8% of manufacturing profits. Liu et al. (2021) find that a 26.7% increase in SO₂ emissions intensity due to earnings pressure can bring cost savings of about 0.4–1.4 cents/share, based on Chinese listed firms. Therefore, the high cost of abatement gives firms a strong incentive to circumvent government environmental regulations, especially as environmental fines have been much lower than the cost of abatement over the past few decades, and firms have had little incentive to reduce emissions. In practice, firms can bypass environmental regulations through various instruments, such as manipulating the production and operational data of SO₂ scrubbers and only running them fully when inspections are approaching, thus reducing costs while passing inspections (Xu, 2011; Karplus and Wu, 2019). Therefore, we propose the following hypothesis:

H1: *Ceteris paribus*, peer performance positively affects firms' pollution emissions intensity.

We argue that peer performance influences managers' decisions on pollution emissions, mainly through capital market pressures and compensation pressures. From the perspective of capital market pressures, analysts use peer performance as a benchmark for making earnings forecasts for target firms (De Franco et al., 2015). Peer firms' performance determines the direction of analysts' earnings forecasts for target firms within the same industry. When peer firms perform well, analysts will revise the earnings forecasts of target firms upwards (Du and Shen, 2018), implying that managers face increased performance expectations in capital markets. The existing literature finds that managers are concerned with meeting short-term earnings expectations, for example, by manipulating earnings to meet or beat analysts' forecasts (Burgstahler and Dichev, 1997; Degeorge et al., 1999; Du and Shen, 2018). When peers outperform, managers are motivated to increase pollution emissions for the sake of cost savings to meet the benchmarks set by market expectations, given the negative consequences of being unable to meet market expectations (Bartov et al., 2002; Graham et al., 2005). We expect capital market pressure to be an economic mechanism by which peer performance influences corporate pollution emissions, and propose hypothesis H2:

H2: *Ceteris paribus*, peer performance leads to an increase in pollution emissions through capital market pressure.

From the perspective of compensation pressure, many firms apply relative performance evaluations to assess managers' efforts and determine their compensation contracts (Aggarwal and Samwick, 1999; Gong et al., 2011). Theoretically, relative performance evaluation principles can absorb common industry shocks and effectively evaluate managers' efforts (Holmstrom, 1982). However, when relative performance evaluation is used as an internal corporate governance mechanism, the higher performance of peer firms can negatively affect managers' contracts. Higher performance from peer firms negatively affects managers' compensation. Moreover, managers are more likely to be fired than their peers if they fail to yield better or at least comparable performance (Jenter and Kanaan, 2015). Therefore, managers will have strong incentives to save costs by increasing SO₂ emissions when their compensation contracts are based on relative performance evaluation (Du and Shen, 2018; Infuehr, 2022). We expect compensation pressure to be another mechanism through which peer performance affects corporate pollution emissions, and propose hypothesis H3:

H3: *Ceteris paribus*, peer performance leads to an increase in pollution emissions through compensation pressure.

3. Research design

3.1. Sample selection and data sources

Since individual manufacturing establishments are the primary source of pollution emissions (Liu et al., 2021), we select establishment-level data to measure pollution emissions. The pollution emissions data come from the China Environmental Survey and Reporting Database (ESR) obtained from the Ministry of Environmental Protection of China, which contains rich information on firms' environmental behavior and offers reliable data quality (He et al., 2020; Liu et al., 2021). We use the China Industrial Enterprise Database (CIED) to capture the basic information, geographic location, ownership and financial characteristics of establishments. In addition, we obtain financial, affiliated subsidiary, stock return and analyst forecast data from the China Stock Market & Accounting Research Database (CSMAR), CSR data from Hexun.com, relative performance evaluation and officer turnover data by manual collection, and city-level data from statistical yearbooks.

We select our sample firms from the main board on the Shanghai and Shenzhen stock exchanges from 2003 to 2014. Considering that the ESR database was updated until 2014, we select 2014 as the end year of the sample. Before the empirical estimation, matching the above micro-databases is essential but challenging since the ESR, CIED and CSMAR are independent databases without unified identification. We conduct explicit one-to-one matching according to key variables to solve the matching problem. First, following Brandt et al. (2012), we obtain the establishment-level variables of enterprise identity information in the CIED, including legal person code and enterprise name, to construct industrial enterprise panel data. Second, similar methods are used to construct pollution panel data from the ESR. Third, the panel dataset of pollution by industrial enterprises is matched to enterprise identity information. Finally, we follow the procedures of Liu et al. (2021) to match the panel dataset of polluting industrial enterprises with the CSMAR based on the list of listed firms and their subsidiaries in the CSMAR database, obtaining 22,872 establishment-year initial samples.

We screen our sample by excluding observations of financial firms' subsidiaries (45 observations) and observations with missing variables (4385 observations), leading to 18,442 establishment-year observations of 1210 listed firms and 4096 establishments. All continuous variables are winsorized at the 1% and 99% levels. Table 1 reports the sample distribution by year and industry.

3.2. Main variable definition

3.2.1. Peer performance

Following Leary and Roberts (2014), we capture peer performance based on the stock performance of peer firms, rather than their accounting performance, to mitigate endogeneity issues. Peer stock performance allows us not only to exclude common industry shocks to mitigate potential omitted variable issues but also to avoid

Table 1
Sample distribution.

Panel A: sample distribution by year			
Year	# of observations	% of observations	Mean of SO ₂ emissions
2003	835	4.53%	1.20
2004	1099	5.96%	1.25
2005	1142	6.19%	1.37
2006	1226	6.65%	0.56
2007	1393	7.55%	0.43
2008	1416	7.68%	0.34
2009	1457	7.90%	0.39
2010	1190	6.45%	0.27
2011	2261	12.26%	0.61
2012	2375	12.88%	0.55
2013	1778	9.64%	0.80
2014	2270	12.31%	0.53
Total	18,442	100.00%	0.65

Notes: This panel lists the year's distribution of the main sample. The unit of SO₂ emissions is 1 kg, and the unit of gross industrial output is 1000 CNY.

Panel B: sample distribution by industry			
Industry name	# of observations	% of observations	Mean of SO ₂ emissions
Mining and Washing of Coal	321	1.74%	0.16
Extraction of Petroleum and Natural Gas	7	0.04%	0.00
Mining of Ferrous Metal Ores	131	0.71%	0.26
Mining of Non-ferrous Metal Ores	274	1.49%	0.06
Mining and Processing of Nonmetal Ores	73	0.40%	1.20
Processing of Food from Agricultural Products	794	4.31%	0.14
Manufacture of Foods	797	4.32%	0.25
Manufacture of Beverage	954	5.17%	0.38
Manufacture of Tobacco	8	0.04%	0.06
Manufacture of Textile	585	3.17%	0.35
Manufacture of Textile Apparel	138	0.75%	0.14
Manufacture of Leather	25	0.14%	0.30
Manufacture of Timber	140	0.76%	0.69
Manufacture of Furniture	23	0.12%	0.10
Manufacture of Paper	336	1.82%	0.99
Printing, Reproduction of Recording Media	114	0.62%	0.03
Manufacture of Articles for Culture, Education and Sport Activities	45	0.24%	0.16
Processing of Petroleum, Coking, Processing of Nuclear Fuel	178	0.97%	0.46
Manufacture of Chemical Raw Materials and Chemical Products	2035	11.03%	0.62
Manufacture of Medicines	2250	12.20%	0.24
Manufacture of Chemical Fibers	139	0.75%	0.79
Manufacture of Rubber	174	0.94%	0.23
Manufacture of Plastic	598	3.24%	0.48
Manufacture of Nonmetallic Mineral Products	1497	8.12%	0.76
Manufacture & Processing of Non-ferrous Metals	989	5.36%	0.48
Manufacture of Metal Products	488	2.65%	0.05
Manufacture of General-Purpose Machinery	666	3.61%	0.03
Manufacture of Special-Purpose Machinery	485	2.63%	0.02
Manufacture of Transport Equipment	1205	6.53%	0.03
Manufacture of Electrical Machinery and Equipment	121	0.66%	0.08
Manufacture of Communication Equipment	1399	7.59%	0.04
Manufacture of Measuring Instruments	104	0.56%	0.02
Manufacture of Artwork	61	0.33%	0.05
Recycling and Disposal of Waste	18	0.10%	0.03
Production and Supply of Electric and Heat Power	1235	6.70%	5.05
Production and Distribution of Gas	17	0.09%	1.33
Production and Distribution of Water	18	0.10%	0.07
Total	18,442	100.00%	0.65

Note: This panel lists the industry distribution of the main sample.

measurement errors due to earnings manipulation by peer managers (Du and Shen, 2018). Previous literature often treats other firms in the focal firm's industry as its peer group due to their having similar operating environments and common shocks. Following Leary and Roberts (2014), we use the average idiosyncratic equity returns of other firms within a one-digit industry as classified by the China Securities Regulatory Commission (CSRC) as a proxy for peer performance. Specifically, we first decompose the raw return using the following model:

$$Return_{i,j,t} = \beta_0 + \beta_m(R_{m,t} - R_{f,t}) + \beta_{ind}(R_{-i,j,t} - R_{f,t}) + \varepsilon_{i,j,t} \quad (1)$$

where $Return_{i,j,t}$ refers to the raw return for firm i in industry j over month t , and $R_{m,t}$ and $R_{f,t}$ represent the market return and risk-free rate in the month t . $R_{-i,j,t}$ is the value-weighted one-digit industry return excluding firm i itself. We estimate Eq. (1) for each firm in a rolling window of 60 months before year t , requiring at least 36 months of historical return data in each regression. Using the estimated coefficients of Eq. (1), we compute the idiosyncratic equity returns as follows:

$$Idio_{i,t} = Return_{i,t} - \hat{\beta}_0 - \hat{\beta}_m(R_{m,t} - R_{f,t}) - \hat{\beta}_{ind}(R_{ind,t} - R_{f,t}) \quad (2)$$

where $Idio_{i,t}$ represents idiosyncratic equity returns for firm i in year t . We construct a proxy variable (*PeerIdio*) for peer performance as the average idiosyncratic equity returns of all other firms in the same industry.

3.2.2. Firm-level pollution emissions intensity

Following Liu et al. (2021), we select SO₂ emissions as a proxy for environmental pollution emissions at the establishment level. As one of the primary sources of air pollution, SO₂ emissions are a major concern for environmental law enforcement departments, and SO₂ emissions data are released with relatively high accuracy and reliability (Liu et al., 2021). We construct a proxy for pollution emissions intensity as the total SO₂ emissions scaled by the total output adjusted for inflation (*Emission*).¹

3.3. Baseline estimation framework

To test hypothesis H1, we use the pooled ordinary least squares model to investigate the relationship between peer performance and pollution emissions. Specifically, we construct the following regression Eq. (3):

$$Emission_{i,j,t} = \beta_0 + \beta_1 PeerIdio_{j,t} + \beta_k Controls + YearFE + IndustryFE + Prov \times YearFE + \varepsilon_{i,j,t} \quad (3)$$

where $Emission_{i,j,t}$ refers to the SO₂ emissions intensity for manufacturing establishment i of listed firm j in year t , $PeerIdio_{j,t}$ indicates the mean idiosyncratic returns of listed firm j 's industry peers and *Controls* represent a set of control variables that may affect pollution emission intensity at firm and city level. *YearFE*, *IndustryFE*, *Prov* $\times$ *YearFE* and $\varepsilon_{i,j,t}$ denote year fixed effects, industry fixed effects, province-year fixed effects and the random error term, respectively. Detailed definitions of key variables are presented in Appendix A1.

3.4. Summary statistics

Panel A of Table 1 shows the sample distribution by year. The average SO₂ emissions show a downward trend, decreasing from 1.20 in 2003 to 0.53 in 2014, reflecting China's increasingly stringent environmental regulations over the past two decades. Panel B of Table 1 presents the sample distribution by industry. The industry with the largest SO₂ emissions is the production and supply of electric and heat power, with the data indicating that production in this industry releases 5.05 kg of SO₂ per 1000 CNY of output. Other industries whose *Emission* values are larger than 1 are high-energy-consuming and polluting industries.

Table 2 reports the descriptive statistics of the main variables of interest. First, the mean SO₂ emissions intensity is 0.650, meaning that an average establishment in our sample releases 650 g of SO₂ per 1000 CNY output. The standard deviation of *Emission* in our sample is 2.067, suggesting significant differences

¹ The SO₂ emissions data are measured in kg, and the unit value of output is 1000 CNY. We convert the total output values into constant 2014 prices using the consumer price index.

Table 2
Summary statistics.

Variables	# of Observations	Mean	Std.	Min	p25	p50	p75	Max
<i>Emission</i>	18,442	0.650	2.067	0.000	0.000	0.025	0.277	16.267
<i>PeerIdio</i>	18,442	0.000	0.053	−0.123	−0.015	0.011	0.030	0.110
<i>Idio</i>	18,442	−0.010	0.300	−0.604	−0.213	−0.048	0.140	1.025
<i>Size</i>	18,442	19.620	1.483	16.308	18.597	19.472	20.553	23.334
<i>ROA</i>	18,442	0.040	0.062	−0.255	0.014	0.037	0.067	0.198
<i>Age</i>	18,442	2.350	0.780	0.000	1.946	2.303	2.773	4.304
<i>SOE</i>	18,442	0.410	0.492	0.000	0.000	0.000	1.000	1.000
<i>Tang</i>	18,442	0.410	0.221	0.024	0.237	0.391	0.577	0.904
<i>Lev</i>	18,442	0.530	0.185	0.093	0.410	0.534	0.657	1.111
<i>PT</i>	18,442	0.220	0.417	0.000	0.000	0.000	0.000	1.000
<i>GDPgr</i>	18,442	12.260	3.814	−19.380	10.100	12.210	14.500	109.000

among establishments. The mean value of *PeerIdio* is 0.04%, indicating that peers' idiosyncratic returns are close to zero by construction, consistent with the results reported by Leary and Roberts (2014) and Du and Shen (2018). The mean value of *Idio* is −1%, indicating that focal firms recorded negative idiosyncratic returns from 2003 to 2014. In terms of control variables, the average return on assets is 4%, the ratio of liabilities to assets is 53%, the proportion of state-owned enterprises is 41% and the average GDP actual growth rate at the city level is 12.26%, which are consistent with real-world business activities and existing literature.

4. Peer performance and pollution emissions

4.1. Baseline regression results

Table 3 reports the results for the effect of peer performance on pollution emissions in all specifications of Eq. (3). Column (1) only includes the year, industry and province-year fixed effects, and the coefficient of *PeerIdio* is significantly positive at the 1% level. In Column (2), we further add a set of variables to control for establishment and listed-firm characteristics. The coefficient of *PeerIdio* is less than that in Column (1) ($\beta_1 = 1.662 > 1.542$) and significantly positive at the 5% level (t -value = 2.44). In Column (3), we further add the control variables at the city level, and the coefficient of *PeerIdio* is still significantly positive at the 5% level (t -value = 2.45).

Overall, the coefficients of *PeerIdio* are significantly positive across all specifications, indicating a positive relationship between peer performance and pollution emissions. The impact of peer performance on emissions is also economically meaningful. For example, using the coefficient in Column (3), a one standard deviation increase in *PeerIdio* is associated with approximately a 12.64 percent increase in pollution emissions, equivalent to an increase in SO₂ emissions of 82.16 g/1000 CNY of industrial output,² representing on average a 1.406 million CNY cost saving from the additional pollution emissions.³

These results are consistent with the view that managers face short-term performance pressures when peer firms outperform under standard performance-based compensation schemes; thus, they engage in increasing SO₂ emissions for cost savings in response to performance pressure from peer firms. The results support Hypothesis H1.

² Note that $1.55 \times 0.053 / 0.65 = 0.1264$, where 1.55 is the estimated coefficient on *PeerIdio* in Column (3) of Table 3, 0.053 is the standard deviation of *PeerIdio* and 0.65 is the mean SO₂ emissions of our sample. $0.65 \text{ kg/1000 CNY} \times 12.64\% \times 1000 = 82.16 \text{ g/1000 CNY}$ of industrial output.

³ We calculate cost saving as follows. First, we aggregate total industrial output at the listed-firm level, and the average total output in our final sample is 3.057 billion, resulting in an average of 251 tons SO₂ emissions during the firm-year. Second, based on a court case regarding SO₂ emissions in 2014, we assess the cost per ton of SO₂ emissions as 5,600 CNY (data from: <https://www.informea.org/en/court-decision/all-china-environment-federation-vs-dezhou-jinghua-group-zhenhua-decoration-glass-co>). Third, we estimate that the cost saving from emitting 251 tons of SO₂ is approximately 1.406 million CNY. Using the coefficient based on emissions scaled by output without inflation adjustment (2.09, untabulated), the cost saving from emitting 520 tons of SO₂ is approximately 2.911 million CNY.

Table 3
Baseline results.

Dep. Var.=	(1) <i>Emission</i>	(2) <i>Emission</i>	(3) <i>Emission</i>
<i>PeerIdio</i>	1.662*** (2.60)	1.542** (2.44)	1.550** (2.45)
<i>Idio</i>		−0.015 (−0.47)	−0.015 (−0.45)
<i>Size</i>		−0.083*** (−4.74)	−0.083*** (−4.74)
<i>ROA</i>		−0.202 (−0.70)	−0.204 (−0.71)
<i>Age</i>		0.031 (1.24)	0.031 (1.24)
<i>SOE</i>		−0.019 (−0.47)	−0.019 (−0.48)
<i>Tang</i>		0.225*** (2.63)	0.226*** (2.64)
<i>Lev</i>		−0.166 (−1.22)	−0.167 (−1.23)
<i>PT</i>			−0.021 (−0.64)
<i>GDPgr</i>			−0.006 (−1.31)
_cons	0.645*** (31.75)	2.205*** (6.41)	2.287*** (6.55)
Year FE	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes
Prov × Year FE	Yes	Yes	Yes
Observations	18,442	18,442	18,442
R-squared	0.435	0.438	0.438

Notes: Table 3 reports the baseline results for the effect of peer performance on pollution emissions in different specifications of Eq. (3). Column (1) only includes the year, industry and province-year fixed effects; Column (2) further includes a set of variables to control for establishment and listed-firm characteristics, and Column (3) further adds the control variables at the city level. Variable definitions are in Appendix A1. Standard errors are clustered at the establishment level, and *t*-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

4.2. IV estimations

Our baseline results are unlikely to suffer from reverse causality and omitted-variable issues due to the construction of proxy variables (*PeerIdio*) for peer performance. First, we estimate idiosyncratic equity returns using the past 60 months' equity returns, and it is unlikely that a firm's subsequent SO₂ emissions drive previous peer idiosyncratic returns. Second, we exclude common shocks from the market and industry level in the construction of *PeerIdio*. The baseline results are unlikely to be driven by common components omitted at the market or industry level. However, the relationship between peer performance and corporate pollution emissions may remain endogenous. For example, the estimation of idiosyncratic equity returns contains noise and common factors that are not entirely removed, leading to biased or inconsistent estimated coefficients in Eq. (3).

In this section, we construct a desirable IV for peer performance to alleviate endogeneity concerns. Following Leary and Roberts (2014) and Du and Shen (2018), we construct *PeerCustIdio*, which is the mean idiosyncratic return of the major customers of peer firms. Specifically, this indicator excludes the focal firm's own customers and is computed as a leave-one-out mean. As shown by Cohen and Frazzini (2008), the shock

to customers can predict the equity returns of supplier firms but not that of other firms that do not have active customer–supplier links in the same industry. Drawing on Leary and Roberts (2014) and Du and Shen (2018), we define peer customers as entities operating in different industries and sharing no supply chain connections with the focal firm. This ensures that customer-driven shocks to peers do not directly affect the focal firm's emission levels except through the *PeerIdio* channel, thereby establishing *PeerCustIdio* as a valid IV. To strengthen the exclusion restriction, we first include the focal firm's sales growth rate as an approximate proxy for customer performance indicators to isolate the customer peer-specific channel better. We find that controlling for the sales growth rate does not affect the IV estimation results. Second, we conduct a placebo test to verify that *PeerCustIdio* does not correlate with the focal firm's sales or costs, thus strengthening the exclusion restriction. In Column (1) of Table 4, we find that the relationship between *PeerCustIdio* and the focal firm's sales performance is statistically nonsignificant, suggesting that better peer customer performance will only reduce focal firms' sales growth through increased peer performance, further confirming the reliability of the IV.

The first-stage regression results are shown in Column (2) of Table 4, and the IV *PeerCustIdio* is significantly and positively correlated with the endogenous variable *PeerIdio*, consistent with existing literature (e.g., Du and Shen, 2018). We perform under-identification and weak-identification tests to confirm the validity of the IV in Column (2). The Kleibergen–Paap rk LM statistic of the under-identification test is 31.285 (p -value is 0.00), and the values of both the Cragg–Donald Wald F-statistic and Kleibergen–Paap rk Wald F-statistic in the test of weak IVs are greater than the critical value of 16.38. Thus, our IVs are reasonable. The second-stage regression results in Column (3) show that the coefficient of $\widehat{PeerIdio}$ is significantly positive at least at the 5% level, suggesting that the baseline results of Table 3 still hold after alleviating the endogeneity concerns.

Recognizing that the focal firm's sales growth may be affected by peer performance, we remove this control variable in our IV estimation to prevent it from absorbing part of the peer effect channel we aim to isolate. As presented in Columns (4) and (5) of Table 4, the IV results remain robust, indicating that the IV estimation results remain consistent regardless of whether the focal firm's sales growth is controlled for, which helps mitigate endogeneity concerns.

4.3. Robustness tests

To assess the sensitivity of our baseline results, we conduct a battery of robustness checks, and the baseline results remain robust.

First, we include more measures for pollution emissions and re-estimate the baseline specifications to exclude the concern that particular pollutants influence the baseline results. We use dust emissions (*Dust*), industrial wastewater emissions (*IWW*) and ammonia nitrogen emission (*ANE*) as proxies for pollution emissions and scale them by inflation-adjusted industrial output. In addition, following Chen et al. (2018a), we construct a variable ($Emission^{sale}$), which measures SO₂ emissions scaled by the total operating income adjusted for inflation. Table 5 reports the results when using these alternative measures of pollution emissions intensity. The coefficients of *PeerIdio* are significantly positive at least at the 10% level, consistent with the baseline results in Table 3.

Second, to avoid the undue influence of within-listed-firm residual correlations on standard error estimates, we cluster the regression standard errors by listed firm instead of by establishment. In Column (1) of Table 6, the coefficient of *PeerIdio* is still positive and significant at the 5% level, consistent with the baseline results.

Third, we refer to Chen et al.'s (2018b) classification of high-polluting industries and re-estimate the baseline model after excluding observations of high-polluting industries and find that the baseline results remain robust (Column (2) of Table 6), ruling out the possibility that policy-driven emissions peaks are driving our results.

Fourth, we add establishment-level fixed effects into Eq. (3) to alleviate the endogeneity issues caused by unobservable heterogeneity and time-invariant omitted variables at the establishment level. Column (3) of Table 6 reports the results, and the coefficient of *PeerIdio* is still positive and significant at the 1% level.

Table 4
IV estimation.

	(1)	(2)	(3)	(4)	(5)
	Placebo test	Controlling <i>SaleGrowth</i>		Not controlling <i>SaleGrowth</i>	
		First-stage	Second-stage	First-stage	Second-stage
Dep. Var.=	<i>SaleGrowth</i>	<i>PeerIdio</i>	<i>Emission</i>	<i>PeerIdio</i>	<i>Emission</i>
<i>PeerIdio</i>			18.622** (2.18)		57.479* (1.79)
<i>PeerCustIdio</i>	−0.050 (−1.04)	0.010*** (5.65)		0.003* (1.89)	
<i>Idio</i>	0.083*** (2.93)	0.001 (0.68)	−0.050 (−1.19)	0.001 (1.08)	−0.066 (−0.90)
<i>Size</i>	0.025*** (4.50)	0.000 (0.07)	−0.055*** (−3.46)	−0.000 (−0.84)	−0.063*** (−3.22)
<i>ROA</i>	0.565*** (3.72)	−0.002 (−0.45)	−0.511 (−1.55)	−0.002 (−0.45)	−0.444 (−1.01)
<i>Age</i>	−0.145*** (−11.30)	−0.001*** (−2.75)	0.074*** (2.75)	−0.001*** (−2.88)	0.084* (1.71)
<i>SOE</i>	−0.025 (−1.47)	−0.001 (−0.97)	−0.057 (−1.25)	−0.001* (−1.84)	0.030 (0.46)
<i>Tang</i>	−0.031 (−0.75)	0.002 (1.17)	0.386*** (4.03)	0.001 (0.51)	0.330*** (2.84)
<i>Lev</i>	0.021 (0.46)	−0.006*** (−3.26)	−0.044 (−0.30)	−0.007*** (−3.68)	0.257 (0.96)
<i>PT</i>	0.014 (0.60)	−0.001 (−1.19)	0.006 (0.14)	−0.000 (−0.45)	0.003 (0.05)
<i>GDPgr</i>	0.009* (1.95)	0.001*** (3.04)	−0.035*** (−2.66)	0.000*** (3.41)	−0.019** (−2.00)
<i>SaleGrowth</i>		−0.000 (−0.37)	−0.040 (−1.53)		
Constant	0.005 (0.04)	0.015*** (2.91)		0.019*** (4.12)	
Year FE	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes
Prov × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	9565	9565	9565	13,134	13,134
R-squared	0.118	0.668		0.635	
Under-identification test		31.285		16.258	
Cragg–Donald F-statistic		33.680		1.26	
Kleibergen–Paap rk F-statistic		31.890		20.496	

Notes: Table 4 presents the two-stage IV estimation of Eq. (3). We use the mean idiosyncratic returns of the top five customers of peer firms as the IV (*PeerCustIdio*). In Column (2) and Column (4), the weak IV tests report both Cragg–Donald Wald F-statistics and Kleibergen–Paap rk F-statistics. The under-identification test of the IV adopts Kleibergen–Paap rk LM statistics. Variable definitions are in Appendix A1. Standard errors are clustered at the establishment level, and *t*-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

5. Economic mechanism

5.1. Capital market pressure

Since Liu et al. (2021) show that capital market pressure increases firms' emissions, we first focus on verifying whether peer performance affects analysts' forecast revisions. Suppose that analysts refer to peer performance to set performance forecasts for target firms within the same industry. In that case, we would expect peer performance to be positively correlated with analysts' forecast revisions for target firms. Following Du and Shen (2018), we estimate the following regression model:

$$LRevision_{i,j,t-1} = \beta_0 + \beta_1 PeerIdio_{j,t} + \beta_k Controls + YearFE + IndustryFE + Prov \times YearFE + \varepsilon_{i,j,t} \quad (4)$$

Table 5
Alternative measures of pollution emissions.

Dep. Var.=	(1) Dust emissions (<i>Dust</i>)	(2) Industrial wastewater emissions (<i>IWW</i>)	(3) Ammonia nitrogen emission (<i>ANE</i>)	(4) SO ₂ emissions scaled by income (<i>Emission^{sale}</i>)
<i>PeerIdio</i>	4.086** (2.05)	1.657** (2.20)	0.017* (1.72)	1.912** (2.08)
<i>Idio</i>	0.025 (0.29)	−0.078 (−1.35)	−0.001 (−0.60)	−0.022 (−0.55)
<i>Size</i>	−0.102*** (−2.79)	−0.117*** (−4.94)	−0.000 (−0.96)	−0.069*** (−3.54)
<i>ROA</i>	−0.154 (−0.19)	−0.854** (−1.96)	0.012 (1.61)	−0.167 (−0.45)
<i>Age</i>	−0.091 (−1.33)	0.075* (1.76)	0.001 (0.92)	−0.011 (−0.35)
<i>SOE</i>	−0.148* (−1.65)	0.166** (2.57)	0.001 (0.46)	−0.003 (−0.06)
<i>Tang</i>	−0.279 (−1.24)	0.709*** (5.08)	0.008*** (3.01)	0.541*** (5.31)
<i>Lev</i>	−0.014 (−0.05)	0.146 (0.81)	0.006** (2.19)	−0.054 (−0.32)
<i>PT</i>	−0.139* (−1.79)	−0.091* (−1.89)	−0.002** (−2.12)	−0.052 (−1.21)
<i>GDPgr</i>	−0.031** (−2.28)	−0.009 (−1.56)	0.000 (0.01)	−0.015 (−1.05)
<i>_cons</i>	3.379*** (3.96)	2.838*** (5.78)	0.011 (0.99)	2.093*** (5.22)
Year FE	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Prov × Year FE	Yes	Yes	Yes	Yes
Observations	18,441	16,999	16,758	16,171
R-squared	0.161	0.220	0.082	0.372

Notes: Table 5 reports robustness-test results using alternative measures of pollution emissions. Variable definitions are in Appendix A1. Standard errors are clustered at the establishment level, and *t*-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

where $LRevision_{i,j,t-1}$ is the last analyst forecast consensus minus the first analyst forecast consensus for listed firm *j* in year *t*−1, scaled by the share price at the beginning of year *t*−1.⁴ Other settings for Eq. (4) are the same as those for Eq. (3).

The results are shown in Column (1) of Table 7. The coefficient of *PeerIdio* is significantly positive at the 5% level (*t*-statistic is 2.16), indicating a positive relationship between peer performance and analysts' forecast revisions. The results support the view that analysts consider peer performance when setting performance forecasts for target firms (Du and Shen, 2018).

Next, we verify whether capital market pressure is a potential mechanism through which peer performance affects firms' emissions. We employ two measures to capture the pressure of the capital market. First, we calculate the proportion of analysts who revise their earnings forecasts upward and define the dummy variable *LRevisionUp*, which equals one if more than half of the analysts revise their earnings forecasts upward for target firms in year *t*−1, and zero otherwise. A higher number of analysts revising upward implies higher pressure on managers of target firms to achieve performance expectations from capital markets. We expect the positive effect of peer performance on pollution emissions to be more pronounced in firms where over half of the analysts revise upward. We report the results in Column (2) of Table 7. The coefficient of *PeerIdio* × *LRevisionUp* is significantly positive at the 1% level, consistent with our expectations.

⁴ We use lagged analyst forecast revisions to mitigate potential reverse causality, i.e., analysts may forecast cost reductions (including reductions in pollution emission costs) rather than firms' responding to analyst forecasts.

Table 6
Other robustness tests.

Dep. Var.=	(1) Clustering by listed-firm level <i>Emission</i>	(2) Excluding highly polluting industries <i>Emission</i>	(3) Establishment fixed effects <i>Emission</i>
<i>PeerIdio</i>	1.550** (1.99)	1.100** (2.06)	1.364*** (2.61)
<i>Idio</i>	−0.015 (−0.37)	−0.010 (−0.39)	−0.018 (−0.60)
<i>Size</i>	−0.083*** (−4.59)	−0.074*** (−6.45)	−0.007 (−0.16)
<i>ROA</i>	−0.204 (−0.69)	−0.844*** (−3.59)	−0.081 (−0.29)
<i>Age</i>	0.031 (1.20)	0.008 (0.49)	−0.055 (−1.16)
<i>SOE</i>	−0.019 (−0.44)	0.044 (1.41)	−0.031 (−0.43)
<i>Tang</i>	0.226** (2.32)	0.258*** (4.20)	−0.167 (−1.30)
<i>Lev</i>	−0.167 (−1.09)	−0.145 (−1.48)	−0.212 (−1.10)
<i>PT</i>	−0.021 (−0.63)	−0.033 (−1.25)	0.006 (0.28)
<i>GDPgr</i>	−0.006 (−1.39)	−0.005 (−1.40)	0.000 (0.05)
_cons	2.287*** (6.32)	1.808*** (7.68)	1.107 (1.24)
Year FE	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes
Prov × Year FE	Yes	Yes	Yes
Establishment FE	No	No	Yes
Observations	18,442	13,363	17,813
R-squared	0.438	0.305	0.797

Notes: Table 6 reports robustness-test results using establishment-level fixed effects, clustering at the listed-firm level, and excluding highly polluting industries. Variable definitions are in Appendix A1. Standard errors in Columns (2) and (3) are clustered at the establishment level while those in Column (1) are clustered at the listed-firm level. *t*-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Second, following Liu et al. (2021), we calculate earnings surprise, equal to the firm's actual earnings per share (EPS) minus the analysts' forecast consensus EPS. Then, we construct an indicator variable, *MeetFeps*, equal to one if the earnings surprise is between zero and two cents, and zero otherwise. If a firm's actual EPS far exceeds or far underperforms analysts' forecasts, managers have no incentive to increase SO₂ emissions in response to peer performance. However, if a firm's performance is likely to just meet or beat analysts' forecasts, managers have the incentive to increase pollution emissions in response to the capital market pressure stemming from peer performance. Therefore, we expect the positive effect of peer performance on emissions to be more pronounced in firms whose performance just meets market expectations. We report the results in Column (3) of Table 7. The coefficient of *PeerIdio* × *MeetFeps* is significantly positive at the 1% level, which is consistent with our expectation. Taken together, the above evidence supports the capital market pressure mechanism through which peer performance affects pollution emissions.

5.2. Compensation pressure

To validate the compensation pressure mechanism, we manually collect relative performance evaluation information from listed firm announcements, financial reports and equity incentive plans.⁵ We construct an

⁵ Since we begin to collect relative performance evaluation information on listed firms in 2006, the calendar year 2006 is the first year in Column (4) of Table 7.

Table 7
Economic mechanism.

	(1)	(2)	(3)	(4)
	Capital market pressure			Compensation pressure
Dep. Var.=	<i>LRevision</i>	<i>Emission</i>	<i>Emission</i>	<i>Emission</i>
<i>PeerIdio</i>	0.010** (2.16)	1.165* (1.81)	1.260** (2.01)	0.652 (1.05)
<i>PeerIdio</i> × <i>LRevisionUp</i>		2.447*** (3.51)		
<i>LRevisionUp</i>		0.017 (0.52)		
<i>PeerIdio</i> × <i>MeetFeps</i>			2.930*** (4.17)	
<i>MeetFeps</i>			−0.088** (−2.01)	
<i>PeerIdio</i> × <i>RPE</i>				1.345** (2.18)
<i>RPE</i>				−0.016 (−0.41)
<i>Idio</i>	−0.001*** (−3.97)	−0.007 (−0.21)	−0.007 (−0.21)	0.009 (0.30)
<i>Size</i>	−0.000 (−0.50)	−0.083*** (−4.74)	−0.082*** (−4.73)	−0.097*** (−5.88)
<i>ROA</i>	0.015*** (8.08)	−0.239 (−0.83)	−0.116 (−0.40)	−0.735*** (−2.68)
<i>Age</i>	0.000** (1.99)	0.031 (1.25)	0.031 (1.22)	0.020 (0.83)
<i>SOE</i>	−0.000** (−2.40)	−0.018 (−0.46)	−0.018 (−0.45)	−0.001 (−0.03)
<i>Tang</i>	−0.001 (−1.52)	0.227*** (2.66)	0.227*** (2.66)	0.197** (2.47)
<i>Lev</i>	0.001* (1.67)	−0.166 (−1.23)	−0.160 (−1.17)	−0.059 (−0.45)
<i>PT</i>	0.001** (2.34)	−0.022 (−0.67)	−0.020 (−0.60)	−0.046 (−1.47)
<i>GDPgr</i>	−0.000 (−0.00)	−0.006 (−1.30)	−0.006 (−1.30)	−0.003 (−0.92)
_cons	−0.001*** (−3.97)	−0.007 (−0.21)	−0.007 (−0.21)	0.009 (0.30)
Year FE	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Prov × Year FE	Yes	Yes	Yes	Yes
Observations	18,442	18,442	18,442	15,366
R-squared	0.103	0.438	0.439	0.346

Notes: Table 7 reports the baseline results on the capital market pressure and compensation pressure mechanisms through which peer performance affects pollution emissions. Variable definitions are in Appendix A1. Standard errors are clustered at the establishment level, and *t*-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

indicator variable, *RPE*, which takes the value one if the firm's executive compensation contract is explicitly based on relative performance evaluation, and zero otherwise. In this specification, we add *RPE* and the interaction term of *RPE* and *PeerIdio* to the baseline regression, and report the results in Column (4) of Table 7. The coefficient of *PeerIdio* × *RPE* is significantly positive at the 5% level, suggesting that the positive relationship between peer performance and corporate emissions is more pronounced in firms where executive compensation is associated with relative performance evaluation. The results are consistent with Du and Shen (2018), who find that peer performance increases the compensation pressure on managers through relative perfor-

mance evaluation. We conclude that the above evidence supports the compensation pressure mechanism through which peer performance affects pollution emissions.

6. Cross-sectional analyses

6.1. The moderating role of corporate social responsibility performance

“CSR” denotes a series of corporate activities and policies that assess, manage and govern a firm’s responsibilities and their impact on society and the environment (Christensen et al., 2018). When anticipating positive future performance, focal firms are more likely to engage in CSR (Lys et al., 2015). Such CSR engagement complements financial disclosure, enhances information transparency (Bajaj et al., 2023) and helps alleviate capital market pressures from peer performance. Dhaliwal et al. (2012) argue that stand-alone CSR reports are associated with lower analyst forecast errors, supporting the view that analysts rely less on peers when nonfinancial information improves. Furthermore, increased CSR disclosure by firms builds reputation capital (McWilliams and Siegel, 2001; Melo and Garrido-Morgado, 2012; Qiu et al., 2016). Such reputational benefits also trigger stronger reputational risks or penalties in cases of poor performance in CSR, such as environmental pollution incidents (Shiu and Yang, 2017; Christensen et al., 2018). CSR disclosure also attracts external monitoring from media and analysts (Reverte, 2009; Gao et al., 2016) and mitigates management’s myopic behavior (Kim et al., 2012; Christensen et al., 2018). Therefore, a firm that actively discloses CSR information is more likely to control its environmental emissions, helping to mitigate the effect of peer performance on pollution emissions.

In addition, firms do not operate in isolation and often compete with other firms in the product market. As CSR activities help a firm obtain a competitive advantage (Flammer, 2015; Cao et al., 2019a), increasing CSR activities can pose a competitive threat to peers. In response, firms will increase their engagement in CSR to be more competitive (Cao et al., 2019a). Therefore, firms engaging in more CSR activities will exert constraints on their peers and help to moderate the positive effect of peer performance on SO₂ emissions.

To align with the standard treatment of SO₂ emissions, our study uses the environmental dimension score extracted from Hexun’s CSR framework to measure the heterogeneity in CSR performance. The Hexun environmental performance score from 2009 to 2014 is sourced from Hexun.com, an organization that specializes in CSR ratings for Chinese-listed firms. Hexun’s CSR framework is built upon five core dimensions: shareholder responsibility, employee responsibility, responsibilities to suppliers and client/consumer interests, environmental responsibility and social responsibility. The environmental score is a composite measure based on five facets: environmental awareness, certification of environmental management systems, the amount of environmental investment, the number of pollutant types and the number of energy conservation types. The weighting of each indicator varies across different industries. This discretionary variation confirms that our measure of environmental performance is not driven by mechanically overlapping items but rather a tailored, industry-sensitive assessment.

We first construct an environmental performance variable for focal firms at the listed-firm level, *Focal E-score*, which is equal to the natural logarithm of the Hexun environmental score plus one in year *t*. Second, we construct an environmental performance score variable for peer firms, *Peer E-score*, which is equal to the average Hexun environmental performance score of all other firms within the same industry at the listed firm level. We map moderators from the listed-firm level to subsidiaries at the establishment level, assigning the same environmental score to plants belonging to the same listed firm through the CSMAR database’s directory of listed firms and their subsidiaries. In the specification, we add *Focal E-score* (*Peer E-score*) and its interaction term with *PeerIdio* to the baseline regression, which reflects the moderating effect of environmental performance on the relationship between peer performance and pollution emissions.

We report the results in Table 8. In Column (1), the coefficient of *PeerIdio* × *Focal E-score* is significantly negative at the 5% level, indicating that firms’ ramping up of SO₂ emissions in response to performance pressure from peer firms is reduced if they are actively engaged in environmental activities. In terms of economic implications, a one-unit increase in *Focal E-score* decreases the effect of peer performance (by one standard deviation) on pollution emissions by an additional 7.3%, equivalent to a decrease in SO₂ emissions of 47.45 g/1000 CNY of industrial output, representing on average a 0.81 million CNY cost expenditure from

Table 8

The moderating role of environmental performance.

Dep. Var.=	(1) Focal firms' environmental performance <i>Emission</i>	(2) Peers' environmental performance <i>Emission</i>
<i>PeerIdio</i> × <i>Focal E-score</i>	−0.895** (−2.01)	
<i>Focal E-score</i>	0.021 (1.10)	
<i>PeerIdio</i> × <i>Peer E-score</i>		−0.349** (−2.37)
<i>Peer E-score</i>		0.002 (0.14)
<i>PeerIdio</i>	1.235* (1.84)	2.106** (2.49)
<i>Idio</i>	0.012 (0.37)	0.020 (0.61)
<i>Size</i>	−0.100*** (−6.11)	−0.077*** (−5.34)
<i>ROA</i>	−0.803*** (−2.58)	−1.043*** (−3.54)
<i>Age</i>	0.034 (1.31)	−0.009 (−0.34)
<i>SOE</i>	0.002 (0.04)	0.025 (0.61)
<i>Tang</i>	0.066 (0.78)	0.319*** (4.18)
<i>Lev</i>	−0.068 (−0.52)	0.021 (0.17)
<i>PT</i>	−0.048 (−1.46)	−0.046 (−1.41)
<i>GDPgr</i>	−0.001 (−0.42)	−0.002 (−0.61)
_cons	2.461*** (7.07)	1.946*** (6.58)
Year FE	Yes	Yes
Ind FE	Yes	Yes
Prov × Year FE	Yes	Yes
Observations	12,745	12,747
R-squared	0.391	0.356

Notes: Table 8 reports the moderating role of corporate environmental performance. Variable definitions are in Appendix A1. Standard errors are clustered at the establishment level, and *t*-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

reducing pollution emissions. This result is consistent with our expectation that firms actively engaging in environmental activities are more likely to control their emissions to avoid reputational penalties.

In Column (2), the coefficient of *PeerIdio* × *Peer E-score* is significantly negative at the 5% level, suggesting that peer firms engage in more pro-environmental activities, leading to a decrease in other firms' pollution emissions in the same industry. Specifically, a one-unit increase in *Peer E-score* decreases the effect of peer performance (by one standard deviation) on pollution emissions by an additional 2.8%, equivalent to a decrease in SO₂ emissions of 18.2 g/1000 CNY of industrial output, representing on average a 0.31 million CNY cost expenditure from reducing pollution emissions. In sum, the results provide evidence that a firm's own pro-environmental activity or that of its peer firms helps to mitigate the positive effect of peer performance on pollution emissions.

6.2. The effect of state ownership

While the baseline model focuses on firms' economic motivation (i.e., earnings target) to increase emissions in response to peer performance pressures, we further explore how SOEs, which face the dual motivation of economic goals and social goals (e.g., employment and social stability) (Bai et al., 2006), address the relationship between peer performance and emissions. Prior studies indicate that SOE managers may prioritize performance pressures over strict compliance with government environmental regulations. SOEs have natural political ties to the government, unlike private firms, granting them higher bargaining power with the government (Yang and Tang, 2022) and reducing the penalty risk for engaging in misconduct (Chaney et al., 2011; You and Du, 2012). Moreover, SOEs are affiliated with the government, and their managers are appointed by officials. Local officials' career incentives are tied to GDP growth, which incentivizes SOE managers to focus on achieving economic targets rather than environmental targets, thereby weakening the enforcement of environmental regulations (He et al., 2020; Jia, 2024).

To measure the heterogeneity introduced by SOEs, we add the lagged *SOE* and its interaction term with *PeerIdio* to the baseline regression to identify the moderating effects of state ownership on the relationship between peer performance and pollution emissions intensity. Column (1) of Table 9 reports the regression results. The coefficient of $PeerIdio \times LSOE$ is significantly positive at the 5% level, suggesting that the positive effect of peer performance on pollution emissions is more profound in SOEs. In economic terms, a one standard deviation increase in *PeerIdio* is associated with an approximately 10.9% greater rise in pollution emissions from SOEs compared with non-SOEs, equivalent to an increase in SO_2 emissions of 70.85 g/1000 CNY of industrial output, representing on average a 1.21 million CNY cost saving from the additional pollution emissions. This result is consistent with our expectation that SOE managers are more likely to increase emissions in response to performance pressure from peer firms.

There are differences between central and local SOEs regarding objectives, privileges and incentives for compliance. For example, central SOEs typically prioritize national strategic goals and face stricter regulation; in contrast, local SOEs are more aligned with regional GDP growth and employment goals and tend to benefit from more relaxed law enforcement due to their close ties with local officials (He et al., 2020; Jia, 2024). Therefore, we further test whether there are differences in the environmental externalities of peer performance between central and local SOEs. We decompose SOEs into central SOEs (*SOEC*) and local SOEs (*SOEL*) and then interact the terms with *PeerIdio* separately. To address potential concerns regarding omitted variables and reverse causality, we include firm-level political affiliation indicators (*PC*) as a control variable. In Column (2) of Table 9, we find that the coefficient of $PeerIdio \times LSOEC$ is positive but not significant, while the coefficient of $PeerIdio \times LSOEL$ is significantly positive. These coefficients are significantly different at the 5% level, indicating that peer pressure amplifies pollution more in local SOEs; this aligns with their regional growth mandates and weaker environmental accountability, whereas central SOEs might be less responsive to such pressures.

6.3. The effect of economic importance and environmental regulation

With the development of economic reforms in China, political conformity, which was the sole important criterion for promotion before the reforms, has given way to economic growth and other performance-based indicators (Li and Zhou, 2004). Promotions for local officials are increasingly based on economic growth performance (Maskin et al., 2000; Li and Zhou, 2004; Zhang, 2012). To better promote economic growth, local officials often have strong incentives to relax the enforcement of environmental regulations (Cao et al., 2019b; He et al., 2020; Wu and Cao, 2021; Jia, 2024). New industrial projects that can increase GDP and boost local fiscal revenues will be approved, even if they fail to meet environmental standards (Cai et al., 2016), because boosting local GDP and creating tangible political achievements are the most straightforward levers for obtaining short-term returns (Cao et al., 2019b). In this scenario, local government officials focus on firms contributing to local GDP development. These firms, representing a large proportion of total industrial output, have the potential to stimulate local economic growth rapidly. As a result, firms with GDP importance to local economic development have stronger bargaining power in emission law enforcement (Liu et al., 2021).

Table 9
The moderating effect of state ownership.

Dep. Var.=	(1) SOEs <i>Emission</i>	(2) Central vs. local SOEs <i>Emission</i>
<i>PeerIdio</i> × <i>LSOE</i>	1.342** (2.06)	
<i>LSOE</i>	−0.090** (−2.48)	
<i>PeerIdio</i> × <i>LSOEC</i>		0.166 (0.31)
<i>PeerIdio</i> × <i>LSOEL</i>		1.257* (1.89)
<i>LSOEC</i>		−0.008 (−0.20)
<i>LSOEL</i>		−0.076* (−1.81)
<i>PeerIdio</i>	0.620 (0.85)	0.738 (1.10)
<i>Idio</i>	−0.014 (−0.41)	−0.015 (−0.45)
<i>Size</i>	−0.083*** (−4.65)	−0.085*** (−4.77)
<i>ROA</i>	−0.212 (−0.73)	−0.218 (−0.75)
<i>Age</i>	0.029 (1.19)	0.027 (1.08)
<i>Tang</i>	0.230*** (2.70)	0.224*** (2.63)
<i>Lev</i>	−0.162 (−1.20)	−0.165 (−1.21)
<i>PT</i>	−0.023 (−0.70)	−0.023 (−0.70)
<i>GDPgr</i>	−0.006 (−1.26)	−0.006 (−1.26)
<i>PC</i>	0.002 (0.86)	0.002 (0.82)
_cons	2.330*** (6.57)	2.374*** (6.71)
Year FE	Yes	Yes
Ind FE	Yes	Yes
Prov × Year FE	Yes	Yes
Observations	18,442	18,442
R-squared	0.438	0.438

Notes: Table 9 reports the moderating effect of state ownership. Variable definitions are in Appendix A1. Standard errors are clustered at the establishment level, and *t*-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Following Liu et al. (2021), we capture the GDP importance of firms at the prefectural level. Specifically, the prefecture-level total industrial output is aggregated by the index of industrial output value in the CIED. Then, we divide the industrial output value of each enterprise by the aggregated prefecture industrial output and obtain the GDP importance of each establishment. We define a dummy variable, *LEI*, for GDP importance to divide the sample into two categories. *LEI* equals one if the establishment's GDP importance is larger than the median in year *t*−1, and zero otherwise. In the regression model, we add *LEI* and its interaction term with *PeerIdio* to the baseline regression. Column (1) of Table 10 reports the regression results. The coefficient of *PeerIdio* × *LEI* is significantly positive at the 5% level, indicating that the positive effect of peer perfor-

Table 10
The moderating effect of economic importance and environmental regulation.

Dep. Var.=	(1) Economic Importance <i>Emission</i>	(2) Environmental Regulation <i>Emission</i>
<i>PeerIdio</i> × <i>LEI</i>	1.156** (2.01)	
<i>LEI</i>	−0.295*** (−5.90)	
<i>PeerIdio</i> × <i>ERS</i>		−2.998** (−2.43)
<i>PeerIdio</i>	0.873 (1.24)	2.753*** (3.11)
<i>Idio</i>	−0.014 (−0.42)	−0.016 (−0.48)
<i>Size</i>	−0.022 (−1.20)	−0.082*** (−4.73)
<i>ROA</i>	−0.071 (−0.25)	−0.197 (−0.68)
<i>Age</i>	0.039 (1.55)	0.031 (1.24)
<i>Tang</i>	0.222*** (2.59)	0.227*** (2.65)
<i>Lev</i>	−0.137 (−1.00)	−0.167 (−1.23)
<i>PT</i>	−0.021 (−0.66)	−0.022 (−0.66)
<i>GDPgr</i>	−0.006 (−1.25)	−0.006 (−1.26)
<i>SOE</i>	−0.023 (−0.58)	−0.019 (−0.47)
_cons	1.206*** (3.40)	2.287*** (6.55)
Year FE	Yes	Yes
Ind FE	Yes	Yes
Prov × Year FE	Yes	Yes
Observations	18,442	18,442
R-squared	0.441	0.438

Notes: Table 10 reports the moderating effect of economic importance and environmental regulation. *ERS* is omitted due to multicollinearity with *Prov* × *Year* fixed effects. Variable definitions are in Appendix A1. Standard errors are clustered at the establishment level, and *t*-statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

mance on pollution emissions is more profound in firms that have greater importance to GDP. We conclude that firms with bargaining power with the government are more likely to increase emissions in response to performance pressure from peer firms.

In addition, whether firms increase their emissions in response to peer performance depends on the intensity of the local government's environmental enforcement. When local governments are under pressure to meet economic growth targets, the opportunity cost of pursuing environmental protection is high, which causes them to prioritize economic growth targets. In that case, local governments are more inclined to engage in short-term behavior and have strong incentives to relax the enforcement of environmental regulations (He et al., 2020). Under China's current political system, where local environmental protection bureaus' management, personnel and finances are subordinate to local governments (Liu et al., 2021), local governments can relax environmental regulations. Under such circumstances, weaker environmental regulation reduces the cost of corporate pollution emissions. Conversely, stringent environmental regulations increase the cost of corpo-

rate pollution emissions by raising pollution fees, fines and other penalties, thereby incentivizing companies to reduce or eliminate pollutant emissions and resource consumption in their production and operations (Chang and Yu, 2024; Tang et al., 2025). Therefore, we expect that a greater intensity of environmental regulation by local governments will weaken the positive relationship between peer performance and establishment-level pollutant emissions.

To measure the heterogeneity in environmental regulation, we follow Wu et al.'s (2020) approach by constructing an environmental regulation intensity index at the provincial level. Specifically, the index is constructed as follows:

First, we normalize the three sub-indicators (industrial SO₂ removal rate, industrial wastewater compliance rate and industrial solid waste comprehensive utilization rate) via the min–max method:

$$pm_{ij}^n = \frac{pm_{ij} - \min(pm_j)}{\max(pm_j) - \min(pm_j)} \quad (5)$$

where pm_{ij} represents the j th indicator for the i th province; $\max(pm_j)$ and $\min(pm_j)$ represent the maximum and minimum values of indicator j across all provinces in China, respectively; and pm_{ij}^n indicates the normalized value of indicator j for the i th province.

Then, we compute an adjustment coefficient for each sub-indicator in different provinces:

$$W_{ij} = \frac{p_{ij}}{\sum_i p_{ij}} / \frac{gdp_i}{\sum_i gdp_i} \quad (6)$$

p_{ij} represents the discharge of the j th pollutant in the i th province. gdp_i is the GDP value of the i th province.

Finally, the environmental regulation intensity for a respective province is derived by computing the weighted average of the three normalized sub-indicators, using these adjustment coefficients as weights:

$$ER = \left(\sum_{j=1}^3 W_{ij} pm_{ij}^n \right) / 3 \quad (7)$$

After constructing the provincial environmental regulation intensity index, we proceed to define the dummy variable (ERS),⁶ which takes the value of one if province p has a higher environmental regulation intensity in year t than in year $t-1$, which indicates that the ex-ante environmental regulation intensity is increasing in province p , and zero otherwise. We add ERS and its interaction term with $PeerIdio$ to Eq. (3) and report the results in Column (2) of Table 10. The coefficient of $PeerIdio \times ERS$ is significantly negative at the 5% level, indicating that environmental regulation mitigates the positive relationship between peer performance and SO₂ emissions, consistent with our expectation.

7. Conclusion

This paper investigates the environmental externality caused by the effect of peer performance on establishments' pollution emissions. The empirical results show that higher peer performance produces higher-intensity focal-firm SO₂ emissions. The positive effect of peer performance on pollution emissions is more pronounced in firms where over half of the analysts revise upward, where the performance just meets market expectations, and where executive compensation is associated with relative performance evaluation, indicating that capital market pressure and compensation pressure are mechanisms through which peer performance affects pollution emission. Heterogeneity analysis shows that CSR activity by focal firms or peer firms and regional environmental regulations help mitigate the environmental externalities of peer performance, while firms with state ownership and high GDP importance are more likely to increase emissions in response to peer performance. The above evidence emphasizes peer performance's environmental externality and provides implications for balancing the relationship between economic benefits and environmental sustainability.

⁶ To avoid confounding effects from the 2015 New Environmental Protection Law, ERS is measured for 2003–2014, and is set to precede emissions in year t to preserve timing.

It is worth noting that our findings may not fully apply to the post-2015 environmental regulatory framework, as our sample only covers the period up to 2014. In particular, the revision of China's Environmental Protection Law in 2015 implies a significant increase in enforcement intensity, which would impose significant constraints on pollution emissions, thereby affecting the documented relationships. Specifically, the amended Environmental Protection Law introduced a series of targeted enforcement mechanisms capable of altering the status quo. First, it established a daily penalty system, enabling continuous fines for ongoing environmental violations. Second, it introduced unprecedented administrative detention penalties, representing the most severe administrative sanction available against polluters. Finally, government officials who falsify, misreport or conceal pollution data, or who commit major environmental violations, will face mandatory resignation. Therefore, future research could explore how the new environmental regulatory settings affect the relationship between peer performance and firms' emissions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A1. Variable Definitions

Variable	Definition
Emission variables	
<i>Emission</i>	The amount of total SO ₂ emissions (in kilograms) scaled by inflation-adjusted industrial output (per 1000 CNY) at the establishment level.
<i>Dust</i>	The amount of dust emissions scaled by inflation-adjusted industrial output at the establishment level.
<i>ANE</i>	The amount of ammonia nitrogen emissions scaled by inflation-adjusted industrial output at the establishment level.
<i>IWW</i>	The amount of industrial wastewater emissions scaled by inflation-adjusted industrial output at the establishment level.
<i>Emission^{sale}</i>	The amount of total SO ₂ emission scaled by inflation-adjusted operating income (per 1000 CNY) at the establishment level.
Independent variable	
<i>PeerIdio</i>	The average idiosyncratic equity returns of all other firms within a one-digit industry classified by the CSRC at the listed-firm level.
Instrumental variable	
<i>PeerCustIdio</i>	The mean idiosyncratic returns of the major customers of peer firms.
Firm control variables	
<i>Idio</i>	The idiosyncratic equity returns at the listed-firm level, estimated by Eqs. (1) and (2).
<i>Size</i>	The natural logarithm of total assets at the establishment level.
<i>ROA</i>	Net income scaled by total assets at the establishment level.
<i>Age</i>	The natural logarithm of the age of the firm at the establishment level.
<i>SOE</i>	An indicator variable set to one if the firm is state-owned, and zero otherwise.

(continued on next page)

Appendix A1 (continued)

Variable	Definition
<i>Tang</i>	Intensity of tangible assets, calculated as fixed assets divided by total assets at the beginning of the year at the establishment level.
<i>Lev</i>	Total debt scaled by total assets at the listed-firm level.
<i>PC</i>	Equal to one if the directors or senior executives have work experience in government departments, and zero otherwise.
City-level control variables	
<i>PT</i>	Indicator variable equal to one if a new city-level mayor takes office, and zero otherwise.
<i>GDPgr</i>	Measured as the natural logarithm of current-year city GDP growth rate.
Mechanism variables	
<i>LRevision</i>	The last analyst forecast consensus minus the first analyst forecast consensus for listed firms in year $t-1$.
<i>LRevisionUp</i>	Equal to one if more than half of the analysts revise their earnings forecasts upward for target firms in year $t-1$, and zero otherwise.
<i>MeetFeps</i>	Equal to one if the earnings surprise is between zero and two cents, and zero otherwise.
<i>RPE</i>	Equal to one if the firm's executive compensation contract is explicitly based on relative performance evaluation, and zero otherwise.
<i>Focal E-score</i>	Equal to the natural logarithm of the environmental performance score plus one in year t .
<i>Peer E-score</i>	Equal to the average environmental performance score of all other firms within the same industry at the listed-firm level.
<i>LEI</i>	Equal to one if the establishment's GDP importance is larger than the median in year $t-1$, and zero otherwise.
<i>ERS</i>	Equal to one if province p has a higher environmental regulation intensity in year t than in year $t-1$, and zero otherwise.

Appendix A2. Correlation Analysis

	<i>Emission</i>	<i>PeerIdio</i>	<i>Idio</i>	<i>Size</i>	<i>ROA</i>	<i>Age</i>	<i>SOE</i>	<i>Tang</i>	<i>Lev</i>	<i>PT</i>	<i>GDPgr</i>
<i>Emission</i>	1	-0.06*	0.00	0.03*	-0.05*	-0.06*	0.09*	0.30*	0.07*	-0.00	0.03*
<i>PeerIdio</i>	-0.09*	1	0.05*	0.04*	0.09*	-0.01	-0.03*	-0.04*	-0.06*	-0.02*	-0.03*
<i>Idio</i>	-0.00	0.12*	1	0.01	0.06*	0.00	0.01	-0.01	-0.02*	-0.01	-0.02*
<i>Size</i>	0.07*	0.05*	-0.00	1	0.02*	0.11*	0.25*	0.10*	0.17*	-0.01	-0.12*
<i>ROA</i>	-0.04*	0.08*	0.08*	0.04*	1	0.01*	-0.02*	-0.02*	-0.44*	-0.03*	0.02*
<i>Age</i>	-0.06*	0.01*	0.00	0.12*	0.01	1	0.13*	-0.20*	-0.01	0.01	-0.16*
<i>SOE</i>	0.07*	-0.03*	-0.01	0.27*	-0.00	0.15*	1	0.09*	0.14*	-0.00	-0.04*
<i>Tang</i>	0.25*	-0.04*	-0.01	0.12*	-0.01	-0.19*	0.10*	1	0.06*	0.00	0.03*
<i>Lev</i>	0.07*	-0.05*	-0.02*	0.16*	-0.45*	-0.01	0.13*	0.07*	1	-0.01	0.00
<i>PT</i>	-0.00	-0.02*	-0.01	-0.01	-0.02*	0.01	-0.00	0.00	-0.01	1	-0.05*
<i>GDPgr</i>	0.03*	-0.06*	0.00	-0.12*	-0.01	-0.12*	-0.05*	0.01	-0.00	-0.04*	1

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The transmission effect of local government fiscal burdens: Evidence from commercial credit



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ABSTRACT

We investigate how local government fiscal pressure is transmitted to corporate commercial credit provision. Heightened fiscal pressure significantly reduces firms' net commercial credit supply. Mediation analysis reveals three transmission channels: expanded debt issuance crowds out corporate loan availability; intensified tax administration increases corporate tax burdens; and reduced government subsidies constrain corporate cash flows. Collectively, these mechanisms compel firms to curtail commercial credit extension. Heterogeneity analysis demonstrates that regions heavily dependent on debt, land revenue or tax revenue experience amplified adverse impacts; firms with higher customer concentration and supplier concentration and weaker institutional backing exhibit greater vulnerability. We demonstrate the microeconomic consequences of fiscal stress, emphasizing the importance of diversified revenue structures and robust government–business relationships for sustainable economic development.

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1. Introduction

The global economy is confronting unprecedented fiscal stress, with government debt surpassing 100 trillion USD and debt-to-GDP ratios reaching historic peaks across both developed and emerging markets

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(International Monetary Fund, 2024). This mounting fiscal burden creates a fundamental tension between the necessity of fiscal consolidation for sustainability and the risk that aggressive austerity measures will disrupt private sector activity and undermine economic recovery (Alesina et al., 2019; De Vries et al., 2020). Understanding how fiscal pressure is transmitted from the public to the private sector represents a critical challenge for policymakers and researchers alike, particularly as governments navigate the delicate balance between fiscal discipline and growth preservation. This study examines trade credit, the deferred payment arrangements between firms in commercial transactions, as a key transmission channel through which government fiscal stress affects corporate financial behavior and supply chain stability (Adelino and Ferreira, 2023; Ersahin et al., 2024).

China provides an ideal institutional setting for examining fiscal transmission mechanisms. Chinese local governments face substantial and growing fiscal pressure: the aggregate fiscal gap reached 8.2 trillion RMB in 2022 (6.8% of GDP), with debt-to-revenue ratios exceeding 250% in fiscally stressed regions (Ma and Chen, 2022; Liu and Xie, 2023). This crisis stems from a distinctive institutional arrangement—fiscal decentralization with political centralization. The 1994 tax-sharing reform created a structural mismatch between revenue authority (centralized) and expenditure responsibilities (decentralized), generating persistent fiscal gaps that widened following the 2008 stimulus and the 2016 business-to-VAT reform (Jia et al., 2021; Peng et al., 2022). Constrained by rigid fiscal rules yet facing binding expenditure commitments, local governments respond through three channels: debt expansion, tax intensification, and subsidy retrenchment (Fan et al., 2021; Chen et al., 2023; Wang et al., 2025). This multi-instrument adjustment process creates an ideal laboratory for studying fiscal transmission: the severity of fiscal pressure provides sufficient variation for identification; institutional constraints force governments to employ visible adjustment strategies; and the absence of federal transfers or bailout expectations ensures that fiscal shocks are transmitted directly to local firms. Moreover, with trade credit serving as a primary financing channel for private enterprises, China's extensive inter-firm credit networks render commercial credit provision a sensitive margin for detecting fiscal spillovers (Ersahin et al., 2024). These features enable us to trace fiscal pressure transmission through specific channels and identify heterogeneous effects across fiscal structures and firm characteristics.

Previous research extensively examines the effects of fiscal policy on corporate investment, employment and leverage decisions (Born et al., 2020; Magud et al., 2022; Ando et al., 2025). Studies demonstrate that fiscal consolidation reduces corporate investment by 15–25% and employment by 8–12% during austerity episodes (Magud et al., 2022). However, prior literature predominantly focuses on direct fiscal–corporate linkages through taxation and subsidies, overlooking indirect transmission through inter-firm credit networks. Trade credit, accounting for 60–80% of corporate short-term liabilities in emerging markets, serves as the primary working capital financing mechanism and supply chain lubricant (Ersahin et al., 2024). Moreover, recent evidence reveals that trade credit networks play a critical role in transmitting financial shocks across supply chains, with disruptions contributing to output losses comparable to bank credit contractions (Acemoglu et al., 2015; Costello, 2020). Yet the relationship between government fiscal pressure and corporate trade credit provision remains unexplored. The theoretical mechanism linking fiscal stress to trade credit differs fundamentally from monetary transmission channels. While monetary policy operates primarily through credit availability and interest rates (Bottero et al., 2022; Wang, 2025), fiscal policy affects firms through multiple channels: a direct cash flow channel that operates via taxation and subsidies; an indirect credit market channel that works through government borrowing; and expectational channels regarding future fiscal capacity (Blanchard, 2019; Bernardini and Forni, 2021; Shi et al., 2024). This research gap is particularly problematic because trade credit networks can amplify fiscal shocks through supply chain propagation, potentially creating systemic vulnerabilities. The failure to understand fiscal transmission through trade credit channels limits both theoretical frameworks and policy design, as fiscal consolidation strategies may inadvertently destabilize commercial relationships and working capital management across entire supply chains.

This study aims to examine how local government fiscal pressure is transmitted to corporate trade credit provision, identify the underlying transmission mechanisms and assess heterogeneous effects across institutional contexts and firm characteristics. Specific research questions are as follows:

- Does local government fiscal pressure reduce corporate net trade credit provision?
- Do credit crowding-out, tax intensification and subsidy cuts mediate this relationship?

- Do fiscal structures (debt, land and tax dependence) and firm characteristics (concentration and ownership) moderate these effects?

To address these questions, we empirically analyze a comprehensive panel dataset of all A-share listed firms in China from 2007 to 2022, matched with prefecture-level fiscal information. We use firm and year fixed effects to isolate the impact of local fiscal conditions on corporate behavior and combine instrumental-variable estimation with a quasi-natural experiment to strengthen causal inference. We further conduct mediation, robustness and heterogeneity analyses to explore the underlying transmission mechanisms and assess the stability of the results.

This study contributes to the literature in several ways. First, it reveals trade credit to be a critical channel through which government fiscal distress affects real economic activity. This transmission pathway is overlooked in prior research examining the effects of fiscal policy on investment and employment (Born et al., 2020; Magud et al., 2022). Our analysis demonstrates how fiscal pressure propagates through commercial relationships, with potential supply chain amplification effects (Ersahin et al., 2024). Second, we decompose transmission mechanisms into three distinct pathways, namely credit market crowding-out, intensified tax enforcement and subsidy retrenchment, moving beyond aggregate fiscal effects to reveal how different policy instruments operate through separate financial constraint margins. Third, we document substantial heterogeneity across fiscal structures and firm characteristics: cities with volatile revenue and firms with weak bargaining power experience disproportionately large effects, revealing systematic asymmetries with implications for spatial inequality (Jacques, 2021; Ma and Chen, 2022). Fourth, our findings offer actionable policy insights. Evidence that debt-heavy consolidation harms private credit access suggests that revenue diversification and targeted support for vulnerable supply chain participants are essential to mitigate collateral damage from fiscal retrenchment.

The remainder of the article is organized as follows. Section 2 presents the literature review and hypothesis development. Section 3 provides the data sources, definitions of the variables and the baseline regression model. Section 4 reports our empirical analyses, including baseline and mediating analyses, endogeneity and robustness tests and heterogeneity analysis. A conclusion and policy implications are presented in Section 5.

2. Literature review and hypotheses

2.1. Fiscal pressure and corporate commercial credit

Fiscal pressure is an economic phenomenon resulting from the mismatch between government revenue and expenditure, arising primarily because the elasticity of revenue fails to keep pace with the rigidity of expenditure. Governments are responsible for maintaining social stability, infrastructure and public welfare (Sun and Yuan, 2020). To manage fiscal pressure, governments implement measures that affect both macroeconomic policies and micro-level corporate behaviors, such as taxation and earnings management (Chen, 2016; Wen et al., 2023; Zhang et al., 2023a). This literature review examines the relationship between fiscal pressure and corporate commercial credit, highlighting how government actions to alleviate fiscal stress impact corporate credit practices.

Fiscal pressure typically arises from a gap between government revenue and expenditure. Historical and contemporary studies provide insights into the causes of fiscal pressure. Yu and Korman (2006) identify industrial decline as a factor that reduces tax revenue and increases public demands. In China, the 2008 financial crisis led to a stimulus package and substantial local government debt, exacerbating fiscal pressure in subsequent years (Ma and Qin, 2022). Further, VAT reduction policies from 2015 to 2018 widened the fiscal gap (Guo, 2019). These episodes illustrate how both exogenous shocks and policy adjustments can create sustained fiscal imbalances, making it essential to understand the transmission mechanisms through which fiscal stress affects the real economy.

Governments employ various measures to alleviate fiscal pressure, primarily through increasing revenue and reducing expenditure (Wen et al., 2023). These measures have significant implications for corporate operations.

To increase revenue, governments rely on both budgeted and non-budgeted sources. Budgeted revenue primarily comes from taxation. Studies indicate that local governments push tax departments to enforce stricter tax collection and administration, often by setting high-growth tax targets, while digital governance tools such as government social media further strengthen tax compliance by reducing avoidance incentives (Chen, 2017; Yu et al., 2018; Jiang et al., 2023). Supporting industries closely related to key tax sources and expanding financial sources with high tax returns are also common strategies (Xi et al., 2017; Xie et al., 2017). However, these actions can increase the corporate tax burden, potentially compromising long-term sustainability (Sun, 2021). Non-budgeted revenue includes land transfer revenue and government debt. Post-tax distribution reform in China allowed local governments to retain land revenue, providing a significant non-budgeted revenue stream (Chen et al., 2002; Fan, 2015). Government debt, another crucial source, can create future fiscal pressure due to high leverage levels and potentially crowd out bank loans to corporations, negatively affecting the real economy (Fan, 2015; Demirci et al., 2019; Xu et al., 2020).

To reduce expenditure, governments often cut back on grants and subsidies. Government subsidies are essential for providing financial support to companies, fostering social stability and promoting economic development (Bai et al., 2019; Liang et al., 2024). However, fiscal pressure can lead to reduced subsidies, particularly for less profitable firms (Branstetter et al., 2023). Instead, governments may focus subsidies on highly profitable or high-tech potential enterprises to generate excess tax revenue and attract external investments, benefiting both the government and enterprises (Wen et al., 2023).

Commercial credit is a critical financing tool for businesses, especially in times of economic uncertainty. It involves borrowing and lending among enterprises within supply chain relationships, providing an alternative to traditional financing channels (Zhang et al., 2012; Giannetti et al., 2011). Two main theories explain companies' commercial credit behavior. The buyer's market hypothesis suggests that suppliers extend commercial credit to gain competitive advantages and market share (Hu and Wu, 2022). The default risk hypothesis views commercial credit as a venture investment, where suppliers benefit if customers meet their obligations beyond the agreed terms (Cunat, 2006). However, suppliers must consider macroeconomic conditions and customers' financial health (Love et al., 2007). The alternative financing theory posits that commercial credit is a means of alleviating financial constraints, especially when traditional financing is limited or subject to uncertainty that intensifies corporate cash retention motives (Allen et al., 2005; Geng et al., 2021; Lu and Yang, 2023). Suppliers may prefer to lend to financially constrained customers to maintain supply chain stability, despite the associated risks (Fang, 2014; Ersahin et al., 2024).

Several factors influence corporate decisions regarding commercial credit. Macro factors include monetary policy, the financial environment and institutional reforms, which shape information transparency and financing constraints, and significant economic events, which affect the cost and availability of financing (Cloyne et al., 2023; Zhang and Zhao, 2023). Internally, capital status, management decisions and financial background play crucial roles (Meltzer, 1960; Zhang, 2020). Effective commercial credit policies can help businesses remain competitive, build customer relationships and optimize supply chain efficiency.

In conclusion, fiscal pressure significantly impacts corporate commercial credit behaviors. Government measures to alleviate fiscal stress, such as increased taxation and reduced subsidies, can indirectly influence corporate financing decisions. Understanding the dynamics between fiscal pressure and corporate commercial credit is vital for balancing government fiscal health and corporate sustainability. This knowledge can guide policy formulation to achieve win-win outcomes for governments and businesses, ensuring economic stability and growth.

2.2. *Research hypotheses*

Under increasing fiscal pressure, local governments typically increase fiscal revenue and curtail expenditure to mitigate fiscal risks. This includes issuing government debt, strengthening tax administration and reducing subsidies. Fiscal policies can influence corporate capital allocation behaviors, while commercial credit policies affect working capital. Commercial credit is used for operational and financing purposes (Petersen and Rajan, 1997; Fisman and Love, 2003). For operational purposes, suppliers extend commercial credit to attract or retain customers, aiming to boost sales and maintain relationships. Additionally, commercial credit serves as a significant short-term funding alternative to bank loans due to the lower information asymmetry and

interest rates in closed supply chain relationships (Daniel et al., 2013). However, a company's financial capacity influences its commercial credit strategies (Schwartz, 1974). When liquidity is low and financial constraints are high, companies tend to reduce their provision of commercial credit to customers and seek commercial credit financing from suppliers.

Measures to alleviate fiscal pressure can reduce companies' cash flows, increasing financial constraints and worsening financial performance. Thus, fiscal pressure is expected to affect companies' commercial credit behaviors. For example, a decline in government subsidies directly reduces the cash received by companies. Public debt can crowd out private firm investment by tightening funding constraints (Huang et al., 2020). Furthermore, due to information asymmetry, fiscal support can be perceived as government endorsement, signaling future income potential (Han et al., 2017). A reduction in fiscal support can negatively impact market investors' perceptions of a company. Consequently, in a deteriorating external business environment, companies may increase their commercial credit financing and reduce their provision of commercial credit.

In conclusion, government policies implemented under fiscal pressure can have adverse effects on companies' financial performance, prompting them to accelerate the cash cycle and obtain commercial credit from suppliers. As companies have greater discretion over extending commercial credit to customers than over obtaining it from suppliers, this research uses net commercial credit to capture the balance between commercial credit provision and financing. Based on the above analysis, we propose the following hypothesis:

H1: Increased local fiscal pressure negatively impacts net commercial credit flows.

The research further explores the mediating mechanisms through which fiscal pressure affects net commercial credit flows. Under heightened fiscal pressure, local governments increasingly rely on public debt issuance to alleviate budgetary constraints. Given the relatively high credit ratings and implicit guarantees associated with government debt, banks tend to reallocate credit to public borrowers, resulting in a tightening of bank loan supply to local firms. This contraction in loan availability reflects a supply-side crowding-out effect rather than firms' voluntary borrowing decisions, thereby imposing externally driven financing constraints on corporate borrowers (Huang et al., 2020). Facing constrained access to bank loans, which serve as a primary funding source, firms must seek alternative financing channels. Additionally, in the corporate bond market, local governments implicitly guarantee companies. Increased fiscal pressure, however, reduces local governments' willingness and ability to rescue enterprises from default risks (Luo and Liu, 2016), lowering investors' confidence in corporate bonds and firms' ability to raise required funds (Chen et al., 2010; Shi et al., 2024). Firms turn to supply chain financing as a substitute when both bank credit and bond markets tighten; this is especially true for firms lacking the governance mechanisms required to mitigate bond issuance costs (Liang et al., 2025). This strategic adjustment manifests as increased trade credit financing from suppliers to alleviate capital shortages, coupled with reduced trade credit provision to customers to preserve liquidity and compensate for elevated capital costs (Biais and Gollier, 1997). Based on the above analysis, we propose the following hypothesis:

H2-1: When fiscal pressure increases, decreased loan availability reduces net commercial credit provision.

Strengthening tax administration is another crucial means for governments to expand fiscal revenue. The government-business relationship is vital for companies' sustainable and strategic development (Liu and Liu, 2023). Companies have little incentive to avoid administrative policies. Therefore, when tax collection intensifies, companies generally reduce their earnings management and tax avoidance behaviors (Feng et al., 2023), leading to higher tax expenses and reduced liquidity. To increase liquidity, companies may manage commercial credit to shorten cash conversion periods, thereby decreasing net commercial credit flows. Consequently, companies are expected to reduce their net commercial credit provision due to the higher tax burdens induced by stricter tax administration under fiscal pressure. Based on the above analysis, we propose the following hypothesis:

H2-2: When fiscal pressure increases, the resulting increased tax burden reduces net commercial credit provision.

The research also considers the role of reducing government subsidies in cutting government expenditure. A decrease in government subsidies directly impacts companies' cash holdings and productivity, as subsidies often come in the form of rebates, exemptions and investments (Qi et al., 2023). As subsidies aim to encourage industry development, they are perceived as government endorsements in inefficient markets (Yan and Li, 2018). Therefore, a decline in government subsidies may further constrain finances. Companies with fewer

subsidies tend to increase their cash holdings to ensure smooth operations and research, reducing their net commercial credit provision. Based on the above analysis, we propose the following hypothesis:

H2-3: When fiscal pressure increases, decreased subsidies lead to a reduction in net commercial credit supply.

The theoretical framework guiding this research is shown in Fig. 1.

3. Empirical methodology

3.1. Data resource

We utilize prefecture-level data spanning 2007–2022 to assess fiscal pressure and data from A-share listed companies to evaluate corporate commercial credit. The city-level data are primarily sourced from the National Bureau of Statistics of China and China Statistical Yearbooks, while the corporate-level data are mainly derived from the China Stock Market & Accounting Research database. Our sample comprises A-share market-listed companies, excluding those in the finance industry or under special treatment. We also exclude observations with missing financial or macroeconomic data, resulting in a final dataset of 38,688 observations. To mitigate the influence of outliers, continuous variables are winsorized at the 1% and 99% levels.

3.2. Variables

3.2.1. Corporate commercial credit

Following Wu et al. (2015), we utilize receivables (*NetCredit*) to measure the net commercial credit supplied by companies. *NetCredit* is determined by the difference between the sum of accounts receivable, notes receivable and prepayments and the sum of accounts payable, notes payable and advances received, scaled by total assets. This measure indicates the proportion of net commercial credit extended to business partners relative to the enterprise's total assets, exclusive of funds utilized by business partners, such as accounts payable, notes

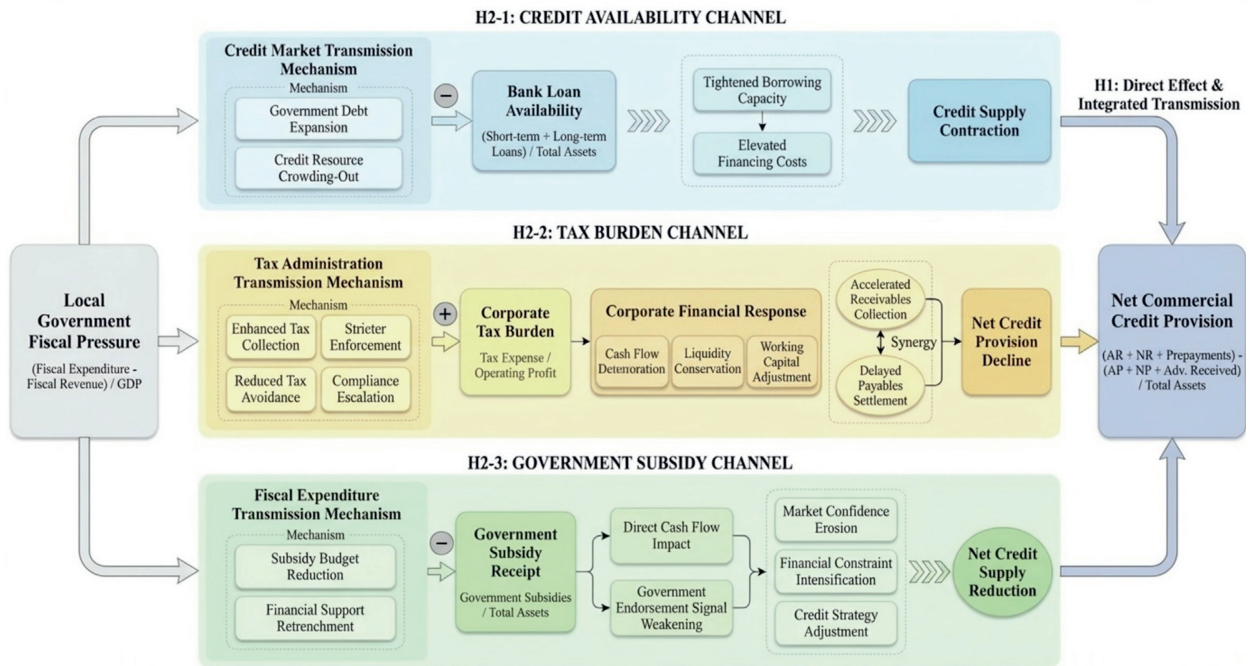


Fig. 1. Theoretical framework.

payable and advances received. A higher value of *NetCredit* implies that a greater level of operating capital is provided to business partners compared with financing from supply chain companies.

3.2.2. Fiscal pressure

“Fiscal pressure” refers to the difference between fiscal revenue and expenditure, that is, between the revenue available and the expenditure required. Following Wen et al. (2023) and Sun (2021), this research uses the standardized local government fiscal gap, that is, “(local public budget expenditure – local public budget revenue)/ local gross domestic product,” to assess prefecture-level fiscal pressure (*Pressure*).

3.2.3. Mediating variables

(1) Bank loan availability

Referring to Cai et al. (2024), we employ the ratio of total short-term and long-term loans to total assets at the end of the year to measure the loan availability of an enterprise (*Access*).

(2) Degree of tax burden

Referring to Kong and Yuan (2021), we employ the ratio of corporate tax expense over operating profits to measure a company’s tax burden (*TaxBurden*).

(3) Degree of subsidy received

Referring to Branstetter et al. (2023), we adopt the ratio of government subsidy over assets at the year-end to measure the level of subsidy received by a company (*Subtensity*).

3.2.4. Control variables

We control the following company-level variables: size, financial leverage, cashflow ratio, dual role of the board chairman, profitability, operating expense ratio, firm age, shares in financial institutions, nature of property rights and board size. Additionally, we control the city factor of population density. The details are shown in Table 1. We control fixed effects at the firm level to eliminate bias caused by non-time-

Table 1
Definitions of variables.

Type	Variable	Name	Definition
Explained Variable	<i>NetCredit</i>	Commercial credit	The net value of receivables (i.e., accounts receivable, notes receivable and prepayments) and payables (i.e., accounts payable, notes payable and advances received) scaled by year-end assets
Explanatory Variable	<i>Pressure</i>	Fiscal pressure	The gap between local fiscal expenditure and revenue scaled by local GDP
Mediating Variable	<i>Access</i>	Bank loan availability	The sum of total short-term and long-term loans scaled by total assets
	<i>TaxBurden</i>	Degree of tax burden	The ratio of tax expenses to operating profits
	<i>Subtensity</i>	Degree of subsidy received	The ratio of government subsidy received to total assets
Control Variable	<i>Popdensity</i>	Population density	The logarithm of the ratio of population to land area
	<i>Size</i>	Company size	The logarithm of total assets
	<i>Lev</i>	Financial leverage	The ratio of total debt to net assets
	<i>Cashflow</i>	Cashflow ratio	The ratio of net cash flow from operating activities to the current liabilities
	<i>Dual</i>	Dual Role of the Board Chairman	A dummy variable that equals 1 if the CEO also serves as the chairperson of the board of directors, and 0 otherwise
	<i>ROA</i>	Profitability of the company	The ratio of net income after tax to total assets
	<i>Ofee</i>	Operating expense ratio	Operating expense divided by operating revenue
	<i>Age</i>	Firm age	The natural logarithm of the company’s age in the capital market
	<i>FinInst</i>	Shares in financial institutions	A dummy variable that equals 1 for companies with shares in other financial institutions, and 0 otherwise
	<i>SOE</i>	Nature of property rights	A dummy variable that equals 1 for state-owned enterprise, and 0 otherwise
	<i>Board</i>	Size of the board	The logarithm of the total number of directors

varying characteristics at the firm level. Additionally, considering the impact of national macroeconomic fluctuations and other related factors, we further control for the year-fixed effect (Zhang et al., 2023b).

3.3. Regression model

To examine the relationship between increased fiscal pressure and the allocation of corporate commercial credit (H1), we construct regression model (1):

$$NetCredit_{i,l,t} = \beta_0 + \beta_1 Pressure_{l,t} + \gamma Control_{i,l,t} + \delta_i + \tau_t + \varepsilon_{i,l,t} \quad (1)$$

where i denotes the companies, l denotes the city in which the company is incorporated, and t denotes the year. $NetCredit_{i,l,t}$ represents the net level of commercial credit of company i in year t . $Pressure_{l,t}$ indicates the fiscal pressure status of city l in year t . $Control_{i,l,t}$ represents the control variables. δ_i and τ_t denote factors that do not change across companies and across time, respectively. $\varepsilon_{i,l,t}$ is the random error term, and β_0 , β_1 and γ are the coefficients. Next, we use Baron and Kenny (1986) method to test the mediation models for the impacts of fiscal pressure on net commercial credit supply. Based on Eq. (1) above, we establish the following equations to test H2-1, H2-2 and H2-3.

For H2-1, we adopt Eq. (2) and Eq. (3). The specific equations are as follows:

$$Access_{i,l,t} = \alpha_0 + \alpha_1 Pressure_{l,t} + \gamma Control_{i,l,t} + \delta_i + \tau_t + \varepsilon_{i,l,t} \quad (2)$$

$$NetCredit_{i,l,t} = \eta_0 + \eta_1 Pressure_{l,t} + \eta_2 Access_{i,l,t} + \varphi Control_{i,l,t} + \delta_i + \tau_t + \varepsilon_{i,l,t} \quad (3)$$

In Eq. (2) and Eq. (3), $Access_{i,l,t}$ represents the level of loan availability of company i in year t in city l . $Control_{i,l,t}$ represents the control variables. δ_i and τ_t denote factors that do not change across companies and across time, respectively. $\varepsilon_{i,l,t}$ is the random error term, and β_0 , β_1 , γ , η_0 , η_1 and ψ are the coefficients. Symbols in the following groups of mediating models have similar meanings. To verify the mediating effects of tax burden (H2-2), we employ Eq. (4) and Eq. (5), in which $TaxBurden_{i,l,t}$ denotes the level of the tax burden of company i in year t in city l . The specific equations are as follows:

$$TaxBurden_{i,l,t} = \alpha_0 + \alpha_1 Pressure_{l,t} + \gamma Control_{i,l,t} + \delta_i + \tau_t + \varepsilon_{i,l,t} \quad (4)$$

$$NetCredit_{i,l,t} = \eta_0 + \eta_1 Pressure_{l,t} + \eta_2 TaxBurden_{i,l,t} + \varphi Control_{i,l,t} + \delta_i + \tau_t + \varepsilon_{i,l,t} \quad (5)$$

Finally, we construct Eq. (6) and Eq. (7) to test H2-3, regarding the mediation effect of the level of subsidy received. $Subtensity_{i,l,t}$ means the level of government subsidy received by the company i in year t in city l . The specific equations are as follows:

$$Subtensity_{i,l,t} = \alpha_0 + \alpha_1 Pressure_{l,t} + \gamma Control_{i,l,t} + \delta_i + \tau_t + \varepsilon_{i,l,t} \quad (6)$$

$$NetCredit_{i,l,t} = \eta_0 + \eta_1 Pressure_{l,t} + \eta_2 Subtensity_{i,l,t} + \varphi Control_{i,l,t} + \delta_i + \tau_t + \varepsilon_{i,l,t} \quad (7)$$

4. Results

4.1. Descriptive statistics

Table 2 presents a descriptive statistical overview of the variables used in this study. The mean value of net corporate commercial credit is -0.0079 , indicating that companies on average receive slightly more commercial credit than they provide within the supply chain. This negative mean suggests that firms generally act as net recipients of commercial credit, consistent with financing constraints in emerging markets. The variable exhibits moderate volatility, with a standard deviation of 0.1476 , reflecting heterogeneity in commercial credit practices across companies. The relatively small absolute value of the mean, close to zero, indicates a balanced position between commercial credit provision and financing across the sample.

After standardization, fiscal pressure shows a mean of 0.0003 , with a median of -0.1886 and a standard deviation of 0.9969 . The standardization allows for better interpretation of the economic magnitude of the effects. The distribution suggests considerable variation in fiscal pressure across different regions and time peri-

Table 2
Descriptive statistics.

Variable	Obs.	Mean	S.D.	Min.	Median	Max.
<i>NetCredit</i>	38,688	−0.0079	0.1476	−0.6922	0.0031	0.6784
<i>Pressure</i>	38,688	0.0003	0.9969	−6.6348	−0.1886	27.1286
<i>Access</i>	38,688	0.1363	0.1320	0.0000	0.1061	0.8265
<i>TaxBurden</i>	38,688	0.0737	0.0816	0.0000	0.0567	0.5552
<i>Subtensity</i>	38,688	0.0098	0.0422	0.0000	0.0024	1.3155
<i>Popdensity</i>	38,688	8.0497	0.6256	6.3700	8.0523	9.3177
<i>Lev</i>	38,688	0.4273	0.2052	0.0534	0.4210	0.8872
<i>ROA</i>	38,688	0.0256	0.0854	−0.2200	0.0348	0.2235
<i>Ofee</i>	38,688	0.1579	0.1277	0.0138	0.1226	0.6725
<i>Size</i>	38,688	22.1503	1.3089	19.8050	21.9540	26.1906
<i>Cashflow</i>	38,688	0.0472	0.0702	−0.1641	0.0463	0.2476
<i>Dual</i>	38,688	0.2698	0.4439	0.0000	0.0000	1.0000
<i>FirmAge</i>	38,688	2.8602	0.3697	1.6094	2.8904	3.5264
<i>FinInst</i>	38,688	0.0627	0.2423	0.0000	0.0000	1.0000
<i>SOE</i>	38,688	0.3797	0.4853	0.0000	0.0000	1.0000
<i>Board</i>	38,688	2.1298	0.2011	1.6094	2.1972	2.7081

ods, with some areas experiencing substantial fiscal stress while others maintain relatively stable fiscal conditions.

Regarding the mediator variables, *Access* has a mean of 0.1363, indicating that bank loans constitute approximately 13.6% of total assets for the average firm. *TaxBurden* shows a mean of 0.0737 with a standard deviation of 0.0816, suggesting moderate but varied tax burdens across companies. *Subtensity* exhibits a mean of 0.0098, indicating that government subsidies represent about 1% of total assets on average, with substantial variation (standard deviation of 0.0422) reflecting targeted subsidy policies.

The control variables yield results consistent with general conditions at both the city and company levels. The average firm size (*Size*) is 22.15 (logged total assets), with leverage (*Lev*) averaging 42.73%. The sample comprises 38.0% state-owned enterprises (*SOE*), and 27.0% of firms have CEO duality (*Dual*). These characteristics confirm that the sample of 38,688 firm-year observations is representative for addressing the research problem.

4.2. Baseline results

Table 3 examines the impact of local governments' fiscal pressure on enterprises' commercial credit behavior. Firm-fixed effects and year-fixed effects are included in column (1). In column (2), the control variables at the city and firm levels are further considered. The estimated coefficients of *Pressure* in columns (1) and (2) indicate negative relationships between fiscal pressure and the provision of net commercial credit, both significant at the 10% level. The coefficient in column (2) is −0.0233, suggesting that a one standard deviation increase in standardized fiscal pressure leads to a 0.0233 decrease in net commercial credit scaled by total assets. This economically meaningful effect supports H1, demonstrating that companies under higher fiscal pressure reduce their provision of net commercial credit to business partners.

To provide a more comprehensive understanding of companies' commercial credit behaviors, the research further decomposes net commercial credit into its financing and provision components. Following Lin and Dong (2024), we measure the degree of commercial credit financing through the sum of accounts payable and notes payable plus advances received, scaled by total assets (*UpCredit*). This reflects the working capital that companies obtain from their suppliers. Similarly, we measure the degree of commercial credit provision through the sum of accounts receivable and notes receivable plus prepayments, scaled by total assets (*DownCredit*), representing the credit that companies extend to their customers.

Table 3
Baseline results.

Variable	(1) <i>NetCredit</i>	(2) <i>NetCredit</i>	(3) <i>UpCredit</i>	(4) <i>UpCredit</i>	(5) <i>DownCredit</i>	(6) <i>DownCredit</i>
<i>Pressure</i>	−0.0236* (−1.97)	−0.0233* (−1.93)	0.0209*** (2.67)	0.0203** (2.50)	−0.0072* (−1.74)	−0.0075* (−1.92)
<i>Popdensity</i>		0.0020 (0.39)		−0.0047 (−0.80)		−0.0026 (−0.82)
<i>Size</i>		−0.0024 (−0.79)		−0.0117*** (−5.81)		−0.0153*** (−6.47)
<i>Lev</i>		−0.1565*** (−14.53)		0.2306*** (22.50)		0.0714*** (7.92)
<i>Cashflow</i>		−0.2686*** (−19.14)		0.1181*** (14.14)		−0.1602*** (−17.03)
<i>Dual</i>		−0.0033 (−1.25)		0.0001 (0.07)		−0.0035** (−2.23)
<i>ROA</i>		0.0484*** (7.49)		0.0184*** (3.50)		0.0702*** (13.33)
<i>Ofee</i>		−0.0402** (−2.28)		−0.1136*** (−8.11)		−0.1604*** (−13.55)
<i>FirmAge</i>		−0.0109 (−0.69)		−0.0010 (−0.07)		−0.0100 (−1.00)
<i>FinInst</i>		−0.0030 (−0.77)		0.0013 (0.36)		−0.0032 (−1.24)
<i>SOE</i>		−0.0016 (−0.25)		0.0084** (2.21)		0.0065 (1.37)
<i>Board</i>		−0.0005 (−0.07)		0.0062 (1.15)		0.0065 (1.15)
Constant	−0.0078*** (−36.52)	0.1465* (1.85)	0.1620*** (1622.28)	0.3589*** (5.48)	0.1606*** (1096.19)	0.5339*** (8.68)
Company FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	38,688	38,688	38,688	38,688	38,688	38,688
R-squared	0.7080	0.7297	0.7233	0.7628	0.7619	0.7779

Notes: t-values are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Columns (3) and (4) reveal that companies significantly increase their commercial credit financing when local fiscal pressure intensifies. The coefficient of *Pressure* on *UpCredit* is 0.0203 in column (4), indicating that firms actively seek more credit from suppliers under fiscal stress. Conversely, columns (5) and (6) show that companies reduce their provision of commercial credit, with a coefficient of −0.0075 in column (6). This asymmetric response—increasing credit financing while decreasing credit provision—demonstrates that under tight fiscal policies, companies strategically manage their working capital to preserve liquidity and improve financial conditions in anticipation of reduced cash flows, consistent with Denis and Sibilkov (2010).

The high R-squared values (ranging from 0.708 to 0.778) indicate that our model explains a substantial portion of the variation in commercial credit behaviors, while the large sample of 38,688 observations provides robust statistical power for our analyses.

4.3. Mediation analysis

Based on the theoretical analyses, we now report empirical tests of the mediating effects of loan availability, tax burden and government subsidy received and how they affect the mechanisms linking fiscal pressure and companies' behavior to commercial credit.

4.3.1. Level of loan availability

Columns (1) and (2) of Table 4 present the mediating effect of corporate loan availability on the relationship between fiscal pressure and corporate commercial credit behavior, testing H2-1. In column (1), the coef-

Table 4
Mediating effects analysis of loan availability, tax burden and subsidy level.

Variable	(1) <i>Access</i>	(2) <i>NetCredit</i>	(3) <i>TaxBurden</i>	(4) <i>NetCredit</i>	(5) <i>Subtensity</i>	(6) <i>NetCredit</i>
<i>Pressure</i>	−0.0070*** (−3.75)	−0.0212* (−1.69)	0.0169** (2.52)	−0.0214* (−1.86)	−0.0009* (−1.72)	−0.0232* (−1.93)
<i>Access</i>		0.2994*** (17.50)				
<i>TaxBurden</i>				−0.1134*** (−4.35)		
<i>Subtensity</i>						0.1229*** (3.44)
Constant	−0.2963*** (−4.67)	0.2352*** (3.23)	0.1144** (2.40)	0.1595** (2.05)	0.1956*** (7.52)	0.1225 (1.56)
Company FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	38,688	38,688	38,688	38,688	38,688	38,688
R-squared	0.8079	0.7440	0.5399	0.7320	0.2881	0.7311
Sobel test (z-value)		2.3451**		−3.4572***		2.8988***
Bootstrap test (95% confidence interval)	[−0.0045, −0.0008]		[−0.0032, −0.0007]		[−0.0040, −0.0012]	

Notes: t-values are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

coefficient of *Pressure* on *Access* is −0.007, significant at the 1% level, indicating that increased local fiscal pressure significantly reduces corporate loan availability within the jurisdiction. This finding aligns with the crowding-out effect, whereby government debt issuance during fiscal stress reduces bank credit availability to corporations.

Column (2) reveals that both fiscal pressure and loan availability significantly affect net commercial credit (at the 10% and 1% levels respectively), suggesting a partial mediation effect. The Sobel test yields a z-value of 2.3451 ($p < 0.05$), and the bootstrap 95% confidence interval [−0.0045, −0.0008] based on 1,000 replications, with the lower bound approaching zero, provides statistically valid albeit economically modest evidence for the mediation pathway. These results indicate that corporations reduce their net commercial credit provision partly due to the decreased loan availability caused by the crowding-out effects of government borrowing. With reduced access to traditional financing, companies prioritize maintaining liquidity by accelerating cash collection and reducing credit extension to customers.

4.3.2. Degree of tax burden

Columns (3) and (4) in Table 4 examine the mediating role of corporate tax burden in the relationship between fiscal pressure and commercial credit provision. The coefficient of *Pressure* on *TaxBurden* in column (3) is 0.017, significant at the 5% level, demonstrating that heightened fiscal pressure leads to an increased corporate tax burden. Under fiscal constraints, governments intensify tax enforcement to boost revenue, reducing corporate incentives for tax avoidance and earnings management.

In column (4), fiscal pressure and tax burden show significant negative effects on net commercial credit at the 10% and 1% levels, respectively, indicating partial mediation. The Sobel test confirms a significant indirect effect ($z = -3.4572$), and the bootstrap 95% confidence interval [−0.0032, −0.0007] excludes zero, validating the negative mediation pathway. These findings support H2-2, demonstrating that stricter tax administration under fiscal pressure increases corporate tax burdens, directly reducing cash holdings and incentivizing firms to minimize credit extension while extending payment periods to preserve liquidity.

4.3.3. Level of subsidy received

Columns (5) and (6) in Table 4 examine the mediating effect of government subsidies on the fiscal pressure-commercial credit relationship. Column (5) shows that fiscal pressure significantly reduces subsidy intensity at the 10% level, consistent with governments' curtailing discretionary spending to address fiscal gaps. This reduction is particularly pronounced for less profitable firms, which governments view as yielding lower tax returns.

Column (6) demonstrates that while fiscal pressure continues to exert a negative effect on net commercial credit (significant at the 10% level), subsidy intensity shows a positive association at the 1% level, confirming partial mediation. The Sobel test reveals a significant indirect effect ($z = 2.8988$, $p < 0.01$), and the bootstrap 95% confidence interval $[-0.0040, -0.0012]$ confirms the mediation effect. These results validate H2-3, showing that reduced government subsidies under fiscal pressure directly impact corporate cash flows and signal reduced government support, prompting firms to accelerate cash collection cycles to maintain operational stability.

4.4. Endogeneity tests

This research investigates the impact of fiscal pressure, a macroeconomic factor, on the corporate behavior of commercial credit supply, an individual factor. Various elements can influence companies' credit provision behaviors, including company characteristics and the policies and implicit performance of the governments where these companies are located. Although this study employs control variables at the city and corporate levels and uses a fixed-effects model to account for omitted variables, potential endogeneity issues may still arise due to unobserved factors. To address this concern, we employ the two-stage least-squares (2SLS) method and a difference-in-differences (DID) approach, leveraging the policy shift from a business tax to a value-added tax (VAT).

4.4.1. 2SLS Estimation

To address potential endogeneity, we employ a 2SLS approach using government health expenditure per capita (*Medpp*) as an instrumental variable for fiscal pressure. Following Guo (2024) and Liu et al. (2024), we argue that *Medpp* satisfies the relevance and exclusion restrictions required for a valid instrument.

The relevance condition is satisfied because government health expenditure represents a significant and relatively rigid component. Health expenditure commitments are largely predetermined by demographic factors, healthcare infrastructure and social insurance obligations, creating systematic pressure on local fiscal resources. As health expenditure increases, the fiscal gap widens mechanically, particularly given the inflexibility of this expenditure relative to discretionary spending. The exclusion restriction is plausibly satisfied, as government health expenditure per capita affects individual corporate credit decisions only through its impact on overall fiscal pressure. Health expenditure levels are determined by population health needs, demographic structure and healthcare policy mandates rather than corporate financial decisions. Moreover, unlike infrastructure or industrial subsidies, health spending has no direct connection to corporate operations or financing choices, making it unlikely to influence commercial credit provision except through the fiscal pressure channel.

The 2SLS estimation proceeds as follows:

First stage:

$$Pressure_{i,t} = \beta_0 + \beta_1 Medpp_{i,t} + \gamma Control_{i,t} + \delta_i + \tau_t + \varepsilon_{i,t} \quad (8)$$

Second stage:

$$NetCredit_{i,t} = \alpha_0 + \alpha_1 \widehat{Pressure}_{i,t} + \gamma Control_{i,t} + \delta_i + \tau_t + \varepsilon_{i,t} \quad (9)$$

where *Medpp* represents government health expenditure per capita at the city level and *Pressure* ($\widehat{Pressure}$) represents the fitted value from the first stage.

Table 5 presents the 2SLS results. The first-stage regression shows a significant negative relationship between *Medpp* and *Pressure* (-0.0025 , significant at the 5% level), confirming instrument relevance. This neg-

Table 5
Two-stage least-squares regression results.

Variable	(1) First stage <i>Pressure</i>	(2) Second stage <i>NetCredit</i>
<i>Medpp</i>	−0.0025** (−2.49)	
<i>Pressure</i>		−0.0179** (−2.52)
Company FE	YES	YES
Year FE	YES	YES
Unidentifiable test LM value	8.561***	
Weak instrumental variable test F-value	118.599	
10% maximal IV size	16.38	
Observations	38,688	38,688

Notes: t-values are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

ative relationship is consistent with the economic intuition that higher per capita health expenditure is typically observed in economically advanced cities with more resilient revenue streams and superior fiscal self-sufficiency, which effectively mitigates structural fiscal pressure despite high service commitments. The weak instrument test yields an F-statistic of 118.599, substantially exceeding the conventional threshold of 10, eliminating weak instrument concerns. The underidentification test (LM statistic = 8.561, significant at the 1% level) decisively rejects the null hypothesis of underidentification.

The second-stage results show that instrumented fiscal pressure continues to exert a significant negative effect on net commercial credit provision (−0.0179, significant at the 5% level). The magnitude of this effect is comparable to that in the baseline ordinary least-squares regression, suggesting that measurement error or omitted variable bias may have attenuated our baseline estimates. This finding reinforces our main result that fiscal pressure significantly reduces corporate commercial credit provision.

4.4.2. DID analysis

To further address endogeneity concerns and establish causality, we exploit the staggered implementation of China's business tax to value-added tax (B2V) reform as a quasi-natural experiment. Following Wen et al. (2023), we employ a DID approach to identify the causal effect of fiscal pressure on commercial credit provision.

The B2V reform provides an ideal setting for causal identification, as it generated exogenous variation in local fiscal pressure across regions and time. The reform began with Shanghai as the pilot city in 2012, expanded to eight additional provinces and cities (Beijing, Tianjin, Jiangsu, Anhui, Zhejiang, Fujian, Hubei and Guangdong) between August and December 2013, and had achieved nationwide implementation by May 2016.

The reform intensified local fiscal pressure through two primary channels. First, it transformed the business tax—previously retained entirely by local governments as their largest revenue source—into VAT revenue shared between central and local governments, directly reducing local fiscal resources. Second, the VAT's input credit mechanism, while eliminating double taxation, simultaneously eroded the local tax base and reduced associated surcharges, further constraining local revenue. Following Peng et al. (2022) and Chen et al. (2023), we implement a generalized DID specification:

$$NetCredit_{i,t} = \beta_0 + \beta_1 Pressure_{i,t} \times Treat_{i,t} + Treat_{i,t} + \gamma Control_{i,t} + \delta_i + \tau_t + \varepsilon_{i,t} \quad (10)$$

Given the staggered implementation, *Treat* equals 1 for observations in pilot cities after B2V implementation (with a one-year lag for cities implementing in the second half of the year to account for policy adjustment effects) and 0 otherwise.

Table 6 presents the DID results. Column (1) shows that the interaction term between fiscal pressure and the reform indicator yields a coefficient of −0.4037, significant at the 1% level, indicating that the B2V reform's

Table 6

Difference-in-differences analysis around the replacement of business tax with value-added tax.

Variable	(1) <i>NetCredit</i>	(2) <i>NetCredit</i>
<i>Treat</i> × <i>Pressure</i>	−0.4037*** (−3.81)	−0.3931*** (−4.18)
<i>Treat</i>	0.0140** (2.15)	0.0136** (2.12)
Constant	0.1593* (1.94)	0.2257** (2.57)
Company FE	YES	YES
Year FE	YES	YES
Observations	38,688	36,234
R-squared	0.7231	0.7399

Notes: t-values are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

intensification of fiscal pressure significantly reduced net commercial credit provision. The positive coefficient on *Treat* alone (0.014, significant at the 5% level) suggests some initial benefits from tax burden reduction, but these appear to have been overwhelmed when combined with heightened fiscal pressure.

To address concerns about confounding effects from the 2008 financial crisis, column (2) restricts the sample period to 2009–2022. The interaction term remains negative and significant (−0.3931, significant at the 1% level), confirming the robustness of our findings. These results demonstrate that the negative relationship between fiscal pressure and commercial credit provision is causal rather than merely correlational, as reverse causality cannot explain the differential impact of an exogenous policy shock across the treatment and control groups.

4.5. Robustness tests

To ensure the reliability of our findings, we conduct comprehensive robustness tests covering both alternative variable measurements and sample period adjustments. These analyses are designed to verify that our main results are not driven by specific model settings or external shocks.

We first focus on alternative measures of the key explanatory and dependent variables. For fiscal pressure, we construct two broader proxies following Cai et al. (2024). *Pressure2* incorporates government-managed funds by adding their revenue–expenditure gap to the general budget gap, scaled by local GDP. *Pressure3* further includes implicit government debt measured through urban investment bond issuance, thereby capturing off-budget fiscal burdens. As reported in Table 7, columns (1) and (2), both measures produce negative and statistically significant coefficients at the 1% and 5% levels, confirming the robustness of our baseline findings.

Turning to commercial credit provision, we test three alternative specifications of the dependent variable. Column (3) of Table 7 employs the one-period lag of *NetCredit* to mitigate potential simultaneity concerns. Column (4) replaces the baseline variable with *NetCredit2*, which excludes prepayment and advance receipt items, over which firms have limited discretion, and is calculated as accounts receivable plus notes receivable minus accounts payable and notes payable, scaled by total assets. Both specifications yield negative coefficients (significant at the 1% level), consistent with our baseline results. Column (5) uses the growth rate of the cash conversion cycle (*Cashcycle*) as an alternative proxy, shifting the focus to working capital management efficiency. The coefficient remains negative and significant at the 10% level, providing complementary evidence from a cash management perspective.

Finally, to address potential confounding effects from the 2008 financial crisis, we examine the sensitivity of our results to the sample period. The financial crisis years (2007–2009) were marked by extraordinary disruptions in commercial credit patterns and unprecedented government interventions globally. To ensure that our findings reflect fundamental fiscal transmission mechanisms rather than crisis-specific anomalies, we exclude observations from 2007–2009 in column (6) of Table 7, reducing the sample to 34,866 firm-year observations. The coefficient of fiscal pressure remains negative (−0.0229) and statistically significant at the 1% level, demon-

Table 7
Robustness tests.

Variable	(1) <i>NetCredit</i>	(2) <i>NetCredit</i>	(3) <i>L.NetCredit</i>	(4) <i>NetCredit2</i>	(5) <i>Cashcycle</i>	(6) <i>NetCredit</i>
<i>Pressure2</i>	−0.0951*** (−5.82)					
<i>Pressure3</i>		−0.0039** (−2.10)				
<i>Pressure</i>			−0.0121*** (−3.62)	−0.0170*** (−6.98)	−0.0520* (−1.72)	−0.0229*** (−4.91)
Constant	0.1677** (2.07)	0.1617* (1.96)	0.0779 (0.97)	0.1817*** (3.40)	−2.0992*** (−4.41)	0.0169 (0.19)
Company FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	38,688	38,688	34,263	38,688	38,688	34,866
R-squared	0.7266	0.7225	0.7283	0.7389	0.7676	0.7804

Notes: The table presents robustness tests using alternative variable measurements and sample restrictions. Columns (1)–(2) employ alternative fiscal pressure measures. Column (3) uses a lagged dependent variable. Column (4) uses an alternative commercial credit measure. Column (5) employs the cash cycle growth rate. Column (6) excludes the financial crisis period (2007–2009). t-values are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

strating that our findings are robust and not driven by the exceptional circumstances of the financial crisis period. This result reinforces our interpretation that the negative relationship between fiscal pressure and commercial credit provision reflects a fundamental economic mechanism rather than a crisis-induced artifact.

4.6. Heterogeneity tests

The relationship between fiscal pressure and commercial credit provision may vary across institutional contexts and firm characteristics. We examine heterogeneity in two dimensions: city-level fiscal revenue structures and firm-level operational characteristics.

4.6.1. City-level factors

Land transfer income, tax collection and government debt issuance constitute the three primary revenue channels for local governments in China (Wu et al., 2015; Jia et al., 2021). We examine how governments' reliance on these different revenue sources moderates the transmission of fiscal pressure to corporate credit behavior.

(1) Dependence on land revenue

Columns (1) and (2) of Table 8 examine heterogeneity based on local governments' dependence on land revenue. Following Wang et al. (2022), we measure land revenue dependence (*Landratio*) as land transfer income scaled by government fund revenue, with cities above the mean classified as highly dependent. The results reveal a more pronounced negative effect in high-dependence cities (−0.0311, significant at the 10% level) than low-dependence cities (−0.02, significant at the 5% level). This differential impact suggests that governments that are heavily reliant on land revenue have limited fiscal flexibility when land markets cool, transmitting greater pressure to local enterprises. The volatile nature of land revenue makes these governments particularly vulnerable to fiscal shocks, constraining their ability to support local businesses during stress periods.

(2) Dependence on taxation

Columns (3) and (4) of Table 8 examine the moderating role of tax revenue dependence. Following Chen (2017), we measure tax dependence (*Taxratio*) as tax revenue scaled by the sum of general budgetary and government fund revenue. The coefficient of fiscal pressure is −0.0347 (significant at the 5% level) in high tax-dependent cities versus −0.0174 (significant at the 5% level) in low tax-dependent cities. This pattern indicates that companies in tax-dependent jurisdictions face amplified pressure, as governments in these jurisdictions

Table 8
Heterogeneity results at the prefecture–city level.

Variable	Dependence on land revenue		Dependence on taxation		Dependence on debt	
	(1) High <i>NetCredit</i>	(2) Low <i>NetCredit</i>	(3) High <i>NetCredit</i>	(4) Low <i>NetCredit</i>	(5) High <i>NetCredit</i>	(6) Low <i>NetCredit</i>
<i>Pressure</i>	−0.0311* (−1.86)	−0.0200** (−2.20)	−0.0347** (−1.99)	−0.0174** (−2.18)	−0.0310*** (−3.05)	−0.0191** (−2.15)
Constant	0.1059 (0.93)	0.1287 (1.18)	0.2673* (1.93)	0.1014 (1.14)	0.1842 (1.28)	0.1523* (1.72)
Company FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	17,138	21,550	14,307	24,381	13,242	25,446
R-squared	0.8009	0.7559	0.7903	0.7504	0.7856	0.7423

Notes: t-values are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

intensify collection efforts to meet revenue targets. As corporate profits directly determine the tax base, aggressive tax enforcement in these regions creates a feedback loop that further constrains corporate liquidity and credit provision.

(3) Dependence on debt

Columns (5) and (6) in Table 8 analyze heterogeneity based on government debt burden. We employ the debt ratio (*Debratio*)—local year-end debt balance divided by comprehensive financial resources—using the 120% threshold established by China’s Ministry of Finance for risk classification. High-debt cities show a coefficient of −0.031 (significant at the 1% level), compared with −0.0191 (significant at the 5% level) in low-debt cities. This pattern suggests that when local governments operate under binding debt constraints, their fiscal adjustment space becomes markedly limited. In such environments, fiscal pressure is more likely to be transmitted through channels that directly affect corporate liquidity, including intensified revenue extraction and expenditure compression, than absorbed through additional borrowing. As a result, firms located in highly indebted jurisdictions face a more pronounced deterioration in financing conditions and respond by more aggressively retrenching commercial credit provision.

4.6.2. Firm-level factors

Table 9 examines how firm characteristics moderate the fiscal pressure–commercial credit relationship, focusing on supply chain structure and institutional backing.

(1) Customer concentration

Columns (1) and (2) examine heterogeneity based on customer concentration, measured by the proportion of sales to the top five customers. Companies with high customer concentration show a coefficient of −0.0344

Table 9
Heterogeneity results at the firm level.

Variables	Customer centralization		Supplier centralization		State ownership	
	(1) High <i>NetCredit</i>	(2) Low <i>NetCredit</i>	(3) High <i>NetCredit</i>	(4) Low <i>NetCredit</i>	(5) SOEs <i>NetCredit</i>	(6) Non-SOEs <i>NetCredit</i>
<i>Pressure</i>	−0.0344** (−2.18)	−0.0214* (−1.95)	−0.0278* (−1.74)	−0.0213** (−2.08)	−0.0147* (−1.76)	−0.0298** (−2.61)
Constant	0.3002 (2.60)	−0.0370 (−0.34)	0.2666 (1.94)	0.0962 (1.04)	0.2458** (2.14)	−0.0028 (0.69)
Company FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	15,726	22,962	15,296	23,392	14,685	24,003
R-squared	0.7558	0.7630	0.7786	0.7563	0.7648	0.7571

Notes: t-values are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

(significant at the 5% level), while those with low concentration exhibit a coefficient of -0.0214 (significant at the 10% level). The more pronounced negative effect in high- than low-concentration firms suggests that dependence on major customers amplifies vulnerability during fiscal stress periods. When fiscal pressure tightens the financial environment, concentrated customer relationships transform from revenue stability anchors into transmission channels of systemic risk. These firms face dual constraints, namely deteriorating liquidity alongside heightened exposure to major customers' financial distress, compelling more aggressive trade credit retrenchment to preserve cash buffers. This pattern reveals that strategic customer relationships, while valuable in stable periods, may intensify rather than mitigate the impact of macroeconomic shocks, as relationship-specific investments create lock-in effects that limit firms' flexibility in reallocating working capital across their customer portfolio.

(2) Supplier concentration

Columns (3) and (4) investigate the role of supplier concentration, measured by the proportion of purchases from the top five suppliers. Firms with high supplier concentration display a coefficient of -0.0278 (significant at the 10% level), while those with low concentration show a coefficient of -0.0213 (significant at the 5% level). The stronger effect in high- than low-concentration firms suggests that dependence on few suppliers limits bargaining power when seeking commercial credit financing. These firms face a double burden: a reduced ability to obtain supplier credit and the simultaneous need to preserve cash, resulting in sharper reductions in credit provision.

(3) State ownership

Columns (5) and (6) examine heterogeneity by state ownership. Fiscal pressure significantly reduces net commercial credit provision across ownership types, but the magnitude of this effect differs markedly. For state-owned enterprises, the estimated coefficient is -0.0147 (significant at the 10% level), whereas for non-state-owned enterprises, the effect is substantially larger, with a coefficient of -0.0298 (significant at the 5% level). This divergence indicates that state ownership provides meaningful insulation through implicit government backing and softer budget constraints, which buffer these firms via preferential credit access and delayed enforcement. Private firms lacking such institutional shields bear the brunt of fiscal adjustment and respond by more aggressively curtailing trade credit to preserve liquidity. This ownership-based asymmetry reveals how institutional proximity to government determines differential exposure to fiscal shocks, with market-based firms bearing disproportionate adjustment costs during consolidation episodes.

5. Conclusion and policy implications

This study provides comprehensive evidence of how local government fiscal pressure is transmitted to corporate commercial credit provision through China's intertwined fiscal-financial system. Drawing on 38,688 firm-year observations from 2007 to 2022, we establish three key findings. First, fiscal pressure significantly reduces net commercial credit supply, with firms simultaneously increasing payables while curtailing receivables to preserve liquidity. Second, transmission operates through distinct yet reinforcing channels: government debt crowds out bank lending; intensified tax enforcement raises corporate tax burdens; and subsidy retrenchment directly constrains cash flows. Third, heterogeneity analyses reveal systematic vulnerabilities: cities dependent on volatile sources of revenue (land, debt) and firms with concentrated suppliers or private ownership experience disproportionately large impacts. These findings advance understanding of fiscal-corporate spillovers beyond direct taxation-subsidy linkages, demonstrating how fiscal stress propagates through credit markets and supply chains with potential systemic implications. By decomposing mechanisms and documenting asymmetric effects, this research illuminates the microeconomic costs of fiscal consolidation and highlights risks when debt-financed adjustments substitute for structural reforms.

The policy implications demand attention at multiple levels. At the central level, the findings underscore the importance of fiscal system reforms. Revenue diversification through property taxation and improved inter-governmental transfer design may alleviate local dependence on pro-cyclical revenue, thereby reducing the volatility of fiscal pressure transmission to the corporate sector. Debt management requires particular vigilance: while borrowing provides short-term relief, credit market crowding-out imposes hidden costs on private enterprise financing that compound over time. For local governments, consolidation strategies should balance multiple instruments rather than over-relying on tax enforcement, which creates feedback loops constraining

the tax base itself. Targeted support for supply chain critical nodes—particularly private firms with concentrated suppliers—can prevent localized disruptions from cascading. For corporate managers, the findings emphasize strategic imperatives: firms in fiscally stressed jurisdictions should prioritize financial flexibility through diversified financing sources and supply chain relationships, while investments in innovation capacity and government relations provide buffers against fiscal spillovers. Finally, regulatory authorities should strengthen their monitoring of regions where debt ratios exceed prudential thresholds, as these jurisdictions face higher risks of aggressive revenue extraction, which destabilizes commercial credit networks essential for economic resilience.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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