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The political economy of mandatory disclosure: a literature review



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ABSTRACT

Reviewing the literature on mandatory corporate disclosure from a political economy perspective, we synthesize the classic justifications for disclosure regulations while emphasizing why voluntary disclosure often fails to achieve socially efficient transparency. We also highlight how legal institutions, enforcement capacity, and political forces shape the design, credibility, and effectiveness of disclosure mandates. Drawing on evidence from international and China-focused studies, we review empirical findings on how mandatory disclosure affects investor protection, information environments, and firm behavior, showing that similar reporting rules yield different outcomes across institutional settings. We further extend the discussion to ESG and climate-related disclosure to examine emerging evidence on transparency gains, real effects, compliance costs, and regulatory trade-offs, including debates on materiality and regulatory objectives. Overall, the literature suggests that mandatory disclosure remains a central governance instrument in modern capital markets, but its effectiveness depends on its enforcement, institutional context and political economy constraints.

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1. Introduction

Mandatory disclosure—regulatory requirements that oblige firms to publish standardized and specific information—is a core pillar of modern securities regulation and capital market governance (Easterbrook

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and Fischel, 1984). Through periodic and event-driven filings, including financial statements, accompanying notes, management discussion and analysis, and other mandatory reports, disclosure rules shape the information environment in which investors form their beliefs and where capital is allocated (Benston, 1973; Healy and Palepu, 2001; Shleifer and Wolfenzon, 2002; Bushee and Leuz, 2005; Greenstone et al., 2006). A central premise of disclosure regulation is that transparency, rather than merit-based intervention, enables markets to discipline firms through pricing, monitoring, and capital allocation.

Historically, mandatory disclosure regimes in advanced economies have emerged in response to major market failures and financial scandals that have eroded investor confidence. In the United States, the Securities Acts of 1933 and 1934 institutionalized disclosure as the primary regulatory response to information asymmetry following the Great Depression (Benston, 1973). Subsequent reforms, including the Sarbanes–Oxley Act of 2002 and the Dodd–Frank Act of 2010, further expanded disclosure obligations, reflecting a regulatory philosophy that emphasizes investor protection through transparency rather than direct state intervention in corporate decision-making.

In recent years, the scope of mandatory disclosure has expanded beyond traditional financial reporting to include corporate social responsibility (CSR) and environmental, social, and governance (ESG) information, including climate-related risks and social impacts. This expansion reflects the growing recognition that firm activities generate externalities that are not fully captured by financial accounting alone and that can be relevant to both investors and regulators. China has been an active participant in this global shift, introducing CSR and environmental disclosure mandates for selected firms well before comparable requirements in some advanced economies (see Fig. 1). Notably, China’s approach to ESG disclosure is closely linked to the state’s objectives in environmental governance, industrial policy and social stability, further underscoring the importance of the institutional context for understanding disclosure regulations.

A large literature in economics, finance, and accounting studies mandatory disclosure, examining both the motivations for disclosure regulations and their financial and real effects. Early work emphasizes the association between disclosure quality and stock prices or the cost of capital (e.g., Lang and Lundholm, 1996; Botosan, 1997; Leuz and Verrecchia, 2000). Subsequent research examines how disclosure requirements affect agency conflicts, corporate governance, and capital market development (e.g., Shleifer and Wolfenzon, 2002; Hail and Leuz, 2006), as well as the costs of regulation, including compliance costs, proprietary costs, and induced changes in firms’ reporting and operating practices (e.g., Iliev, 2010; Christensen et al., 2017; Jayaraman and Wu, 2019). A central insight from this literature is that the benefits of mandatory disclosure

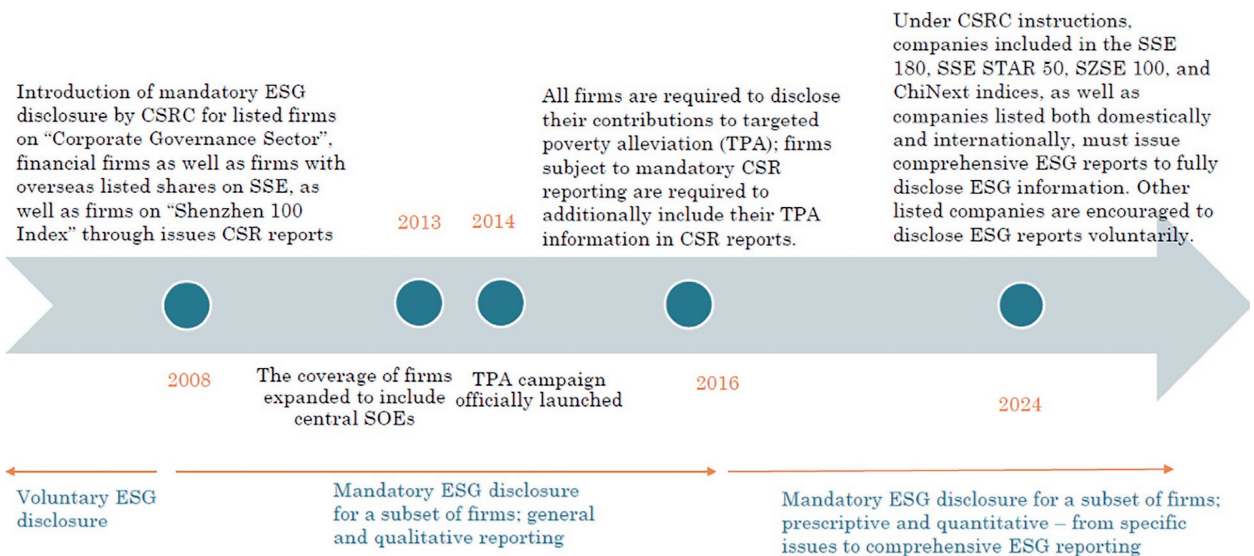


Fig. 1. The evolution of ESG disclosure in China over time. Modified from Jiang et al. (2025), “Nudging through Mandating ESG Disclosure,” Working Paper.

are not universal: they depend critically on legal institutions, enforcement mechanisms, and political constraints.

This article reviews the literature on mandatory disclosure from a political economy perspective, with a particular focus on its relevance to China. Rather than treating disclosure mandates as purely efficiency-enhancing responses to market failures, the political economy perspective emphasizes that disclosure rules are shaped by political incentives, interest group competition, and institutional constraints. In the Chinese context, these forces are particularly salient, given the dominant role of the state as regulator, owner, and enforcer, and the limited role of private litigation and market-based enforcement. Accordingly, we organize the review around three core questions: Why does mandatory disclosure arise? How do political and institutional forces shape its design and enforcement? What are the consequences of disclosure mandates for firms, investors, and real economic activity?

The remainder of this article proceeds as follows. We first outline the economic justifications for mandatory disclosure, briefly reviewing classic arguments based on information asymmetry, agency conflicts, and coordination, while emphasizing how these mechanisms operate differently in the Chinese institutional environment. We then adopt a political economy perspective to examine how disclosure requirements are designed and implemented, highlighting the role of state ownership, regulatory enforcement, and political incentives. Next, we turn to the expanding domain of sustainability and climate-related disclosure, discussing how China's ESG mandates reflect distinct regulatory objectives and political considerations. We conclude by synthesizing insights from the literature and outlining directions for future research on mandatory disclosure in China and other emerging markets.

2. Theoretical foundations of mandatory disclosure

The economic case for mandatory disclosure is traditionally grounded in a small number of canonical market failures related to information production and use. These include information asymmetry between insiders and investors, the public-good nature of information, agency conflicts within firms, and coordination failures due to limited comparability. Although these justifications are well established in economics, finance, and accounting, their relevance for policy depends critically on the institutional context. In China, where ownership is concentrated, the state plays a central role as regulator and owner, and enforcement relies predominantly on public authorities, these mechanisms operate differently from those in mature market economies.

2.1. *Information asymmetry and adverse selection*

The most basic justification for disclosure regulation is information asymmetry between corporate insiders and outside investors. In the absence of credible disclosure, investors rationally undervalue securities to reflect their average quality, generating adverse selection costs that raise firms' cost of capital and distort financing and investment decisions (Akerlof, 1970; Myers and Majluf, 1984). Mandatory disclosure mitigates these frictions by constraining selective revelation and improving the overall information environment, with standard models predicting gains in liquidity and reductions in information risk (Diamond and Verrecchia, 1991).

In China, adverse selection concerns are exacerbated by weak private enforcement and limited litigation risk, which reduces insiders' incentive to voluntarily disclose unfavorable information (Piotroski and Wong, 2012). As a result, mandatory disclosure plays a particularly important role in supporting investor participation, although its effectiveness ultimately hinges on enforcement credibility rather than solely on formal disclosure requirements.

2.2. *Information as a public good*

A second rationale for mandatory disclosure stems from the public-good properties of information. Because disclosed information is largely non-rivalrous and imperfectly exclusive, firms do not internalize the full social benefits of transparency, such as improved market liquidity and information spillover to peer firms (Arrow, 1962; Hirshleifer, 1971; Coffee, 1984). This divergence between private incentives and social value can lead to a systematic under-provision of credible information.

Mandatory disclosure addresses this incentive problem by establishing a baseline level of public information that supports market-wide transparency and reduces reliance on costly private information acquisition (Grossman and Stiglitz, 1980; Leuz and Wysocki, 2016). These considerations are particularly salient in emerging economies like China, where public disclosures serve as a primary information infrastructure for a market dominated by retail investors and where private information intermediation is relatively low (Tan et al., 2024).

2.3. Agency conflicts and opportunism

Agency theory provides a third motivation for regulating disclosure. When managers or controlling shareholders pursue private benefits, opacity facilitates opportunistic behavior at the expense of outside investors (Jensen and Meckling, 1976). Mandatory disclosure increases the observability and verifiability of firm outcomes, thereby strengthening monitoring by investors, boards, auditors, and regulators (Fama and Jensen, 1983; Bushman and Smith, 2001).

In China, the dominant agency problem is often not between managers and dispersed shareholders, but between controlling shareholders—frequently the state or founding families—and minority investors (Jiang and Kim, 2020). Disclosure mandates are therefore particularly important for exposing related-party transactions and other forms of expropriation. However, when controlling owners exert political influence or when enforcement is uneven, disclosure alone may be insufficient to discipline behavior, highlighting the complementarity between disclosure rules and institutional enforcement.

2.4. Standardization, comparability and coordination

Beyond these incentive-based justifications, mandatory disclosure serves a coordination function by promoting standardization and comparability. Common reporting standards reduce investors' information processing frictions and thus improve the efficiency of cross-firm comparisons and market-wide information aggregation (Hirshleifer and Teoh, 2003; Leuz and Wysocki, 2016). Empirical evidence shows that greater comparability enhances the production of information by analysts and strengthens external monitoring (De Franco et al., 2011; Chen et al., 2018a, 2018b).

In China, standardization has played a central role in the development of the capital market, given the heterogeneity of corporate ownership structures and reporting traditions. However, comparability gains depend on consistent application and credible enforcement. When enforcement is uneven or politically constrained, formal standardization may coexist with substantial variations in reporting quality, thus limiting its governance benefits.

3. Voluntary versus mandatory disclosure

A central question in the disclosure literature is whether market forces alone can generate an efficient information environment, or whether regulatory intervention is required. Classical theory shows that, under certain strong assumptions, voluntary disclosure can lead to extensive information disclosure. In practice, however, these assumptions rarely hold, particularly in institutional environments characterized by weak enforcement and concentrated ownership. This section briefly reviews the benchmark logic of voluntary disclosure, then focuses on the reasons why voluntary transparency fails, thus motivating mandatory disclosure, especially in China.

3.1. Voluntary disclosure as a benchmark

Canonical unraveling models show that, under ideal conditions, voluntary disclosure can induce a near-complete revelation of private information (Grossman, 1981; Milgrom, 1981). When disclosure is credible, costless, and perfectly observed, investors rationally interpret silence as bad news. Firms with favorable private information therefore have an incentive to disclose it to distinguish themselves from lower-quality

firms, triggering an unraveling process in which non-disclosure is increasingly penalized. In this context, formal disclosure mandates are not necessary.

These results, however, rely on restrictive assumptions that are unlikely to hold in real-world corporate reporting settings. As a result, the unraveling benchmark serves primarily as a theoretical reference point rather than a realistic description of disclosure equilibria.

3.2. *Why voluntary disclosure fails*

A large literature identifies several obstacles that prevent voluntary disclosure from converging to full revelation. First, disclosure is costly. Firms face preparation, verification, and assurance costs, as well as legal and enforcement risks when disclosed information is inaccurate or subsequently contradicted by outcomes (Verrecchia, 1983; Skinner, 1994; Houston et al., 2019). Disclosure may also entail proprietary costs when competitively sensitive information is revealed to rivals, suppliers, or customers (Healy and Palepu, 2001). When such costs are present, non-disclosure becomes observationally ambiguous, weakening the adverse inference that underpins unraveling.

Second, investors may not know whether managers are well informed. When information arrives intermittently or with heterogeneous precision, silence may reflect the absence of a sufficiently informative signal rather than the withholding of bad news (Dye, 1985; Jung and Kwon, 1988). In this case, non-disclosure is no longer a clear negative signal, and equilibrium disclosure becomes partial or threshold-based rather than complete.

Third, investors have limited attention and information processing capacity. Even when firms voluntarily disclose information, such disclosure may be complex, dispersed or insufficiently salient, reducing its impact on prices and weakening the disciplinary role of markets (Hirshleifer and Teoh, 2003). When non-disclosure is not perfectly observed or interpreted, the unraveling logic fails.

These frictions are particularly strong in China. Weak private enforcement, limited litigation risk, and the predominance of retail investors reduce the penalties associated with non-disclosure. At the same time, concentrated ownership and political influence can weaken voluntary transparency, as controlling shareholders and managers face limited market discipline when withholding unfavorable information. As a result, voluntary disclosure is unlikely to achieve socially efficient transparency in the Chinese institutional environment.

3.3. *Mandatory disclosure as an institutional response: Benefits and costs*

The failure of voluntary disclosure to achieve efficient transparency has led regulators to rely on mandatory disclosure as a core institutional response to information frictions. By requiring the periodic release of material information, disclosure mandates establish a regulatory framework that constrains firms' ability to strategically withhold or delay unfavorable information. In principle, such mandates mitigate adverse selection, reduce information asymmetry between insiders and investors, and improve the overall information environment, thereby supporting price discovery, market liquidity, and investor participation.

Additional evidence regarding the importance of mandatory disclosure for investor protection comes from firms' voluntary decisions to subject themselves to stricter disclosure regimes through cross-listing. Firms from jurisdictions with weaker disclosure standards or enforcement often choose to list their securities on markets with more demanding reporting and enforcement requirements, particularly in the United States. Coffee (2002) characterizes this behavior as "bonding": by opting for a stricter regulatory regime, firms credibly commit to better disclosure quality and stronger investor protection. Firms' willingness to incur substantial compliance, audit, and legal costs associated with cross-listing suggests that credible mandatory disclosure, backed by enforcement, confers significant benefits in terms of investor trust and access to external capital.

As mentioned, mandatory disclosure is not without cost. Compliance entails preparation, verification, and audit costs, which can disproportionately burden small firms or those with limited reporting capabilities (Bushee and Leuz, 2005; Leuz et al., 2008; Leuz and Wysocki, 2016). Extensive disclosure requirements may also contribute to information overload, increasing the volume and complexity of reported information and reducing the salience of economically relevant signals to investors (Bloomfield, 2002; Hirshleifer and

Teoh, 2003). As a result, the marginal benefits of additional disclosure may diminish and, in some cases, become negative (Leuz and Wysocki, 2016).

Mandatory disclosure may also impose proprietary costs by forcing firms to reveal competitively sensitive information to their rivals, suppliers, or customers. The theory predicts that such costs can distort disclosure incentives and real decisions, as firms trade off transparency against competitive disadvantage (Verrecchia, 1983; Dye, 1986). Empirical work confirms that proprietary considerations are an important determinant of firms' disclosure choices (Ellis et al., 2012). Anticipating these costs, firms that are most affected by disclosure mandates have an incentive to lobby for exemptions, delays, or flexible implementation, thus shaping regulation through political processes (Zhou, 2022).

Finally, disclosure mandates can induce real and reporting responses that attenuate their intended informational effects. Firms may adjust their investment timing, organizational structure, or operational decisions to manage their exposure to unfavorable disclosure (Leuz et al., 2008). At the reporting level, increased disclosure requirements can encourage conservative, coarse, or boilerplate disclosures that formally satisfy regulatory requirements while limiting incremental information (Li et al., 2018).

An important implication of this discussion is that the case for mandatory disclosure is inseparable from the strength of investor protection and enforcement institutions. When private contract, litigation, and reputation mechanisms are effective, voluntary disclosure and market discipline can partially replace regulatory mandates. In contrast, when private enforcement is weak, disclosure incentives deteriorate, and mandatory disclosure becomes a central mechanism to protect outside investors and maintain market participation (La Porta et al., 1998; Ball, 2006; Leuz and Wysocki, 2016). In such environments, disclosure regulations serve not only to improve information production but also to compensate for institutional gaps in investor protection.

4. Political economy perspective: Public versus private interests

Although economic theory provides an efficiency-based rationale for mandatory disclosure, a large literature emphasizes that disclosure regulations are also the outcome of political processes. Rather than being designed solely to maximize social welfare, disclosure rules are shaped by interest group competition, lobbying, and institutional constraints. A political economy perspective therefore shifts attention from the normative desirability of disclosure to the processes through which disclosure mandates are designed, implemented, and enforced.

4.1. Public interest theory: Investor protection and market efficiency

Public interest theory provides the canonical normative justification for disclosure regulation. From this perspective, regulation corrects market failures that undermine investor protection and capital market efficiency, particularly information asymmetry and coordination problems in information production (Pigou, 1932). Mandatory disclosure is justified as a mechanism to ensure that investors, especially dispersed and less informed investors, have access to timely and reliable information necessary for informed decision-making (Benston, 1973; Easterbrook and Fischel, 1984).

Beyond investor protection, public interest theory emphasizes the efficiency-enhancing role of disclosure. By improving transparency, disclosure mandates facilitate price discovery, reduce information risk, and support the allocation of capital to more productive uses (Healy and Palepu, 2001; Leuz and Wysocki, 2016). Importantly, disclosure regulations are not intended to guarantee investment outcomes but to establish a minimum information infrastructure that allows markets to function effectively.

Public interest arguments also highlight the role of disclosure regulations in addressing collective action problems. Individual firms may lack incentives to voluntarily provide socially optimal levels of information, even when aggregate transparency would improve market outcomes. Mandatory disclosure overcomes this coordination failure by imposing uniform reporting obligations, thereby supporting comparability and market-wide information aggregation (Coffee, 1984).

Although public interest theory offers a coherent, efficiency-based rationale for regulating disclosure, it implicitly assumes that regulators act primarily to maximize social welfare. A large political economy

literature questions this assumption by emphasizing the role of private interests and political incentives in shaping regulatory outcomes.

4.2. Private interest theory and regulatory capture

Private interest theories view disclosure regulation as the product of political competition between stakeholders with asymmetric incentives and organizational capabilities. Because disclosure mandates impose concentrated costs on regulated firms, such as compliance expenses, litigation risks, and proprietary losses, firms and industry groups have a strong incentive to influence the scope, timing, and enforcement of disclosure rules. Conversely, the benefits of disclosure are diffuse and widely shared, making collective action by investors more difficult.

Stigler's (1971) theory of economic regulation and Peltzman's (1976) model of political competition formalize these dynamics, predicting that regulation reflects compromises that maximize political support rather than social welfare. Applied to disclosure regulation, this perspective implies that lobbying pressures often result in weakened mandates, delayed implementation, selective exemptions, or discretionary enforcement rather than outright deregulation.

Empirical evidence supports these predictions. Firms facing higher expected compliance costs or greater proprietary concerns are more likely to lobby against disclosure requirements or seek to influence their design (Zhou, 2022). Political connections further amplify firms' influence, particularly in settings where regulators have substantial discretion (Christensen et al., 2021). Cross-country evidence shows that disclosure regimes and enforcement intensity vary systematically with political institutions, legal traditions, and the relative power of corporate versus investor interests (La Porta et al., 1998; Ball, 2006).

Accounting standard-setting provides a particularly transparent institutional setting for examining political influence on disclosure regulations. Because accounting rules have important distributional consequences, standard-setting is inherently political rather than purely technical (Zeff, 2002). Although formal due process procedures, such as public consultations and comment letters, enhance legitimacy, they also create structured channels through which private interests can shape regulatory outcomes (Leuz and Wysocki, 2016).

A large literature documents that firms, auditors, and industry groups actively lobby standard setters when proposed rules threaten to increase transparency, reduce discretion, or impose significant compliance costs. Watts and Zimmerman (1978) propose a political cost perspective in which firms' positions on accounting standards reflect anticipated wealth effects. Empirical studies confirm that political pressures influence regulatory outcomes. For example, Ramanna (2008) shows that impairment-based goodwill accounting expands managerial discretion by relying on unverifiable fair value estimates, illustrating how politically acceptable compromises may weaken verifiability and informational content.

International evidence further suggests that the formal independence of standard setters does not insulate accounting regulation from political influence. Ball (2006) and Christensen et al. (2013) show that domestic political institutions and enforcement capacity play a central role in shaping both the adoption and implementation of international accounting and disclosure standards.

4.3. Disclosure mandates as an outcome of competing interest groups

In practice, mandatory disclosure policies rarely reflect a purely public interest objective or a complete capture of regulation by private interests. Instead, a large political economy literature views disclosure regulation as the equilibrium outcome of competition among interest groups with divergent preferences. Becker's (1983) framework conceptualizes regulation as a political equilibrium in which organized groups exert influence to advance their interests, subject to institutional and political constraints. From this perspective, disclosure mandates emerge as negotiated compromises rather than as welfare-maximizing solutions.

Applied to disclosure regulations, this framework highlights the conflicting incentives faced by key stakeholders. Investors, analysts, and public interest advocates benefit from more comprehensive and standardized disclosure, which improves transparency and reduces information asymmetry. In contrast, firms and industry groups bear concentrated compliance, litigation, and proprietary costs, giving them a strong incentive to resist stricter disclosure requirements or to seek exemptions and flexibility in their implementation. As a result,

disclosure regimes typically combine minimum transparency requirements with substantial discretion in application and enforcement.

Empirical evidence is broadly consistent with this view. Cross-country studies document a systematic variation in disclosure requirements and enforcement intensity across political systems, legal traditions, and institutional environments (La Porta et al., 1998; Ball, 2006). Even within jurisdictions, disclosure reforms are often incremental and contested, reflecting shifting political coalitions rather than decisive moves toward an informational optimum (Becker, 1983; Zeff, 2002). Periods of financial crisis or scandal can temporarily tilt the political balance toward greater transparency, leading to the expansion of disclosure mandates that may later be moderated or reinterpreted (Leuz and Wysocki, 2016).

The competing interest group perspective helps to reconcile the limitations of both public and private interest theories. Although public interest theory emphasizes investor protection and efficiency, political constraints often limit the feasibility of strict disclosure rules. Conversely, private interest theories predicting pervasive regulatory capture are tempered by countervailing forces, including investor advocacy, media scrutiny, judicial oversight, and reputational concerns faced by regulators and standard setters (Peltzman, 1976; Becker, 1983; Ball, 2006; Leuz and Wysocki, 2016). As a result, disclosure regulations typically reflect both informational objectives and political compromises rather than a single dominant interest.

From this perspective, an effective disclosure policy design requires acknowledging political economy constraints rather than ignoring them. Disclosure mandates that impose excessive compliance or proprietary costs or that threaten powerful constituencies are more likely to be diluted, delayed, or weakly enforced (Stigler, 1971; Zeff, 2002; Christensen et al., 2021). At the same time, overly permissive regimes risk failing to deliver meaningful transparency and investor protection, undermining market confidence and capital allocation efficiency.

From an investor protection perspective, political economy considerations shape not only whether disclosure mandates are adopted but also who ultimately benefits from them. Disclosure rules that appear stringent on paper may offer limited protection to outside investors if enforcement is weak, exemptions are widespread, or regulatory discretion is exercised unevenly. As a result, understanding disclosure regulations requires moving beyond formal rules to examine how political incentives and institutional constraints affect the enforcement of disclosure and its effectiveness in protecting minority investors (La Porta et al., 1998; Ball, 2006; Leuz and Wysocki, 2016).

The cross-listing and bonding literature provides important political economy insights into disclosure regulation. When domestic political constraints weaken the credibility of disclosure mandates, firms may seek to escape these constraints by voluntarily subjecting themselves to external regulatory regimes with stricter enforcement. This behavior illustrates both the limitations of disclosure regulations shaped by domestic political compromises and the value that investors place on credible and enforceable disclosure commitments (Coffee, 2002; Lang et al., 2003; Doidge et al., 2004).

In summary, mandatory disclosure should be understood as a politically mediated institutional response to information frictions in capital markets. Recognizing the role of competing interests clarifies why disclosure regimes vary across jurisdictions and over time, why formal rules may diverge from enforcement outcomes, and why regulatory design inevitably involves trade-offs between transparency objectives and political feasibility. This political economy perspective provides an essential foundation for evaluating the effectiveness of disclosure mandates and for guiding future research on the interaction between regulation, politics, and information in capital markets.

5. Institutions, enforcement and cross-country differences

Mandatory disclosure regimes do not operate in a vacuum. Their effectiveness depends critically on the legal, regulatory, and institutional environments in which disclosure rules are implemented and enforced. A large cross-country literature in accounting, finance, and law documents substantial heterogeneity in disclosure regimes across countries and emphasizes that differences in legal origin, enforcement capacity, and political institutions shape both the design of disclosure rules and their economic consequences. This section synthesizes cross-country evidence showing that similar disclosure mandates can generate very different transparency and investor protection outcomes depending on the institutional context.

5.1. *Legal origins and the design of disclosure regimes*

There are marked cross-country differences in mandatory disclosure requirements. A central finding of the law and finance literature is that common law countries, such as the United States and the United Kingdom, generally impose more extensive disclosure and accounting requirements than civil law countries. These differences are rooted in historical variations in investor protection and the role of capital markets within legal systems (La Porta et al., 1998).

In common law countries, securities regulation has traditionally emphasized transparency and information disclosure as the primary tools for protecting outside investors. Strong protection of private property rights, reliance on capital markets for corporate financing, and a legal tradition that facilitates private contracting all contribute to a disclosure-oriented regulatory philosophy. In contrast, many civil law systems have historically placed greater weight on state involvement, creditor protection, or tax collection, with financial reporting serving objectives other than informing dispersed equity investors. As a result, disclosure requirements in civil law countries are often less extensive or less focused on timely market transparency.

The legal origins determine not only the scope of disclosure requirements but also the role that disclosure plays in capital market governance. In systems characterized by dispersed ownership and arm's length financing, outside investors rely heavily on public information to allocate capital, making mandatory disclosure a central regulatory instrument (La Porta et al., 1998; Rajan and Zingales, 1998). In contrast, in environments with concentrated ownership or relationship-based financing, the demand for extensive public disclosure is often weaker, as monitoring relies more on private information and direct control (Allen and Gale, 2000; Ball et al., 2003). These structural differences help to explain persistent cross-country variations in disclosure regimes.

From an investor protection perspective, these legal origin differences imply that mandatory disclosure plays fundamentally different roles in different institutional environments. In common law systems, disclosure complements strong private enforcement and arm's length governance, whereas in civil law and relationship-based systems, disclosure often substitutes—imperfectly—for weaker private enforcement mechanisms. This distinction helps to explain why disclosure mandates that appear similar on paper can have different economic effects across countries and underlines the importance of their enforcement and implementation.

5.2. *Enforcement infrastructure: Public versus private enforcement*

The effectiveness of disclosure mandates depends critically on enforcement institutions. Ball et al. (2000) show that the properties of reported earnings vary systematically across countries with different legal and institutional environments, even when formal accounting standards appear similar. This evidence underscores that “rules on the books” are insufficient: identical disclosure requirements can yield different reporting outcomes depending on the institutions that support compliance, credibility, and discipline.

A central distinction in the literature concerns the relative roles of private and public enforcement in translating disclosure rules into outcomes. In legal and financial tradition, disclosure is closely linked to private enforcement mechanisms, most notably liability standards that enable investors to seek redress for misstatements and omissions. La Porta et al. (2006) argue that disclosure requirements are most effective when paired with strong private enforcement through civil liability, because the threat of investor action increases the expected costs of misreporting. Their cross-country evidence shows that disclosure and liability rules are strongly associated with measures of stock market development, whereas indicators of formal public enforcement authority are less strongly related to market depth. However, the effectiveness of public enforcement on broader regulatory issues, beyond mere disclosure, is a subject of debate (Djankov et al., 2003; Jackson and Roe, 2009).

Empirical evidence from major disclosure reforms reinforces the central role of enforcement. Christensen et al. (2013) examine the European Union's mandatory IFRS adoption and show that liquidity improvements are concentrated in countries that simultaneously strengthen the enforcement of financial reporting standards. Countries that adopt IFRS without meaningful enforcement reforms exhibit limited liquidity changes. More broadly, Hail and Leuz (2006) show that the capital market benefits associated with stronger disclosure regimes are most pronounced in countries with credible legal systems.

This emphasis on enforcement credibility is consistent with evidence from cross-listing and bonding. Firms from environments with weak enforcement that voluntarily subject themselves to regimes with stricter private and public enforcement effectively import enforcement institutions along with disclosure rules. The literature on cross-country enforcement thus reinforces a central argument: disclosure mandates protect investors not by mechanically increasing information but by making that information credible and actionable within a supportive institutional framework.

5.3. Regulatory competition and global harmonization of disclosure standards

In addition to domestic institutions, disclosure regimes are shaped by the forces of regulatory competition and international harmonization. As capital markets become increasingly integrated, countries are incentivized to align their disclosure and accounting standards with those used in major financial centers to attract investment, facilitate cross-border listings, and reduce information frictions for global investors. Importantly, harmonization debates underscore that convergence in disclosure rules is neither a substitute for enforcement nor a shortcut to investor protection.

A common explanation of international harmonization emphasizes network effects. Ramanna and Sletten (2014) show that countries' decisions to adopt IFRS are influenced by the choices of their trading partners, competitors, and regional peers. As more economically connected countries adopt a common reporting standard, the benefits of harmonization, such as comparability and reduced information processing costs, increase, thus encouraging other countries to follow suit.

Regulatory competition also plays a role. By adopting internationally recognized disclosure standards, countries may seek to enhance the credibility of their capital markets and signal their commitment to investor protection. Empirical studies document that IFRS adoption is often associated with increased cross-border investment and analyst coverage (Covrig et al., 2007; DeFond et al., 2011; Tan et al., 2011), consistent with better comparability for international investors.

However, the harmonization of standards does not guarantee the harmonization of outcomes. Christensen et al. (2013) shows that the liquidity benefits of mandatory IFRS adoption are concentrated in countries that simultaneously strengthen their enforcement. When enforcement institutions remain weak, IFRS adoption alone has little impact on transparency or market outcomes. Political considerations also matter: in some cases, adoption reflects external pressures or political commitments rather than domestic demand for transparency (Ball, 2006). As a result, formal convergence may outpace institutional capacity, thus limiting real effects.

5.4. The role of political institutions

Political institutions play a central role in shaping the design, scope, and effectiveness of mandatory disclosure regimes. Disclosure regulations are ultimately the product of political decision-making, and their evolution reflects broader institutional features such as democratic accountability, regulatory independence, policy ideology, and the ability of political systems to sustain reforms over time.

Political accountability influences the demand for transparency. In democratic systems with competitive elections, a free press, and an active civil society, politicians face stronger incentives to protect the public interest through disclosure rules (Bushman et al., 2004; Dyck et al., 2008). Financial scandals and crises often amplify these pressures, leading to an expansion of mandatory disclosure, as illustrated by the U.S. Securities Acts of 1933 and 1934 and the Sarbanes–Oxley Act of 2002 (Mahoney, 2001; Coates, 2007). In political systems with weaker accountability, disclosure reforms may be slower, more selective, or unevenly enforced.

Regulatory independence also shapes disclosure outcomes. Independent securities regulators and accounting standard setters can, in principle, enforce disclosure requirements more consistently by insulating technical decisions from short-term political pressures (Zeff, 2002; Ramanna, 2008). In practice, political influence often remains salient. Governments may soften disclosure requirements for state-owned enterprises or politically connected firms, undermining the credibility and uniformity of disclosure regimes (Leuz and Oberholzer-Gee, 2006; Chaney et al., 2011; Correia, 2014).

Policy ideology further affects the objectives of disclosure regulations. Market-oriented regimes tend to frame disclosure as a tool for investor protection and efficient capital allocation, whereas stakeholder-oriented regimes emphasize broader social accountability (Nobes, 1998; Ball et al., 2000). These differences are particularly visible in the expansion of non-financial disclosure. The European Union’s “double materiality” framework contrasts with the historically investor-centric approach of US securities regulation, reflecting political and institutional preferences rather than mere technical disagreements (Barker and Eccles, 2018; Christensen et al., 2021).

Finally, political institutions shape the dynamic evolution of disclosure regimes. Disclosure reforms are rarely implemented in a single step; instead, they emerge through incremental and contested processes reflecting shifting political coalitions. Crises create opportunities for reform (Coffee, 2002), while subsequent implementation often involves resistance from affected firms and industry groups seeking to limit compliance costs (Watts and Zimmerman, 1978; Zeff, 2002). Maintaining high disclosure standards therefore requires continued political support, regulatory oversight, and engagement by third-party actors such as investors, the media, and civil society (Miller, 2006; Dyck et al., 2010). When political commitment weakens, disclosure regimes may erode in practice even if formal rules remain unchanged (Daske et al., 2013).

Taken together, this literature underscores that the effectiveness of mandatory disclosure depends not only on legal rules and enforcement capacity, but also on the broader political institutions within which disclosure regulations are embedded. These political economy considerations are particularly salient in emerging disclosure domains, such as ESG and climate reporting, where the distributional consequences are large and regulatory objectives go beyond traditional investor protection.

6. ESG and sustainability as emerging domains

In recent years, mandatory disclosure has expanded beyond traditional financial reporting to include ESG-related information. This expansion reflects the growing recognition that climate and broader ESG issues can shape firms’ cash flows, risk exposure, and regulatory and reputational constraints, and thus influence capital allocation (e.g., Edmans, 2011; Lins et al., 2017). Fig. 2 presents a world map of jurisdictions where mandatory ESG or CSR disclosure is enacted. Figs. 3 and 4 show the changes in the adoption rate of sustainability reporting at the global and regional levels over time.

Furthermore, ESG disclosure differs from conventional financial reporting in both its objectives and measurement: many ESG metrics involve forward-looking assessments, qualitative judgments and complex externalities that are not easily captured by established accounting frameworks (Kotsantonis and Serafeim,

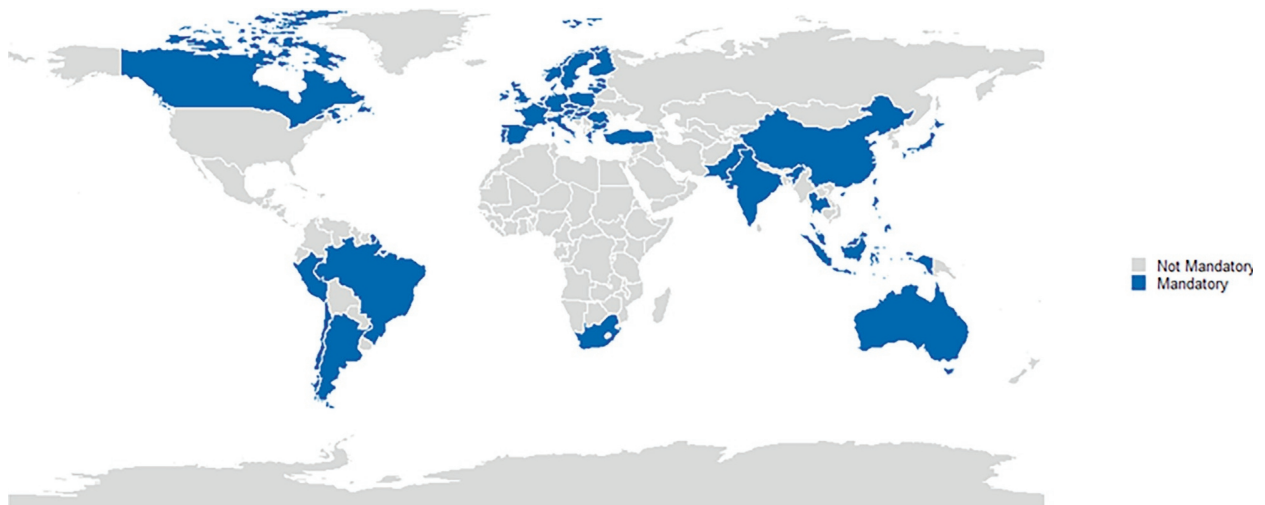


Fig. 2. Mandatory ESG/CSR disclosure around the world. Data Source: Carrots & Sticks.

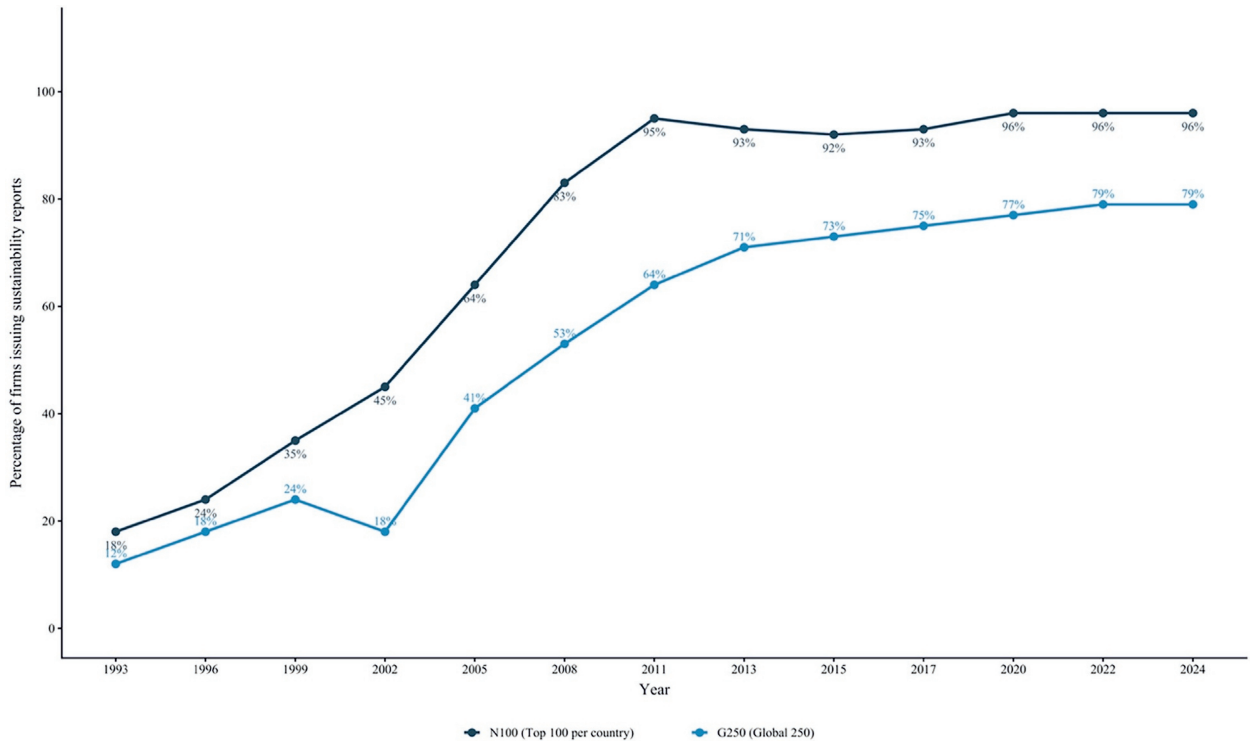


Fig. 3. **Global adoption rates of sustainability reports (1993–2024).** Data Source: KPMG Survey of Sustainability Reporting 2024, 2022. N100 refers to a global sample of the top 100 companies by revenue in 58 countries, territories and jurisdictions. G250 denotes the top 250 companies by revenue that are included in the 2023 Global Fortune 500 ranking.

2019; Christensen et al., 2021). These features make ESG mandates more politically contested, more heterogeneous across jurisdictions, and more dependent on regulatory design and enforcement than traditional financial disclosure.

6.1. Expansion of mandatory disclosure beyond financial information

Over the past decade, disclosure regimes in many jurisdictions have expanded beyond financial statements to include ESG and sustainability information, intended to support both valuation and accountability objectives (Christensen et al., 2021). A key driver is the rising financial relevance of non-financial factors, such as climate risk exposure, supply chain practices, and human capital, for firms' long-horizon cash flows and risk profiles (e.g., Edmans, 2011; Lins et al., 2017). Institutional investors have played a central role in raising ESG disclosure on regulatory agendas, as large asset owners increasingly seek comparable information to assess their portfolio exposure and engage with firms on long-term strategy and risk management (Gillan et al., 2021). Consistent with this demand-side channel, Ilhan et al. (2023) show that firms with more climate-conscious institutional ownership provide better quality climate risk disclosures and that investor engagement influences disclosure practices.

Despite these parallels with the rationale for financial disclosure, ESG reporting differs in important ways. Many sustainability metrics are not anchored in a single measurement system and often require external impact estimates or forward-looking judgments, which increases the scope for discretion and the risk of measurement error (Kotsantonis and Serafeim, 2019; Christensen et al., 2021). ESG issues also commonly involve externalities that extend beyond shareholders to other stakeholders, creating incentives for selective disclosure, impression management, or withholding of socially sensitive information (Kim and Lyon, 2011). These



Fig. 4. **Global adoption rates of sustainability reports by region (2011–2024)**. Data Source: KPMG Survey of Sustainability Reporting 2022, 2024. The rate is calculated based on 5800 N100 companies. In 2024, the regional classification was revised: the Americas were split into North America and Latin America and Middle East & Africa into the Middle East and Africa.

features complicate reliance on purely voluntary reporting and strengthen the case for standardized and, increasingly, mandatory disclosure.

Consistent with these developments, regulators have moved toward ESG mandates in the main jurisdictions. The European Union’s Non-Financial Reporting Directive (NFRD) and its replacement by the Corporate Sustainability Reporting Directive (CSRD) represent a systematic effort to compel large firms to disclose standardized ESG information. Similarly, policymakers in the United Kingdom, the United States, and other jurisdictions have moved toward mandatory climate-related disclosures in accordance with frameworks such as the Task Force on Climate-related Financial Disclosures (TCFD). Table 1 summarizes the diversity of mandatory ESG disclosure across jurisdictions. This expansion reflects continuity with previous justifications for disclosure regulations, namely reducing information asymmetry and improving comparability, while raising new conceptual and political questions, particularly around materiality and regulatory objectives. We next examine these debates.

6.2. Materiality and regulatory objectives: Single versus double materiality

A central debate in ESG disclosure concerns materiality and, more broadly, the objectives that disclosure requirements are intended to serve. In traditional securities regulation, materiality is typically investor-oriented: information is material if a reasonable investor would consider it important when making investment or voting decisions. This “single materiality” approach underpins US securities law and is embedded in frameworks such as the Sustainability Accounting Standards Board (SASB) (Khan et al., 2016) and, more recently, the International Sustainability Standards Board (ISSB).

Under single materiality, ESG disclosure is justified insofar as environmental or social issues affect firm value through expected cash flows, risk, or cost of capital. For example, climate risk becomes a relevant disclosure item when it exposes firms to transition risks, regulatory penalties, or physical disruptions with finan-

Table 1
Cross-country comparison of mandatory ESG disclosure regimes.

Jurisdiction	Regulation (official/standard name)	Enactment year	Scope	Materiality concept	Enforcement strength	Primary regulatory objective
China	Shanghai and Shenzhen Stock Exchange CSR Reporting Guidelines	2008	Selected listed firms (e.g., state-owned enterprises, financial firms)	Broad CSR/ Stakeholder	Medium	Stakeholder governance and social accountability
United Kingdom	Companies Act 2006 (Strategic Report and GHG Emissions Disclosure Requirements)	2013	UK-listed firms	Financial materiality (climate risk)	Strong	Investor information + behavioral discipline
European Union	Non-Financial Reporting Directive (2014/95/EU); Corporate Sustainability Reporting Directive	2017/2024	Large public interest entities/large firms	Double materiality	Medium → Strong	Stakeholder accountability and capital market transparency
United States	Dodd-Frank Act Section 1502 (Conflict Minerals) and Section 1503 (Mine Safety); EPA GHG Reporting Program	2010	Sector-specific firms	Issue-specific	Strong	Behavioral change and public accountability
France	Grenelle II Act; Corporate Duty of Vigilance Law	2012/2017	Large firms	Broad stakeholder	Medium	Stakeholder protection and supply chain accountability
Denmark	Danish Financial Statements Act (CSR Reporting Requirement)	2009	Large firms	Broad CSR	Medium	Stakeholder accountability
South Africa	King III/King IV Codes and Integrated Reporting Requirement (JSE)	2010	JSE-listed firms	Integrated value creation	Medium-Strong	Investor information + governance reform
Japan	Corporate Governance Code and Sustainability Disclosure in Annual Securities Reports	2015	Listed firms	Financial materiality focused on sustainability	Medium	Investor-oriented governance and risk disclosure
Singapore	SGX Sustainability and Climate Reporting Rules	2016/2023	SGX-listed firms	Financial materiality (climate)	Strong	Investor information and risk pricing
Australia	Corporations Act and AASB Climate-related Financial Disclosure Standards	2024–	Large listed and financial firms	Financial materiality (climate risk)	Strong	Investor information and systemic risk management
New Zealand	Financial Sector (Climate-related Disclosures and Other Matters) Amendment Act	2023	Financial institutions and large firms	Financial materiality (climate risk)	Strong	Investor protection and financial stability
Canada	Canadian Securities Administrators (CSA) Climate-related Disclosure Requirements	2024– (phased)	Large public firms	Financial materiality (climate risk)	Medium-Strong	Investor information
Hong Kong	HKEX ESG Reporting Guide and Climate Disclosure Requirements	2016–	HK-listed firms	Financial materiality	Medium-Strong	Investor information and market transparency
Switzerland	Ordinance on Due Diligence and Transparency in relation to Minerals and Child Labour	2022	Large firms	Stakeholder-oriented	Medium	Supply chain accountability and transparency
Norway	Transparency Act (Åpenhetsloven)	2022	Large firms	Stakeholder-oriented	Medium	Human rights and supply chain accountability

Note: “Enforcement” captures the strength of both formal legal enforcement and informal market-based monitoring. “Primary regulatory objective” reflects the main regulatory intent, distinguishing between investor-oriented information provision and stakeholder-oriented accountability or behavioral change.

cial consequences (Bolton and Kacperczyk, 2021). This investor-focused framing aligns ESG disclosure with the traditional objectives of financial reporting and capital market regulation, emphasizing decision usefulness and capital allocation efficiency (Healy and Palepu, 2001; Leuz and Wysocki, 2016).

In contrast, the European Union's "double materiality" framework explicitly expands the scope of mandatory disclosure beyond investor-relevant financial risks. Under double materiality, firms are required to disclose both how sustainability issues affect their performance (financial materiality) and how their activities affect society and the environment (impact materiality). This approach reflects a regulatory objective that goes beyond capital market efficiency to include stakeholder accountability and the management of externalities (Christensen et al., 2021). The CSRD operationalizes this broader conception of materiality by requiring reporting on impacts even when these impacts may not be immediately priced by financial markets.

The divergence between single and double materiality reflects differences in regulatory philosophy rather than measurement disagreements. Investor-oriented regimes treat ESG disclosure as an extension of financial reporting, justified by valuation and risk assessment. Stakeholder-oriented regimes treat disclosure as a governance tool to inform a broader set of constituencies and influence corporate behavior through transparency (Eccles and Krzus, 2018). These differences also influence the evaluation metrics. Under single materiality, effectiveness is often assessed using capital market outcomes such as liquidity and cost of capital; under double materiality, success is evaluated through changes in corporate practices and the reduction of negative externalities. This conceptual divide helps to explain why cross-jurisdictional evidence on ESG mandates is often mixed and why empirical findings depend on regulatory objectives.

Importantly, materiality choices are not purely technical. The scope of disclosure determines whose interests are prioritized and which costs firms are required to internalize. As such, materiality frameworks are shaped by political processes and institutional constraints. Therefore, we next consider the political economy of ESG disclosure mandates.

6.3. Political economy of ESG disclosure requirements

The emergence of mandatory ESG disclosure reflects political economy forces shaped by distributional consequences and competing interests. Compared with traditional financial reporting, ESG disclosure often imposes more heterogeneous costs across firms and industries while generating benefits that extend beyond investors to broader stakeholder groups. As a result, ESG mandates tend to be particularly contested.

On the supply side, firms and industry groups frequently resist expansive ESG disclosure requirements, citing compliance costs, legal liability, competitive disadvantage, and the disclosure of proprietary or sensitive information. These concerns are particularly salient in carbon-intensive industries and sectors with complex global supply chains. On the demand side, ESG disclosure has been actively promoted by institutional investors, civil society organizations, and international policy bodies. Large asset owners increasingly view sustainability risks, especially climate risks, as systemic and long-horizon, creating incentives to push for standardized and mandatory disclosure rather than relying on voluntary reporting (Krueger et al., 2020). International initiatives such as the TCFD and broader commitments stemming from the G20 and COP processes have further elevated ESG transparency as a policy priority. These actors frame ESG disclosure as both an investor-protection tool and a mechanism for disciplining corporate behavior in the presence of economy-wide externalities.

The resulting rules are often the product of a compromise. Political bargaining tends to shape the scope, timing, and stringency through phased implementation, industry exemptions, safe-harbor provisions for forward-looking statements, and the use of narrative disclosure (Kothari et al., 2023). Such design features are consistent with the private interest theories of regulation: organized groups seek to reduce costs while preserving the appearance of compliance. Moreover, the political economy of ESG disclosure varies across jurisdictions. Stakeholder-oriented systems are more likely to integrate broader accountability objectives, while investor-oriented regimes frame ESG disclosure primarily through financial materiality and risk management (Christensen et al., 2021). These differences influence not only the content of the information disclosed but also its enforcement and credibility, thus explaining the heterogeneity of the results.

6.4. Real effects of mandatory ESG disclosure

A growing body of empirical literature examines the effects of mandatory ESG and sustainability disclosure on firms and capital markets. Compared with traditional financial reporting, this literature is more recent and more heterogeneous, reflecting differences in regulatory design, metric quality, and policy objectives.

Lin et al. (2024) study the global evolution of E&S disclosure in annual reports using large-scale textual analysis and show that, although the quantity of ESG-related disclosure has increased markedly over time, disclosure quality has not improved accordingly. They further document that voluntary ESG reporting frameworks are associated with more informative disclosure, whereas disclosure mandates mainly increase the volume of disclosure but lead to more boilerplate, less specific, and more standardized narratives, suggesting that regulation can expand reporting without necessarily improving textual specificity.

Research highlights that equity investors are plausible primary users of ESG information, but evidence regarding the valuation and performance effects of ESG reporting remains limited and mixed, partly due to the endogenous relationship between ESG reporting and firms' underlying ESG activities. Recent evidence shows that mandatory ESG disclosure can generate economically meaningful real effects on capital markets by improving firms' information environment. Using a global panel of firms across 65 countries, Krueger et al. (2024) document that the introduction of mandatory ESG disclosure regimes leads to significant improvements in stock liquidity, including lower bid-ask spreads, reduced price impact, and fewer zero-return days. The magnitude of these effects is economically sizable and comparable to the liquidity improvements observed after major financial reporting reforms. Importantly, the effects are stronger when disclosure mandates are issued by government authorities, require full compliance, and are supported by strong informal enforcement, and they are more pronounced for firms with a weaker pre-existing information environment. These findings suggest that, when properly designed and enforced, ESG disclosure regulation can meaningfully reduce information asymmetry and produce tangible capital market benefits under well-designed and credibly enforced regimes, rather than being limited to symbolic compliance.

In addition to these capital market effects, increasing evidence shows how ESG disclosure regulations can have real effects on firms' operating and investment decisions. Christensen et al. (2021) conceptualize that mandatory disclosure functions as a feedback loop where stakeholder reactions, ranging from investor monitoring to societal pressure, incentivize firms to change their underlying activities. Theoretically, mandates can improve corporate ESG performance through enhanced corporate governance, closer links between sustainability and financial performance, increased reputational costs from external stakeholders, and easier peer benchmarking (Cao et al., 2019).

Empirical evidence across various jurisdictions supports the notion that mandatory reporting leads to substantial changes in firm behavior, although often at an economic cost. Specifically, studies on mandates in China, the United Kingdom, and the United States consistently find significant reductions in carbon emissions and improvements in workplace safety following disclosure requirements (Christensen et al., 2017; Chen et al., 2018b; Tomar, 2023). However, these improvements are frequently accompanied by declines in profitability and productivity, suggesting a trade-off between social performance and traditional financial metrics. Disclosure mandates can also affect firms' capital allocation decisions and may induce regulatory avoidance or activity relocation, thereby reshaping the industry structure and the allocation of economic activity (e.g., Rauter, 2020). Taken together, this evidence indicates that ESG reporting regulations can have broad real effects on firm behavior and market structure, well beyond their informational role in capital markets.

Furthermore, recent evidence shows that corporate responses to disclosure mandates tend to be stronger among firms with higher baseline emissions, greater exposure to investor activism, or more stringent enforcement (Chen et al., 2018b; Jouvenot and Krueger, 2021). This heterogeneity underlines that disclosure mandates interact with monitoring institutions and market discipline, rather than mechanically producing behavioral change. Table 2 summarizes the findings of recent studies on these real effects.

The literature also emphasizes the costs and limitations. Sustainability reporting requires non-trivial preparation, verification, and assurance, which can be burdensome for small firms or those with complex operations. The forward-looking and qualitative nature of many ESG metrics raises concerns about measurement errors and reporting discretion. In the absence of detailed standards and enforcement, firms may respond with symbolic or boilerplate disclosure that satisfies formal requirements without materially

Table 2
Academic findings on the effects of ESG disclosure policies.

Study	Country/Setting	Regulation/ Mandate	Research design	Main channel	Capital market effects	Real effects on firms	Documented costs/Trade-offs
Lin et al. (2024)	Global	ESG disclosure in annual reports	Large-scale textual analysis	Reporting incentives and standardization	—	↑ Disclosure quantity, ↓ textual specificity	More boilerplate, lower informativeness
Krueger et al. (2024)	65 countries	Mandatory ESG disclosure regimes	DiD	Information environment	↑ Liquidity (↓ bid-ask spreads, ↓ price impact, ↓ zero-return days)	—	—
Ioannou & Serafeim (2019)	4 countries (China, Denmark, Malaysia, South Africa)	CSR disclosure mandates	DiD + IV	Disclosure incentives	↑ Tobin's q (via increased disclosure)	↑ CSR disclosure volume and assurance	Identification concerns (reporting vs. real effects)
Chen et al. (2018b)	China	Stock exchange CSR mandate (2008)	DiD	Public pressure	—	↓ SO ₂ and wastewater emissions; ↓ profitability	Profitability decline
Christensen et al. (2017)	United States	Mine safety disclosure (Dodd-Frank §1503)	RD/DiD	Public scrutiny	Stronger market reaction to disclosed violations	↑ Safety; ↓ productivity	Productivity loss
Tomar (2023)	United States	Facility-level GHG disclosure	DiD	Peer benchmarking	—	↓ Emissions (~7.9%)	—
Jouvenot & Krueger (2021)	United Kingdom	Mandatory carbon emissions disclosure	DiD	Investor pressure	Negative return reactions for high emitters	↓ Emissions	Abatement and compliance costs
Downar et al. (2021)	United Kingdom	Mandatory carbon emissions disclosure	DiD	Stakeholder pressure	—	↓ Emissions	Compliance costs
Fiechter et al. (2022)	European Union	Non-Financial Reporting Directive	DiD	Anticipation and benchmarking	—	↑ CSR activities (esp. low-CSR firms)	Compliance costs
Rauter (2020)	European Union & Canada	Extractive payment disclosure mandates	DiD	Public shaming	—	↓ Investment; ↓ licenses	Capital reallocation distortions
Grewal et al. (2019)	European Union	Non-financial disclosure directive	Event study	Regulatory cost expectations	Negative announcement returns	—	Expected proprietary and political costs
Andreicovici et al. (2023)	United States	SEC payment disclosure rule	Event study	Public scrutiny	Negative market reaction	—	Expected business activity costs

improving informativeness. Christensen et al. (2021) emphasize that mandatory ESG disclosure may not automatically yield capital market benefits and that poorly designed mandates risk information overload and low-salience reporting, echoing previous debates in the financial disclosure literature regarding the trade-off between more information and decision usefulness.

6.5. Carbon emissions disclosure as a case study

Carbon emissions disclosure provides a focused case for evaluating mandatory ESG reporting. Compared with broader sustainability disclosure, carbon information is relatively well-defined, quantitatively measurable, and closely linked to both financial risks and externalities. These features make carbon emissions disclosure a useful benchmark for assessing whether mandatory transparency can improve the information environment and induce real change.

A notable example is the UK mandate requiring listed firms to disclose their greenhouse gas (GHG) emissions in their annual reports, implemented in 2013. Studies exploiting this policy document substantial increases in the availability and comparability of emissions data, thus limiting firms' ability to obscure their environmental performance. More importantly, evidence suggests meaningful real effects. Jouvenot and Krueger (2021) find that firms subject to the UK mandate significantly reduce their carbon emissions following its implementation, primarily through operational adjustments rather than divestment alone. These findings confirm that transparency disciplines firms through investor scrutiny, regulatory attention, and reputational concerns.

Furthermore, the literature on carbon emissions disclosure highlights political economy constraints. Firms in carbon-intensive industries often resist stringent requirements, citing compliance costs, competitive concerns, and litigation risk (Christensen et al., 2021). As with previous episodes of disclosure regulation, the final form and effectiveness of climate disclosure mandates depend on how regulators balance these private costs against public benefits and on whether rules are specific, comparable, and credibly enforced. Carbon emissions disclosure thus illustrates both the promises and limitations of mandatory ESG reporting: well-designed mandates can improve transparency and induce real behavioral change, but their effects depend critically on regulatory design, enforcement, and the broader institutional environment.

7. Conclusions

The literature reviewed in this article indicates that the effectiveness of mandatory disclosure depends not only on whether reporting requirements exist but also on how regulatory objectives are defined, how disclosure rules are designed, and how credibly they are enforced. This conditionality becomes even more salient as disclosure regimes extend to ESG and climate domains, where measurement challenges, heterogeneous firm exposure, and political contestation are more pronounced.

A first implication concerns the alignment between regulatory objectives and the intended users of the information disclosed. Mandates designed primarily to support investor decision-making tend to emphasize financially material information, comparability, and decision usefulness. In contrast, disclosure regimes aimed at broader accountability objectives adopt broader conceptions of materiality and evaluate success using outcomes that may not be fully captured by standard capital market metrics. The ESG literature highlights that ambiguity regarding regulatory purpose can complicate both compliance and evaluation, particularly when mandates are assessed using market outcomes that do not correspond to their stated objectives (Christensen et al., 2021). The explicit formulation of regulatory goals is therefore an essential element in the design of coherent mandates.

A second implication concerns the trade-offs between informational benefits and compliance costs. Mandatory disclosure can mitigate information asymmetry, improve comparability, and, in sustainability contexts, support accountability for externalities. However, reporting involves preparation, verification, and assurance costs that are unevenly distributed across firms and sectors and may generate unintended responses, such as boilerplate disclosure or strategic substitution in real activities. These trade-offs highlight the value of focusing mandates on domains where information frictions or externalities are substantial, and of developing standardized and decision-relevant metrics that reduce discretion and improve verifiability.

A third implication is that disclosure rules protect investors and shape behavior only to the extent that they are credible and enforceable. Cross-country evidence consistently shows that disclosure mandates yield meaningful outcomes when supported by effective enforcement, through civil liability, regulators, or complementary market-based mechanisms, rather than by the mere formal adoption of rules (La Porta et al., 2006). At the same time, political economy research emphasizes that disclosure regulations are vulnerable to lobbying, selective exemptions, and uneven enforcement. Institutional features that promote transparency in rule-making, broaden participation, and enable periodic review are therefore important safeguards for sustaining regulatory effectiveness and protecting the public interest (Leuz and Wysocki, 2016).

The case of ESG and climate disclosures illustrates how these considerations interact. Carbon emissions disclosure, in particular, suggests that specific, measurable and verifiable requirements are more likely to improve transparency and induce real behavioral responses, especially when standards are sufficiently granular and enforcement is credible. At the same time, mixed capital market effects caution against evaluating ESG mandates solely through short-horizon financial outcomes when regulatory objectives go beyond investor protection (Christensen et al., 2021).

Overall, this review highlights that mandatory disclosure is a fundamental governance instrument in modern capital markets, while emphasizing that its effects are context-dependent and politically mediated. Similar reporting rules can generate different outcomes across countries and disclosure domains, depending on legal infrastructure, enforcement capacity, and political institutions. As sustainability reporting continues to evolve, future research could further clarify how markets process newly mandated information, how disclosure interacts with real corporate decisions and externalities, and how regulatory design choices shape both informational and behavioral outcomes.

China's experience with mandatory disclosure underscores these broader lessons. In a market characterized by concentrated ownership, limited private enforcement, and strong regulatory involvement, disclosure has functioned less as a self-enforcing market institution and more as a governance mechanism whose effectiveness hinges on enforcement credibility and institutional commitment. Evidence from China illustrates both the potential of mandatory disclosure to enhance transparency and investor protection and its limitations when political incentives or enforcement constraints dilute credibility. As China's disclosure regime continues to evolve, particularly in ESG and climate domains, it offers a valuable laboratory for understanding how the institutional context shapes the real effects of transparency mandates on emerging capital markets.

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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Does competition stimulate R&D investment? Insights from antitrust law



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ABSTRACT

This study examines the impact of changes in market equilibrium, from collusion to competition, on firms' R&D investments by leveraging the staggered enactment of antitrust legislation in 32 countries, which effectively addresses endogeneity concerns in the innovation literature. We argue and find that restoring competition by dissolving collusion requires increased R&D investment by firms to effectively compete for market share. The effect is stronger among firms operating in more concentrated industries before the reform and among those with greater financial flexibility and higher risks. Increased R&D investment is associated with improvements in both return on equity and Tobin's Q, indicating real and market performance gains. These effects are amplified in countries with a stronger rule of law and a weaker pre-reform innovation capacity. Overall, the findings highlight the role of antitrust enforcement in fostering innovation and firm performance through the restoration of competitive market structures.

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1. Introduction

Antitrust law remains, to this day, one of the few legal domains fundamentally shaped by economic reasoning, given its constant relevance to issues of market concentration and consumer welfare. Reflecting this influence, antitrust enforcement has been adopted globally to curb cartelization, promote competition, and

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reshape market dynamics (Gilbert, 2023). Recent rulings, such as the \$1 million fine imposed on GameStop,¹ €3 million on Qualcomm,² and €2.4 billion on Google,³ underscore the strengthening of antitrust enforcement by regulators, with substantial penalties reflecting a more assertive stance against corporate antitrust violations. Although there is no universally accepted definition, antitrust laws generally refer to legal frameworks that promote fair competition and prevent market abuses. In the United States, they are known as antitrust laws, while in most other countries they are called competition laws or antimonopoly laws. For instance, in China, such regulations are governed by the Anti-Monopoly Law, enacted in 2008. These laws typically prohibit anti-competitive agreements, abuses of market dominance, and mergers that may harm competition, with the aim of protecting consumer welfare and market efficiency (Hawke and Middleton, 2011).

Although antitrust enforcement has become of practical importance in recent decades, the global enactment of antitrust laws has intensified regulatory scrutiny over firm behavior. In response, a growing body of research examines the effects of antitrust regulation on firm outcomes, including green innovation (Feng and Li, 2024), foreign direct investment (Mariotti and Marzano, 2021), capital structure (Dasgupta and Žaldokas, 2019), mergers (Chung et al., 2024), and IPO activity (Duong et al., 2024). However, relatively little is known about how changes in market structure, induced by antitrust legislation, influence firms' incentives to invest in research and development (hereafter, R&D investment).⁴ Our paper addresses this gap by exploiting the staggered adoption of antitrust laws across countries to estimate their causal effect on corporate R&D investments. As we focus on R&D investment, three considerations guide our choice. First, antitrust laws are particularly salient in industries where innovation, intellectual property, and technological change are central. Their application to the "new economy," characterized by tech and knowledge-intensive sectors, has been debated (Posner, 2017), even as economic theory suggests that competitive pressure encourages innovation in products and processes, making R&D investment a key adjustment margin. Second, R&D investment is the most widely available and internationally comparable measure of technology investment. It captures both the pace and direction of technological change and has become increasingly central to firm performance (Brown et al., 2022). Third, R&D investment is inherently risky: its cost is tangible but its return is uncertain. This asymmetry allows firms to use their R&D investments strategically to modify their risk exposure, making them particularly responsive to changes in market structure and competition (Shen and Zhang, 2013). These features make R&D investment a particularly informative outcome through which to examine the effects of antitrust regulation.

Although studies examine the relationship between competition and R&D investment, they are largely confined to product market competition in single-country contexts. For example, Aghion et al. (2005) document a non-linear effect of competition on patenting using UK firms, while Thakor and Lo (2022) find a positive association between competition and R&D investment in the U.S. biopharmaceutical sector. In the context of emerging markets, Yu et al. (2021) show that China's 2008 antitrust law negatively affects patent output. Our study departs from this literature in four key ways. First, we exploit the staggered adoption of antitrust laws across 32 countries in a difference-in-differences framework, using non-adopting countries as a control group. This setting allows us to treat the enactment of antitrust laws as an exogenous shock to firms' investment environment, enabling us to identify the differential effects of antitrust legislation on corporate R&D investment. Second, rather than relying on narrow firm-level proxies for product market competition, which are typically derived from annual reports, we examine the broader institutional framework established by formal antitrust legislation. Unlike product market competition measures, which capture competitive intensity at the firm level, antitrust laws encompass a wide range of enforcement tools designed to prohibit anticompetitive behavior, including collusive agreements to fix prices or wages, rig bids, allocate customers or markets, and

¹ <https://www.ftc.gov/news-events/news/press-releases/2024/09/gamestop-ceo-ryan-cohen-pay-nearly-1-million-penalty-settle-antitrust-law-violation>.

² https://timesofindia.indiatimes.com/articleshow/113463963.cms?utm_source=contentofinterest&utm_medium=text&utm_campaign=cppst..

³ <https://www.usnews.com/news/business/articles/2024-09-10/google-loses-final-eu-court-appeal-against-2-4-billion-euro-fine-in-antitrust-shopping-case>.

⁴ Throughout the paper, we use the terms "research and development" and "R&D investment" interchangeably. The variable used to measure this construct is called "R&D" for brevity, and we refer to it as "R&D expenditure" to indicate the specific data item used in the analysis.

engage in predatory pricing. This broader scope allows us to capture structural changes in competition at the country level. Third, we use R&D investment as our outcome variable, as it is a tangible and internationally comparable proxy for technology investment and is widely recognized as a key driver of competitive advantage and future firm performance (Brown et al., 2022). Finally, the mixed theoretical and empirical findings on competition and innovation underscore the need for cross-country analysis to better isolate the effects of antitrust policies from country-specific confounding factors.

Therefore, our study fills an important gap in the literature by examining the staggered passage of antitrust regulations globally. Although studies examine the relationship between competition and innovation, their findings are mixed. On the one hand, breaking collusion stimulates production expansion and technological progress (Arrow, 1972). Colluding firms, which rely on restricted output and price fixing, often lack incentives to innovate (Dasgupta and Žaldokas, 2019) and tend to engage in cooperative R&D arrangements that suppress individual firm efforts (Duso et al., 2014). The transition to competitive environments pressures firms to reduce their costs, improve their quality, and pursue technological upgrades to survive (Yu et al., 2021), and may lead self-serving managers to overinvest in R&D (Shen and Zhang, 2013). In essence, antitrust laws enhance competitive pressure, which may incentivize firms to invest more in R&D to maintain or improve their market position. By altering the strategic environment, such laws may also prompt firms to explore novel technologies and investment opportunities that would be less attractive in more collusive settings. Empirical evidence corroborates this argument, showing that increased competition is associated with higher R&D investment (Tang, 2006; Vives, 2008). On the other hand, increased competition also introduces market uncertainty, discouraging firms from making substantial R&D investments due to volatile returns (Schumpeter, 1934; Tang, 2006). Monopoly rents under collusion can finance innovation (Kamien, 1987), while antitrust enforcement may restrict price flexibility, limit innovation-enhancing mergers, and reduce excess profits available for R&D investment (Yu et al., 2021). Empirical evidence shows that increased competition can reduce innovation inputs (Hyo, 2019). Taken together, the literature offers mixed evidence, and the overall impact of competition on R&D investment remains unclear.

We contribute to this debate by examining the effect of antitrust law adoption on firm-level R&D investment using a comprehensive global dataset comprising 92,569 firm-year observations from 10,807 unique firms across 47 countries, including 32 adopters and 15 non-adopters of antitrust laws. Leveraging a staggered difference-in-differences framework, we find that the enactment of antitrust laws leads to a statistically and economically significant increase in R&D investment at the firm level. These findings support our baseline hypothesis that increased competition stimulates innovation through increased R&D investment. Our identification strategy is validated through parallel trend tests, placebo tests, and a series of robustness checks, including alternative sample definitions and variations across countries and over time in the accounting treatment of R&D expenditures. We further explore the mechanisms underlying the baseline effect. First, firms operating in markets characterized by lower pre-reform competitiveness and higher levels of collusion exhibit higher post-reform R&D investments, consistent with the hypothesis that competitive pressure stimulates innovation. Second, the effect is concentrated among financially unconstrained firms, suggesting that internal financing capacity amplifies firms' responsiveness to competition. Third, firms with a higher ex-ante propensity to take risks show larger increases in R&D investments, underscoring the role of managerial incentives. We also show that the increase in R&D investment has tangible real and market implications: the treated firms experience significant improvements in their return on equity and Tobin's Q, indicating better operating performance and market valuation. Finally, at the country level, we find that the effect is stronger in countries with a stronger rule of law and lower baseline R&D investments, suggesting that institutional quality and initial innovation status determine the effectiveness of antitrust reform.

Our study contributes to the literature on antitrust policies. Prior work examines the motivations for adopting antitrust laws in developing economies and the institutional challenges surrounding their enforcement (Waked, 2016). More recent evidence from a sample of 20 countries suggests that antitrust laws can curb monopolistic gains following mergers, thereby enhancing consumer welfare (Chung et al., 2024). In the context of China's 2008 Anti-Monopoly Law, Gao et al. (2025) find that increased business risk post-enactment leads to greater tax avoidance behavior. We extend this literature by offering the first cross-country causal evidence on how the adoption of antitrust laws affects firm-level R&D investment. Using a novel identification strategy, we show that firms in countries with antitrust laws invest more in R&D than those in non-adopting

countries, underscoring how competitive pressure stimulates innovation. Importantly, we also find that firms that increase their R&D investments post-reform see their value improve, suggesting that markets reward firms perceived as strengthening their competitive advantage in the wake of a regulatory change.

Second, we contribute to the growing literature on the relationship between competition and innovation. Aghion et al. (2005) document an inverted-U relationship between product market competition and innovation using firm-level data from the United Kingdom. Other research, such as Thakor and Lo (2022), focuses on the U.S. biopharmaceutical sector and finds that increased competition is positively associated with firm-level R&D investment. We extend this literature by investigating how the enactment of competition laws at the country level affects firm-level R&D investment. Consistent with the view that dismantling market power fosters innovation (Belderbos et al., 2013), we find that the adoption of antitrust laws leads to a measurable increase in R&D investment among affected firms. More generally, our findings contribute to the literature linking institutional frameworks to innovation decisions, highlighting how macro-level legal reforms shape firm-level innovation strategies (Wang, 2010).

Finally, our study contributes to the literature on how heterogeneity at the firm and country levels influences innovation responses to policy reforms. Belderbos et al. (2013) and Yang et al. (2025) emphasize the role of firm-specific factors in determining R&D investment behavior. Consistent with this view, we find that firms exposed to higher risks and lower financial constraints exhibit stronger R&D investment responses following the enactment of competition laws, highlighting how internal frictions mediate the impact of regulatory shocks on innovation. At the country level, our findings suggest that although stronger institutional frameworks, such as a strong rule of law, support innovation, even countries with historically low R&D investment can stimulate firm-level innovation by implementing competition laws. These results underscore that competitive pressure, when reinforced by legal reform, fosters a more favorable environment for R&D investment by strengthening firms' incentives to innovate.

The remainder of the paper is structured as follows: Section 2 reviews the related literature and develops the testable hypotheses. Section 3 presents the data, summary statistics, and empirical methodology. Section 4 reports the main empirical findings. Section 5 concludes the study.

2. Related literature and hypothesis development

2.1. The impact of antitrust laws on R&D investment

Historically, antitrust policies aimed to preserve competitive market structures and protect the public interest. Over time, however, the interpretation of "competition" under antitrust laws has narrowed and become increasingly framed through the lens of economic efficiency, shaped by the rise of neoclassical price theory in the mid-20th century (Flynn, 1990). Rooted in the Sherman Act of 1890, antitrust laws address various restrictions, including horizontal agreements (e.g., cartels), vertical restrictions (e.g., resale price maintenance), monopolization, and mergers (Farmer, 2010). Although some advanced economies adopted such laws in the early 20th century (Chung et al., 2024), the global diffusion of competition laws accelerated in the early 2000s (Bradford and Chilton, 2019). For example, China enacted its first Anti-Monopoly Law in 2008, aimed at regulating dominant market behavior. Despite the heterogeneity of their implementation, the antitrust regimes of different countries have increasingly converged toward common standards, led by the U.S., EU, and international institutions such as the OECD and the ICN (Cheng, 2012). Theoretically and empirically, competition is associated with greater innovation incentives (Aghion et al., 2005; Tang, 2006; Vives, 2008). Intensified competition pushes firms to invest in R&D to differentiate their products, defend their market positions, and ensure their future growth. Arrow (1972) contends that dismantling collusion promotes technological progress by increasing firms' incentives to innovate. Conversely, colluding firms are less likely to innovate, as they benefit from reduced pressure due to inflated prices and stable market shares (Dasgupta and Žaldokas, 2019). Furthermore, Duso et al. (2014) find that colluding firms engage in R&D cooperation, which diminishes individual firms' R&D investments. This cooperation tends to centralize innovation efforts, thereby reducing the incentive for individual firms to invest in new technologies or products. Consistent with the view that competition fosters innovation, Tang (2006) finds a positive association between competition and R&D investment across countries. In addition, Duong et al. (2024) show that the arrival of new firms following antitrust

reforms forces incumbents to innovate to remain competitive. As noted by Wang et al. (2024a, 2024b) and Federico et al. (2020), the enforcement of antitrust laws, by curbing monopolistic behavior and dismantling collusive market structures, intensifies competitive pressure and alters firms' strategic resource allocation. In response, firms are forced to invest in risky R&D activities as a means of differentiation, customer acquisition, and long-term survival under the discipline of market selection. This shift not only enables firms to pursue innovation-driven rents and durable competitive advantages but also helps erode the dominance previously exerted by cartels, thereby fostering a more innovation-friendly market environment. Although some studies suggest that increased competition enables managerial risk-taking and overinvestment in R&D (Yung and Chen, 2018), the overall consensus is that competition fosters innovation through increased market pressure. Drawing on this literature, we argue that the staggered adoption of antitrust laws globally disrupts collusion and strengthens competition. This shift, in turn, forces firms to increase their R&D investments to remain competitive and foster innovation. Accordingly, we propose the following hypothesis:

H1. The staggered adoption of antitrust laws positively influences firms' R&D investments.

An alternative perspective, rooted in Schumpeterian theory (Schumpeter, 1934), posits that increased competition following the breaking of collusion can introduce significant market uncertainty, thereby discouraging firms from undertaking risky and long-term R&D investments. Consistent with this argument, Xie et al. (2023) show that monopolistic or state-protected industry structures are associated with higher gross margins and better control of resources, conditions that are conducive to making long-term, high-risk investments, including R&D. In collusive markets, firms often earn supernormal profits through price fixing and output restrictions, which can provide stable internal financing for innovation (Kamien, 1987). When antitrust enforcement disrupts these arrangements, increased rivalry compresses profit margins and increases market volatility, potentially constraining firms' ability to invest in R&D. Several studies support this view. For example, Hyo (2019) finds that the restoration of competition reduces innovation inputs, as firms prioritize cost-efficiency and short-term survival over long-term technological progress. Similarly, Aghion et al. (2005) highlight that the relationship between competition and innovation is not linear, suggesting that beyond a certain threshold, intense competition actually discourages innovation. Thus, although antitrust-driven competition can stimulate innovation under certain conditions, it can also harm R&D investments by reducing financial slack and increasing strategic uncertainty.

2.2. *Heterogeneity in the impact of antitrust laws on R&D investment*

Although we hypothesize that the staggered adoption of antitrust laws generally increases firms' R&D investments (H1), the magnitude of this effect is likely to vary across industries and firms based on ex-ante characteristics. In this section, we explore how pre-reform industry concentration, financial constraints, and firm-level risk-taking influence the R&D investment response to antitrust reforms.

2.2.1. *Industry concentration and competition*

Firms' R&D expenditures are shaped by the competitive structure of industries and their long-term innovation strategies, which ultimately influence the competitiveness of the entire economy (Chen and Li, 2018). Theoretical models suggest that product market competition shapes innovation incentives in non-linear ways. Aghion and Howitt (1992) argue that increased competition erodes post-entry rents, discouraging innovation, while others (Tishler and Milstein, 2009) suggest a U-shaped relationship, where innovation first declines and then increases as competition intensifies. He and Wintoki (2016) find that increased competition is particularly relevant for firms with high R&D investment intensity. Evidence from China's Zhongguancun Science and Technology Park supports this view. Wang et al. (2024a, 2024b) find that firms in industries with high market concentration, those facing relatively limited pre-reform competition, experience greater innovation effects following antitrust reforms. These competitive shocks generate both treatment and selection effects, which in turn stimulate R&D investment. Moreover, in moderately concentrated markets where excessive monopoly rents can be appropriated through innovation, curbing anticompetitive behavior appears especially conducive to the growth of R&D investment. Building on this, we argue that the adoption of antitrust laws disproportionately affects firms in more concentrated industries. These firms, previously insulated by collusion or market

power, face stronger competitive pressures following the reform and may possess both the slack and the strategic incentive to respond by increasing their innovation to maintain their competitive advantage.

In brief, monopolistic advantage means that firms in concentrated industries have little incentive to innovate under low competition. After the adoption of antitrust reforms, however, these firms are forced to invest more in R&D, as competitive pressure increases the marginal returns on these investments. In contrast, firms without monopolistic advantage, already operating under competitive pressure, experience smaller incremental changes in their R&D behavior following the reforms. Accordingly, we propose the following hypothesis:

H2. The positive effect of the adoption of antitrust laws on R&D investment is stronger for firms in more concentrated industries (i.e., with lower pre-reform competition).

2.2.2. Financial constraints

R&D investment is especially sensitive to financing frictions due to its high risk, intangible returns, and limited collateral value, and financially constrained firms often face adverse selection and moral hazard problems that limit optimal investment in innovation (Brown et al., 2012). He and Wintoki (2016) show that financial constraints materially reduce R&D investment outlays. In the Chinese context, Du et al. (2022) find that slack resources, such as cash buffers, facilitate R&D investment by enabling internal capital reallocation. Similarly, Guo et al. (2020), focusing on small and medium-sized enterprises, show that financial slack supports risk-taking through increased R&D investment. These investments, in turn, enhance absorptive capacity and allow firms to develop innovative products and services that improve their performance. Building on these insights, we argue that antitrust-induced competition increases the need for innovation while simultaneously exposing firms to intensified resource constraints. Under such conditions, financially constrained firms may lack the flexibility to increase their R&D investments, even in the face of rising competitive pressure. In contrast, financially unconstrained firms are more likely to respond by increasing their R&D investments, given their greater capacity to absorb risks and finance long-term risky projects. Accordingly, we propose the following hypothesis:

H3. The positive effect of the adoption of antitrust laws on R&D investment is stronger for financially unconstrained firms.

2.2.3. Risk-taking and managerial incentives

R&D investments are inherently risky, and corporate risk-taking is central to firms' strategic responses in dynamic markets. As Bromiley et al. (2017) argue, R&D investments are characterized by high uncertainty, with frequent project failures and unsuccessful product outcomes. As such, R&D investment not only reflects risk-taking behavior but also contributes to increasing firms' risk. In competitive environments, this dynamic can be amplified, particularly for firms that already have high ex-ante risk profiles. These firms may view increased competition following antitrust reform as an opportunity, or a necessity, to redouble their efforts in innovation to maintain their strategic relevance. Managerial preferences further influence this relationship. Yung and Chen (2018) find that risk-seeking managers allocate more resources to R&D investment, while Shen and Zhang (2013) argue that the opaque and intangible nature of R&D investment allows such managers to pursue aggressive innovation strategies that increase stock volatility, which can enhance the value of equity-based compensation. Drawing on these insights, we posit that firms exposed to higher pre-reform risk are more likely to increase their R&D investments in response to the adoption of antitrust laws. These firms may view the regulatory shock not only as a threat to existing rents but also as an opportunity for strategic repositioning through innovation-led risk-taking.

H4. The positive effect of the adoption of antitrust laws on R&D investment is stronger for firms with a higher ex-ante propensity to take risks.

3. Data, summary statistics, and methodology

We begin with a sample of publicly listed non-financial firms worldwide, sourced from DataStream and Worldscope, covering the period from 2000 to 2020. Our sample period begins in 2000 due to limited reporting of R&D expenses prior to this year. The dataset is compiled from various sources: firm-level financial data are obtained from DataStream, the timeline of anti-collusion reforms for each country is based on Dasgupta and

Žaldokas (2019),⁵ and the rule of law index is derived from Kaufmann et al. (2007). Additionally, R&D expenditures at the country level are collected from the World Bank, and common ownership data are constructed using the Thomson Reuters ownership dataset. We exclude firm-year observations with missing values for assets, R&D expenses,⁶ and other control variables. Our final sample comprises 92,569 firm-year observations from 10,807 unique firms across 47 countries. Of these, 32 countries implemented antitrust reforms during the sample period, while 15 countries did not. Following Hu et al., (2023), we exclude countries⁷ that adopted antitrust laws prior to the sample period. Table 1 shows the breakdown by country of the sample composition, mean R&D investment, and year of enactment. China and Japan are the most represented in the treated sample, while Macedonia is the least represented. Israel (26.76%) has the highest R&D investment. Table 2 provides the industry-specific summary statistics of the sample, detailing sample proportions and average R&D investment by NAICS sector code. The manufacturing sector, which constitutes 65.54% of the full sample, has the highest average R&D investment, at 1.28%, indicating its dominant representation in the dataset and a relatively high investment in R&D compared with other sectors. Table 3 summarizes the key variables used in the study. R&D investment has a mean of 3.3%, with a significant variation, as indicated by a standard deviation of 4.9%, which aligns with the summary statistics reported in cross-country studies on R&D investment (Hillier et al., 2011). Firm size (SIZE) has a mean of 5.458 on the logarithmic scale, with a considerable variation (1.731), reflecting the diversity of firm sizes in the sample. In terms of tangibility (PPE), the mean of 26.9% suggests that a large proportion of firms' assets are tied to physical capital. Leverage (LEV) indicates an average debt ratio of 17.7%, with firms varying significantly in their use of debt.

Given the reverse causality concerns emphasized in the corporate investment and competition literature (Wang et al., 2024a, 2024b), we adopt a difference-in-differences specification with robust standard errors to estimate the impact of anti-collusion reforms on firms' R&D investments, incorporating controls and fixed effects (Hu et al., 2023).

$$\begin{aligned} \text{R\&D}_{i,c,t} = & \alpha + \beta_1 \text{TREAT}_{i,c} \times \text{POST}_{c,t} + \beta_2 \text{TREAT}_{i,c} + \beta_3 \text{POST}_{c,t} + \sum \beta_m \text{Firm Controls}_{i,c,t} \\ & + \sum \beta_k \text{Country Controls}_{c,t} + \text{fixed effects} + \varepsilon_{i,t} \end{aligned} \quad (1)$$

where *i*, *c*, and *t* represent the firm, the country, and the year, respectively. Following cross-country studies on R&D investment (Hillier et al., 2011; Mazzi et al., 2019), we measure R&D investment (R&D) as R&D expenditures scaled by total assets. The variable TREAT is a binary indicator that takes the value of 1 for firms operating in countries with antitrust laws during the sample period and 0 otherwise, while POST is a binary variable indicating the period after the implementation of anti-collusion reforms. The coefficient on POST × TREAT (β_1) is the key variable of interest; it captures the differential effect of these reforms on R&D investments for firms subject to antitrust laws. Following the literature, we include firm-level controls, including size (SIZE), tangibility (PPE), advertising (ADV), intangibility (INTAN), and leverage (LEV). Additionally, we incorporate key country-level controls such as the logarithm of GDP (LOG_GDP) to account for macroeconomic conditions, and the Corporate Governance Index (CGI) to capture the overall quality of governance, which could influence firms' strategic decisions, including investment in R&D. To account for unobserved heterogeneity, we include industry, year, and country fixed effects, following the approach of Duong et al. (2024). These fixed effects control for factors that vary across industries, years, and countries but remain constant within these dimensions, allowing us to isolate the impact of anti-collusion reforms on R&D investment. $\varepsilon_{i,t}$ denotes the error term. The definitions of all variables are provided in Appendix A. The standalone effect of POST and TREAT is omitted due to multicollinearity with the fixed effects.

⁵ Numerous studies use the enactment of antitrust laws as an effective exogenous shock to establish causality (Dasgupta and Žaldokas, 2019; Chung et al., 2024; Duong, et al., 2024).

⁶ Some studies treat missing data on R&D expenses as 0, and our results remain consistent when we adopt this approach.

⁷ France, the United States, South Korea, the United Kingdom, Brazil, Germany, Canada, and the Republic of Ireland adopted the reform before our sample period. In the robustness test reported in Table 1, the results remain consistent with our baseline results even when these countries are included in the sample.

Table 1
Country-level summary statistics and sample composition.

Country	Firm-year observations	Mean R&D	Year of enactment
Argentina	40	7.9270%	2018
Australia	5260	0.6236%	2003
Austria	83	0.3015%	2006
Bangladesh	44	0.0297%	None
Belgium	424	0.2978%	2004
Chile	47	0.0297%	2009
China	27,228	0.0619%	2008
Colombia	21	1.3583%	None
Denmark	428	5.3023%	2007
Egypt	40	0.0297%	2005
Finland	410	1.7068%	2004
Greece	702	0.0297%	2006
Hong Kong	3242	0.0297%	2016
Hungary	22	4.3416%	2003
India	2752	0.2509%	2009
Indonesia	415	0.0886%	None
Israel	1295	26.7554%	2005
Italy	163	0.1070%	2007
Japan	23,315	1.0304%	2005
Jordan	127	0.0633%	None
Kazakhstan	36	0.3204%	None
Macedonia	20	0.6308%	None
Malaysia	172	5.1953%	2010
Mexico	31	0.0297%	2006
Netherlands	372	0.3085%	2002
New Zealand	187	19.6781%	2004
Norway	342	11.6786%	2005
Pakistan	355	0.0297%	2007
Peru	49	5.4581%	2005
Philippines	184	0.5223%	2009
Poland	92	0.0297%	2004
Republic of Serbia	33	0.0297%	None
Romania	39	0.5159%	None
Russia	403	0.0934%	2007
Saudi Arabia	144	0.1852%	None
Singapore	405	5.1058%	2006
South Africa	156	0.1765%	None
Spain	181	0.5509%	2008
Sri Lanka	23	0.1094%	None
Sweden	1482	3.1476%	2002
Switzerland	982	2.9861%	2004
Taiwan	18,694	0.0297%	2012
Thailand	78	0.0419%	2016
Tunisia	118	0.1282%	None
Turkey	1883	0.2427%	None
Ukraine	22	0.0399%	None
United Arab Emirates	28	0.0297%	None

Table 1 presents the breakdown by country of the sample composition, mean R&D, and year of enactment of reforms. All continuous variables are winsorized at the 1st and 99th percentiles.

4. Empirical results

4.1. Baseline results

Fig. 1 depicts the mean R&D for the treatment firms over the 3 years before and 3 years after the enforcement of antitrust reforms. The mean R&D increases significantly in the implementation year (year 0), indicat-

Table 2
Industry-level summary statistics.

Industry classification	NAICS sector code	Sample proportion	Average R&D
Agriculture, Forestry, Fishing and Hunting	11	0.47%	0.08%
Mining, Quarrying, and Oil and Gas Extraction	21	5.39%	0.20%
Construction	23	6.45%	0.06%
Manufacturing	31–33	65.54%	1.28%
Wholesale Trade	42	2.51%	0.85%
Retail Trade	44–45	0.79%	0.04%
Transportation and Warehousing	48–49	0.58%	2.61%
Information	51	4.49%	1.27%
Real Estate and Rental and Leasing	53	0.45%	1.02%
Professional, Scientific, and Technical Services	54	6.69%	0.11%
Administrative and Support and Waste Management	56	0.57%	0.37%
Educational Services	61	0.19%	1.52%
Health Care and Social Assistance	62	0.35%	0.03%
Arts, Entertainment, and Recreation	71	0.19%	0.12%
Accommodation and Food Services	72	0.34%	0.03%
Other Services	81, 91, 55	0.13%	0.03%

Table 2 provides the industry-specific summary statistics of the sample, detailing sample proportions and average R&D investment by NAICS sector code.

Table 3
Summary statistics.

Variable	N	Mean	SD	p25	p50	p75
R&D	92,569	0.033	0.049	0.005	0.017	0.036
R&D_EXP_CAPX	92,569	0.029	0.035	0.005	0.017	0.036
SIZE	92,569	5.458	1.731	4.223	5.370	6.619
PPE	92,569	0.269	0.179	0.124	0.246	0.386
INTAN	92,569	0.030	0.045	0.002	0.011	0.039
ADV	92,569	0.003	0.007	0.000	0.000	0.000
LEV	92,569	0.177	0.159	0.027	0.145	0.290
LOG_GDP	92,569	10.086	0.866	9.564	10.547	10.693
CGI	92,569	164.12	50.67	104.81	188.437	207.614
Variables for additional analyses						
COLLUSION	75,102	2.084	8.012	0.000	0.000	0.000
HHI	82,298	0.082	0.245	0.000	0.000	0.004
CASH	80,225	0.172	0.153	0.064	0.130	0.233
FIRM RISK	79,469	0.027	0.029	0.008	0.018	0.035
ROE	90,545	0.083	0.128	0.029	0.077	0.137
TOBIN'S Q	92,569	2.853	3.306	0.730	1.263	3.081
RULE_OF_LAW	92,569	71.724	21.574	48.08	83.65	89.42
RD_PERC_GDP	69,577	2.350	0.878	2.022	2.245	3.174
IFRS	92,569	0.565	0.496	0.000	1.000	1.000

This table provides the summary statistics of all variables used in the study. All continuous variables are winsorized at the 1st and 99th percentiles. The number of observations for the variables used in the additional analyses may vary depending on data availability across different databases.

ing an immediate response by firms to the policy change, and continues to rise, reaching its peak 3 years after the reform.

Table 4 presents the results of Eq. (1), analyzing the effect of antitrust reforms on firms' R&D investments. In Column 1, R&D is regressed on $POST \times TREAT$ along with fixed effects. The coefficient on $POST \times TREAT$ is statistically significant at the 1% level, with a positive estimate of 0.004, suggesting that firms sub-

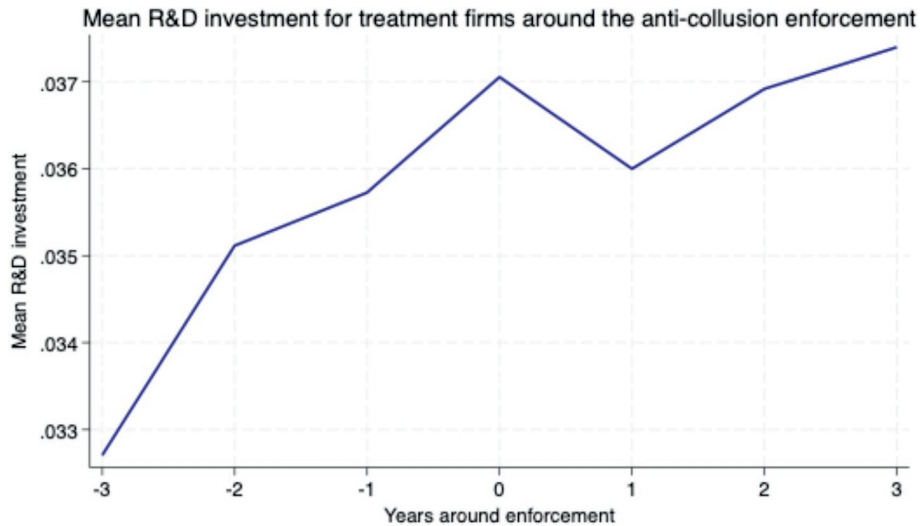


Fig. 1. Mean R&D investment for treatment firms around the anti-collusion enforcement.

ject to antitrust laws increase their R&D investments in the post-reform period. Column 2 extends the analysis by adding firm-level controls (size, tangibility, intangibility, advertising expenditure, and leverage) and country-level controls (GDP and governance quality). After including these additional controls, the coefficient on $POST \times TREAT$ remains statistically significant at the 1% level. This suggests that, after accounting for other factors, firms subject to anti-collusion reforms still experience a notable increase in their R&D investments. In Column 3, the analysis is restricted to the treatment sample, focusing specifically on firms subject to antitrust laws to examine how R&D investments evolve in the post-reform period. Due to this restriction, the sample size decreases from 92,569 to 89,616 observations. Here, the coefficient on $POST$ is 0.004, which is statistically significant at the 1% level, further supporting the idea that the post-reform period shows an increase in R&D investments among the treated firms. In all specifications, the impact of antitrust laws on R&D investment is both economically and statistically significant at the 1% level. For example, in Column 2, R&D investments increase by 0.4% in the post-reform period for the treatment sample compared with the control sample. In terms of control variables, $SIZE$, PPE , and LEV exhibit negative associations with R&D, while $INTAN$ positively influences R&D and LOG_GDP is positively associated with R&D.

4.2. Robustness tests

4.2.1. Alternative sample, firm fixed effects, dynamic trends, and placebo tests

We assess the robustness of our results in Table 5. Column 1 includes all countries that adopted the reform prior to the sample period, allowing us to verify that their inclusion does not affect our main findings. Including observations from these countries expands our sample size to 151,518. In Column 2, we exclude countries with fewer than 100 firm-year observations to ensure that the results are not driven by small samples with high R&D investments. This adjustment reduces the sample size to 91,821.⁸ In Column 3, we include firm fixed effects to account for unobserved, time-invariant heterogeneity at the firm level. The baseline results remain significant in all specifications.⁹

Next, in Column 4, we evaluate the validity of the parallel trend assumption underlying the difference-in-differences framework by adopting a dynamic event-study specification, following the methodology of Hu et al. (2023). Specifically, we include a set of indicator variables to capture the dynamic effect of antitrust laws

⁸ We thank the reviewer for this insightful suggestion.

⁹ Controlling for firm fixed effects reduces the sample to 92,043 firm-year observations, as singleton observations are dropped due to the lack of within-firm variation.

Table 4
Baseline results.

Variable	(1) R&D	(2) R&D	(3) R&D
POST × TREAT	0.004*** (0.000)	0.004*** (0.000)	
POST			0.004*** (0.000)
SIZE		−0.006*** (0.000)	−0.006*** (0.000)
PPE		−0.044*** (0.000)	−0.045*** (0.000)
INTAN		0.035*** (0.003)	0.031*** (0.007)
ADV		−0.070 (0.131)	−0.075 (0.119)
LEV		−0.023*** (0.000)	−0.023*** (0.000)
LOG_GDP		0.003*** (0.000)	0.003*** (0.000)
CGI		0.000 (0.976)	−0.000 (0.525)
Constant	0.030*** (0.000)	0.048*** (0.000)	0.055*** (0.000)
Fixed effects?	Yes	Yes	Yes
Observations	92,569	92,569	89,616
R-squared	0.180	0.258	0.253

P-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All columns include fixed effects from Eq. (1).

over time: three lead indicators (PRE_3, PRE_2, PRE_1) for the three years preceding the reform, a contemporaneous indicator (POST) for the transition year, and three lag indicators (POST_1, POST_2, POST_3) for the three years following the reform. PRE_k (POST_k) is coded as 1 only for the kth year before (after) the adoption of the antitrust law, and 0 otherwise.

Each of these time indicators is interacted with the treatment group indicator (TREAT). The coefficients on the pre-reform interaction terms are not statistically significant, indicating no differential trends in R&D investment between the treatment and control groups prior to the reform. In contrast, the coefficients for the post-reform period are consistently positive and statistically significant (except for POST_1), indicating that the increase in R&D investment is attributable to the reform rather than to pre-existing trends. The non-significance of POST_1 × TREAT may reflect a gradual adjustment, as the impact strengthens in subsequent years (POST_2 × TREAT and POST_3 × TREAT), or a “wait-and-see” approach by firms that initially monitor enforcement and peer responses before committing further resources.

Finally, in Column 5, we implement a placebo test to ensure that the observed treatment effect does not persist during a non-treatment period. In this test, we artificially assign placebo reform years by designating the 2 years prior to the actual reform year (years −2 and −1) as the reform years. We then estimate the interaction between this placebo indicator and the treatment group dummy. The coefficient is not statistically significant, confirming that no treatment effect is detected during the placebo period and supporting the validity of our identification strategy.

Table 5
Alternative sample, firm fixed effects, dynamic trends, and placebo tests.

Variable	(1) Including firms from countries that enacted the law before sample period	(2) Excluding countries with fewer than 100 firm-year observations	(3) Firm fixed effects	(4) Dynamic trend	(5) Placebo
POST × TREAT	0.004*** (0.000)	0.004*** (0.000)	0.002*** (0.008)		0.001 (0.405)
PLACEBO × TREAT					
PRE_3 × TREAT				0.000 (0.969)	
PRE_2 × TREAT				-0.000 (0.740)	
PRE_1 × TREAT				-0.001 (0.602)	
POST × TREAT				0.002** (0.037)	
POST_1 × TREAT				0.001 (0.319)	
POST_2 × TREAT				0.002* (0.064)	
POST_3 × TREAT				0.004** (0.033)	
Constant	0.099*** (0.000)	0.048*** (0.000)	0.035*** (0.000)	0.0307*** (0.00123)	0.047*** (0.000)
Controls?	Yes	Yes	Yes	Yes	Yes
Fixed effects?	Yes	Yes	Yes	Yes	Yes
Observations	151,518	91,821	92,043	31,154	20,539
R-squared	0.408	0.258	0.808	0.211	0.288

P-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All columns include fixed effects and controls from Eq. (1), unless stated otherwise.

Table 6
Alternative R&D investment measure and controls for accounting treatment changes.

Variable	(1) R&D_EXP_CAPX	(2) R&D_EXP_CAPX	(3) R&D_EXP_CAPX	(4) Controlling for IFRS
POST × TREAT	0.003*** (0.000)	0.003*** (0.000)		0.003*** (0.000)
POST			0.003*** (0.000)	
Constant	0.027*** (0.000)	0.040*** (0.000)	0.044*** (0.000)	0.040*** (0.000)
Controls?	No	Yes	Yes	Yes
Fixed effects?	Yes	Yes	Yes	Yes
Observations	92,569	92,569	89,616	92,569
R-squared	0.179	0.271	0.264	0.271

P-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All columns include fixed effects and controls from Eq. (1), unless stated otherwise.

4.2.2. Addressing accounting treatment differences in R&D investments and controlling for cross-country variations

Another important concern pertains to cross-country heterogeneity in the accounting treatment of R&D investments. Although some countries permit the capitalization of R&D costs, others mandate full or partial expensing. Moreover, these practices may evolve over time, raising concerns about the comparability of R&D investment measures across countries. To address this concern, we follow Dinh et al. (2020), Oswald et al. (2022), and Ryu and Zarowin (2024) and construct an alternative measure of R&D investment by combining the amounts of R&D expenditure both expensed and capitalized for the year. Using data from Thomson Reuters Datastream, we obtain annual R&D capitalization and define an alternative R&D investment measure—R&D_EXP_CAPX—as the sum of R&D expenses and capitalized R&D, scaled by total assets. This measure captures the total R&D investment for the year and mitigates concerns related to cross-country differences in accounting practices. We re-estimate our baseline regressions using R&D_EXP_CAPX as the dependent variable, and the results are reported in Table 6. In Column 1, R&D_EXP_CAPX is regressed on the interaction term POST × TREAT, along with country, industry, and year fixed effects. The coefficient on POST × TREAT is 0.003 and statistically significant at the 1% level, consistent with our main findings. Column 2 augments the specification by including the firm-level and country-level control variables. The coefficient on POST × TREAT remains robust and significant at the 1% level. In Column 3, we restrict the sample to the treated firms and examine their post-reform change in R&D_EXP_CAPX. Due to this restriction, the sample size decreases from 92,569 to 89,616 observations. The coefficient on POST is again 0.003 and significant at the 1% level, closely mirroring the result in Column 3 of Table 4, which uses our original R&D measure. In all specifications, the main result persists even after accounting for cross-country variations in R&D capitalization practices. This provides strong support for the robustness and generalizability of our findings.

A final concern relates to cross-country heterogeneity in regulatory mandates governing R&D investment disclosure. The countries in our sample may have introduced mandatory R&D investment reporting requirements at different times, potentially affecting measurement consistency. To mitigate this concern, we draw on prior evidence (Chen et al., 2017; Dinh et al., 2020), showing that the adoption of IFRS is associated with significant improvements in R&D investment disclosure practices, particularly by strengthening firms' incentives and institutional pressures to report innovation-related expenditures more transparently. Building on this insight, we incorporate the year of IFRS adoption as a country-level control in our robustness analysis. As shown in Column 4 of Table 6, our core results remain statistically and economically significant, indicating that our findings are not driven by differences in disclosure regulations between countries.

4.3. Heterogeneity in the impact of antitrust laws on R&D investment

4.3.1. Industry concentration and competition

Our baseline results support our hypothesis that disrupting collusive activities through anti-collusion reforms leads to increased R&D investment. To further explore this relationship, we examine H2, which posits that the positive effect of the adoption of antitrust laws on R&D investment is stronger for firms in more concentrated industries. First, we use the ex-ante Herfindahl–Hirschman Index (HHI) as a measure of market competition. The HHI is a commonly used index to assess the level of concentration in a market, with a higher value indicating less competition and a more concentrated market structure. The index is calculated by summing the squares of the market shares of all firms in the industry. In this study, we measure the ex-ante HHI prior to the implementation of anti-collusion reforms, which allows us to capture the competitive dynamics of the market before the reforms take effect. Second, we use common institutional ownership as a measure of competition. Azar et al. (2018) find that common institutional ownership is associated with reduced competition. Building on this insight, Yao et al. (2024) show that concentrated horizontal holdings by common owners lead to reduced corporate risk-taking and increased market collusion, which is anti-competitive. Following this literature, we analyze how the association between R&D investment and antitrust reforms varies for firms with the highest and lowest levels of pre-reform common ownership. Following Azar et al. (2018), we measure common ownership as the number of peer firms in the same industry held by the same institutional blockholder. Firms are classified into high and low collusion groups based on the median of their ex-ante average values for these measures, calculated separately in each country.

The results of our subsample analysis are presented in Table 7. Column 1 focuses on firms with below-average common ownership, representing lower levels of collusion, while Column 2 examines firms with above-average common ownership, indicating higher levels of collusion. Columns 3 and 4 analyze the subsamples based on the HHI, with Column 3 representing firms in markets with a low HHI (high competition) and Column 4 representing firms in markets with a high HHI (low competition). In all specifications, the coefficients on $POST \times TREAT$ are consistently stronger in the low competition subsamples (high collusion or high HHI), indicating that the effect of antitrust laws on R&D investment is more pronounced in these contexts. Importantly, the differences in coefficients between the subsamples are statistically significant, as shown in Table 7: the coefficient in the high collusion group is significantly higher than that in the low collusion group (difference = -0.008 , $p < 0.01$), and the coefficient in the high HHI group is significantly higher than that in the low HHI group (difference = -0.003 , $p < 0.10$). Specifically, the results demonstrate that firms operating in markets with higher pre-reform collusion experience a greater increase in R&D investments following the

Table 7
Impact of firm-level ex-ante competition.

Variable	(1) Low collusion (CO)	(2) High collusion (CO)	(3) Low HHI (HHI)	(4) High HHI (HHI)
POST \times TREAT	0.002* (0.089)	0.010*** (0.000)	0.000 (0.926)	0.003** (0.028)
Constant	0.054*** (0.000)	0.016 (0.492)	0.043*** (0.000)	0.088*** (0.000)
Diff. in coefficients		$-0.008***$		$-0.003*$
P-value		(0.000)		(0.086)
Controls?	Yes	Yes	Yes	Yes
Fixed effects?	Yes	Yes	Yes	Yes
Observations	31,943	6875	17,173	15,871
R-squared	0.238	0.438	0.278	0.286

P-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All columns include fixed effects and controls from Eq. (1).

implementation of anti-collusion reforms, compared with firms in markets with lower collusion. This finding highlights the important role of competitive pressure in stimulating innovation, particularly in environments previously characterized by limited competition.

4.3.2. Financial constraints

Next, we examine H3, which posits that the positive effect of antitrust reforms on R&D investment is more pronounced among financially unconstrained firms. To test this hypothesis, we rely on two ex-ante firm-level indicators that capture financial constraints based on pre-reform averages. First, we use the level of cash and cash equivalents, a commonly used proxy in the literature, where a higher value (scaled by total assets) indicates lower financial constraints. Second, we use the debt-to-asset ratio, with higher leverage reflecting greater financial constraints. Based on the distribution of these measures in the pre-reform period, we classify firms into high and low constraint groups in each country. Specifically, firms with below-median cash holdings or above-median leverage are classified as financially constrained, whereas those with above-median cash and below-median leverage are classified as financially unconstrained.

Table 8 presents the results of our subsample analysis based on firms' financial constraints. Columns 1 and 2 partition the sample using ex-ante cash holdings, where firms with above-median cash levels are classified as financially unconstrained (Column 1) and those with below-median cash as financially constrained (Column 2). Columns 3 and 4 use ex-ante leverage as an alternative proxy, classifying firms with below-median leverage as financially unconstrained (Column 3) and those with above-median leverage as financially constrained (Column 4). In both cash- and leverage-based specifications, the coefficient on $POST \times TREAT$ is higher and more statistically significant for firms with lower financial constraints. Specifically, for the cash-based specification, the coefficient is 0.005 ($p < 0.01$) for financially unconstrained firms, versus 0.001 (not significant) for constrained firms. The difference between the two groups is statistically significant at the 5% level ($p = 0.039$). Similarly, in the leverage-based specification, the coefficient is 0.004 ($p < 0.01$) for unconstrained firms and 0.003 ($p < 0.01$) for constrained firms, with the difference being significant at the 5% level ($p = 0.032$). These results suggest that the positive effect of antitrust reforms on R&D investment is amplified among firms with greater financial flexibility. The findings are consistent with the prediction that financially unconstrained firms are better positioned to respond to increased competitive pressure by reallocating resources to innovation. In contrast, constrained firms may lack the ability to adjust their investment behavior when market incentives change.

4.3.3. Risk-taking and managerial incentives

Finally, we examine H4, which posits that the positive effect of antitrust reforms on R&D investment is more pronounced for firms with a higher ex-ante propensity to take risks. To test this hypothesis, we use ex-ante firm-level risk measures that reflect firms' risk-taking behavior prior to the reform. Specifically, following Shen et al. (2023), we compute risk-taking using a 3-year rolling window to calculate the volatility of return on assets (ROA). We then take the average of this volatility measure over the pre-reform period to capture each firm's baseline risk propensity. Based on the distribution of this measure in the pre-reform period, we classify firms into high and low risk-taking groups in each country. Firms with ROA volatility above their country-specific median are categorized as high risk, while those with values below the median are categorized as low risk.

Table 9 tests H4. Column 1 presents the results for firms with above-median ROA volatility (high risk-taking firms), while Column 2 focuses on those with below-median ROA volatility (low risk-taking firms). The results strongly support the hypothesis. The coefficient on $POST \times TREAT$ is 0.005 ($p < 0.01$) for high-risk firms, indicating a substantial increase in R&D investment following antitrust reforms. In contrast, the coefficient for low-risk firms is 0.001 (not significant), suggesting no observable treatment effect in this group. The difference in coefficients between the two subsamples is both economically meaningful (0.004) and statistically significant at the 1% level ($p = 0.000$). These results suggest that the innovation-enhancing impact of antitrust reforms is concentrated among firms exposed to higher ex-ante risk. These findings imply that firms with a higher ex-ante propensity to take risks are more responsive to competitive changes induced by antitrust reforms.

Table 8
Impact of firm-level ex-ante financial constraints.

Variable	(1) Financially unconstrained (CASH)	(2) Financially constrained (CASH)	(3) Financially unconstrained (LEV)	(4) Financially constrained (LEV)
	POST × TREAT	0.005***	0.001	0.004***
	(0.001)	(0.133)	(0.000)	(0.001)
Constant	0.047*** (0.006)	0.019* (0.067)	0.021 (0.205)	0.052** (0.017)
Diff. in coefficients		0.004**		0.001**
P-value		(0.039)		(0.032)
Controls?	Yes	Yes	Yes	Yes
Fixed effects?	Yes	Yes	Yes	Yes
Observations	19,629	19,668	22,675	22,540
R-squared	0.279	0.192	0.293	0.241

P-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All columns include fixed effects and controls from Eq. (1).

Table 9
Impact of firm-level ex-ante risk.

Variable	(1) High risk (FIRM_RISK)	(2) Low risk (FIRM_RISK)
POST × TREAT	0.005*** (0.000)	0.001 (0.580)
Constant	0.027** (0.025)	0.050*** (0.003)
Diff. in coefficients		0.004***
P-value		(0.000)
Controls?	Yes	Yes
Fixed effects?	Yes	Yes
Observations	20,750	21,268
R-squared	0.309	0.250

P-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All columns include fixed effects and controls from Eq. (1).

4.4. Value implications of antitrust laws on R&D investment

Our baseline results support the hypothesis that disrupting collusive behavior through anti-collusion reforms leads to increased R&D investment. We next examine the economic implications of this increase by analyzing its effect on return on equity (ROE) and firm value (TOBIN'S Q). Specifically, we measure ROE as net income divided by shareholders' equity, and firm value using TOBIN'S Q, defined as the ratio of the firm's market value to its book value.

Table 10
Value implications of the impact of laws on R&D investment.

VARIABLE	(1) ROE	(2) TOBINS'Q
RD × POST × TREAT	0.328*** (0.000)	1.999* (0.062)
Constant	0.297*** (0.000)	11.122*** (0.000)
Controls?	Yes	Yes
Fixed effects?	Yes	Yes
Observations	90,545	92,569
R-squared	0.043	0.276

P-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All columns include fixed effects and controls from Eq. (1).

Table 10 reports the results assessing the economic impact of increased R&D investment induced by anti-trust reforms. In particular, we investigate whether this increase translates into better firm performance, proxied by ROE and TOBIN'S Q, using the following empirical specification:

$$\begin{aligned} \text{VALUE}_{i,c,t} = & \alpha + \beta_1 \text{TREAT}_{i,c} \times \text{POST}_{c,t} \times \text{R\&D}_{i,c,t} + \beta_2 \text{TREAT}_{i,c} \times \text{POST}_{c,t} + \beta_3 \text{TREAT}_{i,c} \\ & \times \text{R\&D}_{i,c,t} + \beta_4 \text{POST}_{c,t} \times \text{R\&D}_{i,c,t} + \beta_5 \text{TREAT}_{i,c} + \beta_6 \text{POST}_{c,t} \\ & + \sum \beta_m \text{Firm Controls}_{i,c,t} + \sum \beta_k \text{Country Controls}_{c,t} + \text{fixed effects} + \varepsilon_{i,t} \end{aligned} \quad (2)$$

where i , c , and t represent the firm, the country, and the year, respectively. VALUE is measured using ROE in Column 1 and TOBIN'S Q in Column 2 of Table 10. All other variables are defined as in Eq. (1), with their full definitions provided in Appendix A. The model includes industry, year, and country fixed effects, and standard errors are clustered at the firm level. $\varepsilon_{i,t}$ is the robust standard error. For brevity, Table 10 reports only the coefficient on the variable of interest, the triple interaction term ($\text{TREAT}_{i,c} \times \text{POST}_{c,t} \times \text{RD}_{i,c,t}$), which captures the differential effect of increased R&D investment on firm value for the treated firms following the implementation of antitrust reforms.

Column 1 shows that the interaction term is positively associated with ROE, with a coefficient of 0.328, significant at the 1% level. This suggests that the increase in R&D investment of the treatment firms attributable to antitrust reforms is accompanied by improved profitability. Column 2 reports the results using TOBIN'S Q as the dependent variable. The coefficient on the triple interaction term is 1.999 and significant at the 10% level, indicating a positive association between R&D investment and market-based firm value in the post-reform period for the treated firms. Taken together, these findings suggest that the antitrust-driven increase in R&D investment not only reflects increased innovation efforts but also translates into improvements in both accounting performance and market valuation.

4.5. Impact of country-level factors

Finally, we examine the country-level factors that influence the relationship between antitrust reforms and R&D investment. Countries with a stronger rule of law tend to enforce regulations more effectively (Berglöf and Claessens, 2006). Consequently, the association between antitrust reforms and R&D investment should be more pronounced among firms in countries with better governance. Using the rule of law score developed by Kaufmann et al. (2007), which captures the extent to which regulations are effectively enforced in a country, we divide the sample into high (above average) and low (below average) governance groups based on the mean value of this measure. Columns 1 and 2 of Table 11 present the results. The results

Table 11
Impact of country-level factors.

Variable	(1) Weak rule of law (RULE_OF_LAW)	2) Strong rule of law (RULE_OF_LAW)	(3) Low ex-ante R&D intensity (RD_GDP)	(4) High ex-ante R&D intensity (RD_GDP)
POST × TREAT	-0.000 (0.704)	0.010*** (0.000)	0.007*** (0.000)	0.002 (0.643)
Constant	0.050*** (0.000)	-0.034 (0.570)	0.090*** (0.000)	-0.020 (0.493)
Diff. in coefficients		-0.010*** (0.000)		0.006* (0.091)
P-value		Yes	Yes	Yes
Controls?	Yes	Yes	Yes	Yes
Fixed effects?	Yes	Yes	Yes	Yes
Observations	55,409	37,160	10,704	62,988
R-squared	0.242	0.267	0.243	0.277

P-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All columns include fixed effects and controls from Eq. (1).

show a stronger association between antitrust laws and R&D investment in the high governance sample (Column 2) than in the low governance sample (Column 1), with the difference in coefficients being statistically significant ($p < 0.01$). Furthermore, we investigate the moderating role of ex-ante country-level R&D investment on the relationship between antitrust laws and R&D investment. Using country-level R&D spending data from the World Bank, we classify the sample into high and low R&D investment groups. The results in Column 3 indicate a significant positive effect of antitrust laws on R&D investment in the low R&D investment countries, where baseline innovation activity is relatively limited. In contrast, for the high-R&D investment group (Column 4), the coefficient is positive but not statistically significant. The difference between these subsamples is marginally significant ($p < 0.10$), highlighting that the innovation-enhancing effects of antitrust laws are more evident in countries with lower initial innovation capacity. This finding implies that in countries with already robust innovation ecosystems, the incremental impact of antitrust reforms on R&D investment may be less pronounced, as firms may already have established innovation strategies in place.

5. Conclusion

This study leverages the staggered enactment of antitrust laws as an exogenous shock to explore the impact of competition on R&D investment. Addressing endogeneity concerns in the innovation literature, our findings reveal that disrupting collusive practices leads to a significant increase in firms' R&D investments. Our cross-sectional analyses reveal important heterogeneity in the treatment effect. The impact is more pronounced among firms operating in less competitive markets prior to the reform, consistent with theoretical predictions that competition enhances innovation incentives, particularly when antitrust enforcement disrupts collusive arrangements in concentrated industries. Firms that are ex-ante financially unconstrained and exhibit a higher propensity to take risks demonstrate a stronger innovation response, highlighting the complementary role of financial flexibility and managerial risk tolerance in amplifying the impact of competitive reforms on R&D investment. We next examine the real and market consequences of the post-reform increase in R&D investment. Firms subject to the reform exhibit higher return on equity and Tobin's Q, suggesting that competition-induced innovation enhances both firm performance and market valuation. Finally, the impact of antitrust reforms is shaped by the institutional context. The association between antitrust laws and R&D investment is stronger in countries with a stronger rule of law, where enforcement is more credible. Moreover, the effects are amplified in countries with lower baseline R&D investments, suggesting that competition policies are particularly potent in stimulating innovation when innovation systems are underdeveloped.

Our findings suggest that policymakers should emphasize the enforcement of competition laws to break up collusive practices, particularly in industries with historically low levels of competition. Additionally, countries should invest in enhancing their law enforcement capacities, as the innovation benefits of competition are amplified where enforcement is strong. Our study also has some limitations. First, the results should be interpreted with caution due to the sample imbalance, which stems from cross-country differences in firm coverage and data availability. Second, cross-country variation in R&D investment disclosure regulations may introduce measurement inconsistencies; therefore, our findings should be interpreted in light of this limitation.

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Appendix A. Variable definitions

Variable	Definition
R&D	Research and Development (R&D): Measured as R&D expenditure scaled by total assets.
R&D_EXP_CAPX POST	R&D expenses and R&D capitalized for the year scaled by total assets. Reform indicator: A binary variable equal to 1 for the period after the implementation of the reform, and 0 otherwise.
TREAT	Country indicator: A binary variable equal to 1 for firms in countries with lenient laws during the sample period, and 0 otherwise.
SIZE	Log of assets: Represents the logarithm of total assets.
PPE	Plant, property, and equipment: Measured as plant, property, and equipment scaled by total assets.
INTAN	Intangible assets: Measured as reported intangible assets scaled by total assets.
ADV	Advertising expenses: Measured as advertising expenses scaled by total assets.
CASH	Cash: Measured as cash and cash equivalents scaled by total assets.
LEV	Leverage: Measured as total debt scaled by total assets.
CO	Common ownership: Following Azar et al. (2018), measured as the number of peer firms in the same industry held by the institutional blockholder.
HHI	Sum of the squares of the market shares of all firms in the industry.
FIRM_RISK	Following Shen et al. (2023), firm-level risk-taking is measured by the volatility of return on assets (ROA), computed using a 3-year rolling window.
ROE	Return on equity: Measured as net income divided by shareholders' equity.
TOBIN'S Q	Tobin's Q: Defined as the ratio of the firm's market value to its book value.
LOG_GDP	Log GDP: Data on GDP (log-transformed) come from the World Bank.
CGI	Governance quality: Measured as the average value of the six Worldwide Governance Indicators developed by Kaufmann (2007).
RULE_OF_LAW	Rule of law: Reflects the quality of legal frameworks and regulations, following Kaufmann (2007).
RD_GDP	R&D expenditure (% of GDP): Data come from the World Bank.

All continuous variables are winsorized at the 1st and 99th percentiles.

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The smart manufacturing revolution: how industrial robotics reshape supplier networks



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ABSTRACT

Supplier diversification is a crucial corporate strategy for ensuring uninterrupted production and secure supply chains. This study investigates how industrial robots reshape corporate suppliers' allocation strategies. Using data from China's A-share listed firms during 2012–2022, we find that extensive robot adoption significantly reduces supplier concentration. This shift is primarily driven by enhanced market power and expanded product diversity. The diversification effect is more pronounced in regions with less developed market institutions characterized by pronounced government intervention, underdeveloped private sectors and weak legal systems, as well as within more technology-intensive and competitive industries and among firms with a larger share of low-skilled workers. We identify a trade-off of automation-driven supplier diversification: enhanced firm performance and supply chain resilience but reduced inventory efficiency and increased transaction costs. Our findings offer valuable insights for managers and policymakers seeking to optimize automation investments and improve robotics integration into supply chain management.

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1. Introduction

As a cornerstone of Industry 4.0 technologies, industrial robotics is fundamentally reshaping production systems and business models worldwide. Robotics integration enables unprecedented levels of automation, precision and flexibility, leading to substantial gains in productivity, quality consistency and operational efficiency. Evidence from the International Federation of Robotics (IFR) consistently demonstrates positive links between robotics adoption and productivity growth in major economies. Beyond manufacturing operations, robotics is also influencing corporate strategic decisions (Dixon et al., 2021; Luo and Qiao, 2024). Consequently, global industrial strategies are centered around the transformative potential of industrial robotics.

Supply chains comprise essential connections within global production networks. Increasing global trade volatility, exemplified by the U.S.–China trade war and technology sanctions such as the Huawei chip ban, has intensified the need for resilient supply chains. Nations with resilient industrial and supply chains can remain competitive in an increasingly uncertain economic environment. At the firm level, supply chain viability and resilience are key determinants of sustainable operations (Hosseini et al., 2019; Ivanov and Dolgui, 2020; Cheng et al., 2022). Supplier concentration, defined as a firm's reliance on limited key suppliers for procurement (Saboo et al., 2017; Chen et al., 2023; Liang, 2025), is a crucial factor influencing supply chain resilience (Jiang et al., 2023). Supplier configuration presents a fundamental strategic dilemma. Concentrated suppliers may enhance transaction efficiencies by improving inventory turnover (Hu and Shan, 2020) and collaborative synergies (Zou et al., 2024); however, excessive dependence reduces bargaining power, increases vulnerability to disruptions and may harm financial stability (Zhang et al., 2020; Li et al., 2024a, 2024b). Concurrently, the Fourth Industrial Revolution (Acemoglu and Restrepo, 2022) is transforming corporate paradigms through Industry 4.0 technologies, which manifest as intelligent suppliers, automated factories, smart products and heightened customer expectations. These shifts are reshaping firms' supplier configuration strategies. Crucially, such technologies may either mitigate buyer–supplier power imbalances, thus facilitating the benefits of concentration, or enhance supply chain visibility and flexibility, thereby reducing barriers to diversification.

This study examines how the adoption of industrial robots is reshaping corporate supplier allocation strategies in China, the world's largest manufacturing hub. According to the IFR 2024 World Robotics Report, China has been the largest industrial robotics market for 10 consecutive years, accounting for 51% of all such installations in 2023. China's widespread adoption of robotics across diverse regions and industries offers an exceptional basis for empirical research. Using a sample of China's A-share listed manufacturing companies from 2012 to 2022, we investigate how industrial robot adoption affects corporate supplier concentration strategies. We find that industrial robot adoption significantly promotes corporate supplier diversification. This result holds after robustness checks using the difference-in-difference (DiD) and propensity score matching (PSM) approaches, alternative variable specifications and the exclusion of other influencing factors. Further analysis shows that industrial robot applications enhance market power and product diversity, thereby promoting supplier diversification. Moreover, we demonstrate that robot adoption more strongly impacts diversified supplier strategies among firms operating in regions with lower levels of marketization, characterized by greater government intervention, weaker private sector development and lower legal institutional quality, as well as among firms in more technology-intensive and competitive industries and firms employing a larger proportion of low-skilled labor. We also identify a trade-off inherent to automation-driven supplier diversification: although it is associated with improved firm performance and reduced supply chain risk, it simultaneously leads to decreased inventory efficiency and increased transaction costs.

Our paper thus contributes to several lines of research. First, we bridge a crucial gap between the industrial automation and supply chain strategy literatures. While prior research predominantly examines the operational impacts of robotics (Bard, 1986; Dixon et al., 2021; Koch et al., 2021; Eder et al., 2024; Luo and Qiao, 2024; Li, 2025; Zheng and Wang, 2025), we provide the first large-scale evidence that robot adoption actively reshapes strategic supplier configurations. By showing how industrial robotics reduce supplier concentration through enhanced market power and product diversity, we establish a technological basis for supply chain diversification strategies. Second, we significantly advance the literature on the drivers of supplier concentration. Previous work is focused disproportionately on the economic consequences of supplier concentration (Cheng et al., 2022; Jiang et al., 2023; Liang, 2025), while devoting limited attention to its determinants.

We address this gap by identifying industrial robotics as a key driver. Our findings will enable firms to enhance their competitive position by strategically configuring their suppliers based on robotics application. Third, our study expands the measurement of corporate technological advancement. Prior research often uses research and development (R&D) investment or patents as proxies for technological level. We instead select industrial robotics as a physical manifestation of technological change. Our approach concretizes the abstract concept of technological progress.

The remainder of this paper proceeds as follows: in Section 2, we review the related literature and develop our hypotheses. In Section 3, we present our research design. We present our empirical results in Section 4. Finally, we present our conclusions and the implications in Section 5.

2. Literature review

2.1. *Economic consequences of adopting industrial robotics*

Amid the accelerating information revolution, artificial intelligence is leading the manufacturing sector toward an inevitable smart transformation. Industrial robots, which are key enablers of this transition, increasingly are a subject of both macroeconomic and microeconomic studies.

From a macroeconomic perspective, industrial robots introduce a “substitution effect” in labor markets, particularly where tasks previously performed by labor can be automated, due to the comparative advantages of labor and technology (Autor et al., 2003). As early as the 1990s, developed countries such as the U.S. and Europe experienced labor market displacement due to robotics, as demonstrated by reduced shares of labor in national incomes and declines in employment-to-population ratios (Humlum, 2019; Karabarbounis and Neiman, 2014). Acemoglu and Restrepo (2020) highlight the negative effects of industrial robots on employment and wages in U.S. labor markets: for every additional robot per thousand workers, the employment-to-population ratio falls by 0.2 percentage points, and wages decrease by 0.42%.

Similar trends are observed in China. The diffusion of industrial robotics has created an “employment-polarization” effect by replacing medium-skill jobs while increasing demand for both high- and low-skill labor (Zhang et al., 2024). Acemoglu et al. (2016) argue that this “job-creation effect” appears in sectors where robots generate new positions, such as robotic technicians, suggesting that the long-term benefits of robotics may outweigh the short-term costs. Fernández-Macías et al. (2021) contend that current robotic technologies represent a continuation of industrial automation, rather than a disruptive leap. Using data from 42 countries, Jung and Lim (2020) find that industrial robots improve labor productivity, although the benefits accrue disproportionately to higher-skill workers.

From an economic growth perspective, industrial robots help mitigate the negative effects of aging populations and improve total factor productivity (TFP), thus driving economic growth (Park et al., 2021; Gong et al., 2023; Eder et al., 2024). In particular, once the demographic dividend fades, the economic growth-boosting effect of industrial robots becomes markedly stronger as aging economies adopt automation more intensively to offset labor shortages and raise productivity (Acemoglu and Restrepo, 2018). Examining robot usage data from 77 countries and regions between 1993 and 2019, Gong et al. (2023) find that industrial robots boost economic growth primarily through labor substitution and improved TFP. Similarly, Eder et al. (2024) report that robotization positively affects labor productivity across all countries.

From a microeconomic perspective, industrial robots are more commonly adopted by larger, more productive and more export-oriented firms (Koch et al., 2021). In contrast to the macro-level substitution effect, at the firm level, labor demand may rise, particularly with respect to high-skill maintenance roles (Acemoglu and Restrepo, 2020). Dixon et al. (2021) show that robot adoption can reduce managerial costs and improve executive performance, which may exacerbate wage inequality. Lin et al. (2022) find that large-scale robot use initially improves low- and mid-skill workers’ performance and export quality, although these effects diminish after a threshold is reached.

Industrial robots also enhance technological innovation (Luo and Qiao, 2024), promote green production and innovation (Zhang et al., 2022; Gan et al., 2023) and increase firms’ competitiveness (Shen et al., 2025). Chen and Liu (2025) demonstrate that industrial robots significantly reduce the intensity of pollution emissions by improving productivity and promoting technological progress, while Luan et al. (2024) find that

robot adoption is negatively associated with the disclosure of negative environmental indicators. Additionally, robots are reported to improve export product quality (Li, 2025) and upgrade firms' positions in global value chains (Zheng and Wang, 2025).

2.2. *Factors influencing supplier concentration*

The strategic importance of supply chain management is attracting considerable academic and practical interest, catalyzed by Industry 4.0 and the COVID-19 pandemic. Polyviou et al. (2023) stress that firms must balance supplier diversity and efficiency when designing supply chain strategies, because stable upstream and downstream relationships are essential for achieving a competitive advantage.

Externally, global uncertainty is reshaping supply chains. Firms are diversifying their supply networks in the post-pandemic environment (Cherrafi et al., 2022), and climate risks such as extreme weather continue to disrupt food, mining and logistics sectors worldwide (Ghadge et al., 2020). Internally, a firm's innovation capacity influences its supplier concentration. He et al. (2024) show that the adoption of Fintech enables Chinese manufacturers, especially state-owned enterprises, to concentrate their suppliers.

Firms with greater bargaining power often reduce their supplier base to increase their leverage over the remaining suppliers. This occurs because large firms can negotiate better terms and reduce their transaction costs by consolidating suppliers (Porter, 1980). Patatoukas (2012) documents that dominant customers, defined as those whose purchases exceed 10% of a supplier's annual sales, reduce their active suppliers while simultaneously extracting lower supplier mark-ups, thus confirming that bargaining leverage reduces the incremental benefit of diversification.

However, other studies indicate that companies with greater market power may also choose to maintain a larger number of suppliers to ensure risk diversification and supply continuity. For instance, Caniëls and Gelderman (2005) explain that while market power allows a company to reduce its suppliers, businesses often choose diversification to reduce the risks associated with supply chain disruptions. Similarly, Dyer and Singh (1998) discuss how strategic alliances with multiple suppliers enable firms to remain flexible and prevent supplier hold-ups; these advantages can enable firms to maintain broad supplier bases and maximize their bargaining power and profits. Zhang et al. (2020) suggest that firms should increase the number of suppliers and choose an appropriate or optimal degree of supplier concentration while avoiding an overreliance on major suppliers that would probably lead to excessive cash holdings. Consistent with this finding, Kale and Shahrur (2007) provide international evidence that firms with a larger market share concentrate their procurement only when they are financially unconstrained; these firms also retain a broader set of suppliers to hedge against the risk of hold-up when their cash buffers are low.

In conclusion, bargaining power compresses a firm's supplier base only when the firm's financial slack and disruption risk are low; otherwise, large buyers diversify suppliers to protect their cash flow stability.

2.3. *Benefits and costs of supplier concentration*

A high supplier concentration can lower contracting costs by enabling firms to negotiate favorable terms through economies of scale. Chen et al. (2023) show that Chinese firms with concentrated supplier bases benefit from volume rebates and discounts, which reduce their operating costs. Such concentration can also foster long-term, relationship-specific investments that enhance operational efficiency (Zhang et al., 2020).

However, Liang (2025) argues that an excessive supplier or customer concentration creates power imbalances that reduce productivity. Such concentration increases dependence on a few suppliers and thus increases a firm's vulnerability to disruptions. Key supplier failures or operational issues can cause significant bottlenecks and earnings volatility (Chen et al., 2023). Zhang et al. (2020) highlight a trade-off between risk and efficiency, such that concentrated supply bases lower costs but expose firms to supplier-specific shocks, in turn leading to an increase in precautionary cash holdings and reduced flexibility. Jiang et al. (2023) shows that high concentration enhances resilience during disruptions but slows recovery.

The innovation literature presents a nuanced view of the relationship between supplier concentration and corporate innovation. Empirical studies generally report a negative association between supplier concentration and R&D expenditure (Ho et al., 2023) and find that geographical concentration further impedes inno-

vation (Xiong et al., 2023). This inhibitory effect is often attributed to reduced knowledge diversity and increased costs of switching (Jin et al., 2025). However, some evidence suggests that the focal relationship is non-linear. For instance, Chen et al. (2022a, 2022b) identify an inverted U-shaped curve between supplier concentration and R&D output. This perspective is supported by Dong et al. (2022), who argue that an optimal level of supplier concentration balances the advantages of knowledge transfer against the risks of a supplier hold-up, thereby maximizing investment in innovation.

From a capital market perspective, Dhaliwal et al. (2016) show that firms with more concentrated supplier bases face higher equity capital costs as investors factor supply chain disruption risks into their pricing. The evidence suggests that an optimal supplier concentration level balances cost economies, innovation potential and downside risks. High concentration lowers firms' costs but increases their vulnerability and limits innovation, while low concentration offers flexibility at the cost of higher transaction costs and less favorable terms.

2.4. Hypothesis development

The rapid adoption of industrial robots in the manufacturing sector is transforming production systems, profitability models and supply chain dynamics. This technological shift may extend beyond operational efficiency and to influence firms' supply chain positioning and supplier management strategies.

First, industrial robots enhance firms' market power and expand market share through productivity gains, innovation capacity and export competitiveness, which collectively enhance supplier diversification. Industrial robots are superior to human labor in the execution of repetitive and physically demanding operations. The capabilities of robots encompass tasks such as welding, painting, assembly, material handling and packaging with enhanced speed and precision (Graetz and Michaels, 2018; Ji and Wang, 2019). Automation-driven efficiency improves productivity, profitability and quality (Graetz and Michaels, 2018; Jung and Lim, 2020; Dixon et al., 2021; Fan et al., 2021; Perez-Grau et al., 2021; Cilekoglu et al., 2024; Li et al., 2025; Zheng and Wang, 2025). These benefits enable firms to implement competitive pricing strategies and increase their market share relative to their less automated competitors (Bloom et al., 2021; Koch et al., 2021; Acemoglu and Restrepo, 2022). Concurrently, robots stimulate innovation (Gan et al., 2023; Wang et al., 2023; Chen et al., 2024a, 2024b; Luo and Qiao, 2024; Wang et al., 2025) and export growth (Eckel et al., 2015; Brynjolfsson et al., 2019; Li, 2025; Zheng and Wang, 2025), which further strengthen firms' competitive positioning.

A market share expansion increases a firm's production requirements and thus necessitates larger raw material volumes. As dependence on a single supplier creates a bottleneck risk, firms are compelled to diversify their sources to ensure adequate capacity and mitigate disruptions (Cheng et al., 2022). Enhanced market power also enables firms to strategically realign their suppliers. Productivity advantages confer leverage in bargaining, while innovative leadership facilitates the setting of technical standards (Zheng and Wang, 2025). These forces allow firms to implement multi-vendor contracts and rigorous supplier screening. Standardized robotic processes further reduce the costs of switching suppliers (Luo and Qiao, 2024). Thus, market power facilitates supplier diversification by improving firms' negotiation capacity and reducing dependency.

Second, the inherent flexibility of industrial robots enables product diversification, thereby catalyzing demand for heterogeneous supplier networks. An industrial robot is defined as an "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes . . . for use in automation applications in an industrial environment" (IFR, 2024). Unlike rigid automation, robots can rapidly reconfigure production processes without costly retooling (Bard, 1986; Dixon et al., 2021; Luo and Qiao, 2024). This adaptability allows firms to manufacture customized or small-batch products alongside standardized lines. Heterogeneous product portfolios require various material inputs and specialized components and thus inherently require diversified supplier networks to avoid sourcing constraints. Based on the above literature review, we propose the following hypothesis:

H1a: Industrial robot adoption reduces supplier concentration.

Conversely, however, industrial robot adoption may reinforce supplier concentration through two mechanisms. First, while supplier concentration traditionally entails large operational risks, including vulnerability to supply disruptions (Cheng et al., 2022), diminished bargaining power and financial instability due to part-

ner dependency (Zhang et al., 2020), robotic automation can transform this dynamic by increasing firms' market power. The efficiency gains from industrial robot adoption establish competitive asymmetries that strengthen firms' negotiating positions. Firms with this enhanced leverage can secure favorable contractual terms that mitigate the traditional risks of supplier concentration (Dass et al., 2015). Simultaneously, firms with improved market power can capitalize on the benefits of concentration, such as reduced transaction costs through streamlined coordination (Lanier et al., 2010), increased input stability via relational investments (Cheng et al., 2022) and improved production efficiency through integrated operations (Patatoukas, 2012). Consequently, industrial robot adoption allows firms to exploit concentration efficiencies while neutralizing their associated vulnerabilities, thereby encouraging the use of supplier concentration strategies.

Second, the technical specifications of industrial robots inherently restrict supplier diversification. These robots are characterized by high precision, efficiency and intelligence (Luo and Qiao, 2024; Zheng and Wang, 2025) and require inputs that meet stringent tolerance standards. Firms are compelled to enter consolidated partnerships due to the limited pool of qualified suppliers. Firms' attempts to diversify their suppliers may cause component incompatibility and production disruptions that increase operational uncertainty. Firms thus prioritize technical reliability over risk mitigation and maintain concentrated supplier relationships. We therefore propose the following alternative hypothesis:

H1b: Industrial robot adoption increases supplier concentration.

3. Research design

3.1. Data and sample

We use a sample of China's A-share listed firms from 2012 to 2022. Following previous studies (Li et al., 2024a, 2024b), we obtain data on industrial robots from the IFR and firm-level information from the China Stock Market & Accounting Research database. The sample is selected as follows: (1) ST and ST* firms and (2) firms in the financial industry are excluded, and (3) observations with missing values for key variables are removed. The final sample consists of 25,795 firm-year observations from 3841 firms. To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

3.2. Variables

3.2.1. Dependent variable

Following Ahsan et al. (2023) and Zhao (2025), supplier concentration is defined as the procurement share of a firm's top five suppliers among its total annual procurement. A lower value of this variable indicates a lower supplier concentration level and greater diversification of the firm's supplier network.

3.2.2. Independent variable

Following previous studies (Gan et al., 2023; Liu et al., 2025a, 2025b), we employ the Bartik variable approach to measure firm-level exposure to industrial robot (*Robots*). This method builds on Acemoglu and Restrepo (2022), who use Bartik instruments (Goldsmith-Pinkham et al., 2020) to disaggregate macro-level robot exposure at the firm level. Specifically, we construct our measure of robot exposure using Eq. (1),

$$Robot_{i,j,t} = \frac{Prodep_{i,j,t=2012}}{Manu_{t=2012}} \times \frac{Rob_Stock_{j,t}}{Labor_{j,t=2011}} \quad (1)$$

where $\frac{Rob_Stock_{j,t}}{Labor_{j,t=2011}}$ measures industry-level robot penetration in China, calculated as the stock of industrial robots in industry j at year t ($Rob_Stock_{j,t}$) divided by the total employment in industry j in the base year 2011 ($Labor_{j,t=2011}$); and $\frac{Prodep_{i,j,t=2012}}{Manu_{t=2012}}$ measures the relative scale of firm i 's production workforce within the Chinese manufacturing sector, calculated as the ratio of firm i 's number of production employees in sector j in the base year 2012 ($Prodep_{i,j,t=2012}$) to the median value across all manufacturing firms in 2012 ($Manu_{t=2012}$). This approach enables us to decompose industry-level robot adoption to the firm level and construct a firm-specific measure of robot exposure (*Robots*).

3.2.3. Control variable

Following the literature (Zhou et al., 2024; Jin, 2025), we include a set of corporate-level fundamental variables to control for firm-specific characteristics. These encompass firm size (*Size*), financial leverage (*Lev*), listing age (*Age*), R&D expenditure (*R&D*), corporate labor productivity (*Productivity*), capital intensity (*Cap*) and firm value (*TobinQ*), as well as corporate governance features, specifically board independence (*Independence*) and ownership concentration (*Top5*). Detailed definitions of all variables are presented in Appendix I.

3.3. Model setting

We use Model (2) to examine how industrial robot adoption affects supplier concentration,

$$Supplier5_{i,t} = \alpha + \beta Robots_{i,t} + \gamma Controls_{i,t} + \mu_i + \delta_j + \rho_d + \varepsilon_{i,t} \quad (2)$$

where $Supplier5_{i,t}$ denotes the supplier concentration of firm i in year t , $Robots_{i,t}$ represents the level of industrial robot adoption and $Controls_{i,t}$ represents a vector of the control variables. The model also includes year (μ_i), industry (δ_j) and city (ρ_d) fixed effects. $\varepsilon_{i,t}$ denotes the error term.

4. Empirical results

4.1. Summary statistics

Table 1 presents the summary statistics for the key variables. The mean value of supplier concentration (*Supplier5*) is 33.53, consistent with the literature (Dai et al., 2025); this value indicates that procurement from the top five suppliers accounts for approximately 33% of the total procurement expenditure across firms. The mean value of robot penetration (*Robots*) is 7.002, consistent with the findings of Shen et al. (2025). The summary statistics of the other variables are also in line with those reported in previous studies (Yang et al., 2025).

4.2. Benchmark results

Table 2 reports the regression results analyzing the impact of industrial robot adoption on supplier concentration. Column (1) presents the estimates without control variables, while Column (2) incorporates the full set of controls. The coefficient on industrial robot penetration (*Robots*) is negative and significant for both specifications, providing preliminary evidence that an increase in industrial robot adoption reduces supplier concentration. Economically, a one-standard-deviation increase in *Robots* is associated with an approximately 2% reduction in supplier concentration (0.048×4.09). This result suggests that firms with higher robot adoption tend to pursue more diversified supplier strategies, supporting hypothesis H1a.

Table 1

Summary statistics. The table presents summary statistics for the full sample from 2012 to 2022. All continuous variables are winsorized at the 1% and 99% levels. Detailed variable definitions are provided in Appendix I.

Variable	N	Mean	SD	Min	p50	Max
<i>Supplier5</i>	25,795	33.53	18.801	4.030	29.29	96.55
<i>Robots</i>	25,795	7.002	4.090	0.0920	6.936	14.87
<i>Size</i>	25,795	7.741	1.197	4.159	7.639	11.38
<i>Lev</i>	25,795	0.410	0.197	0.0380	0.402	0.937
<i>Age</i>	25,795	2.933	0.319	1.609	2.996	3.611
<i>RD</i>	25,795	5.046	5.178	0.0200	3.780	44.01
<i>Cap</i>	25,795	2.292	1.714	0	1.876	20.00
<i>Independent</i>	25,795	0.378	0.054	0.333	0.364	0.600
<i>Top5</i>	25,795	0.487	0.186	0.209	0.450	0.965
<i>TobinQ</i>	25,795	2.780	2.082	0.822	2.141	24.50
<i>Productivity</i>	25,795	0.956	0.757	0.0640	0.749	5.736

Table 2
Industrial robot adoption and supplier concentration.

Variables	(1) <i>Supplier5</i>	(2) <i>Supplier5</i>
<i>Robots</i>	-0.053** (-2.002)	-0.048** (-1.972)
<i>Size</i>		-5.515*** (-45.002)
<i>Lev</i>		-5.287*** (-7.596)
<i>Age</i>		-0.411 (-1.101)
<i>RD</i>		-0.124*** (-3.427)
<i>Cap</i>		0.040 (0.490)
<i>Independent</i>		-0.618 (-0.343)
<i>Top5</i>		-0.084 (-0.149)
<i>TobinQ</i>		0.470*** (7.128)
<i>Productivity</i>		2.653*** (13.829)
<i>Constant</i>	33.903*** (166.001)	76.854*** (46.874)
<i>Year FE</i>	Yes	Yes
<i>Industry FE</i>	Yes	Yes
<i>City FE</i>	Yes	Yes
Observations	25,795	25,795
Adjusted R-squared	0.164	0.300

This table presents the regression results examining the effect of industrial robot adoption on supplier concentration. *Supplier5* measures the proportion of a firm's total annual procurement expenditure accounted for by its top five suppliers. *Robots* measures firm-level robot penetration. Detailed variable definitions are provided in Appendix I. All continuous variables are winsorized at the 1% and 99% levels. Robust t-statistics, clustered at the firm level, are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Regarding the control variables, the results in Table 2 indicate that firms with higher financial leverage, a larger size, a lower Tobin's Q and greater R&D capability are more likely to maintain a diversified supplier base. These findings are consistent with prior literature (Zhou et al., 2024; Dai et al., 2025).

4.3. Robustness checks

4.3.1. Difference-in-difference design

Firms' industrial robot adoption may be directly influenced by their supplier diversification strategies, as firms may introduce automation technologies to better handle inputs from a broader range of suppliers. This possibility gives rise to concerns about reverse causality. Additionally, unobserved factors, such as the CEO's personality or managerial style, may influence both robot adoption and supplier diversification, leading to omitted variable bias.

To address these endogeneity issues, we use China's Intelligent Manufacturing Pilot Demonstration Policy (IMPDP) as a quasi-natural experiment and implement a staggered DiD design. Initiated in 2015, the IMPDP was designed to accelerate automation in the manufacturing sector. Under this policy, 46 enterprises were designated as pilot participants in the first batch, and three subsequent batches were added between 2016 and 2018, culminating in a total of 305 pilot projects.

Crucially, the timing and selection of the pilot firms were exogenous to firm characteristics, which could not have been foreseen or manipulated prior to the official policy announcements. As the primary objective of the IMPDP was to explore pathways for intelligent manufacturing, a goal unrelated to firms' supplier allocation decisions, it provides a plausible instrument for our staggered DiD approach, as specified in Model (3):

$$Supplier5_{i,t} = \alpha + \beta IM_{d,t} + \gamma controls_{i,t} + \mu_t + \delta_j + \rho_d + \varepsilon_{i,t} \quad (3)$$

where $IM_{d,t}$ is a dummy variable equal to 1 if a firm is headquartered in a city d that has implemented the IMPDP by year t and 0 otherwise. This variable functions analogously to the interaction term in a conventional DiD framework. The model also includes year (μ_t), industry (δ_j) and city (ρ_d) fixed effects to control for potential unobserved heterogeneity.

In Column (1) of Table 3, the coefficient on IM is negative and statistically significant, indicating that the treated firms significantly reduced their supplier concentration after the IMPDP was implemented. Column (2) shows no significant pre-treatment trends prior to the policy's introduction in 2015, thus supporting the par-

Table 3
Difference-in-difference estimation.

VARIABLES	(1) <i>Supplier5</i>	(2) <i>Supplier5</i>	(3) <i>Supplier5</i>
<i>IM</i>	-1.674*** (-2.963)		
<i>Pre3</i>		-0.312 (-0.183)	-0.342 (-0.203)
<i>Pre2</i>		-0.955 (-0.701)	-0.991 (-0.732)
<i>Current</i>		-0.469 (-0.341)	-0.494 (-0.363)
<i>After1</i>		-1.832 (-1.439)	-1.857 (-1.463)
<i>After2</i>		-1.290 (-0.974)	-1.001 (-0.974)
<i>After3</i>		-2.273* (-1.773)	-2.292* (-1.811)
<i>After4</i>		-2.557* (-1.932)	-2.577** (-1.973)
<i>After5</i>		-1.657 (-1.030)	-0.993 (-0.590)
<i>After5_plus</i>			-1.799 (-0.980)
<i>Constant</i>	75.838*** (46.142)	75.837*** (46.110)	75.814*** (45.859)
<i>Controls</i>	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes
<i>City FE</i>	Yes	Yes	Yes
Observations	25,795	25,790	25,790
Adjusted R-squared	0.300	0.300	0.300

This table employs a staggered difference-in-differences (DiD) design, utilizing China's Intelligent Manufacturing Pilot Demonstration Policy (IMPDP) as a quasi-natural experiment. Column (1) reports the DiD estimation results, and Columns (2) and (3) present the parallel trend test results. *Supplier5* measures the proportion of a firm's total annual procurement expenditure accounted for by its top five suppliers. *IM* is a dummy variable that equals 1 if a firm is headquartered in a city that has implemented the IMPDP, and 0 otherwise. Detailed variable definitions are provided in Appendix I. All continuous variables are winsorized at the 1% and 99% levels. Robust t-statistics, clustered at the firm level, are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

allel trends assumption. Given the staggered nature of the IMPDP rollout, however, our estimates could be biased due to heterogeneous treatment effects. To address this issue, we employ the Sun and Abraham (2020) estimator. The results reported in Column (3) remain robust, with no evidence of pre-trends, and further validate our hypothesis.

4.3.2. Propensity score matching approach

Our results suffer from sample selection bias due to the non-random nature of firms' decisions to adopt industrial robots. Such decisions are likely to be influenced by both internal factors, such as firm size, workforce structure and managerial capability, and external policy incentives that promote smart manufacturing. To address this issue, we employ a PSM approach. We define the treatment group as firms whose robot adoption intensity is above the median and use the control variables specified in Model (2) as matching criteria. Using 1:1 nearest-neighbor matching without replacement, each treated firm is matched with a comparable control firm exhibiting similar observable characteristics.

Our post-matching diagnostic tests confirm that the achievement of covariate balance across all matched variables. The regression results based on the matched sample, which are presented in Column (1) of Table 4, continue to support our main findings.

4.3.3. Alternative variable specifications

To address potential measurement errors in the core variables that could bias our coefficient estimates, we redefine the key variables and conduct a series of robustness checks. As shown in Column (2) of Table 4, Panel A, we recalculate supplier concentration using the procurement share of the top three suppliers (denoted as *Supplier3*) to reassess the impact of robot adoption on supplier diversification strategies.

In Column (3), we redefine the independent variable. Following Cai et al. (2025), we perform a textual analysis of corporate annual reports and identify robot-related keywords to measure the extent of intelligent manufacturing adoption. Specifically, we use the natural logarithm of the count of intelligent manufacturing keywords (plus 1) as an alternative proxy for robot adoption intensity (*Robots2*). The results, presented in Table 4, show that the coefficients on both robot adoption measures remain negative and statistically significant, reinforcing the robustness of our main findings.

4.3.4. Ruling out supply chain policy effects

To isolate the impact of industrial robot adoption from concurrent supply chain policies, we control for potential confounding effects stemming from China's Supply Chain Innovation and Application Pilot Program, which was launched by the Ministry of Commerce in 2018. This program requires pilot firms to establish early-warning systems for supply chain risks and to implement diversification strategies. To mitigate the impact of this policy, we exclude all firms designated as pilots under this program, as well as firms headquartered in pilot cities.

As shown in Columns (4) and (5) of Table 4, the coefficient on *Robots* remains negative and significant, reinforcing our core conclusion.

4.3.5. Controlling for digital transformation effects

Previous studies show that corporate digital transformation reduces supply chain concentration (Zhou et al., 2024). To discern whether supplier diversification is driven specifically by industrial robot adoption rather than by broader digitalization efforts, we introduce a control variable representing digital transformation. Following previous studies (Chen and Srinivasan, 2024; Lv et al., 2025), we measure digital transformation intensity (*Digital*) using the natural logarithm of 1 plus the total count of digitalization-related keywords in annual reports and incorporate this variable into Model (2).

As shown in Column (6) of Table 4, the coefficient on *Robots* remains negative and significant at the 10% level. This result demonstrates that robot deployment drives supplier diversification independently of the effects of digital transformation, further corroborating our core findings.

Table 4
Robustness checks.

	(1) PSM	(2) Alternative dependent variable	(3) Alternative independent variable	(4) Exclude supply chain pilot firms	(5) Exclude supply chain pilot cities	(6) Exclude digital transformation effect
Variables	<i>Supplier5</i>	<i>Supplier3</i>	<i>Supplier5</i>	<i>Supplier5</i>	<i>Supplier5</i>	<i>Supplier5</i>
<i>Robots</i>	-0.544** (-2.022)	-0.046* (-1.691)		-0.052** (-2.098)	-0.085** (-2.269)	-0.046* (-1.899)
<i>Robots2</i>			-0.689*** (-5.059)			
<i>Digital</i>						-0.702*** (-3.982)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>City FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,337	17,533	25,450	25,059	11,785	25,743
Adjusted R-squared	0.304	0.281	0.301	0.299	0.345	0.300

This table reports the results of additional robustness checks. Column (1) reports the estimates obtained using propensity score matching (PSM). Column (2) uses the procurement share of the top three suppliers (*Supplier3*) as an alternative measure of supplier concentration. Column (3) uses the natural logarithm of 1 plus the frequency of robot-related keywords in annual reports as an alternative proxy for robot penetration (*Robots2*). Columns (4) and (5) respectively exclude the firms and cities affected by China's Supply Chain Innovation and Application Pilot Program. Column (6) controls for the potential confounding effect of digital transformation. *Supplier5* and *Supplier3* measure the proportion of a firm's total annual procurement expenditure accounted for by the top five and top three suppliers, respectively. *Robots* measures firm-level robot penetration. *Digital* is measured as the natural logarithm of 1 plus the frequency of digitalization-related keywords in annual reports. Detailed variable definitions are provided in Appendix I. All continuous variables are winsorized at the 1% and 99% levels. Robust t-statistics, clustered at the firm level, are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

4.4. Mechanism analysis

We hypothesize that industrial robot adoption promotes supplier diversification by improving firms' market power and facilitating corporate product diversification. To test the first channel, we measure market power as the ratio of a firm's revenue to the total industry revenue, following Liu et al. (2025a, 2025b). We then conduct a subsample analysis based on the sample median of market power. If industrial robots drive supplier diversification by strengthening firms' market power, the effect of robot adoption should be more pronounced among firms with initially lower market power, as these firms have greater potential for improvement in this dimension.

To test the second channel, we measure product diversification using the inverse Herfindahl–Hirschman Index (1–HHI), calculated as in Eq. (4),

$$\text{Diversity}_{i,t} = 1 - \sum \left(\frac{\text{Product}_{i,j,t}}{\sum \text{Product}_{i,j,t}} \right)^2 \quad (4)$$

where $\text{Product}_{i,j,t}$ denotes the revenue from product j of firm i in year t , and $\sum \text{Product}_{i,j,t}$ is the total revenue of firm i in year t . If robot adoption enables supplier diversification by expanding a firm's product offerings, we should observe a stronger effect among firms with initially low levels of product diversification, as these firms have greater scope for expansion into new product areas.

As shown in Table 5, the coefficient on *Robots* is negative and significant in the subsamples of firms with lower market power and lower product diversification. These results are consistent with our expectation and prove our hypothesis that industrial robot adoption facilitates corporate product diversification and product market power.

4.5. Cross-sectional analysis

4.5.1. Regional-level heterogeneity

The documented impact of industrial robot adoption on supplier configuration reflects the sample average. However, firms vary considerably in terms of geographic location, industry attributes and firm-specific characteristics, and these characteristics may differentially shape how industrial robot applications influence sup-

Table 5
Mechanism analysis.

	(1) Low market power	(2) High market power	(3) High product diversity	(4) Low product diversity
Variables	<i>Supplier5</i>	<i>Supplier5</i>	<i>Supplier5</i>	<i>Supplier5</i>
<i>Robots</i>	−0.067** (−2.015)	−0.011 (−0.335)	0.017 (0.406)	−0.069* (−1.697)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes
<i>City FE</i>	Yes	Yes	Yes	Yes
Observations	12,897	12,898	7996	7996
Adjusted R-squared	0.307	0.348	0.313	0.347
Chow test p value	0.000***		0.000***	

This table presents the results of mechanism tests conducted to examine whether industrial robot adoption reduces supplier concentration by enhancing firms' market power and facilitating product diversification. *Supplier5* measures the proportion of a firm's total annual procurement expenditure accounted for by its top five suppliers. *Robots* measures firm-level robot penetration. *Market Power* is defined as a firm's revenue share relative to the total industry revenue. *Product Diversification* is measured as 1 minus the Herfindahl–Hirschman index (1 – HHI) based on the revenue distribution across a firm's product lines. Detailed variable definitions are provided in Appendix I. All continuous variables are winsorized at the 1% and 99% levels. Robust t-statistics, clustered at the firm level, are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

plier concentration. To explore these contingent relationships, we conduct a heterogeneity analysis to address regional marketization, industrial dimensions and firm characteristics and thereby generate more nuanced insights into the contextual factors that moderate the main relationship.

Regional disparities in market maturity, policy support, economic foundations (Geng et al., 2025) and resource endowments across China may cause robot adoption to have varying effects on supplier concentration. We examine these heterogeneous effects using three sub-indices from the *China Provincial Marketization Index Report* (Gang et al., 2001): government intervention, development of the non-state economy and legal institutional quality. This approach allows us to assess how regional differences in institutional development influence the relationship between robot penetration and supplier concentration.

The results are presented in Columns (1)–(6) of Table 6. Specifically, robot penetration is shown to significantly reduce supplier concentration in regions with higher levels of government intervention, lower levels of non-state economic development and weaker legal institutions. Market-driven resource allocation is often constrained in regions with strong government intervention, leading firms to depend on limited supply options. Industrial robots can mitigate this dependency by enhancing the level of production automation and reducing firms' reliance on specific suppliers. Similarly, in regions where the non-state economy is underdeveloped, supply chains tend to be dominated by a few large state-owned or monopolistic suppliers. In this context, industrial robots can improve firms' production flexibility and process adaptability and enable them to collaborate with a broader range of small and medium-sized suppliers, thus promoting supplier diversification. In environments with inadequate legal protections, firms face enhanced risks related to contract enforcement, information asymmetry and transaction uncertainty, which often lead firms to depend on a narrow set of familiar suppliers. Industrial robots alleviate these constraints by improving production controllability and standardizing quality, which in turn reduce switching costs and uncertainty when integrating new suppliers. This technological capability thus facilitates firms' diversification into alternative supply channels.

4.5.2. Industry-level heterogeneity

In China, the impacts of industrial robots on supply chain restructuring vary due to heterogeneity in R&D intensity and labor dependency across industries. We first analyze how differences in technological inputs influence the impact of industrial robots on firms' supplier allocation strategies by categorizing the sample firms into non-technology-intensive and technology-intensive industries.¹

The regression results, shown in Columns (1) and (2) of Table 7, demonstrate that industrial robot adoption significantly reduces supplier concentration only within technology-intensive industries. Characterized by high R&D investment, complex technological processes and stringent requirements for production precision and stability, these industries are better positioned to standardize and flexibilize production through automation. In these industries, the adoption of industrial robots helps mitigate firms' technological dependence on specific suppliers for key components, thereby enhancing their ability to collaborate with a broader range of suppliers and facilitate more diversified supplier configurations. In comparison, non-technology-intensive industries typically feature simpler production processes and lower technological thresholds and often lack both the resources and incentives to expand their supplier networks in the short term.

We next measure industry competition intensity using the HHI and use the median value to split the sample into high- and low-competition sectors (Chen et al., 2022a, 2022b). The regression results, shown in Columns (3) and (4) of Table 7, reveal that industrial robot penetration significantly reduces supplier concentration only in highly competitive industries, which exhibit a substantially larger coefficient than that observed on less-competitive sectors. This result indicates that robot adoption more strongly promotes supplier diversification in competitive environments.

These findings suggest that firms operating in more competitive industries are more inclined to diversify their suppliers when deploying robotic technologies. In industries characterized by substantial firm homogeneity and product substitutability, customers' have elevated expectations regarding product quality. Industrial

¹ Technology-intensive industries are defined according to the China Securities Regulatory Commission 2012 Industry Classification Standard, which encompasses the following secondary sectors: Automobile Manufacturing (C36), Electrical Machinery (C38), Computer/Communication Equipment (C39), Instrumentation (C40), Transport Equipment (C37), Specialized Equipment (C35) and high-tech segments of Metal Products (C33).

Table 6
Regional-level cross-sectional analysis.

	(1) High government intervention	(2) Low government intervention	(3) Low non-SOE development	(4) High non-SOE development	(5) Low legal protection	(6) High legal protection
Variables	<i>Supplier5</i>	<i>Supplier5</i>	<i>Supplier5</i>	<i>Supplier5</i>	<i>Supplier5</i>	<i>Supplier5</i>
<i>Robots</i>	-0.063* (-1.702)	-0.024 (-0.753)	-0.077** (-2.181)	-0.019 (-0.580)	-0.065* (-1.941)	-0.017 (-0.476)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>City FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,947	12,828	12,937	12,838	14,412	11,363
Adjusted R-squared	0.331	0.290	0.325	0.296	0.330	0.285
Chow test p value	0.000***		0.000***		0.000***	

This table presents the subsample regression results pertaining to the heterogeneous effects of industrial robot penetration on supplier concentration across regions with varying degrees of marketization. Regional marketization levels are captured using three sub-indices from the China Provincial Marketization Index Report: government intervention, development of the non-state economy and legal institutional quality. Column pairs (1) and (2), (3) and (4) and (5) and (6) report the results for subsamples split using the median value of government intervention, the development level of the non-state economy and the quality of legal institutions, respectively. Detailed variable definitions are provided in Appendix I. All continuous variables are winsorized at the 1% and 99% levels. Robust t-statistics, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 7
Industry-level cross-sectional analysis.

	(1) Non-technology-intensive industries	(2) Technology-intensive industries	(3) Competitive industries	(4) Non-competitive industries
Variables	<i>Supplier5</i>	<i>Supplier5</i>	<i>Supplier5</i>	<i>Supplier5</i>
<i>Robots</i>	0.002 (0.058)	-0.077** (-2.277)	-0.092** (-2.557)	0.002 (0.046)
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes
<i>City FE</i>	Yes	Yes	Yes	Yes
Observations	11,999	13,796	11,051	11,033
Adjusted R-squared	0.378	0.275	0.263	0.364
Chow test p value	0.000***		0.000***	

This table presents subsample regression results analyzing the heterogeneous effects of industrial robot adoption on supplier concentration across different industries. Columns (1) and (2) report the results for non-technology-intensive and technology-intensive industries, respectively. Columns (3) and (4) respectively report the results for industries with high and low levels of competition, as determined by a median split of the Herfindahl–Hirschman index (HHI). Detailed variable definitions are provided in Appendix I. All continuous variables are winsorized at the 1% and 99% levels. Robust t-statistics, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

robot adoption helps firms achieve standardized production and improve their responsiveness to volatile demand, while supplier diversification strengthens their supply chain agility. Together, these advantages allow firms to gain a competitive edge by increasing their adaptability. Conversely, in less competitive sectors with stable market conditions, firms often find that maintaining long-term relationships with a limited number of suppliers is sufficient to meet their operational needs and minimize management costs. Under these conditions, robotic technologies offer less distinct competitive advantages.

4.5.3. Firm-level heterogeneity

Industrial robots are characterized by efficiency and standardized production, and their adoption primarily transforms corporate production models by displacing low-skilled labor. Therefore, we examine the heterogeneous effects of employee education levels on the role of robotics at the firm level. Following Jin et al. (2023), we measure the education level of a given firm as the proportion of employees who hold a bachelor's or higher degree or higher and use the median value to split the sample into a low-education group and a high-education group.

The results, shown in Table 8, indicate that industrial robot penetration is significantly and negatively associated with supplier concentration in the low-education group, whereas this relationship is statistically non-significant in the high-education group. Firms with lower education levels generally exhibit a shortage of employees with advanced skills, lower production flexibility and a reduced capacity to adapt to complex supply chain structures (Chen et al., 2024a, 2024b). Consequently, these firms tend to rely on a limited number of core suppliers to minimize operational uncertainty. In such contexts, industrial robots compensate for gaps in workforce skills by enhancing firms' automation and standardizing processes, thereby enabling them to collaborate with a broader range of suppliers and ultimately reduce their supplier concentration.

4.6. Analysis of economic consequences

We further examine the multifaceted impacts of supplier diversification strategies and consider both their potential benefits and associated costs for corporations.

We first analyze the impact of supplier concentration on firms' performance and stock market valuation, using the book-to-market ratio (*BM*) and return on total assets (*ROA*) in period $t + 1$ as key metrics. We fur-

Table 8
Firm-level cross-sectional analysis.

Variables	(1)	(2)
	Lower education level	Higher education level
	<i>Supplier5</i>	<i>Supplier5</i>
<i>Robots</i>	-0.059* (-1.722)	-0.030 (-0.863)
<i>Controls</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes
<i>Industry FE</i>	Yes	Yes
<i>City FE</i>	Yes	Yes
Observations	12,795	12,794
Adjusted R-squared	0.323	0.334
Chow test p value	0.000***	

This table examines the heterogeneous effects of robot penetration on supplier concentration by firms' education level. Firms are split into low- and high-education groups based on the median share of employees with a bachelor's or higher degree. Detailed variable definitions are provided in Appendix I. All continuous variables are winsorized at the 1% and 99% levels. Robust t-statistics, clustered at the firm level, are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

ther draw on Bray and Mendelson (2012) and measure the firm-level supply chain risk (*SupplyRisk*) as the deviation between a firm's production volatility and demand volatility. A higher value of this metric reflects greater misalignment between upstream supply and downstream demand within the focal firm's supply chain, i.e., elevated supply chain risk. As the supplier concentration is measured in percentage points, we multiply the economic outcome variables by 100 to facilitate interpretation in subsequent empirical analyses.

Table 9 reports the results regarding the beneficial economic consequences for corporations. Specifically, a higher supplier concentration not only negatively affects firms' market valuation and business performance

Table 9
Benefits of supplier diversification strategies.

Variables	(1)	(2)	(3)
	<i>BM</i>	<i>ROA</i>	<i>SupplyRisk</i>
<i>Supplier5</i>	-2.639*** (-3.851)	-0.017*** (-3.109)	0.060*** (9.292)
<i>Year FE</i>	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes
<i>City FE</i>	Yes	Yes	Yes
Observations	25,423	25,768	24,865
Adjusted R-squared	0.611	0.054	0.425

This table presents regression results analyzing the beneficial impacts of supplier diversification on firms' performance, stock market performance and supply chain risk. Firm performance is measured using the book-to-market ratio (*BM*) and return on total assets (*ROA*), while supply chain risk (*SupplyRisk*) is constructed as the deviation between production volatility and demand volatility, where a higher value indicates greater risk. To facilitate the interpretation of coefficient estimates, all outcome variables are multiplied by 100, as the supplier concentration is measured in percentage points. Detailed variable definitions are provided in Appendix I. All continuous variables are winsorized at the 1% and 99% levels. Robust t-statistics, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

but also exacerbates their supply chain risk. Specifically, a one-unit increase in supplier concentration leads to statistically significant declines in both *BM* and *ROA*. This result suggests that overreliance on a limited number of suppliers erodes a firm's profitability and diminishes its valuation in the capital market. Concurrently, an increase in supplier concentration significantly increases a firm's supply chain risk (*SupplyRisk*), indicating greater vulnerability to external disruptions such as raw material shortages and price fluctuations. These findings provide economically meaningful support for the results of our benchmark regression: by reducing supplier concentration and promoting supplier diversification, industrial robots can indirectly improve firms' performance, enhance their capital market valuation and effectively mitigate their supply chain risk.

Second, we explore the implications with respect to supply chain efficiency and managerial expenses. Following Feng et al. (2015), we measure supply chain efficiency using the inventory turnover period (*Stockday*), defined as the natural logarithm of 365 divided by the inventory turnover ratio. A shorter turnover period indicates faster inventory conversion and greater logistics, information and cash flow operational efficiency within the supply chain. Consistent with Keng et al. (2020), we also construct a measure of entertainment expenses (*Entertainment*) by taking the logarithm of the sum of six sub-items listed under "management expenses": business entertainment, travel, conference, overseas training, board meeting fees and vehicle fees.

Table 10 reports the results related to these associated trade-offs. The empirical results show that supplier concentration significantly enhances firms' supply chain efficiency (*Stockday*) while reducing entertainment expenses (*Entertainment*). In other words, closer relationships with fewer suppliers lead to more centralized and stable material flows, which enhance firms' operational efficiency and reduce the relational costs incurred in maintaining a broad supplier network. In contrast, although supplier diversification helps mitigate firms' supply chain risk and improves their performance and market valuation, it also introduces coordination challenges and higher relational expenditures. These findings highlight the major trade-off inherent in supplier diversification strategies: while they strengthen firms' resilience and market outcomes, they may also reduce efficiency and increase operational expenses.

5. Conclusions and implications

Industrial robotics is catalyzing both the transformative evolution of China's manufacturing sector and a broader technological revolution. Beyond its established role in optimizing labor structures

Table 10
Costs of supplier diversification strategies.

Variables	(1) <i>Stockday</i>	(2) <i>Entertainment</i>
<i>Supplier5</i>	-0.004*** (-8.513)	-0.004*** (-10.135)
<i>Year FE</i>	Yes	Yes
<i>Industry FE</i>	Yes	Yes
<i>City FE</i>	Yes	Yes
Observations	25,522	18,764
Adjusted R-squared	0.410	0.542

This table examines the operational costs associated with supplier diversification, focusing on the effects on supply chain efficiency and managerial expenses. Supply chain efficiency is measured by inventory turnover days (*Stockday*), calculated as the logarithm of 365 divided by the inventory turnover ratio; a lower value indicates higher efficiency. Managerial expenses are captured by entertainment expenditures (*Entertainment*), constructed as the natural logarithm of the sum of six expense items: business entertainment, travel, conferences, overseas training, board meeting fees and vehicle costs. Detailed variable definitions are provided in Appendix I. All continuous variables are winsorized at the 1% and 99% levels. Robust t-statistics, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

and production efficiency, robotics also profoundly influences strategic corporate decision-making. Bridging industrial automation and supply chain strategy, this study examines how robotics adoption reshapes supplier concentration dynamics among China's A-share listed firms and reveals the underlying operational mechanisms.

Our findings establish that industrial robot adoption encourages firms to diversify their supplier base. This effect is primarily operationalized through the strengthening of firms' market positioning and broadening of product portfolios. This diversification effect is intensified in regions with underdeveloped markets, which exhibit characteristics such as pronounced government intervention, constrained private sector development and low legal institutional quality, as well as in technology-intensive, highly competitive industrial sectors and among firms with a large proportion of low-skilled workers. Further analysis reveals that automation-induced supplier diversification entails both benefits and costs. On the one hand, a reduced supplier concentration is associated with improved firm performance and lower supply chain risk. On the other hand, it may lead to decreased inventory efficiency and increased transaction costs.

These insights provide crucial strategic guidance for firms seeking to leverage China's competitive advantage in robotics production and enhance their resilience. First, manufacturing enterprises should embrace intelligent transformation as a strategic imperative. Given the uneven robot adoption landscape in China, our findings demonstrate that robotics implementation can mitigate power imbalances in buyer-supplier relationships and reduce firms' dependency risks. These benefits strengthen firms' bargaining positions and improves their supply chain resilience. Consequently, companies should prioritize developing robotics capabilities, with industry leaders maintaining their technological edges while followers accelerate their technological efforts to catch up. Second, the heterogeneous effects observed across regions, industries and enterprises necessitate contextual implementation strategies. Firms require tailored robotics strategies that are aligned with their operational ecosystems, rather than standardized approaches.

While this research contributes to an understanding of the economic impact of robotics on supply chain configuration, viewed through the lens of supplier concentration, we acknowledge some practical limitations. The considerations of supplier management are multifaceted, including supplier stability, geographic clustering and other factors beyond concentration risks. Thus, while our findings illuminate the topic of robotics-driven risk diversification, optimal supplier configuration will require holistic assessment. Future studies should investigate how Industry 4.0 technologies collectively reconfigure supply networks, particularly the interactions among technological capabilities, operational frameworks and relational dynamics.

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. All authors confirm that there are no conflicts of interest related to the research design, data collection, analysis, or interpretation of results in this study.

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Appendix I. Definitions of key variables

Variable	Measurement
<i>Supplier5</i>	Supplier concentration, measured as the proportion of a firm's total annual procurement expenditure accounted for by its top five suppliers.
<i>Supplier3</i>	Supplier concentration, measured as the proportion of a firm's total annual procurement expenditure accounted for by its top three suppliers.
<i>Robots</i>	Firm-level exposure to industrial robots, constructed using a Bartik instrument that interacts industry-level robot penetration with the firm's baseline production workforce scale (as in Section 3.2).
<i>Robots2</i>	The natural logarithm of 1 plus the frequency of intelligent manufacturing-related terms in corporate annual reports.
<i>Size</i>	The natural logarithm of the total number of employees.
<i>Lev</i>	The ratio of total liabilities to total assets.
<i>Age</i>	The natural logarithm of 1 plus the firm's listing duration (in years).
<i>R&D</i>	The ratio of research and development expenditure to operating revenue.
<i>Productivity</i>	A firm's operating revenue per employee, scaled by the industry-average revenue per employee.
<i>Cap</i>	The ratio of total assets to total operating revenue.
<i>TobinQ</i>	A firms' market capitalization divided by its total assets.
<i>Independence</i>	The proportion of independent directors on the director board.
<i>Top5</i>	The total shareholding percentage of the top five shareholders.
<i>IM</i>	A dummy variable equal to 1 if a firm is headquartered in a city that has implemented the Intelligent Manufacturing Pilot Demonstration Policy, and 0 otherwise.
<i>Digital</i>	The natural logarithm of 1 plus the frequency of digitalization-related keywords in annual reports.
<i>Product Diversity</i>	Product diversification, defined as 1 minus the Herfindahl–Hirschman index (1–HHI), where HHI is computed from a firm's sales revenue across different product lines (as in Section 4.4).
<i>Market Power</i>	The ratio of a firm's annual sales to the total sales of its industry in a given year.
<i>Government Intervention</i>	A sub-index of province-level government intervention obtained from the China Provincial Marketization Index Report. A higher score indicates a lower level of government intervention in the market.
<i>Non-SOE Development</i>	A sub-index of province-level non-state-owned-enterprises (SOEs) obtained from the China Provincial Marketization Index Report. A higher score indicates a higher level of non-SOE development.
<i>Legal Protection</i>	The sub-index for province-level legal protection obtained from the China Provincial Marketization Index Report. A higher score indicates a higher level of legal protection in a province.
<i>Technology-Intensive</i>	Technology-intensive industries, as defined by the China Securities Regulatory Commission 2012 Industry Classification Standard. This category includes the following secondary sectors: Automobile Manufacturing (C36); Electrical Machinery (C38); Computer, Communication and Other Electronic Equipment (C39); Instrumentation (C40); Railway, Ship, Aerospace and Other Transport Equipment (C37); Special Purpose Equipment (C35); and the high-tech segments of Metal Products (C33).
<i>Competitive industries</i>	High-competition industries, defined as those with an HHI below the annual sample median.

(continued on next page)

Appendix I. (continued)

Variable	Measurement
<i>Education level</i>	The proportion of employees holding a bachelor's or higher degree in a firm.
<i>BM</i>	The ratio of market capitalization to book value of equity.
<i>ROA</i>	The ratio of net income to average total assets.
<i>SupplyRisk</i>	Supply chain risk, measured as the deviation between a firm's production volatility and demand volatility. A higher value indicates higher supply chain risk.
<i>Stockday</i>	Inventory turnover days, computed as $\ln(365/\text{inventory turnover})$.
<i>Entertainment</i>	The natural logarithm of the sum of six entertainment-related expenses: business entertainment, travel, conferences, overseas training, board meeting fees and vehicle costs.

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IPO audit contingent fees and earnings reversal



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ABSTRACT

This study investigates how contingent fees in initial public offering (IPO) audits affect earnings reversals. Using a sample of Chinese firms with IPOs, we find that higher contingent fees are associated with a greater likelihood of post-IPO performance deterioration and worse firm outcomes. This effect is more pronounced among non-state-owned (vs. state-owned) firms and those facing weaker regulatory oversight, lower information quality and higher economic policy uncertainty. Further analysis shows that contingent fees significantly accelerate the IPO process, and that firms are likely to retain the same accounting firm that conducted their IPO audit after going public. We also observe that firms paying higher contingent fees experience worse long-term market performance following their listing. Overall, our results indicate that contingent fees in IPO audits undermine the independence of audits. This study not only contributes to the academic literature on contingent fees in the IPO context but also offers empirical support for regulatory efforts to enhance IPO audit pricing oversight.

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1. Introduction

The initial public offering (IPO) is a pivotal milestone in a firm's life cycle. Firms seeking to secure approval and raise capital for an IPO often have strong incentives to engage in earnings management, which would exacerbate information asymmetry and intensify agency conflicts (Aharony et al., 2000; Huang and Shu, 2014; Lu et al., 2015; Yan and Wang, 2021). These problems are particularly salient in emerging markets, which are characterized by relatively less sophisticated investors. In this context, the independence and quality

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of IPO audits, which serve as key “gatekeepers” between firms and capital markets, are increasingly attracting the attention of investors, regulators and scholars (Hammami et al., 2020; Aobdia et al., 2024).

Audit fees, which provide the income required to cover the costs of audits and sustain the operations of audit firms, crucially influence both auditors’ independence and audit quality (Xie, 2002; Choi et al., 2008; Hoitash et al., 2007). The academic literature generally distinguishes between *normal* and *abnormal audit fees* and provides valuable insights into how these fees affect auditors’ independence (e.g., Frankel et al., 2002; Ashbaugh et al., 2003; Choi et al., 2010; Asthana and Boone, 2012). However, little attention is devoted to *IPO audit contingent fee arrangements*. Anecdotal evidence indicates that, in practice, contingent fee arrangements exist in IPO audits; in other words, whether and how much audit firms are paid depends on future outcomes such as the audit opinion issued, the success of the stock listing or the achievement of certain performance benchmarks. Unlike normal and abnormal audit fees, IPO audit contingent fees tie audit compensation directly to the realization of specific objectives. The phenomenon of audit fees has already raised concerns among practitioners,¹ industry self-regulatory organizations² and regulatory authorities.³ However, empirical discussions offer limited insights into the relationship between IPO audit contingent fees and earnings reversal after an IPO. Therefore, investigating IPO audit contingent fees not only can provide a valuable new perspective to the ongoing discussion regarding the impact of audit fees on audit quality but also can help address the research gap.

Theoretically, the function of a capital market relies on independent and professional audit services. However, contingent fee arrangements in IPO audits may undermine auditors’ independence and, in turn, reduce audit quality. When audit fees are contingent upon clients’ successful listings, audit firms may prioritize the pursuit of contingent fee income, thereby compromising their professional ethics and independence in favor of financial incentives. This conflict of interest may result in an intentional reduction of substantive testing or other essential audit procedures (Choi et al., 2010; Xu, 2018; Wang et al., 2019), such as recommending accounting adjustments or issuing unqualified opinions. This concern is particularly salient in the context of an IPO, where information asymmetry is most pronounced (Chang et al., 2008; Zhu and Zhu, 2018; Song et al., 2024). For instance, contingent fee arrangements intensify conflicts of interest between auditors and investors, distort incentive structures and reduce the effort devoted to audits, thereby impairing the faithful representation of financial information. In IPO audits, such arrangements threaten auditors’ independence and professional integrity and enable some issuers to go public while masking material deficiencies, which ultimately degrades the quality of listed firms.

However, one strand of literature argues that audit contingent fees in IPO engagements may reflect auditors’ input of effort, due diligence and resource dedication throughout the audit process. In other words, this fee essentially is a form of compensation for the additional audit tasks and resource inputs required in the complex IPO audit process. Viewed through this theoretical lens, IPO audit contingent fees might enhance the quality of listed firms (Mitra et al., 2009; Doogar et al., 2015; Ke et al., 2015; Rajgopal et al., 2021; Chen et al., 2022). Specifically, when clients offer relatively low audit fees, auditors confronted with profitability pressures may strategically decrease their substantive testing procedures to control costs, thus increasing the risk of material misstatements in the clients’ financial reports. In such scenarios, contingent fees would act as a compensating mechanism. Specifically, they would offset the costs that auditors incur when exerting more effort, thus enabling the full disclosure of crucial information such as IPO applicants’ operational risks. This disclosure would also mitigate information asymmetry between market participants and ultimately improve the listing firm’s quality. Furthermore, amid an institutional environment characterized by the growing standardization and legalization of securities market regulation, IPO auditors face stricter fiduciary responsibilities, higher potential litigation risks and greater reputational exposure. Given these institutional constraints, contingent fees are less likely to lead auditors to relax their audit standards. Rather, these fees

¹ Source <https://finance.sina.com.cn/wm/2023-11-05/doc-imztqqk4266306.shtml>.

² Source: https://www.cicpa.org.cn/xxfb/news/202311/t20231102_64534.html.

³ For instance, the *Ministry of Finance’s Circular on Prohibiting Accounting Firms from Providing Audit Services on a Contingent Fee Basis* (Cai Kuai [2023] No. 25) explicitly stipulates that accounting firms shall not offer audit services on a contingent fee basis. It emphasizes that the imposition or amount of fees shall not be contingent upon the outcome of the audit work or the achievement of specific objectives.

compensate auditors for the higher audit risk inherent in IPO engagements, thus helping to mitigate moral hazard and alleviate the “lemons problem” (Chen et al., 2022; Song et al., 2024). In summary, competing theoretical predictions persist with respect to the impact of IPO audit contingent fees on earnings reversal. This competition renders the issue an open and interesting empirical question.

This study examines the potential impact of IPO audit contingent fees on post-IPO earnings reversal using a sample of Chinese listed companies from 2006 to 2021. The empirical results indicate that IPO audit contingent fees adversely affect firms’ performance. Specifically, higher IPO audit contingent fees are associated with a greater probability of a firm’s post-IPO earnings reversal. This finding is consistent with the theoretical expectation that contingent fee arrangements may give rise to conflicts of interest for auditors, thereby eroding their professional independence. To address potential endogeneity issues, we use the proportion of IPO withdrawals in the firm’s local market during the previous year as an instrumental variable (IV) and conduct two-stage least squares (2SLS) regression analyses. The validity of this IV is supported by the following arguments: regional IPO withdrawal ratios are plausibly correlated with auditors’ pricing decisions, as higher local withdrawal risks may alter auditors’ risk assessment. However, the IV is unlikely to have a direct causal impact on the post-IPO performance of individual firms. The results derived from IV-2SLS estimations further support the robustness of our main findings.

In the heterogeneity analysis, we investigate four key dimensions: regulatory effectiveness, ownership structure, information quality and perceptions of economic policy uncertainty (EPU). The empirical findings reveal that the positive relationship between IPO audit contingent fees and subsequent post-IPO earnings reversal is more salient for non-state-owned enterprises (non-SOEs) and firms operating in weaker regulatory environments, those with relatively lower information quality and those perceiving higher levels of EPU.

In our extended analyses, we further investigate the economic consequences of IPO audit contingent fees from three interrelated perspectives: IPO listing speed, the duration of auditor–client relationships and post-IPO capital market performance. The empirical findings indicate that higher levels of IPO audit contingent fees significantly shorten the IPO listing cycle and contribute to the formation of longer-term cooperative relationships between audit firms and their IPO clients. However, these apparent advantages are accompanied by a notable deterioration in firms’ long-term post-IPO capital market performance.

With this work, we offer the following contributions. First, we contribute to the literature on audit fees by introducing a practice-based measure of IPO audit contingent fees that is both operationally feasible and economically interpretable when compared with conventional residual-based abnormal fee measures (DeFond et al., 2002; Ghosh and Pawlewicz, 2009; Chan et al., 2021). Through a systematic investigation of the impacts of this measure on earnings reversal, listing speed and long-term capital market performance, we enhance the understanding of how audit contingent fee arrangements influence both audit practitioners and capital market stakeholders. Collectively, these findings shed light on the theoretical implications of audit contingent fees.

Second, this study extends the drivers of auditors’ selection decisions among post-IPO periods. Our empirical analysis reveals that listed companies exhibit a statistically significant preference for retaining audit firms that provided their IPO audit services, as demonstrated by both higher engagement frequencies and greater continuity in auditor–client relationships. This finding suggests that firms’ decisions regarding auditor retention are persistently influenced by the initial provision of IPO-related audit services.

Third, we offer practical insights with respect to enhancing listed company quality, refining audit fee arrangements and promoting healthy capital market development. The literature highlights the key roles of mechanisms such as government accounting oversight (Liu and Wang, 2021; Zhu et al., 2023), stock exchange inquiry regulation (Chen et al., 2019; Xue and Wang, 2022; Wu et al., 2024), China Securities Regulatory Commission (CSRC) review inquiries (Zhang et al., 2021; Wu et al., 2023) and on-site IPO inspections (Song et al., 2024) in improving the quality of listed firms. Our analysis reveals that higher IPO audit contingent fees are strongly associated with greater economic dependence of auditors on their clients, an association that threatens auditors’ independence. This result suggests that the contractual features of IPO audit fees are a crucial but neglected factor affecting firms’ post-IPO performance. Our findings not only provide empirical support for the Ministry of Finance’s accounting regulation [Caikuai 2023 No. 25] but also can guide regulators in optimizing the institutional design of IPO audit fee arrangements. Furthermore, our evidence will help capital market participants understand how to accurately assess the investment implications embedded in IPO audit contingent fees.

2. Institutional background, literature review and hypothesis development

2.1. Institutional background

2.1.1. Evolution and characteristic features of contingent fee practices in IPO audits

Since the restoration of China's certified public accountant (CPA) system following the 1978 Reform and Opening-up, the regulation of accounting firms' service fees has passed through three stages: government-set pricing, government-guided pricing and market-based pricing. During the government-set pricing stage (1980–2009), the government established detailed rules regarding accounting firms' service fees. Specifically, local finance departments were required to work with relevant agencies to set regional fee schedules for CPA services. In the government-guided pricing stage (2010–2013), the government directed the prices of mandatory audit services, while market forces determined the fees for other services. This model helped curb low-price competition in the auditing industry and standardized accounting firms' fee practices. Currently, regulation has been in the market-based pricing stage since 2014, when the National Development and Reform Commission issued the Notice on Lifting Price Controls on Certain Services. This notice explicitly lifted price controls on accounting firms' audit services, allowing market-driven pricing.

Since this deregulation of audit service fees for accounting firms in 2014, however, issues related to contingent fee arrangements in audit services have become increasingly prominent. Due to separation between the buyers (i.e., firms) of audit services and ultimate consumers (i.e., investors), accounting firms are often in a weakened position under market-driven pricing. This can lead to a vicious cycle of low-price competition with the intent to expand market share. This competitive phenomenon is particularly severe with respect to IPO-stage audit fee arrangements, which have a distinctly results-oriented fee structure. IPO audit fees typically comprise two portions: "fixed" and "contingent." The fixed portion, which covers standard audit services, is relatively small; most of the fee goes to the contingent portion. In practice, audit firms can only realize the contingent portion if the client company successfully completes its IPO.

Anecdotal evidence concerning IPO audit contingent fees shows that since the Ministry of Finance issued a notice prohibiting such arrangements in 2023, the CSRC and its local branches (including regional regulatory bureaus and special commissioners' offices) have prioritized the supervision and inspection of accounting firms' IPO audit contingent fees.⁴ In this study, we systematically examine the penalty and warning letters issued by the CSRC and compile 17 publicly disclosed cases of IPO audit contingent fees (as of July 2025) involving 16 accounting firms across 11 provincial-level CSRC bureaus.⁵ In these cases, we find that the accounting firms engaged in contingent fee arrangements during IPO audits, which were typically structured as conditional payments, fee reclassifications or post-IPO service agreements explicitly linked to achieving a successful listing.

For example, a publicly disclosed tender for IPO audit services indicates that a prospective IPO client allocated a total budget of 17.5 million CNY for such services. This budget included 1.5 million CNY for annual audit fees (covering three years plus the most recent period) and 16 million CNY for the IPO-specific audit component.⁶ The contract stipulates that the 16 million CNY IPO audit fees would be paid only if the company successfully issued shares, raised funds and completed capital verification. In other words, the accounting firm would receive most of the audit fee only upon the company's successful IPO, providing a clear example of IPO audit contingent fees. Overall, the above public information provides evidence of both the existence of IPO audit contingent fees and the associated threats to auditors' independence.

Accordingly, we must carefully address the potential issues arising from contingent audit fee arrangements following the deregulation of accounting firms' audit fees. Put simply, the removal of price controls on audit fees does not mean that the government has abandoned its supervisory responsibilities; instead, it highlights the need for relevant government authorities to maintain fair market prices and protect the legitimate rights and interests of market participants (Tian et al., 2025).

⁴ See https://www.thepaper.cn/newsDetail_forward_25778717, <https://finance.sina.cn/2025-01-24/detail-inehatrr4887871.d.html>.

⁵ See https://www.csrc.gov.cn/csrc/c100030/common_xq_list.shtml.

⁶ See <https://finance.sina.com.cn/wm/2023-11-05/doc-imztqqk4266306.shtml>.

Government authorities have introduced supplementary measures to address the disorder caused by contingent fee arrangements after deregulation. For example, in 2023, the Ministry of Finance, the State-owned Assets Supervision and Administration Commission and the CSRC jointly issued the *Measures for Governing the Selection of Accounting Firms by State-owned Enterprises and Listed Companies* (CaiKuai [2023] No. 4) to address concerns that low-fee competition could undermine audit quality. These measures specify that the weight of audit fee quotations in the selection process should not exceed 15 %, while the arithmetic mean of all eligible accounting firms' fee quotations should serve as the benchmark, thereby aiming to mitigate low-fee competition.

Regarding contingent audit fees, in 2023 the Ministry of Finance issued the *Notice on the Strict Prohibition of Accounting Firms from Providing Audit Services on a Contingent Fee Basis* (CaiKuai [2023] No. 25), which explicitly bans such practices to strengthen auditors' independence and prevent conflicts of interest from impairing audit quality. The 2025 Regulations issued by the State Council on *Regulating Intermediary Services for Companies' Public Stock Offerings* (State Council Decree No. 798) clarify that accounting firms may adopt a phased fee structure based on work progress, but the timing and amount of such fees must not be tied to the audit outcome or the success of the company's IPO.

The evolution of accounting firms' audit fee policies generally involves three stages: government-set pricing, dual-track classified pricing and fully market-based pricing. This evolution reflects a broad policy shift toward market-driven fee determination. Given the unique characteristics of the CPA industry and incomplete market development, however, issues such as predatory low-price competition and contingent audit fee arrangements cannot be resolved through deregulation alone. Instead, the regulatory framework for audit fees must be continuously improved to safeguard auditors' independence and increase audit quality.

2.1.2. Definition of contingent fees in IPO audits

Drawing on contingent arrangement theory, relevant contingent fee policy documents and operational considerations for variable measurement, we define an IPO audit contingent fee as an audit fee arrangement in which the payment amount is contingent upon future audit outcomes, the success of the company's public stock issuance or other performance indicators. Such contingent arrangements inherently threaten auditors' independence. In contrast, phased fee structures based on work progress do not qualify as contingent arrangements. IPO audit contingent fees typically take the form of issuance bonuses or post-IPO supplemental agreements to raise audit fees. Building on this conceptualization and analysis of real-world cases, we propose a replicable and conceptually consistent method to construct our empirical measure. Specifically, we calculate IPO audit contingent fees as the total IPO audit fees paid by the company minus three times the annual audit fees for the first post-IPO year, standardized by the company's total assets in the year preceding the IPO.

We define our main variable in this way for the following reason. First, using three times the first post-IPO annual audit fees as the deduction benchmark is justified, as the financial conditions in the first post-IPO year are most temporally proximate to those in the IPO year. Additionally, the IPO audit period typically covers the "three years plus one period," i.e., the three years preceding the IPO and the latest year before the IPO. Therefore, our proposed approach provides a reasonable estimate of the normal pre-IPO audit fees. Second, assuming theoretically that audit costs tend to decrease post-IPO, using the first post-IPO annual audit fees as the normal benchmark would not tend to cause systematic underestimation of the pre-IPO audit costs; it thereby serves as a conservative measure of IPO audit contingent fees. Third, from the perspectives of operational feasibility and replicability, our proposed estimation method is data-accessible, methodologically straightforward and eliminates the need for a complex intermediate process when constructing the variable. Therefore, this approach can help reduce the cost of replicating the variable while enhancing the replicability of the measurement.

2.1.3. Descriptive statistics of IPO audit contingent fees

Based on the above definition, we compile data on the IPO audit contingent fees for Chinese A-share listed companies from 2006 to 2021. Table 1 presents the descriptive statistics, broken down by year, province and industry. For clarity, the data in Table 1 are not standardized by the respective company's total assets in the year preceding the IPO.

Table 1
Descriptive statistics of IPO audit contingent fees (in RMB 10,000).

Panel A: Year breakdown statistics			
Year	N	Proportion	Mean
2006	52	1.69 %	-140
2007	104	3.37 %	-620
2008	60	1.95 %	-170
2009	66	2.14 %	120
2010	244	7.91 %	62
2011	274	8.88 %	37
2012	149	4.83 %	21
2013	2	0.06 %	-1100
2014	122	3.96 %	190
2015	219	7.10 %	200
2016	217	7.04 %	240
2017	431	13.98 %	250
2018	95	3.08 %	290
2019	189	6.12 %	370
2020	387	12.54 %	560
2021	473	15.34 %	580
Total	3084	100.00 %	250
Panel B: Province breakdown statistics			
Province	N	Proportion	Mean
Anhui	90	2.92 %	430
Beijing	291	9.44 %	-120
Chongqing	33	1.07 %	93
Fujian	110	3.57 %	200
Gansu	15	0.49 %	160
Guangdong	595	19.29 %	240
Guangxi	17	0.55 %	220
Guizhou	13	0.42 %	300
Hainan	12	0.39 %	250
Hebei	35	1.13 %	170
Henan	53	1.72 %	190
Heilongjiang	13	0.42 %	220
Hubei	61	1.98 %	250
Hunan	85	2.76 %	280
Jilin	18	0.58 %	200
Jiangsu	446	14.46 %	310
Jiangxi	32	1.04 %	310
Liaoning	41	1.33 %	180
Inner Mongolia	8	0.26 %	360
Ningxia	4	0.13 %	150
Qinghai	3	0.10 %	730
Shandong	166	5.38 %	210
Shanxi	10	0.32 %	170
Shaanxi	37	1.20 %	260
Shanghai	240	7.78 %	260
Sichuan	92	2.98 %	200
Tianjin	32	1.04 %	-290
Xizang	13	0.42 %	340
Xinjiang	26	0.84 %	120
Yunnan	16	0.52 %	160
Zhejiang	477	15.47 %	490
Total	3084	100.00 %	250

Table 1 (continued)

Panel C: Industry breakdown statistics			
Industry	N	Proportion	Mean
Agriculture, forestry, animal husbandry and fisheries	26	0.84 %	170
Mining industry	37	1.20 %	-1100
Manufacturing	2217	71.89 %	1260
Electricity, heat, gas and water production and supply	46	1.49 %	22
Construction industry	73	2.37 %	-34
Wholesale and retail trade	78	2.53 %	280
Transportation, storage and postal services	53	1.72 %	-390
Accommodation and catering industry	4	0.13 %	710
Information transmission, software and information technology services	300	9.73 %	190
Real estate industry	13	0.42 %	-110
Leasing and business services	39	1.26 %	140
Scientific research and technical services	78	2.53 %	350
Water, environmental and public facilities	64	2.08 %	310
Residential services, repairs and other services	1	0.03 %	770
Education	8	0.26 %	200
Health and social care	7	0.23 %	230
Culture, sports and entertainment	40	1.30 %	110
Total	3084	100.00 %	250

This table reports the year, province and industry breakdown statistics of IPO audit contingent fees. For brevity, the values in the table are not scaled by total assets.

Panel A reveals that, over the sample period, the mean value of IPO audit contingent fees is negative only in 2006, 2007, 2008 and 2013; the 2013 figure is due to an extremely limited number of observations caused by the suspension of IPO issuances. In all other years, the mean value is positive. Moreover, the mean value of IPO audit contingent fees exhibits a steady upward trend from 2014 onward, consistent with the 2014 deregulation of audit service fees and the protracted low-price competition in China's audit industry. Panel B presents provincial-level descriptive statistics, which show that our sample is concentrated in Jiangsu, Zhejiang, Guangdong and Beijing. The province-level regions with the highest mean values of IPO audit contingent fees in the sample are Qinghai, Zhejiang and Anhui. Panel C presents industry-level descriptive statistics showing that our sample is concentrated in the manufacturing industry, which has a higher average of IPO audit contingent fees than other industries.

2.2. Literature review

2.2.1. Research on earnings reversals

The literature reveals that a significant post-IPO performance decline—specifically, when a firm's post-IPO performance falls substantially below pre-IPO levels (i.e., earnings reversal)—is widely recognized as an indicator of low quality among listed companies (Carter and Manaster, 1990). Accordingly, earnings reversal is a common empirical proxy for the quality of a listed company (Teoh et al., 1998; Lu et al., 2015; Zhang, 2019). With respect to the determinants of earnings reversal, typical explanations include earnings management effects, regulatory oversight mechanisms and the impact of ownership structures.

First, from the perspective of earnings management, pre-IPO earnings management is a key driver of earnings reversal. The underlying logic is as follows: given the need to meet regulatory profitability requirements and increase the likelihood of a successful IPO, firms have both the incentive and the ability to manipulate their financial statements by inflating their accrued revenues or selecting favorable accounting methods. Such practices exaggerate firms' actual earnings and facilitate financial "window dressing" (Aharony et al., 2000), thereby attracting investors. However, these earnings management methods typically reverse after listing,

making it impossible to sustain the inflated pre-IPO performance and ultimately leading to post-IPO performance deterioration (Teoh et al., 1998). Some studies emphasize that firms under the influence of China's equity issuance system in China may engage in pre-IPO earnings management to boost profitability and improve the probability of passing regulatory censorship (Lu and Zhu, 2001; Chen, 2008), which in turn allows them to compete for scarce IPO opportunities. The subsequent reversal and unsustainability of these firms' pre-IPO earnings management after listing leads to the observed earnings reversal (Huang and Shu, 2014; Lu et al., 2015; Zhang, 2019).

Second, from the perspective of regulatory oversight, China's new share issuance system has undergone a transition from an administrative-based to a market-oriented IPO registration system. Under the approval-based and channel-based systems, the IPO process imposed numerous quantitative criteria for listing eligibility, thus incentivizing firms to inflate their pre-IPO earnings. For instance, Du et al. (2013) argue that the operating performance of companies closely linked to members of the issuance committee gradually returns to the true performance level after listing. Mao et al. (2024) note that the market-oriented IPO registration system reform steers firms toward reducing earnings management and improving the quality of their information disclosure, thereby lowering the likelihood of post-IPO performance deterioration. Regarding year-end earnings reversal, Lu and Zheng (2022) observe that anticipated revisions of accounting standards can induce firms to manipulate their performance. For example, in 2018, some listed companies conducted substantial goodwill impairments in response to expected changes in goodwill amortization policies, leading to a year-end earnings reversal. Furthermore, Zhang et al. (2021) find that CSRC-led IPO value assessment opinions reveal firms' operational information effectively and thus improve capital market efficiency and mitigate post-IPO earnings reversals. Wu et al. (2023) examine how the selection quality of issuance committee members affects IPO outcomes and find that firms reviewed by committee members with an abnormally high selection probability exhibit poorer post-IPO performance.

Third, from the perspective of ownership structure, a concentrated ownership structure or state ownership enables listed companies to establish political connections; however, overreliance on such connections misaligns firms' operational incentives and leads to post-IPO performance deterioration. Fan et al. (2007) examine the relationship between CEOs' political ties and firms' post-IPO market performance and find that more politically connected firms experience a more pronounced decline in market value after listing. In a study of ChiNext firms, Lu et al. (2015) argue that political connections, as a persistent and special resource, crowd out R&D investments and encourage earnings manipulation, thereby causing post-IPO performance deterioration. Wei et al. (2018) document that before listing, nearly 60 % of IPO firms engaged in tax repayments, which signal robust future performance for high-quality firms rather than performance manipulation by low-quality firms. However, Li and Chen (2021) point out that pre-IPO tax avoidance is an important cause of post-IPO earnings reversals. Because the earnings derived from pre-IPO tax avoidance are unsustainable, the rising cost of tax avoidance after listing erodes net tax benefits, and firms subsequently experience an obvious decline in operating performance.

Beyond the aforementioned theoretical explanations, researchers propose several alternative explanations for earnings reversal, focusing on factors such as executive turnover, media coverage and the facial expressions of board chairs. For instance, Cao and Zhang (2012) investigate the phenomenon of concentrated executive resignations following IPOs and find that top executives' departure leads to worse market performance. Xiong and Yang (2017) examine the relationship between media coverage and earnings reversal, showing that a high volume of negative media reports increases the likelihood that a firm will experience post-IPO performance deterioration. Analyzing the link between the facial expressions of board chairs and earnings reversal, Jia et al. (2020) suggest that negative emotional expressions may signal the deliberate concealment of adverse information.

2.2.2. Research on audit fees

- (1) Theoretical discussions on audit fees. Studies emphasize that audit fees not only provide compensation for audit firms' operational costs but also are a crucial determinant of audit quality. In the Chinese context, where the prevalence of small-scale and homogeneous audit firms has encouraged persistent low-price competition, excessively low audit fees pose a major challenge for the audit industry (Wu,

2021). Theoretical research highlights three adverse consequences of low-price competition: insufficient coverage of necessary audit costs, which undermines audit quality (Simunic, 1980; Liu et al., 2002; Qi et al., 2004); a reduced ability to attract and retain professional talent in the audit industry (Lennox et al., 2018; Hammami et al., 2020; Aobdia et al., 2024); and a decrease in auditors' independence under vicious price competition (Hoitash et al., 2007; Chen et al., 2016). As auditors protect the public's interests, extremely low fees can ultimately harm the public's trust (Xie, 2002). While audit fees reflect supply–demand bargaining power (Simunic, 1980), they also capture audit effort (Rajgopal et al., 2021), professional judgment and client dependence (Choi et al., 2008), thus underscoring the important role of this effort in determining audit quality and auditors' independence (Choi et al., 2010).

- (2) **Abnormal audit fees.** Studies on abnormal audit fees typically use methodologies employed in earnings management and investment efficiency research, such as estimating “normal” audit fees using empirical models and treating the residuals as a proxy for abnormal audit fees (DeFond et al., 2002; Ghosh and Pawlewicz, 2009; Chen et al., 2022). However, few studies have explicitly investigated contingent fee arrangements, given the scarcity of directly observable data. Essentially, contingent fees can be conceptualized by their reliance on the realization of specific future events, whereas abnormal audit fees involve separating total audit fees into “normal” and “abnormal” components. Thus, the two constructs differ fundamentally: contingent fees depend on conditional payments linked to targeted outcomes, while abnormal audit fees involve on deviations from expected pricing benchmarks. Nonetheless, these fee types share key commonalities: namely, both can impair auditors' independence and distort their professional incentives.

The literature presents two primary explanations regarding the impact of abnormal audit fees on auditors' professional behavior. Some studies argue that abnormal audit fees may encourage economic dependence between auditors and their clients, thereby impairing auditors' independence and professional judgment and ultimately reducing the audit quality (Magee and Tseng, 1990; Stanley and DeZoort, 2007; Choi et al., 2010; Gao et al., 2017; Xu, 2018). Alternatively, other studies argue that abnormal audit fees may reflect auditors' additional resources, efforts and due diligence during the engagement and act as compensation for increased professional effort, thus potentially enhancing audit quality (Mitra et al., 2009; Doogar et al., 2015; Ke et al., 2015; Rajgopal et al., 2021; Zhu and Zhu, 2018; Chen et al., 2022).

Compared with Liu et al. (2019), who adopt a residual-based measure of abnormal audit fees to examine IPO-related outcomes, we focus on the distinct construct of IPO audit contingent fees. Rather than residual deviations from normal audit fees, theoretically, these contingent fees are contractually tied to specific objectives. Methodologically, in this paper we construct a more direct and replicable measure of IPO audit contingent fees. We then extend the analysis beyond post-IPO performance deterioration to listing speed, auditor retention and long-run stock performance, providing a more comprehensive understanding of the economic consequences of IPO audit contingent fees.

2.2.3. *Summary of the literature review*

In summary, the relevant research is primarily focused on abnormal audit fees; relatively scant attention is directed toward IPO audit contingent fees. In practice, however, IPO audit contingent fee arrangements are not uncommon, and regulatory authorities such as the State Council and the Ministry of Finance have issued prohibitive regulations targeting such arrangements. Despite this situation, in-depth theoretical exploration of IPO audit contingent fees remains limited. Empirically, disclosure documents released by the CSRC indicate that IPO audit contingent fees account for a substantial portion of total audit fees; however, the literature offers limited guidance regarding the construction of valid measures. Theoretically, how IPO audit contingent fees affect earnings reversals remains a contested topic: some researchers argue that such fees compromise auditors' independence, while others contend that they may boost auditors' effort. Under the increasingly stringent regulation of capital markets, efforts must be taken to ensure that auditors fulfill their gatekeeping duties, as this is necessary for enhancing firm quality and advancing the high-quality development of capital markets. Overall, the study of IPO audit contingent fees remains a notable yet underexplored issue.

2.3. Hypothetical development

Earnings reversal refers to the phenomenon in which a firm exhibits strong financial performance before its IPO but a marked decline in performance afterward (Carter and Manaster, 1990). Prior to China's adoption of a registration-based IPO system, its approval-based system imposed explicit financial thresholds; this incentivized pre-IPO firms to conduct rent-seeking and earnings management, thus undermining the efficiency of capital allocation in the market (Lai et al., 2022). Consequently, earnings reversal under the approval-based system is a persistent issue in China's capital markets (Zhang, 2019).

Under the IPO regulatory framework, firms seeking to be eligible for listing must engage audit firms to conduct IPO audits. Consequently, the auditors' professional conduct and the conclusions drawn in their audit reports strongly influence approval decisions regarding firms' IPOs. Theoretically, audit firms act as gatekeepers of the capital market, with both the ability and responsibility to conduct diligent audit engagements, screen high-quality firms and promote market efficiency. Auditors are motivated to maintain a high level of IPO audit service quality to safeguard their professional reputation and attract potential clients (Weber et al., 2008). However, failure to exercise due professional care may result in severe legal sanctions and economic penalties, including fines, suspension of business operations or revocation of professional licenses (Liu et al., 2019).

However, the role of audit firms may be compromised when audit fees are contingent on IPO outcomes, audit opinions or other predetermined performance targets. As the party tasked with auditing the financial statements of IPO firms, auditors' independence and diligence may be reduced if their compensation is tied to their clients' achievement of listing or other specific goals, leading to a misalignment of professional incentives. However, audit firms motivated by the prospect of contingent fees may be incentivized to help their clients satisfy listing requirements to boost the likelihood of IPO success (Liu et al., 2019). In practice, auditors who successfully and effectively guide their clients through an IPO enhance their reputational capital and attract additional business (Yang, 2013), while post-listing firms often demand additional audit and consulting services (Chen et al., 2024). Consequently, contingent fee arrangements may encourage auditors to collude with their clients at the expense of their own independence (Wang et al., 2019). Once the client goes public, however, the frequent reversal of such short-term earnings management reveals the firm's inherent fundamentals, leading to substantial performance discrepancies between the pre- and post-IPO periods and ultimately resulting in earnings reversal.

Notably, some studies argue that IPO audit contingent fees may provide compensation for auditors' additional effort and resources and could indicate high-quality audit services (Doogar et al., 2015; Ke et al., 2015; Rajgopal et al., 2021; Chen et al., 2022). Theoretically, when clients pay low audit fees, audit firms may be forced to reduce their audit efforts to control costs, leading to a decrease in audit quality. In contrast, IPO audit contingent fees may incentivize auditors to allocate sufficient human, financial and technical resources to their audit efforts, thus safeguarding audit quality. Given the high visibility of IPOs and the increasingly strict and effective regulatory environment, mechanisms such as regulatory inquiries and on-site inspections can mitigate the risk that IPO audit contingent fees will undermine auditors' independence. Therefore, auditors face huge reputational costs and regulatory penalty pressures even in the presence of IPO audit contingent fees, prompting diligent audit practices (Chen et al., 2022; Song et al., 2024) and thus reducing the likelihood of post-IPO earnings reversals.

In summary, it remains unclear whether IPO audit contingent fees enhance or mitigate earnings reversal. Based on the above review, we propose the following competing hypotheses for testing.

H1. The higher the IPO audit contingent fee, the greater the extent of post-IPO earnings reversal.

H2. The higher the IPO audit contingent fee, the lesser the extent of post-IPO earnings reversal.

3. Sample, variable definition and research design

3.1. Data and sample

We select IPO firms listed on the Shanghai and Shenzhen A-share markets during 2006–2021 as the initial sample. Subsequently, we exclude firms operating in the insurance and financial industries and those with

Table 2
Variable definitions.

Symbol	Name	Definition
<i>Droa</i>	Earnings reversal	The difference between the return on assets in the year preceding the IPO and the return on assets in the first year following the IPO
<i>Ctgfee</i>	IPO audit contingent fees	The total IPO fees paid to the accounting firm minus three times the audit fees for the first year's financial statements post-listing, scaled by the company's total assets in the year preceding the IPO
<i>Proceed</i>	IPO fundraising scale	The natural logarithm of the actual amount raised during the IPO
<i>Size</i>	Firm size	The natural logarithm of the average total assets over the three years preceding the IPO
<i>Lev</i>	Debt-to-asset ratio	The average debt-to-asset ratio over the three years preceding the IPO
<i>Roe</i>	Profitability	The average return on equity over the three years preceding the IPO
<i>Risk</i>	Operational risk	The standard deviation of the ratio of sales revenue to total assets in the three years preceding the IPO
<i>Soe</i>	Nature of ultimate shareholder	This variable takes a value of 1 when the actual controller of an enterprise prior to its listing is state-owned, and 0 otherwise
<i>Age</i>	Firm age	The natural logarithm of the number of years from a firm's establishment to its IPO
<i>Big10</i>	Whether the audit firm ranks among the top ten	This variable takes a value of 1 for accounting firms ranked among the top 10, and 0 otherwise
<i>Uwfee</i>	Underwriting fees	The natural logarithm of IPO underwriting fees for an IPO firm
<i>Atfee</i>	Legal fees	The natural logarithm of IPO legal fees for an IPO firm
<i>Inftee</i>	Information disclosure fees	The natural logarithm of IPO disclosure costs for an IPO firm
<i>Otftee</i>	Other charges	The natural logarithm of other IPO costs for an IPO firm

missing key variables. To mitigate the effects of outliers, all continuous variables are winsorized at the 1 % and 99 % percentiles. All data used are retrieved from the CSMAR database.

3.2. Variable definition

3.2.1. Earnings reversal

Following Fang (2014) and Lu et al. (2015), we define post-IPO earnings reversal (*Droa*) as the difference between a firm's return on total assets (*ROA*) in the year immediately prior to the IPO and that in the first year after the IPO. A higher value of *Droa* indicates a greater decline in the firm's post-IPO performance.

3.2.2. IPO audit contingent fees

As previously discussed, IPO audit contingent fees (*Ctgfee*) are calculated as the total audit fees paid for the IPO minus three times the firm's first year annual audit fees after the IPO, standardized by the total assets in the year prior to the IPO. In our robustness tests, we adopt alternative measures, including the use of (i) the cumulative audit fees over the first three post-IPO years as the deduction item and (ii) the abnormal audit fees estimated from a residual-based model. The results remain consistent.

3.2.3. Control variables

Following Fang (2014), Shao et al. (2014) and Liu et al. (2019), the following variables are included as control variables in our regression analysis: IPO proceeds (*Proceed*), firm size (*Size*), debt-to-asset ratio (*Lev*), profitability (*Roe*), operational risk (*Risk*), ownership structure (*Soe*), firm age (*Age*), Big 10 audit firm indicator (*Big10*), underwriting fees (*Uwfee*), legal fees (*Atfee*), disclosure expenses (*Inftee*) and other fees (*Otftee*). Detailed variable definitions are presented in Table 2.

3.3. Research design

Following Lu et al. (2015) and Liu et al. (2019), the following empirical model is used to examine how IPO audit contingent fees affect earnings reversal:

$$Droa = \beta_0 + \beta_1 Ctgfee + \gamma Controls + Industry + Listyear + Board + \varepsilon_{it} \quad (1)$$

Here, the dependent variable is earnings reversal (*Droa*), where a higher value indicates a more pronounced decline in post-IPO performance. The key explanatory variable is the IPO audit contingent fees (*Ctgfee*). A significant positive coefficient of *Ctgfee* would suggest that higher contingent fees are associated with compromised auditor independence and a more severe earnings reversal. We include a set of firm-level control variables (*Controls*), along with industry fixed effects (*Industry*), IPO year fixed effects (*Ipoyear*) and listing board fixed effects (*Board*). Standard errors are clustered at the firm level.

4. Empirical results

4.1. Descriptive statistics

Table 3 reports the descriptive statistics. The mean value of *Droa* is 0.068, with a 25th percentile of 0.025, indicating that at least 75 % of sample firms experience a significant post-IPO performance decline; in other words, earnings reversal is prevalent among IPO firms. The mean value of *Ctgfee* is 0.005, with a 25th percentile of 0.001, implying that at least 75 % of firms incur contingent audit fees during IPOs. The mean value of *Big10* is 0.67, suggesting that 67 % of IPOs are audited by top-10 accounting firms. The descriptive statistics for the remaining variables are consistent with those reported in prior studies (Liu et al., 2019; Mao et al., 2024).

4.2. Validity test of the IPO audit contingent fee variable

To further validate *Ctgfee* as a measure, we seek preliminary evidence from both firm-level and audit firm-level perspectives.

If a higher IPO audit contingent fee implies a larger conflict of interest and greater impairment of auditors' independence, then firms with higher IPO audit contingent fees should exhibit lower earnings quality and face higher risks of financial restatements and litigation. To test this conjecture, we construct several indicators. First, we measure earnings quality as the average level of real earnings management (*Rem*) and as accrual-based earnings management. As a proxy for the latter, we use the absolute values of residuals from the Jones model (*Absda1*) and the performance-adjusted Jones model (*Absda2*). Second, we measure financial restatement using the incidence of restatements (*Restateif*) and the average number of restatements (*Restaten*) within three years after the IPO. Third, litigation risk is proxied by the incidence of litigation cases (*Sueif*) and the

Table 3
Descriptive statistics.

Variable	N	Mean	Std	p1	p25	p50	p75	p99
<i>Droa</i>	2374	0.068	0.067	-0.085	0.025	0.055	0.100	0.333
<i>Ctgfee</i>	2374	0.005	0.006	-0.003	0.001	0.003	0.006	0.028
<i>Proceed</i>	2374	10.946	0.723	9.613	10.433	10.857	11.371	13.162
<i>Size</i>	2374	20.379	0.992	18.421	19.724	20.233	20.870	23.891
<i>Roe</i>	2374	0.225	0.100	-0.009	0.159	0.209	0.277	0.569
<i>Lev</i>	2374	0.433	0.165	0.097	0.308	0.434	0.554	0.801
<i>Age</i>	2374	2.509	0.501	0.693	2.303	2.565	2.833	3.401
<i>Soe</i>	2374	0.086	0.281	0	0	0	0	1
<i>Big10</i>	2374	0.670	0.470	0	0	1	1	1
<i>Uwfee</i>	2374	2.106	0.066	1.945	2.061	2.101	2.146	2.291
<i>Atfee</i>	2374	1.687	0.144	1.291	1.586	1.700	1.797	1.960
<i>Inftee</i>	2374	1.793	0.051	1.605	1.768	1.800	1.822	1.927
<i>Otftee</i>	2374	1.113	0.559	0	1.023	1.318	1.469	1.889

This table reports the summary statistics of variables in the baseline regression. All continuous variables are winsorized at the 1st and 99th percentiles. Std, standard deviation. p, percentile.

Table 4
Validity test of IPO audit contingent fees.

Panel A: Earnings quality				
Variable	Lower IPO audit contingent fees	Higher IPO audit contingent fees	Mean difference	p-value
<i>Rem</i>	0.004	0.006	0.002	0.002***
<i>Absda1</i>	0.047	0.050	0.003	0.039**
<i>Absda2</i>	0.044	0.049	0.005	0.001***
Panel B: Financial restatement				
Variable	Lower IPO audit contingent fees	Higher IPO audit contingent fees	Mean difference	p-value
<i>Restateif</i>	0.223	0.227	0.003	0.049**
<i>Restaten</i>	0.307	0.317	0.010	0.092*
Panel C: Litigation risk				
Variable	Lower IPO audit contingent fees	Higher IPO audit contingent fees	Mean difference	p-value
<i>Sueif</i>	0.071	0.083	0.012	0.052*
<i>Suen</i>	0.195	0.277	0.082	0.094*
Panel D: China Securities Regulatory Commission penalty for IPO audit contingent fees				
Variable	Accounting firm was not penalized	The accounting firm was penalized	Mean difference	p-value
<i>Ctgfee</i>	0.004	0.005	0.001	0.021**

This table reports the results of validation of the IPO audit contingent fee variable (*Ctgfee*). Values are the means of the corresponding variables. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

average annual number of litigation cases (*Suen*) over the same three-year period. Panels A to C of Table 4 report the results. The findings indicate that both real and accrual-based earnings management are significantly lower in the group with lower IPO audit contingent fees than in the group with higher fees, demonstrating that lower IPO audit contingent fees are associated with higher earnings quality. Similarly, the likelihood and frequency of financial restatements and litigation are significantly lower when IPO audit contingent fees are lower, suggesting that lower contingent fees are associated with lower levels of post-IPO financial restatement and legal risk.

Because audit engagement contracts are not publicly disclosed, it is difficult to directly identify the contractual characteristics of IPO audit contingent fees. Since 2023, however, the CSRC has prioritized its inspections of such fee practices and identified firms suspected of engaging in IPO audit contingent fee arrangements. Logically, if the CSRC's identification is informative, then these identified firms should have significantly higher IPO audit contingent fees. Consistent with this expectation, Panel D of Table 4 shows that firms audited by audit firms that received CSRC warnings exhibit significantly higher levels of IPO audit contingent fees than other firms.

4.3. Baseline regression

Table 5 reports how IPO audit contingent fees (*Ctgfee*) affect post-IPO earnings reversal. Column (1) presents the regression estimates when control variables are excluded, and a significant positive coefficient on *Ctgfee* is observed. This suggests that higher IPO audit contingent fees are associated with greater post-IPO earnings reversal. Columns (2) and (3) introduce firm-level control variables and other IPO-related fees, and in both columns, the coefficient on *Ctgfee* remains positive and significant at the 1 % statistical level, indicating the robustness of the baseline results. With respect to economic significance, Column (3) shows that a one-standard-deviation increase in *Ctgfee* is associated with a 0.65 % decline in post-IPO performance, which is equivalent to 9.55 % of the sample mean of the dependent variable. Consistent with Hypothesis 1 (H1), these findings indicate that IPO audit contingent fees exacerbate conflicts of interest between auditors and stakeholders, undermine audit independence and ultimately contribute to post-IPO earnings reversal.

Table 5
Baseline regression.

	(1)	(2)	(3)
	<i>Droa</i>	<i>Droa</i>	<i>Droa</i>
<i>Ctgfee</i>	3.419*** (11.287)	1.124*** (4.124)	1.082*** (3.770)
<i>Proceed</i>		0.022*** (8.433)	0.018*** (5.271)
<i>Size</i>		-0.020*** (-8.572)	-0.019*** (-8.335)
<i>Roe</i>		0.298*** (16.607)	0.299*** (16.619)
<i>Lev</i>		-0.079*** (-10.413)	-0.080*** (-10.426)
<i>Age</i>		-0.001 (-0.347)	-0.001 (-0.306)
<i>Soe</i>		-0.002 (-0.675)	-0.002 (-0.596)
<i>Big10</i>		-0.003 (-1.294)	-0.003 (-1.266)
<i>Uwfee</i>			0.048* (1.697)
<i>Atfee</i>			0.001 (0.059)
<i>Inftee</i>			0.001 (0.051)
<i>Otftee</i>			0.000 (0.236)
<i>Constant</i>	0.052*** (28.570)	0.194*** (5.745)	0.126* (1.951)
<i>Industry</i>	Yes	Yes	Yes
<i>Ipyear</i>	Yes	Yes	Yes
<i>Board</i>	Yes	Yes	Yes
<i>N</i>	2374	2374	2374
<i>R²_a</i>	0.176	0.511	0.511

This table reports the results of empirical testing of the relation between IPO audit contingent fees and earning reversal. Detailed variable definitions are given in Table 2. The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

4.4. Robustness tests

4.4.1. Instrumental variable estimation

To further mitigate concerns of potential endogeneity in the relationship between IPO audit contingent fees and post-IPO earnings reversal, we use the lagged regional IPO withdrawal ratio as an IV and estimate a 2SLS regression. The regional IPO withdrawal ratio influences auditors' pricing decisions, thus satisfying the relevance condition, but plausibly does not affect other firms' post-IPO performance. Table 6 reports the results of IV regression. Column (1) exhibits a positive and highly significant coefficient on the IV (*Fail*), with a Kleibergen–Paap rk LM *F*-statistic of 23.143. Column (2) presents the second-stage results: the coefficient on *Ctgfee* remains positive and significant at the 10 % level, confirming the main findings of the baseline regression.

4.4.2. Alternative measurement of the dependent variable

Table 7 presents the results obtained using alternative measures of post-IPO earnings reversal. First, following Xiong and Yang (2017), we construct a dummy variable (*Droadummy*), which is assigned a value of 1 if a firm experiences a post-IPO earnings reversal and 0 otherwise. Column (1) of Table 7 reports the results of logit regression. The coefficient on *Ctgfee* is positive and significant ($p < 0.1$), indicating that IPO audit contingent fees significantly increase the probability of post-IPO earnings reversal. Second, following Liu et al.

Table 6
Instrumental variable estimation.

	(1)	(2)
	<i>Ctgfee</i>	<i>Droa</i>
<i>Fail</i>	0.002*** (3.625)	
<i>Ctgfee</i>		−6.164* (−1.748)
<i>Proceed</i>	−0.001** (−2.062)	0.014*** (2.985)
<i>Size</i>	−0.003*** (−15.429)	−0.040*** (−3.825)
<i>Roe</i>	0.003** (2.283)	0.318*** (13.475)
<i>Lev</i>	−0.001** (−2.050)	−0.089*** (−8.853)
<i>Age</i>	0.000 (0.533)	0.000 (0.067)
<i>Soe</i>	0.001*** (3.286)	0.005 (0.854)
<i>Big10</i>	0.001*** (4.434)	0.003 (0.861)
<i>Uwfee</i>	0.005** (2.004)	0.083** (2.121)
<i>Atfee</i>	0.012*** (13.689)	0.088** (2.005)
<i>Infee</i>	0.011*** (5.611)	0.080* (1.647)
<i>Otfee</i>	0.000 (0.495)	0.001 (0.375)
<i>Industry</i>	Yes	Yes
<i>Ipoyear</i>	Yes	Yes
<i>Board</i>	Yes	Yes
<i>N</i>	2374	2374
<i>Kleibergen–Paap rk LM F</i>	23.143	

This table reports the results of empirical IV estimation. The IV (*Fail*) is defined as the previous-year regional IPO withdrawal ratio. In column (1), the relation between IV and IPO audit contingent fees is tested. In column (2), the second-stage (2SLS) results of IV estimation are presented. The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

(2019), we measure *Droa2* as the difference between the mean return on assets in the two years after the IPO and that in the two years immediately prior to the IPO. *Droe* is measured as the difference between the return on equity in the year after the IPO and that in the year immediately prior to the IPO. Columns (2) and (3) of Table 7 report the regression results when *Droa2* and *Droe* are used to measure earnings reversals, respectively. The estimated coefficient on IPO audit contingent fees (*Ctgfee*) remains positive and significant ($p < 0.1$). To account for industry effects, we also use the industry-adjusted return on assets (*Droa_ind*) as the measure, and Column (4) of Table 7 shows that the coefficient on *Ctgfee* remains positive and significant ($p < 0.05$). These results collectively confirm our main conclusion that higher IPO audit contingent fees are associated with more severe post-IPO earnings reversals.

4.4.3. Alternative measurement of the explanatory variable

To reduce measurement error in the key explanatory variable, we construct four alternative measures of IPO audit contingent fees, following Liu et al. (2019) and Chen et al. (2022). First, we calculate *Ctgfee2* as the total IPO audit fees minus the sum of audit fees in the three years post-IPO, scaled by the total assets

Table 7
Alternative measurement of the dependent variable.

	(1) <i>Droadummy</i>	(2) <i>Droa2</i>	(3) <i>Droe</i>	(4) <i>Droa_ind</i>
<i>Ctgfee</i>	45.636* (1.808)	0.600* (1.833)	0.734* (1.652)	2.166** (2.180)
<i>Proceed</i>	0.447* (1.818)	0.002 (0.472)	-0.018*** (-3.314)	0.026** (2.273)
<i>Size</i>	-0.605*** (-3.900)	-0.006* (-1.687)	0.007* (1.916)	-0.018*** (-2.734)
<i>Roe</i>	9.664*** (5.629)	0.395*** (16.225)	0.138*** (5.390)	0.294*** (5.654)
<i>Lev</i>	-2.448*** (-3.983)	-0.140*** (-12.522)	-0.040*** (-3.091)	-0.081*** (-3.026)
<i>Age</i>	0.131 (0.654)	-0.003 (-1.231)	-0.009** (-2.511)	0.018** (2.098)
<i>Soe</i>	0.146 (0.515)	-0.004 (-1.016)	-0.007 (-1.269)	-0.028** (-2.482)
<i>Big10</i>	-0.114 (-0.644)	-0.001 (-0.241)	-0.003 (-0.791)	-0.007 (-0.780)
<i>Uwfee</i>	-4.673** (-1.969)	0.009 (0.309)	0.059 (1.219)	-0.057 (-0.537)
<i>Atfee</i>	2.458*** (3.154)	0.006 (0.544)	0.010 (0.622)	-0.031 (-0.907)
<i>Infee</i>	4.301* (1.892)	-0.003 (-0.122)	0.054 (1.385)	-0.058 (-0.651)
<i>Otfee</i>	-0.262 (-1.274)	0.000 (0.126)	-0.001 (-0.452)	0.008 (1.176)
Constant	5.882 (1.131)	0.114* (1.646)	-0.134 (-1.346)	0.335 (1.598)
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Ipyear</i>	Yes	Yes	Yes	Yes
<i>Board</i>	Yes	Yes	Yes	Yes
<i>N</i>	2359	2016	2372	2368
<i>R²_alR²_p</i>	0.272	0.533	0.072	0.306

This table reports the results of empirical testing of alternative measures of earning reversal. In column (1), earnings reversal is measured using an indicator variable of whether the sample firm experienced an earning reversal. In column (2), it is measured as the difference between the mean return on assets in the two years after the IPO and that in the two years immediately prior to the IPO. In column (3), it is measured as the difference between the mean return on equity in the years after the IPO and that in the years immediately prior to the IPO. In column (4), an industry-adjusted return on assets measure is used. The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10%, 5% and 1% two-tailed levels, respectively.

in the year prior to listing. Second, *Ctgfee3* captures abnormal audit fees estimated from an audit pricing model that controls for firm size, business complexity and inventory ratio, calculated by industry-year. Third, to address negative values in the original IPO audit contingent fees, *Ctgfee4* replaces all negative values with 0. Fourth, we construct a dummy variable, *Hctgfee*, based on the median of *Ctgfee*, assigning a value of 1 for samples above the median and 0 otherwise. Columns (1) to (4) of Table 8 report the empirical results and show that our conclusions remain robust to these alternative measures.

4.4.4. Controlling for omitted variables

To address omitted variables related to auditor characteristics and regional economic conditions, we incorporate additional control variables. First, as firms may change their auditors after the IPO, we include a dummy variable (*Change*) that equals 1 if a firm's auditor is replaced and 0 otherwise. Second, regional economic characteristics may simultaneously affect both IPO audit contingent fees and a firm's post-IPO performance. We therefore control for a series of regional economic characteristic variables, including the regional

Table 8
Alternative measures of the explanatory variable.

	(1) <i>Droa</i>	(2) <i>Droa</i>	(3) <i>Droa</i>	(4) <i>Droa</i>
<i>Ctgfee2</i>	0.667* (1.874)			
<i>Ctgfee3</i>		0.006** (2.321)		
<i>Ctgfee4</i>			1.146*** (3.894)	
<i>Hctgfee</i>				0.005* (1.891)
<i>Proceed</i>	0.026*** (6.008)	0.018*** (5.194)	0.018*** (5.265)	0.018*** (5.166)
<i>Size</i>	-0.022*** (-7.493)	-0.021*** (-8.889)	-0.019*** (-8.241)	-0.021*** (-8.924)
<i>Roe</i>	0.267*** (12.445)	0.288*** (15.072)	0.299*** (16.619)	0.302*** (16.561)
<i>Lev</i>	-0.091*** (-10.689)	-0.083*** (-9.812)	-0.080*** (-10.387)	-0.082*** (-10.584)
<i>Age</i>	0.000 (0.156)	-0.001 (-0.232)	-0.001 (-0.303)	-0.001 (-0.277)
<i>Soe</i>	-0.002 (-0.500)	-0.001 (-0.292)	-0.002 (-0.592)	-0.001 (-0.371)
<i>Big10</i>	-0.003 (-1.367)	-0.002 (-0.932)	-0.003 (-1.284)	-0.002 (-1.014)
<i>Uwfee</i>	0.008 (0.269)	0.041 (1.347)	0.048* (1.670)	0.050* (1.759)
<i>Atfee</i>	0.006 (0.572)	-0.003 (-0.289)	0.001 (0.055)	0.009 (0.943)
<i>Infee</i>	-0.017 (-0.642)	0.007 (0.233)	0.002 (0.056)	0.009 (0.340)
<i>Otfee</i>	0.000 (0.215)	0.001 (0.435)	0.000 (0.239)	0.001 (0.298)
<i>Constant</i>	0.210*** (2.990)	0.181*** (2.627)	0.123* (1.900)	0.138** (2.113)
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Ipayear</i>	Yes	Yes	Yes	Yes
<i>Board</i>	Yes	Yes	Yes	Yes
<i>N</i>	1672	2108	2374	2374
<i>R²_a</i>	0.545	0.495	0.511	0.507

This table reports the results of empirical testing of alternative measures of IPO audit contingent fees. In Column (1), *Ctgfee2* is calculated as the difference between the total IPO audit fees and the sum of the actual audit fees over the three years post-IPO, scaled by total assets in the year prior to the IPO. In Column (2), *Ctgfee3* represents abnormal audit fees, measured as the residuals estimated using an audit pricing model. In Column (3), *Ctgfee4* is left-censored at 0 to exclude negative values. In Column (4), *Hctgfee* is constructed using the median value of *Ctgfee*, and samples are assigned a value of 1 if *Ctgfee* exceeds the median and 0 otherwise. The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

GDP (*Gdp*), proportion of the primary industry (*First*) and proportion of the secondary industry (*Second*). Finally, we include regional fixed effects in Column (3). The results in Table 9 further confirm the robustness of our earlier findings.

4.4.5. Quantile regression

As the descriptive statistics indicate right skewness, ordinary least squares (OLS) regression may not yield the most efficient and unbiased estimates. Following Bi and Yu (2016), we use quantile regression to examine how IPO audit contingent fees (*Ctgfee*) affect post-IPO earnings reversals. Table 10 reports the quantile regression results from the 10th to 90th percentiles. Columns (1) to (5) show that the coefficients on *Ctgfee* are con-

Table 9
Controlling for omitted variables.

	(1)	(2)	(3)
	<i>Droa</i>	<i>Droa</i>	<i>Droa</i>
<i>Ctgfee</i>	1.092*** (3.802)	0.982*** (3.417)	1.083*** (3.572)
<i>Proceed</i>	0.018*** (5.278)	0.018*** (5.071)	0.018*** (4.650)
<i>Size</i>	-0.019*** (-8.359)	-0.020*** (-8.156)	-0.019*** (-7.375)
<i>Roe</i>	0.300*** (16.656)	0.312*** (15.751)	0.316*** (15.695)
<i>Lev</i>	-0.080*** (-10.377)	-0.077*** (-9.342)	-0.079*** (-8.969)
<i>Age</i>	-0.001 (-0.313)	-0.000 (-0.040)	0.001 (0.344)
<i>Soe</i>	-0.002 (-0.638)	-0.000 (-0.049)	-0.003 (-0.643)
<i>Big10</i>	-0.003 (-1.233)	-0.003 (-1.435)	-0.003 (-1.290)
<i>Uwfee</i>	0.049* (1.703)	0.040 (1.316)	0.031 (0.932)
<i>Atfee</i>	0.001 (0.064)	0.004 (0.401)	0.010 (0.869)
<i>Inftee</i>	0.001 (0.035)	0.019 (0.664)	0.040 (1.303)
<i>Otftee</i>	0.000 (0.218)	0.002 (0.879)	0.003 (1.127)
<i>Change</i>	0.004 (1.083)		
<i>Gdp</i>		0.009** (2.331)	0.024 (0.987)
<i>First</i>		-0.008 (-0.154)	-0.217 (-1.014)
<i>Second</i>		-0.019 (-1.331)	-0.034 (-0.740)
<i>Pergdp</i>		-0.017** (-2.489)	-0.032 (-1.433)
<i>People</i>		-0.011*** (-2.742)	-0.015 (-0.819)
<i>Gdpgrowth</i>		0.068** (2.448)	0.024 (0.987)
<i>Constant</i>	0.127* (1.956)	0.205** (2.330)	0.116 (0.428)
<i>Industry</i>	Yes	Yes	Yes
<i>Ipyear</i>	Yes	Yes	Yes
<i>Board</i>	Yes	Yes	Yes
<i>City</i>	No	No	Yes
<i>N</i>	2374	2112	2028
<i>R²_a</i>	0.511	0.523	0.525

This table reports the empirical results of tests incorporating additional control variables. In Column (1), we add the dummy variable *Change* to control for auditor turnover. In Column (2), we include a series of regional economic characteristic variables. In Column (3), we further incorporate regional fixed effects. The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

Table 10
Quantile regression.

	(1)	(2)	(3)	(4)	(5)
	<i>Q10</i>	<i>Q30</i>	<i>Q50</i>	<i>Q70</i>	<i>Q90</i>
	<i>Droa</i>	<i>Droa</i>	<i>Droa</i>	<i>Droa</i>	<i>Droa</i>
<i>Ctgfee</i>	0.081 (0.301)	0.359 (1.315)	0.397 (1.406)	0.796*** (2.598)	1.532** (2.363)
<i>Proceed</i>	0.014*** (3.718)	0.014*** (4.708)	0.017*** (4.361)	0.013*** (3.023)	0.010* (1.720)
<i>Size</i>	-0.013*** (-5.032)	-0.017*** (-7.956)	-0.017*** (-6.547)	-0.014*** (-4.496)	-0.014*** (-2.799)
<i>Roe</i>	0.121*** (5.418)	0.202*** (10.008)	0.267*** (12.051)	0.322*** (12.845)	0.404*** (10.368)
<i>Lev</i>	-0.048*** (-5.698)	-0.064*** (-8.399)	-0.080*** (-11.290)	-0.091*** (-9.859)	-0.078*** (-4.785)
<i>Age</i>	0.000 (0.178)	-0.002 (-1.001)	-0.006*** (-2.662)	-0.007** (-2.426)	-0.003 (-0.533)
<i>Soe</i>	-0.004 (-1.325)	-0.006** (-2.072)	-0.006 (-1.477)	0.003 (0.390)	0.009 (1.054)
<i>Big10</i>	-0.002 (-0.740)	-0.002 (-0.897)	-0.002 (-0.192)	-0.003 (-1.254)	-0.001 (-0.201)
<i>Uwfee</i>	-0.014 (-0.440)	0.037 (1.336)	0.042 (1.479)	0.089** (2.549)	0.137*** (2.680)
<i>Atfee</i>	0.003 (0.313)	-0.008 (-0.709)	0.002 (0.179)	-0.002 (-0.104)	-0.004 (-0.186)
<i>Infee</i>	0.030 (1.188)	-0.023 (-0.946)	-0.019 (-0.664)	-0.020 (-0.677)	-0.019 (-0.317)
<i>Otfee</i>	0.000 (0.219)	0.003* (1.651)	0.002 (1.360)	0.013*** (3.023)	0.004 (1.076)
<i>Constant</i>	0.137** (2.011)	0.197*** (3.248)	0.164** (2.538)	0.150 (1.645)	0.072 (0.521)
<i>Industry</i>	Yes	Yes	Yes	Yes	Yes
<i>Ipyear</i>	Yes	Yes	Yes	Yes	Yes
<i>Board</i>	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2150	2150	2150	2150	2150
<i>R²_p</i>	0.176	0.261	0.324	0.373	0.411

This table reports the results of quantile regression across the 10th to 90th percentiles with respect to IPO audit contingent fees (*Ctgfee*). The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

sistently positive and gradually increase with higher quantiles, indicating that the impact of IPO audit contingent fees intensifies as the severity of post-IPO earnings reversal increases. At the 70th and 90th percentiles, these coefficients are positive and significant at the 5 % level or higher, suggesting that *Ctgfee* exerts a more pronounced impact on when firms experience more severe post-IPO earnings reversals.

4.4.6. Alternative sample sensitivity

To further check the robustness of our findings, we conduct additional sample-specific sensitivity tests. First, some observations of *Ctgfee* are negative, which may undermine the reliability of the results; accordingly, we re-run the analysis using only samples with a *Ctgfee* value greater than 0. Second, given the disruptive impact of the COVID-19 pandemic on auditors' work and firms' operations, we exclude post-2019 IPOs from our sample. Finally, to address potential distortions caused by the global financial crisis, we exclude IPOs listed during and before 2008. Table 11 presents the corresponding results. Overall, our remain findings remain unchanged when we use these alternative samples.

Table 11
Alternative sample sensitivity.

	(1) <i>Ctgfee</i> > 0 <i>Droa</i>	(2) 2006–2019 <i>Droa</i>	(3) 2009–2021 <i>Droa</i>
<i>Ctgfee</i>	1.121*** (3.528)	0.703* (1.914)	1.107*** (3.855)
<i>Proceed</i>	0.019*** (5.125)	0.026*** (6.033)	0.018*** (5.451)
<i>Size</i>	−0.021*** (−7.540)	−0.022*** (−7.393)	−0.020*** (−8.354)
<i>Roe</i>	0.294*** (14.654)	0.267*** (12.419)	0.299*** (16.413)
<i>Lev</i>	−0.075*** (−8.581)	−0.091*** (−10.700)	−0.077*** (−10.056)
<i>Age</i>	−0.002 (−0.882)	0.000 (0.163)	−0.001 (−0.611)
<i>Soe</i>	−0.002 (−0.591)	−0.002 (−0.506)	−0.002 (−0.522)
<i>Big10</i>	−0.001 (−0.606)	−0.003 (−1.389)	−0.003 (−1.431)
<i>Uwfee</i>	0.066** (2.132)	0.008 (0.259)	0.043 (1.541)
<i>Atfee</i>	0.004 (0.363)	0.005 (0.509)	0.001 (0.130)
<i>Infee</i>	−0.029 (−0.923)	−0.018 (−0.666)	0.009 (0.322)
<i>Otfee</i>	0.001 (0.636)	0.000 (0.188)	0.000 (0.175)
<i>Constant</i>	0.161** (2.159)	0.207*** (2.952)	0.122* (1.842)
<i>Industry</i>	Yes	Yes	Yes
<i>Listyear</i>	Yes	Yes	Yes
<i>Board</i>	Yes	Yes	Yes
<i>N</i>	2031	1672	2325
<i>R²_a</i>	0.511	0.546	0.512

This table reports the results obtained with alternative sample constructions. In Column (1), we exclude observations with negative *Ctgfee* values. In Column (2), we exclude post-2019 IPOs to mitigate the impact of the COVID-19 pandemic. In Column (3), we exclude IPOs listed in 2008 or earlier to address the potential effects of the global financial crisis. The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

5. Heterogeneity analysis

5.1. Regulatory effectiveness

To address prominent issues such as substandard IPO listings, regulatory authorities have implemented various measures to strengthen regulatory oversight, including IPO inquiry reviews, on-site inspections of IPOs and the “double random, one public” supervision mechanism. This scenario naturally gives rise to a critical question: Can effective regulation mitigate concerns about collusion between auditors and IPO firms, thereby attenuating the exacerbating impact of IPO audit contingent fees on post-IPO earnings reversals? To answer this question, we examine the effectiveness of regulatory measures in three dimensions: regulatory geographic proximity, IPO on-site inspections and IPO review inquiries.

First, we consider regulatory geographic proximity. Studies suggest that the marginal costs of information search and processing increase as the geographic distance between regulators and regulated firms also

increases (Agarwal and Hauswald, 2010), a situation that exacerbates information asymmetry and may ultimately lead to regulatory ineffectiveness. Following Xiao et al. (2021), we calculate regulatory distance as the geographic distance between a firm's registered address and the local office of the CSRC and construct a dummy variable ($Hdis$), which is assigned a value of 1 if the distance for a given observation exceeds the sample median and 0 otherwise. Column (1) of Table 12 shows that the coefficient of the interaction term ($Hctgfee \times Hdis$) is positive and significant at the 1 % level. This indicates that a greater regulatory distance leads to a stronger exacerbating effect of IPO audit contingent fees on earnings reversals.

Second, we consider IPO on-site inspections. Research indicates that such inspections can effectively identify potential issues in newly listed companies while clarifying the responsibilities of intermediary institutions (Wang et al., 2025). For instance, the 2024 on-site inspection of Changchun Zhuoyi Bio Co., Ltd. revealed related-party transactions and accounting irregularities, prompting regulators to issue a regulatory letter to the Lixin Accounting Firm, which provided accounting services, and its engaged signing CPAs. The implication is that auditors face heightened regulatory pressure when their clients are selected for on-site inspections, which motivates them to increase their diligence and the strictness of their audit procedures during IPO engagements, ultimately reducing the likelihood of substandard listings. Following Wang et al. (2025), we measure inspection intensity as the number of an audit firm's IPO projects selected for on-site inspections. We then construct a dummy variable ($Inspect$), which is assigned a value of 1 if this number exceeds the sample median and 0 otherwise. Column (2) of Table 12 shows that the interaction term ($Hctgfee \times Inspect$) is negative and significant at the 10 % level, indicating that on-site inspections can deter auditors' potential opportunistic behavior and mitigate the amplifying effect of IPO audit contingent fees on post-IPO earnings reversals.

Finally, we consider IPO review inquiries. In practice, inquiry review is an important mechanism of enhancing information disclosure (Xue and Wang, 2022). Accordingly, IPO review inquiries are expected to reduce information asymmetry and curb pre-IPO earnings manipulation. Following Xue and Wang (2022), we construct a dummy variable, IA , to indicate whether a firm received IPO review inquiries prior to its listing. Column (3) of Table 12 shows that the coefficient on the interaction term ($Hctgfee \times IA$) is negative and significant at the 1 % level, indicating that IPO review inquiries mitigate the effect of IPO audit contingent fees on post-IPO earnings reversals.

Overall, these findings indicate that effective regulation improves IPO quality by curbing potential collusion between auditors and IPO firms, thereby enhancing the overall quality of the IPO firms.

5.2. Nature of property rights

Property rights are a crucial determinant of corporate governance in China, where firms with different ownership structures face distinct incentives and constraints (Xin et al., 2007). Compared with non-SOEs, SOEs are more likely to obtain IPO approval due to their inherent political advantages (Huang and Li, 2016) and are subject to more stringent external oversight and stricter audit scrutiny due to their greater non-economic responsibilities (Li and Zhou, 2013). In contrast, non-SOEs are driven by a stronger demand for external financing and thus more motivated to engage in earnings manipulation to secure their listing objectives. Consequently, we expect IPO audit contingent fees to be more likely to induce post-IPO earnings reversals in non-SOEs than in SOEs.

Accordingly, we construct a dummy variable ($Hctgfee$) to denote high IPO audit contingent fees, using the sample median as the cutoff, and interact this with the property rights nature variable (Soe). Column (1) of Table 13 shows that the estimated coefficient of the interaction term ($Hctgfee \times Soe$) is negative and significant ($p < 0.1$). This result indicates that IPO audit contingent fees significantly attenuate post-IPO earnings reversals in SOEs.

5.3. Information quality

The information quality hypothesis posits that investors have limited access to a firm's information prior to its IPO, which is due to information asymmetry between investors and issuers. Investors thus rely primarily on disclosures in the IPO prospectus when assessing a firm's value (Zhang, 2019). Consequently, when informa-

Table 12
Heterogeneous effects of regulatory effectiveness.

	(1)	(2)	(3)
	<i>Droa</i>	<i>Droa</i>	<i>Droa</i>
<i>Hctgfee</i>	0.002 (0.686)	0.006** (2.276)	0.007** (2.490)
<i>Hctgfee</i> × <i>Hdis</i>	0.010*** (3.041)		
<i>Hctgfee</i> × <i>Inspect</i>		−0.010* (−1.702)	
<i>Hctgfee</i> × <i>IA</i>			−0.009** (−2.106)
<i>Hdis</i>	0.002 (0.785)		
<i>Inspect</i>		0.007 (1.554)	
<i>IA</i>			0.004 (0.917)
<i>Proceed</i>	0.017*** (5.118)	0.018*** (5.190)	0.018*** (5.180)
<i>Size</i>	−0.021*** (−8.899)	−0.021*** (−8.887)	−0.021*** (−8.907)
<i>Roe</i>	0.302*** (16.572)	0.302*** (16.585)	0.302*** (16.539)
<i>Lev</i>	−0.081*** (−10.414)	−0.082*** (−10.656)	−0.081*** (−10.504)
<i>Age</i>	−0.001 (−0.295)	−0.001 (−0.271)	−0.001 (−0.287)
<i>Soe</i>	−0.002 (−0.507)	−0.002 (−0.482)	−0.001 (−0.316)
<i>Big10</i>	−0.002 (−1.122)	−0.002 (−1.055)	−0.002 (−0.966)
<i>Uwfee</i>	0.047 (1.643)	0.050* (1.748)	0.049* (1.728)
<i>Atfee</i>	0.011 (1.089)	0.010 (1.020)	0.010 (0.988)
<i>Inftee</i>	0.008 (0.288)	0.009 (0.343)	0.008 (0.311)
<i>Otftee</i>	0.001 (0.325)	0.001 (0.285)	0.001 (0.268)
<i>Constant</i>	0.144** (2.209)	0.136** (2.083)	0.139** (2.134)
<i>Industry</i>	Yes	Yes	Yes
<i>Ipayear</i>	Yes	Yes	Yes
<i>Board</i>	Yes	Yes	Yes
<i>N</i>	2374	2374	2374
<i>R²_a</i>	0.508	0.507	0.507

This table reports the heterogeneous effects of regulatory effectiveness in three dimensions. In Column (1), we consider the effects of geographic regulatory proximity. In Column (2), we consider the impact of IPO on-site inspections. In Column (3), we consider the role of IPO review inquiries. The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

Table 13
Heterogeneous effects of property rights, information quality and perceived EPU.

	(1)	(2)	(3)
	<i>Droa</i>	<i>Droa</i>	<i>Droa</i>
<i>Hctgfee</i>	0.006** (2.272)	-0.001 (-0.418)	0.005 (1.564)
<i>Hctgfee</i> × <i>Soe</i>	-0.011* (-1.675)		
<i>Hctgfee</i> × <i>Hda</i>		0.011*** (3.188)	
<i>Hctgfee</i> × <i>Hepu</i>			0.006* (1.912)
<i>Hda</i>		-0.000 (-0.059)	
<i>Hepu</i>			0.001 (0.524)
<i>Proceed</i>	0.018*** (5.191)	0.017*** (5.037)	0.018*** (5.173)
<i>Size</i>	-0.022*** (-9.066)	-0.021*** (-8.684)	-0.021*** (-8.909)
<i>Roe</i>	0.302*** (16.558)	0.297*** (16.195)	0.302*** (16.539)
<i>Lev</i>	-0.081*** (-10.497)	-0.084*** (-10.775)	-0.082*** (-10.574)
<i>Age</i>	-0.001 (-0.235)	-0.000 (-0.137)	-0.001 (-0.279)
<i>Soe</i>	0.004 (1.031)	-0.001 (-0.362)	-0.001 (-0.400)
<i>Big10</i>	-0.002 (-0.938)	-0.002 (-1.132)	-0.002 (-1.014)
<i>Uwfee</i>	0.050* (1.761)	0.046 (1.622)	0.050* (1.747)
<i>Atfee</i>	0.009 (0.912)	0.009 (0.928)	0.009 (0.957)
<i>Inftee</i>	0.008 (0.308)	0.008 (0.289)	0.009 (0.342)
<i>Otftee</i>	0.000 (0.221)	0.001 (0.363)	0.001 (0.289)
<i>Constant</i>	0.148** (2.256)	0.143** (2.183)	0.138** (2.117)
<i>Industry</i>	Yes	Yes	Yes
<i>Ipoyear</i>	Yes	Yes	Yes
<i>Board</i>	Yes	Yes	Yes
<i>N</i>	2374	2374	2374
<i>R²_a</i>	0.508	0.510	0.506

This table reports the heterogeneous effects of property rights, information quality and perceived EPU. In Column (1), we consider the effects of property rights. In Column (2), we consider the impact of information quality. In Column (3), we consider the role of perceived EPU. The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

tion asymmetry is more severe, firms are more likely to engage in earnings management to inflate their profitability and secure a successful IPO and more substantial financing (Zhuang et al., 2022). If this logic holds, the amplifying effect of IPO audit contingent fees on post-IPO earnings reversals should be more pronounced among firms with a higher degree of information asymmetry.

To test this expectation, we follow Gao et al. (2019) and use the modified Jones model to estimate discretionary accruals prior to a firm's IPO (DA) as a proxy for information asymmetry. We then construct a dummy variable for high information asymmetry (Hda) using the sample median as the cutoff and interact this with the variable for high IPO audit contingent fees ($Hctgfee$). Column (2) of Table 13 shows that the estimated coefficient of the interaction term ($Hctgfee \times Hda$) is positive and significant ($p < 0.01$). This result indicates that IPO audit contingent fees have a more pronounced effect on post-IPO earnings reversals among firms with a higher degree of information asymmetry.

5.4. Perceived economic policy uncertainty

Research indicates that EPU has a salient impact on corporate operations and management (Gulen and Ion, 2016; Rao et al., 2017; Nie et al., 2020). For instance, increasing EPU exacerbates information asymmetry (Li and Shi, 2016), complicates managerial decision-making and motivates managers to engage in earnings management to cope with future uncertainty, thereby increasing the likelihood of post-IPO earnings reversals. Additionally, heightened EPU influences investors' expectations unfavorably (Zhu et al., 2021), further incentivizing firms to overstate their profits to secure successful IPOs. Accordingly, the amplifying effect of IPO audit contingent fees on post-IPO earnings reversals is expected to be more pronounced for firms confronting higher levels of EPU before an IPO.

To test this expectation, we use firm-level data on perceived EPU from Nie et al. (2020) to capture cross-firm differences in this variable. A dummy variable for high perceived EPU ($Hepu$) is constructed using the sample median as the cutoff and interacted with high IPO audit contingent fees ($Hctgfee$). Column (3) of Table 13 shows that the coefficient of the interaction term ($Hctgfee \times Hepu$) is positive and significant ($p < 0.1$), indicating that higher perceived EPU amplifies the effect of IPO audit contingent fees on post-IPO earnings reversals.

6. Additional analysis

6.1. IPO speed

IPO speed is crucial for firms as it affects their ability to seize timely market opportunities. Rapid listing enables firms to secure a first-mover advantage in competitive markets and expedite capital accumulation while reducing their exposure to market volatility and policy shifts. IPO audit contingent fees may incentivize auditors and thus potentially compromise their professional independence and objectivity. Auditors seeking to secure such contingent fees may loosen their scrutiny of firms' financial statements, overlook potential financial risks or even assist in earnings management, thereby increasing the speed of IPO approval and shortening firms' IPO timelines.

To further explore the impact of IPO audit contingent fees on IPO listing speed, we construct the following empirical model:

$$P = \beta_0 + \beta_1 Ctgfee + \lambda X + Industry + Listyear + \varepsilon_i \quad (2)$$

In Eq. (2), P measures IPO speed. Following Lu et al. (2015), we construct four indicators: $P1$ is the natural logarithm of the interval from the filing submission to the listing announcement date; $P2$ is the natural logarithm of the interval from the filing submission to the CSRC approval date; $P3$ is the natural logarithm of the interval from the filing submission to the first issuance date; and $P4$ is the natural logarithm of the interval from IPO acceptance to the listing announcement date. $Ctgfee$ is the explanatory variable that captures IPO audit contingent fees. X denotes a set of control variables, with reference to Wang and Li (2016), including Roe , Lev , Soe , $Big10$, asset quality ($Quick$), cash holdings ($Cash$), western region dummy variable ($West$), $Uwfee$, $Atfee$, $Inftee$ and $Otftee$. The model also controls for industry and listing year fixed effects.

Table 14 presents the empirical results. In columns (1) to (4), the estimated coefficients of $Ctgfee$ are negative and significant at the 5% level or higher, suggesting that audit firms receiving higher contingent fees are more likely to collaborate with their client firms to expedite the IPO listing. This finding lends support to the arguments of Fang (2014) and Wang and Li (2016), who suggest that to secure timely external financing, firms

Table 14
IPO audit contingent fees and IPO speed.

	(1) <i>P1</i>	(2) <i>P2</i>	(3) <i>P3</i>	(4) <i>P4</i>
<i>Ctgfee</i>	-7.580*** (-3.005)	-7.767** (-2.533)	-7.732*** (-2.986)	-7.882** (-2.463)
<i>Roe</i>	0.273* (1.802)	0.321* (1.676)	0.285* (1.828)	0.237 (1.082)
<i>Lev</i>	-0.373*** (-2.874)	-0.415*** (-2.638)	-0.381*** (-2.863)	-0.211 (-1.164)
<i>Soe</i>	-0.011 (-0.226)	-0.038 (-0.649)	-0.012 (-0.231)	0.030 (0.441)
<i>Big10</i>	-0.032 (-1.133)	-0.041 (-1.179)	-0.032 (-1.123)	0.017 (0.440)
<i>Quick</i>	-0.055*** (-3.624)	-0.074*** (-4.051)	-0.057*** (-3.610)	-0.044** (-2.364)
<i>Cash</i>	0.201 (1.478)	0.214 (1.301)	0.205 (1.463)	0.024 (0.131)
<i>West</i>	-0.047 (-1.055)	-0.041 (-0.816)	-0.047 (-1.047)	-0.039 (-0.545)
<i>Uwfee</i>	-1.089*** (-4.578)	-1.432*** (-4.803)	-1.125*** (-4.593)	-1.656*** (-4.797)
<i>Atfee</i>	0.234* (1.875)	0.176 (1.167)	0.234* (1.827)	-0.198 (-1.021)
<i>Inftee</i>	1.300*** (2.911)	1.842*** (3.382)	1.359*** (2.962)	4.106*** (5.998)
<i>Otftee</i>	-0.283*** (-4.549)	-0.361*** (-4.739)	-0.292*** (-4.584)	-0.149* (-1.649)
<i>Constant</i>	6.364*** (7.723)	6.078*** (6.124)	6.327*** (7.470)	2.355* (1.803)
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Ipyear</i>	Yes	Yes	Yes	Yes
<i>N</i>	1522	1522	1522	1355
<i>R²_a</i>	0.279	0.324	0.279	0.273

This table reports the effects of IPO audit contingent fees on IPO speed. Four indicators are used to measure IPO speed. In Column (1), *P1* is the natural logarithm of the interval from the filing submission to the listing announcement date. In Column (2), *P2* is the natural logarithm of the interval from the filing submission to the CSRC approval date. In Column (3), *P3* is the natural logarithm of the interval from the filing submission to the first issuance date. In Column (4), *P4* is the natural logarithm of the interval from IPO acceptance to the listing announcement date. The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10%, 5% and 1% two-tailed levels, respectively.

may induce auditors to selectively overlook potential issues in financial reporting or assist in earnings management to accelerate the IPO process.

6.2. Accounting firms' audit tenure

The above analysis shows that IPO audit contingent fees accelerate IPO listing speeds but also increase the likelihood of post-IPO earnings reversals, indicating an overall negative impact on auditors' independence. Aligned with this argument, firms paying higher IPO audit contingent fees are more likely to develop interests convergent with those of their audit suppliers, which encourages the formation of long-term collaborative relationships.

We therefore examine the effect of IPO audit contingent fees on auditor tenure. Specifically, *Length* measures the duration of continuous auditor tenure, defined as the time elapsed from the completion of the firm's IPO to the replacement of its auditor. *Count* captures the total number of IPO audit engagements undertaken by the firm's auditor during the sample period. Columns (1) and (2) of Table 15 present estimates from OLS

Table 15
 IPO audit contingent fees and ongoing audit services provided by accounting firms.

	OLS model		Poisson model	
	(1) <i>Length</i>	(2) <i>Count</i>	(3) <i>Length</i>	(4) <i>Count</i>
<i>Ctgfee</i>	22.848*** (3.495)	45.048*** (4.371)	6.914*** (3.730)	11.828*** (4.795)
<i>Proceed</i>	-0.055 (-0.495)	-0.152 (-0.863)	-0.019 (-0.602)	-0.045 (-1.073)
<i>Size</i>	0.130* (1.846)	0.255** (2.099)	0.042** (2.000)	0.061** (2.116)
<i>Roe</i>	0.913** (2.039)	0.589 (0.813)	0.291** (2.198)	0.163 (0.939)
<i>Lev</i>	-0.137 (-0.505)	0.600 (1.402)	-0.044 (-0.595)	0.134 (1.364)
<i>Age</i>	0.087 (0.993)	0.129 (0.727)	0.030 (1.098)	0.027 (0.726)
<i>Soe</i>	-0.213 (-1.488)	-0.720*** (-2.871)	-0.065 (-1.541)	-0.170*** (-2.808)
<i>Big10</i>	0.319*** (4.039)	0.383*** (2.841)	0.094*** (4.111)	0.084*** (2.776)
<i>Uwfee</i>	0.150 (0.135)	0.729 (0.392)	0.026 (0.086)	0.198 (0.494)
<i>Atfee</i>	-0.035 (-0.084)	0.319 (0.474)	-0.031 (-0.276)	0.073 (0.526)
<i>Infee</i>	2.220** (2.464)	1.845 (0.820)	0.748** (2.507)	0.327 (0.806)
<i>Otfee</i>	-0.040 (-0.436)	-0.122 (-0.730)	-0.014 (-0.555)	-0.023 (-0.774)
<i>Constant</i>	-3.378 (-1.485)	-5.420 (-1.167)	-0.834 (-1.243)	-0.503 (-0.557)
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Ipyear</i>	Yes	Yes	Yes	Yes
<i>Board</i>	Yes	Yes	Yes	Yes
<i>N</i>	2374	2374	2374	2374
<i>R²_a</i>	0.405	0.267	0.145	0.141

This table presents the effects of IPO audit contingent fees on audit supplier decisions. *Length* is defined as the time elapsed from the completion of the firm's IPO to the replacement of its IPO auditor. *Count* captures the total number of audit engagements undertaken by the firm's IPO auditor during the sample period. We conduct OLS regressions in Columns (1) and (2) and Poisson regressions in Columns (3) and (4). The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

regression, while columns (3) and (4) present those from Poisson regression. Across all model specifications, the estimated coefficient of *Ctgfee* is positive and statistically significant ($p < 0.01$), indicating that higher IPO audit contingent fees are associated with a longer auditor tenure and a higher frequency of audit engagements.

6.3. Stock returns

Investors' perceptions of IPO audit contingent fees also warrant exploration. Theoretically, although investors tend to have favorable expectations for the performance of newly listed firms, earnings reversals can erode investors' confidence, leading to declines in stock prices and long-term market returns. Furthermore, an earnings reversal undermines corporate credibility and thus may increase a firm's future financing costs and constrain its financing capacity, impairing its long-term growth prospects and overall investment returns.

With reference to Wang and Li (2017), we test this conjecture by measuring the long-term market performance of IPO firms using buy-and-hold abnormal returns (BHAR). Columns (1) to (4) of Table 16 present the

Table 16
 IPO audit contingent fees and stock returns.

	(1) <i>BHAR</i> ₆	(2) <i>BHAR</i> ₁₂	(3) <i>BHAR</i> ₁₈	(4) <i>BHAR</i> ₂₄
<i>Ctgfee</i>	-4.541 (-1.358)	-6.600* (-1.853)	-8.088** (-2.260)	-7.281** (-1.998)
<i>Proceed</i>	-0.301*** (-5.604)	-0.308*** (-5.448)	-0.310*** (-5.330)	-0.305*** (-5.149)
<i>Size</i>	0.064** (2.224)	0.060* (1.951)	0.049 (1.519)	0.044 (1.338)
<i>Roe</i>	0.032 (0.196)	0.040 (0.230)	0.085 (0.473)	0.138 (0.761)
<i>Lev</i>	-0.078 (-0.728)	-0.070 (-0.628)	-0.066 (-0.593)	-0.008 (-0.073)
<i>Age</i>	-0.086*** (-2.855)	-0.089*** (-2.855)	-0.083*** (-2.604)	-0.067** (-2.054)
<i>Soe</i>	-0.011 (-0.191)	-0.015 (-0.241)	-0.004 (-0.063)	-0.001 (-0.016)
<i>Big10</i>	-0.019 (-0.589)	-0.010 (-0.295)	-0.011 (-0.309)	-0.017 (-0.477)
<i>Uwfee</i>	0.779* (1.687)	0.730 (1.512)	0.715 (1.453)	0.714 (1.413)
<i>Atfee</i>	0.068 (0.454)	-0.009 (-0.055)	0.030 (0.191)	0.031 (0.193)
<i>Inftee</i>	-0.361 (-1.158)	-0.481 (-1.501)	-0.540* (-1.650)	-0.680** (-1.978)
<i>Otftee</i>	-0.003 (-0.095)	-0.011 (-0.355)	-0.020 (-0.660)	-0.014 (-0.445)
<i>Constant</i>	1.367* (1.659)	1.995** (2.305)	2.305*** (2.615)	2.478*** (2.689)
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Ipyear</i>	Yes	Yes	Yes	Yes
<i>Board</i>	Yes	Yes	Yes	Yes
<i>N</i>	2374	2374	2374	2374
<i>R</i> ² _a	0.299	0.287	0.289	0.287

This table presents the impacts of IPO audit contingent fees on stock returns. Buy-and-hold abnormal returns (BHAR) are used to measure the long-term market performance of IPO firms. In columns (1) to (4), the dependent variables are respectively the 6-month, 12-month, 18-month and 24-month BHAR. The *t*-statistics, reported in parentheses below the coefficients, are based on robust standard errors clustered by firm. *, ** and *** indicate significance at the 10 %, 5 % and 1 % two-tailed levels, respectively.

regression results, using the BHAR over 6, 12, 18 and 24 months, respectively, as the dependent variables. The results show that, except for the 6-month BHAR (*BHAR*₆), the estimated coefficients of IPO audit contingent fees (*Ctgfee*) in columns (2) to (4) are negative and statistically significant at the 10 % significance level or higher. This indicates that higher IPO audit contingent fees are associated with poorer long-term market performance and thus detrimental to investors' interests.

7. Conclusions

This paper examines how IPO audit contingent fees affect earnings reversals, based on a sample of IPO firms during 2006–2021. The results reveal a significant positive association between IPO audit contingent fees and post-IPO earnings reversals. Cross-sectional analysis shows that this effect is more salient in non-SOEs and in firms with weaker regulatory oversight, lower information quality and high perceived EPU. Extended analysis demonstrates that IPO audit contingent fees expedite firms' IPO process and promote long-term collaboration between IPO firms and the auditors who handled the IPO. Although investors' short-term percep-

tions of the associated risks may be insufficient, higher IPO audit contingent fees ultimately result in lower long-term stock returns.

The policy implications of the aforementioned findings are as follows. First, regulatory authorities should increase their supervision of the information disclosure practices of IPO firms. Specifically, they should increase oversight of pre-IPO companies and conduct on-site inspections to safeguard investors' interests. The gatekeeping obligations of intermediary institutions also must be strictly enforced, particularly under the registration-based IPO system, to ensure due diligence and curb the charging of unreasonable fees. Furthermore, the policy on audit fees should be refined to include targeted supervision of firms suspected of paying excessively high IPO audit contingent fees and the imposition of severe penalties on those that issue inaccurate, misleading or incomplete financial reports.

Second, firms should adhere to standardized, compliant IPO processes when securing listing approval. While IPO contingent audit fees may boost the likelihood of successful IPO approval, they also increase the risk of post-IPO earnings reversals and undermine long-term market performance. Resorting to such opportunistic tactics not only exposes firms to unfavorable market outcomes but may also expose them to regulatory scrutiny and potential penalties. Instead, firms should prioritize enhancing their internal governance and operational efficiency and should use their intrinsic competitive strengths to meet listing requirements.

Third, accounting firms and other intermediary institutions should focus on their core responsibilities and steadily improve the quality of their professional services. As gatekeepers of the capital market, these intermediaries should prioritize long-term, high-quality market development, clarify their respective responsibilities and exert their professional expertise effectively.

Fourth, investors must refine their investment strategies and strengthen their professional investment knowledge. IPO-seeking firms may use IPO contingent audit fees to collude with intermediary institutions and achieve successful listings. In such scenarios, investors lacking professional expertise are likely to suffer losses due to information asymmetry. Particularly under registration-based reform, the market-oriented selection mechanism increases the responsibility placed on investors, requiring them to increase their professional skills and risk management capabilities. Investors should proactively acquire relevant knowledge, accumulate practical experience and embrace value-driven investment strategies to mitigate the risks of such collusion.

Importantly, we note the limitations of our constructed proxy for contingent fees. While this proxy can partially capture the contingent component of total IPO audit fees and boasts merits in terms of economic interpretability and replicability, several limitations persist and require attention in future research. First, measurement is challenging. In practice, contingent fees may be disguised as bundled consulting fees, installment payments tied to post-listing financing or other arrangements. The difficulty of observing such concealed fees in publicly available data may lead to measurement bias. Second, data availability is constrained. As IPO audit engagement covenants are confidential commercial agreements between auditors and firms and not subject to mandatory disclosure, our proxy may not fully reflect the actual situation. Third, contingent fees are inherently intertwined with audit quality, audit risk and other complex factors, and their impacts may be influenced by unobserved variables such as market conditions, regulatory intensity and firm-specific attributes; consequently, it may be difficult to fully disentangle the effects. Future research could mitigate these limitations and draw more robust conclusions as more public information becomes accessible.

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. Approach to constructing contingent fee variables in IPO audits

1. Theoretical discussion

1.1. Conventional method in existing literature to estimate abnormal audit fees

A review of existing research on distinguishing between reasonable and unreasonable components of audit fees reveals that current literature relies primarily on approaches derived from earnings management or investment efficiency estimation. These studies construct empirical models to estimate normal audit fees for annual reports, and subsequently use residuals as proxy variables for abnormal audit fees (DeFond et al. 2002; Francis and Wang 2005; Krishnan et al. 2005; Ghosh and Pawlewicz 2009; Liu et al. 2019; Zhu and Zhu 2018; Chen et al. 2022). For example, Chen et al. (2022) estimates abnormal audit fees using the following model.

$$\begin{aligned} LnFee_{it} = & \alpha_0 + \alpha_1 Size_{it} + \alpha_2 Seg_{it} + \alpha_3 IA_{it} + \alpha_4 Rec_{it} + \alpha_5 Cata_{it} + \alpha_6 Lev_{it} \\ & \alpha_7 Roa_{it} + \alpha_8 Loss_{it} + \alpha_9 IC_{it} + \alpha_{10} Illegal_{it} + \alpha_{11} Clean_{it} + \alpha_{12} Big10_{it} \\ & \alpha_{13} Change_{it} + \sum Year + \sum Industry + \varepsilon_{it} \end{aligned}$$

In this empirical model, $LnFee$ denotes the natural logarithm of actual audit fees. Explanatory variables include asset size ($Size$), business complexity (Seg), inventory ratio (IA), accounts receivable ratio (Rec), current asset ratio ($Cata$), debt-to-equity ratio (Lev), return on assets (Roa), loss status ($Loss$), internal control deficiencies (IC), illegal activities ($Illegal$), audit opinion type ($Clean$), audit by a Big 10 firm ($Big10$), and firm change ($Change$). Fixed effects for year and industry were also controlled.

The residuals obtained through this empirical model constitute the estimated abnormal audit fees. Upon review of relevant studies and to our best knowledge, this estimation model for abnormal audit fees stands as a widely applied methodology in both domestic and international academic research.

1.2. Shortcomings in the existing model for estimating abnormal audit fees

1.2.1. Theoretical differences between IPO audit contingent fees and abnormal audit fees

It should be noted that the above model-based approaches to constructing indicators for estimating abnormal audit fees may exhibit adequate power in identifying the abnormal components of post-listing annual audit fees. However, as a critical step in a company's listing process, IPO audits are affected by more complex underlying factors, involve significantly larger fee amounts, and have more diverse influencing causes. Consequently, traditional model-based approaches for estimating abnormal audit fees may be unsuitable for IPO audits. For instance, the descriptive statistics in our study show that the mean IPO audit fee during the sample period stood at RMB 6.1 million. In contrast, according to data from the *Analysis Report on the 2023 Annual Report Audits of Listed Companies* (published in *The Chinese Certified Public Accountant*, Issue 8, 2024), the mean annual report audit fee for listed companies in 2023 was RMB 1.8227 million. Furthermore, over half of listed companies had audit fees below this mean, and 271 companies paid less than RMB 500,000.

It is evident that IPO audit fees are significantly higher than those typically incurred for annual report audits. This indicates that IPO audits involve a greater number of factors with more profound implications for audit fees. The most significant contributor to the elevated costs of IPO audits likely stems from contingent fees. Therefore, continuing to apply estimation methods for abnormal audit fees in post-listing annual reports to assess IPO audit contingent fees may introduce substantial systematic bias.

1.2.2. The explanatory problem of the abnormal audit fees measurement

In fact, existing models for estimating abnormal audit fees suffer from a high degree of omitted variables and unexplained factors. For instance, there is no rigorous theoretical guideline to support why the residuals

from the empirical regression of the aforementioned model represent the abnormal portion of annual report audit fees. Nor is there a generally accepted theory to clarify why the aforementioned control variables should be included in the model. Specifically, when using these models to estimate abnormal audit fees, it is difficult to provide economically meaningful interpretations, as it proves challenging to assign economic significance to the numerical values of residuals from model estimations. It should be noted, however, that this study acknowledges the shortcomings of existing estimation methods for abnormal audit fees, yet this does not negate their academic contributions. At minimum, these methods provide a feasible and relatively scientific approach within current constraints, thereby contributing to the advancement of research in this field.

Aligned with this logic, the methodology proposed herein for constructing IPO audit contingent fees serves as an attempt to explore new approaches beyond the scope of existing literature. We seek to develop a more operationally feasible, non-model-dependent, and replicable IPO audit contingent fee variable under China's institutional context. This constitutes the most important reason for pursuing these new attempts, rather than merely replicating traditional abnormal audit fee models.

2. Practice discussion

To identify an appropriate and operationally feasible proxy variable that reflects the underlying economic nature of IPO audit contingent fees, we analyzed actual IPO audit engagement covenants in practice and derived the following findings.

Case:

According to an IPO audit service tender notice released by the Wuhu Public Resources Trading Center in Anhui Province in 2023, the client company plans to list in 2026. The budgeted total audit fee payable to the accounting firm is RMB 17.5 million, with the main service requirements as follows: First, annual report audit fees for the “three periods plus one period” amount to RMB 1.5 million in total. The payment terms specify that upon completion of the audit work and issuance of the hardcopy audit report, payment for the current audit period shall be made within 30 days of the provision of a standard invoice for the corresponding amount. Second, IPO listing audit fees total RMB 16 million. Payment shall be made within 30 working days after the company successfully completes its IPO listing and finishes capital verification. Third, supplementary terms of the contract stipulate that if the IPO fails due to causes attributable to the successful bidder, the tendering party retains the right to withhold the audit service payment (or recover any amounts already paid). This confirms the existence of contingent fee arrangements in the audit engagement contract during the company's IPO process.

Summary:

As discussed by the aforementioned real-world case, IPO audit contingent fees are highly likely concealed within the overall IPO listing audit fees. By appropriately deconstructing the total IPO audit fees disclosed by listed companies, we can try to isolate the contingent fee component within the total IPO audit fees.

3. Conceptual framework

3.1. IPO audit contingent fees construction steps

Based on the above case materials, the total budgeted amount of RMB 17.5 million for the IPO audit service contract consists of two parts: RMB 1.5 million for annual report audit fees (covering “three periods plus one additional period”), and RMB 16 million for IPO listing audit services. The contract stipulates that payment for the IPO listing audit services is contingent on the company successfully completing its public offering, listing, and capital verification. It is evident that the accounting firm's actual receipt of these IPO listing audit fees hinges on the company's successful listing. Consequently, this portion of the audit fees constitutes IPO audit contingent fees. Specifically, the case materials indicate that within the entire IPO audit fee contract, the fixed fee payable to the accounting firm is RMB 1.5 million, covering annual audit fees for 2022, 2023, 2024, and 2025. Specifically, the audit fee is RMB 300,000 for 2023 and RMB 400,000 for each of the other years. Given the company's relatively small scale, this audit fee amount is not significantly different from the audit fee data disclosed in the aforementioned issue of *The Chinese Certified Public Accountant* (Issue 8, 2024).

Therefore, based on data availability, this study proposes that the measurement of IPO audit contingent fees can be determined by subtracting three times the audit fee for the first post-listing annual report from the total IPO audit fees a client firm pays. The resulting difference can be treated as IPO audit contingent fees (as shown in the formula below).

$$\text{IPO audit contingent Fees} = \text{Total IPO audit fees} - \text{actual annual report audit fees for the first Post} \\ - \text{Listing Year} \times 3$$

3.2. Explanation regarding the construction of variable

With respect to this measurement method, the following points should be further clarified.

On the one hand, the rationale for using the actual annual report audit fees incurred in the first post-listing year as the benchmark lies in the fact that this timing is closest to the listing even, which makes it a reasonably conservative estimate. Thus, the actual annual report audit fees from the first post-listing year serve as a more appropriate measurement benchmark.

On the other hand, the rationale for multiplying by three years primarily stems from the following two considerations. First, pursuant to Articles 26 (1) and (2) of the *Administrative Measures for the Initial Public Offering and Listing of Shares*, companies are required to provide financial reports for the most recent three fiscal years. Second, the prospectus reporting period requirements specified in the *Content and Format Guidelines No. 57 for Information Disclosure by Companies Issuing Securities: Prospectus (2023 Revision)* stipulate that issuers must provide financial data for the most recent “three years” or “three periods plus one additional period.” This requires IPO-seeking companies to provide audited financial reports for the prior three years. For example, if the company plans to list in 2026, then the successful tenderer (i.e., the accounting firm) is required to conduct annual report audit services for the three-year period spanning 2023, 2024, and 2025, thereby meeting regulatory requirements. Given these two regulatory requirements, both mandate that companies pursuing an IPO provide audited financial reports for the most recent three years.

In summary, this study proposes using the actual annual report audit fees incurred in a company’s first post-listing year as the benchmark, and multiplying this figure by three to represent the normal component of total IPO audit fees for IPO firms. The residual portion can then serve as a proxy variable for IPO audit contingent fees.

For example, using the method for calculating IPO audit contingent fees proposed in this paper, the contingent fees in the case study would be calculated as follows: IPO audit contingent fees = Total IPO audit fees (¥17.5 million) – Actual annual report audit fees for the first post-listing year $\times 3 = ¥17.5 \text{ million} - ¥0.4 \text{ million} \times 3 = ¥16.3 \text{ million}$. This calculated amount is relatively close to the substantive IPO audit contingent fee of ¥16 million stipulated in the contract, with a deviation rate of only 1.8% (¥0.3 million/¥16 million). It should be noted that, as the case company is not yet publicly listed, the 2025 annual report audit fee of RMB 400,000 stipulated in the contract is used for estimation.

3.3. Advantages of this method

Based on the foregoing discussion, this proposed methodology for constructing IPO audit contingent fee indicators has the following advantages.

First, grounded in practice and of pronounced economic significance, the proposed methodology for calculating IPO audit contingent fees is based on current securities regulatory frameworks and real case, and thus aligns with the fundamental economic rationale underlying IPO audit contingent fees.

Second, straightforward to operate, the proposed calculation method for IPO audit contingent fees requires only simple arithmetic operations, thus rendering it easy to replicate.

Third, in terms of interpretability, the economic rationale for the proposed IPO audit contingent fee variable is more easily understandable.

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Scenario disclosure and market expectations: insights from earnings conferences via large language models



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ABSTRACT

A scenario described vividly and in detail is more easily imagined, leading individuals to overestimate the likelihood of its occurrence. We leverage a novel large-language-model (LLM) framework to analyze management speech style during unstructured earnings conferences and construct quantitative measures of scenario oral disclosure. Such disclosure triggers scenario thinking, inflating investors' beliefs about future firm prospects, particularly when firm-specific information is scarce. Scenario disclosure is more pronounced when conveying positive information, with poor relative performance and under negative media sentiment, suggesting that management employs scenario framing to manage expectations. Finally, management scenario disclosure significantly increases stock price crash risk. This represents LLMs' first application to identify and quantify scenario disclosure in earnings conferences, providing guidance for regulation and institutional design.

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1. Introduction

Scenario thinking is a cognitive mode influenced by information structure and imagination. At its core is an individual's ability to infer causal connections between planned actions and future outcomes based on the current state. This process reinforces the availability heuristic: the tendency to assess the likelihood of an event's occurring according to how easily relevant information comes to mind (Tversky and Kahneman, 1973; Hoch, 1984). When a scenario is described with sufficient clarity and vividness, the specific events and details within it become easier to retrieve and imagine. As a result, individuals are more likely to overestimate the probability of the scenario's occurring, leading to belief inflation and probability overestimation (Dawes, 1988; Koehler,

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1991; Pennington and Hastie, 1986, 1988, 1993). In the context of information transmission in capital markets, this cognitive mechanism may amplify the persuasive power of managerial language. When managers employ scenario language that is rich in detail and logical reasoning, market expectations about the firm's future may be unconsciously shaped by such narratives. A systematic examination of how managerial scenario disclosures shape market expectations can thus shed light on the strategies managers use to guide investor cognition and provide a novel approach to identifying potential belief inflation in capital markets.

As an interactive disclosure mechanism, earnings conferences have become increasingly influential in capital markets. The literature shows that various linguistic and behavioral features of management communication during these conferences contain information for the market, such as managerial tone (Mayew and Venkatachalam, 2012; Price et al., 2012; Xie and Lin, 2015; Lin and Xie, 2017), the distribution of tone (Allee and Deangelis, 2015), the degree of alignment between questions and answers (Bian et al., 2021; Rennekamp et al., 2022), linguistic complexity (Bushee et al., 2018; Bushee and Huang, 2024), the use of extreme expressions (Bochkay et al., 2020) and even silence on specific questions (Hollander et al., 2010).

Meanwhile, recent studies suggest that U.S. firms' management teams often engage in intentional guidance behaviors during earnings conferences. For example, Call et al. (2024) find that managers use humor to express confidence or to infuse positive emotion into discussions of negative news. Dai et al. (2022) show that managers employ topic shifting to steer investors toward a more favorable interpretation of firm performance. A concerning phenomenon has arisen in China's earnings conferences: the management of listed companies constructs scenarios by connecting specific details and causal sequences of the current state, planned actions and expected future outcomes. They place a certain object, phenomenon or piece of information in a specific context or against a particular background for understanding and analysis, building a coherent sequence of event development in the minds of conference participants. This enhances the credibility and persuasiveness of the information, giving participants high expectations of the firm's future profit. For instance, rather than simply listing facts, managers may describe the challenges faced by the research and development (R&D) team, their technological breakthroughs and the expected returns from forthcoming products, thereby creating a vivid and positive mental image of the firm's R&D process. Conference participants are more likely to be guided by such scenario narratives, imagining the detailed causal sequence by which managerial actions lead to favorable outcomes (Dawes, 1988). This reduces cognitive effort and may lead to belief inflation regarding the anticipated success of managerial actions (Dawes, 1988; Koehler, 1991). However, such scenario rhetoric tends to have low traceability and lacks the regulatory accountability associated with written disclosures. When the promised outcomes fail to materialize, managers often deflect responsibility by citing changes in competitive conditions or other exogenous factors.

However, there has long been a lack of systematic quantitative research on the scenario language of managerial oral disclosures. Scenario language is typically characterized by high semantic complexity and strong contextual dependence, making it difficult for traditional approaches—such as word-frequency analysis, sentiment dictionaries and manual coding—to capture its underlying structures. In recent years, breakthroughs in large language models (LLMs) have opened new research avenues for capturing and quantifying complex semantics. Unlike traditional text analysis methods that rely on shallow lexical features, LLMs can identify implicit causal chains and situational construction logics in language through contextual associations and semantic reasoning. This capability provides powerful new tools and perspectives for examining the strategic dimension of “how managers speak,” enriching understanding of managerial disclosure behavior beyond the literal content of what is said.

This study introduces a natural language processing framework based on pretrained LLMs to quantify the degree of scenario disclosure in managerial oral communications during earnings conferences and to examine its capital market implications and the motivations for its use. Using transcripts of earnings conferences from listed firms between 2005 and 2021, the analysis shows that a higher degree of scenario disclosure by management is associated with more positive revisions of market beliefs about the firm's future earnings. This effect is more pronounced when the capital market lacks firm-specific information to conduct independent prior assessments. Furthermore, the study finds that scenario disclosure tends to be stronger when management conveys positive (vs. negative) information, when the firm's relative performance is poor (vs. good) and when media sentiment is negative (vs. positive). Taken together, these results suggest that managers are indeed motivated to employ scenario thinking to guide the capital market toward improving earnings expectations,

implying that managers may strategically use scenario narratives to shape investor perceptions. Finally, by examining the capital market consequences of managerial scenario disclosure, the study reveals that such disclosures are associated with a higher future stock price crash risk. This finding indicates that while scenario disclosure may temporarily elevate market expectations, it can also lead to asymmetric downward adjustments when the market later realizes the gap between expectations and actual performance, triggering the concentrated release of negative information.

The potential contributions of this study are as follows. (1) Previous scenario research relies on experimental designs, using manual coding or scenario simulation to identify and validate scenario-related features (Carroll, 1978; Sedor, 2002; Önköl et al., 2013; Johnson et al., 2020; Johnson and Tuckett, 2022). These approaches are often disadvantaged by limited sample sizes, subjectivity and low external validity. This study is among the first to introduce LLMs into the study of capital market disclosure. By leveraging LLMs' deep learning capabilities in semantic representation and contextual understanding, we achieve a breakthrough in identifying complex semantic structures and causal narrative logic. This provides a new analytical pathway to explore how deep semantic features of language shape capital market expectations. (2) Prior studies focus on the impact of management's use of various linguistic and behavioral features during earnings conferences on the nature of information, including linguistic complexity (Bushee et al., 2018; Bushee and Huang, 2024), scripted responses (Lee, 2016), silence (Hollander et al., 2010; Gow et al., 2021), extreme expressions (Bochkay et al., 2020) and humor (Call et al., 2024), as well as the tone of responses (Mayew and Venkatachalam, 2012; Price et al., 2012; Xie and Lin, 2015; Lin and Xie, 2017) and the alignment between questions and responses (Oh et al., 2017; Bian et al., 2021). However, scenario disclosure, a potentially influential but underexplored dimension of managerial oral communication, receives little attention. By constructing a quantitative measure of scenario disclosure and demonstrating its effect on market expectations, this study advances interdisciplinary understanding of how managerial discourse during earnings conferences shapes investor cognition and enriches the literature on managerial disclosure behavior. (3) The findings suggest that while earnings conferences enhance information communication, they may also serve as a tool for narrative manipulation, potentially leading to negative effects on capital markets. Beyond its academic contribution, this study carries important practical implications: regulators and market participants should recognize the risk attributes of earnings conferences and establish appropriate monitoring and accountability mechanisms. For instance, measures such as strengthening post-call commitment tracing and penalties or enhancing transparency in Q&A sessions could help reduce the room for managers to mislead the market through oral narrative strategies.

The remainder of this paper is organized as follows. Section 2 elaborates on the concept of scenario thinking and develops the research hypotheses. Section 3 presents the empirical design, and Section 4 reports and analyzes the empirical results. Section 5 describes further analyses, and the final section concludes the paper.

2. Scenario thinking and research hypothesis

We develop our research hypothesis based on scenario thinking. According to psychological research, a key characteristic of scenario thinking is the process by which individuals imagine a sequence of future events based on readily available and relevant information. Scenario thinking is closely associated with the availability heuristic in cognitive psychology (Dawes, 1988; Koehler, 1991; Pennington and Hastie, 1986, 1988, 1993). More broadly, "heuristics" refers to efficient and practical mental shortcuts that allow individuals to make judgments quickly under cognitive constraints, although they may sometimes lead to systematic biases. The availability heuristic describes the tendency to rely excessively on information that is easily accessible and readily interpretable when assessing probabilities or making judgments under uncertainty (Tversky and Kahneman, 1973; Hoch, 1984). The more vivid and interpretable the information about an event, the more likely individuals are to judge that event as likely to occur (Kahneman et al., 1982; Kahneman and Lovallo, 1993). When direct information has not been previously encoded, individuals must engage in a secondary mental operation: constructing an example or a plausible scenario (Koehler, 1991). Consequently, the outcome of the judgment depends on how easily one can generate a coherent story or explanation for the target event. Scenarios that can be easily and vividly imagined reduce cognitive effort (Tversky and Kahneman, 1973; Kahneman et al., 1982; Kahneman and Lovallo, 1993). When a scenario is described with sufficient

clarity and vividness, individuals are more likely to overestimate the probability of its occurrence, leading to belief inflation (Dawes, 1988; Koehler, 1991).

In short, a defining feature of scenario thinking is its focus on a limited number of plausible development paths rather than a comprehensive consideration of all potential outcomes. This focus may lead individuals to overestimate the likelihood of the events described within the scenario while underweighting the probability distribution of other possible events.

According to psychological research, “scenario disclosure” refers to the process of placing a particular object, phenomenon or piece of information within a specific scenario for understanding and analysis. It reveals the dynamic relationships between the subject and its environment by constructing or reconstructing concrete temporal–spatial conditions, cultural settings, social relationships or practical scenarios. This is typically manifested through the description of the sequence of proposed actions and how they lead to future outcomes (Tversky and Kahneman, 1973; Jungermann, 1985; Schnaars, 1987; Schoemaker, 1993). Two essential elements of scenario disclosure are the specific details and causal sequencing that link the current state, planned actions and expected future outcomes (Sedor, 2002). Earnings conferences represent an interactive communication format free from the constraints of traditional financial disclosures, providing managers with the opportunity to employ diverse scenario language. During these conferences, managers construct scenarios using explicit temporal sequences, detailed actions and causal relationships, clearly illustrating the causal logic from the current state through a series of planned actions to the achievement of anticipated outcomes. This enables information recipients to mentally construct a coherent storyline of events and better visualize the implementation of action plans and their subsequent dynamics and ultimate performance effects, making them more susceptible to scenario thinking (Tversky and Kahneman, 1973; Kahneman et al., 1982; Koehler, 1991; Kahneman and Lovallo, 1993).

When predicting a firm’s future earnings, market participants typically consider all available information, particularly forward-looking information provided by management (Epstein and Palepu, 1999; Sedor, 2002; Matsumoto et al., 2011). When they are presented with information framed in a scenario and mentally imagine the managers’ proposed action plans and the future outcomes, scenario thinking is inadvertently triggered (Tversky and Kahneman, 1973; Jungermann, 1985; Schnaars, 1987; Schoemaker, 1993). Scenario thinking reduces market participants’ cognitive effort, leading them to make probability assessments based on event descriptions (Hoch, 1984; Levi and Pryor, 1987) and the availability of imagination (Tversky and Kahneman, 1973; Kahneman and Lovallo, 1993). This in turn makes it easier for them to recognize the plausibility of managers’ descriptions. Managers’ scenario disclosures provide participants with coherent and easily accessible scenarios whose specific details are easy to retrieve and imagine. Consequently, under the influence of scenario thinking, participants are more likely to overestimate the probability of the scenario’s occurring (Sedor, 2002). For example, during earnings conferences, when management describes in detail a sequence of events in a positively anticipated business expansion scenario, participants may overlook uncertainties related to market competition or economic downturns, leading to inflated beliefs about the firm’s future earnings. Based on this reasoning, we posit that the degree of scenario disclosure in earnings conferences is associated with market participants’ optimistic beliefs about the firm’s future earnings. Accordingly, we propose the following hypothesis:

H1: *Ceteris paribus*, a higher degree of scenario disclosure in earnings conferences will significantly increase market participants’ forecasts of the firm’s future earnings.

3. Research design

3.1. Sample and data sources

We focus on Chinese A-share listed firms from 2005 to 2021 and empirically examine scenario disclosure in earnings conferences. The earnings conferences transcripts are obtained from the China Research Data Service Platform, and analyst forecasts and firm-level financial data are sourced from the China Stock Market & Accounting Research database. To ensure data reliability, the initial sample is processed as follows: (1) excluding firms in the financial and insurance industries; (2) excluding firms with abnormal listing statuses, such as

“ST,” “*ST” and “PT”); and (3) excluding observations with missing key variables. To mitigate the potential impact of extreme values on the results, all continuous variables are winsorized at the 1st and 99th percentiles.

3.2. Model setting and variable definitions

To test the research hypothesis, we construct the following model:

$$DFeps_{i,t+1} = \alpha + \beta Scenario_{i,t} + Controls_{i,t} + INDFE + YearFE + \varepsilon_{i,t} \quad (1)$$

where i and t represent the firm and year, respectively. The variables in the model are defined as follows:

Dependent variable: The change in analysts’ consensus earnings forecasts for the firm’s next period. It is defined as $DFeps = (Feps_{cc} - Feps_{ar}) / Eps$, where $Feps_{cc}$ is the average forecast of analysts for the firm’s next-period basic earnings per share (EPS) within 60 days after the earnings conference. $Feps_{ar}$ is the average forecast of analysts for the next-period basic EPS after the annual report is released but before the earnings conference, and EPS is the actual EPS for the next period. A larger $DFeps$ indicates that analysts’ earnings forecasts for the next period are more optimistic than those in the period before the earnings conference.

Independent variable: The variable *Scenario* represents the level of management’s scenario disclosure in earnings conferences, measured using the ERNIE LLM. “Scenario disclosure” refers to the process of placing a particular object, phenomenon or piece of information within a specific scenario or against a specific background for understanding and analysis. At its core is the construction or reconstruction of concrete temporal-spatial conditions, cultural settings, social relationships or practical scenarios to reveal the dynamic relationships between the subject and its environment, thereby overcoming the cognitive limitations of abstraction and isolation.

The ERNIE LLM, developed independently by Baidu, is an industry-grade knowledge-enhanced LLM. Its core architecture is based on the revolutionary Transformer framework. A key component of the Transformer architecture is the self-attention mechanism, which enables the model to capture dependencies between any two positions within an input sequence. This allows for direct access to global contextual information and facilitates a nuanced understanding of syntax and semantics within sentences. The Transformer architecture is also highly scalable: its performance can be improved by increasing the number of layers, attention heads and hidden dimensions. During the training of the ERNIE LLM, massive volumes of Chinese and English corpora were used to optimize the parameters of the Transformer framework. These corpora are drawn from a wide range of publicly available text sources, including news articles, literary works, academic papers, social media content and web texts. In addition, ERNIE LLM incorporates extensive encyclopedic, commonsense and domain-specific knowledge, which significantly enhances its ability to understand, reason about and interpret textual information.

The massive training corpus and the Transformer architecture enable the ERNIE LLM to learn the intrinsic patterns and structures of language, comprehend implicit information and contextual relationships within text and accurately interpret textual content (Klafka and Ettinger, 2020). Moreover, ERNIE LLM demonstrates strong capabilities in handling complex text comprehension tasks such as dialogues and multi-turn discourse. It has also acquired extensive general knowledge (Bubeck et al., 2023) and reasoning abilities (Binz and Schulz, 2023; Liu et al., 2023), allowing it to learn and adapt based on conversational input and to evaluate textual content in a reliable, consistent and objective manner. Therefore, the ERNIE LLM is particularly well suited for processing earnings conference transcripts, which are presented in the form of natural conversational exchanges. The specific construction steps are as follows.

Using Python to call Baidu Cloud’s ERNIE-3.5-8K API, we measure the degree of scenario disclosure in management responses during earnings conferences. ERNIE-3.58K is a version of the ERNIE 3.5 LLM, inheriting the latter’s advanced techniques and algorithmic framework. The procedure is as follows. First, we engage the ERNIE LLM in a dialogue, enabling it to learn from and adapt to the conversational input and thereby understand the text-analysis task and produce consistent, accurate evaluations. Specifically, we (a) inform the LLM that the input texts are “management responses to questions from investors and analysts during earnings conferences,” to ensure that it understands the production context and nature of the texts; and (b) provide the LLM with the precise definition of “scenario” as “a narrative describing a sequence of events that shows how the proposed actions lead to future outcomes,” thereby establishing a unified evaluation

Table 1
Examples of responses in earnings conferences.

Order	Score	Content of response	Scoring analysis (reasons)
01	85	Our company focuses on wireless communication products. We have established a dedicated Automotive Business Unit, which is mainly engaged in the R&D and production of vehicle-mounted communication antenna products. We also promptly respond to customer needs for communication antenna products involved in the electric vehicle sector. The demand for communication products will increase with the intelligent development of electric vehicles. This will help the company boost its revenue from such products.	The company has clearly proposed the establishment of an Automotive Business Unit, which will focus on the R&D and production of vehicle-mounted communication antenna products and pay attention to the demand for communication antennas in the electric vehicle sector. Beyond proposing the establishment of this unit, the company has mentioned keeping pace with the intelligent development of electric vehicles to develop related communication products. Its actions are specific and go beyond vague strategic planning. The demand for communication products will increase with the intelligent development of electric vehicles, which will help the company boost its revenue from such products. This future outcome is a reasonable prediction based on industry trends and the company's strategic decisions. The narrative covers the background of the company's decisions, specific actions and potential future results in full, with no major omissions. The company first proposed establishing the Automotive Business Unit to develop vehicle-mounted communication antennas, then planned to follow up with relevant product development based on industry trends. This sequence of events is logical and in line with reasonable reasoning.
02	90	The company has specifically established a raised fund management system and signed a tripartite supervision agreement on the deposit and withdrawal of raised funds with banks and sponsor institutions. It has also strengthened investment budget management and project progress management to ensure that the project is of high quality and put into production as soon as possible to generate economic benefits. After the proposed investment project has been completed and put into production, it will help the company expand its production scale, enhance supply guarantee capabilities and meet the needs of the downstream market. The project's phased production will further consolidate and expand the company's market share in the industry, improve the core competitiveness of the company and its products and significantly enhance the risk resistance of the company's future business activities. The successful use of raised funds will expand the company's production and operation scale and improve its comprehensive competitiveness and risk resistance. The company will formulate a scientific plan for the use of over-raised funds in accordance with relevant guidelines and regulations and will make announcements in a timely manner.	Based on the above response content, the company has provided a detailed description of aspects including the establishment of its raised fund management system, the strengthening of investment budget management and project progress management and the future impacts of the proposed investment projects. This description demonstrates high contextual clarity, strong action specificity, sound predictability of future outcomes, high contextual completeness and a logical sequence of events.

Table 1 (continued)

Order	Score	Content of response	Scoring analysis (reasons)
03	96	<p>Taking “Intensifying Efforts in Yunnan, Expanding Nationwide, Building Brands and Enhancing Benefits” as its overall work guideline, the company vigorously implements the “Three Products” strategy (increasing product variety, improving product quality and creating brands) to achieve its business objectives. First, it will build a brand communication system. This system will cover brand positioning, product positioning, product selling points, advertising slogans, advertising communication and a combination of communication methods. With the Yunyan and Baixiang brands as the focus, and integrating the promotion of products with protected original ecological origins, the company will highlight the products’ advantages, such as plateau geographical indication, natural properties and pollution-free quality. Through integrated marketing, it will fully promote the company’s image and brands and form a multi-brand and multi-level product system. Second, it will continuously optimize the marketing system, guided by market orientation. The company will focus on adjustments to product planning, pricing system, channel construction, promotional measures and incentive mechanisms and other factors, as well as restructuring the marketing management system under the guidance of market principles. Third, it will strengthen channel cooperation to further expand the market. For the in-province market, the goal is to consolidate market share, with county and township sales as the focus; it will make intensive efforts across all channels to build a solid base market. For the out-of-province market, the main goals are to increase sales volume and market share, with the promotion of third-party logistics and the development of key supermarkets as the focus. The company will continue to advance and expand the scope of cooperation with salt industry companies outside the province to promote the construction of a multi-channel marketing network.</p>	<p>This text outlines a clear context for the company’s business development over the upcoming period, covering its overall work guideline, specific action plans and expected business outcomes. It provides a detailed roadmap for the company’s business development in the next year, including building a brand communication system, optimizing the marketing system and strengthening channel cooperation, demonstrating clear thinking and concrete action plans. Meanwhile, the text specifies distinct goals and strategies for in-province and out-of-province markets, with a logical sequence of events that reflects strong contextual completeness. Regarding the prediction of future outcomes, although the text does not elaborate on specific operational data or feedback from target markets, its clear work guidelines and strategies provide a certain indication of the positive impact and expected results on future business. Therefore, the overall score is relatively high.</p>

(continued on next page)

Table 1 (continued)

Order	Score	Content of response	Scoring analysis (reasons)
04	75	In 2018, the main risks facing the company's operations included in-depth changes in organizational structure adjustment, effective cost control and operational risks in corporate management and control, product R&D and new industry market development, along with investment risks of M&A projects. The company will proactively address various internal and external risks, assess the situation in a timely manner, actively advance all work initiatives, continuously improve its strategic management and control system and steadily promote the healthy development of the company.	<p>The main risks mentioned by the company include operational risks in areas such as in-depth changes to organizational structure adjustment, cost control and corporate management and control, as well as investment risks related to M&A projects. These contexts demonstrate high clarity. However, specific details and the extent of their potential impact are not elaborated on. The company states that it will proactively address various risks, assess the situation to advance all work initiatives and continuously improve its strategic management and control system. While these action directions are clear, specific action plans—for instance, how to advance organizational structure adjustment or implement cost control measures—are not mentioned.</p> <p>From the company's response, it is impossible to determine what future outcomes these actions will bring. Although the company mentions "steadily promoting the company's healthy development," no specific forecasts or target settings are provided. The company notes key risk points and the overall strategy for risk response, but it does not detail how these risks will specifically affect the company's operations or provide detailed plans for addressing the risks. Thus, contextual completeness needs improvement. From the content of the response, there is no clear description of the sequence of the described series of events.</p>
05	65	Currently, there is no such development. The transfer resistance between the cathode and solid electrolyte of solid-state batteries is very high, which results in the extremely low power density of solid-state batteries. Meanwhile, the manufacturing cost of such batteries remains very high. Thus, there is still a long way to go before their commercialization. As this technology is currently at a nascent stage, the company will arrange for personnel to track and conduct research and development on it.	<p>The response describes the issue of transfer resistance between the cathode and solid-state electrolyte of solid-state batteries, but it does not elaborate on specific details regarding future scenarios. The company states that it will arrange for personnel to track and conduct research and development (R&D) on this technology. This is a specific action plan, yet it lacks details such as specific R&D strategies and resource investment.</p> <p>The response mentions problems with solid-state batteries, including low power density, high manufacturing costs and a long path to commercialization. However, it does not provide clear predictions about the potential positive outcomes of successful R&D or future improvement directions. While the response covers current technical challenges and the company's response strategies, it fails to comprehensively describe possible future development scenarios. The sequence of events in the response is relatively logical: it first describes the current situation, then mentions the challenges faced, and finally proposes the company's response strategies.</p> <p>In summary, although the response describes the scenario to a certain extent, there is room for improvement in terms of the specificity of actions, the predictability of future outcomes and the completeness of the scenario.</p>

Table 1 (continued)

Order	Score	Content of response	Scoring analysis (reasons)
06	50	Since the company went public, as a social enterprise, it has taken on more social responsibilities. Therefore, I feel that the responsibility on my shoulders is far greater than it was before the listing.	The content of this response mainly conveys the speaker's feelings about and attitude toward investors regarding the company's taking on more social responsibilities after going public. However, it lacks specific descriptions of actions and clear statements of how these actions will lead to future outcomes. Although the abstract concept of "social responsibility" is mentioned, no specific plans or initiatives are provided and future scenarios regarding the sequence of events are not clearly described. Therefore, key aspects such as contextual clarity, action specificity, the predictability of future outcomes, contextual completeness and the rationality of the event sequence are relatively insufficient, resulting in a below-average score.

standard. Second, we submit each management response from the earnings conferences to the ERNIE LLM and request a composite score (0–100) for the degree of scenario disclosure in each response. The model also returns the rationale for each score based on the supplied evaluation standard to ensure rating validity and consistency. Finally, the average value of the scenario scores for all management responses in each earnings conference is calculated to measure the conference's level of scenario disclosure. Table 1 presents real examples extracted from earnings conferences, illustrating the management responses, their corresponding scenario disclosure scores and the rationale behind each score. A manual review reveals that the responses in Examples 1–3 provide detailed descriptions of specific action plans, with clear logic and well-defined implementation paths. The anticipated positive impacts of these actions are explicitly identified or implied, thereby establishing a coherent causal chain between the proposed actions and expected outcomes. As a result, these responses receive relatively high scenario scores. In contrast, the responses in Examples 4–6 largely lack concrete descriptions of action plans, leading to lower scenario scores. This pattern demonstrates that the ERNIE LLM effectively captures the scenario-related elements in management responses, thereby validating the soundness of this study's approach to assessing the degree of scenario disclosure in earnings conferences.

Control variables. Following Han et al. (2018), Wang and Wang (2012) and Lin and Xie (2017), this study controls for factors at both the firm level and the earnings conferences level. At the firm level, the control variables include firm size (*Size*); institutional ownership (*Insshr*); ownership concentration, measured by the shareholding ratio of the largest shareholder (*Top1*); return on assets (*Roa*); leverage ratio (*Lev*); CEO–chairman duality (*Dual*); number of analyst followers (*Ananum*); the nature of property rights (*State*); and whether the firm is audited by a Big Four (*Big4*). At the earnings conferences level, the control variables include the number of questions asked during the conference (*Quenum*), the average tone of the earnings conference (*Tone*) and the number of days between the earnings conference and the annual report release (*Lag*). Detailed definitions of all of the variables are provided in Table 2.

3.3. Descriptive statistics

Table 3 reports the descriptive statistics of the main variables used in this study. The mean value of *DFeps* is -0.110 , with a standard deviation of 0.530 . The mean value of *Scenario* is 70.579 , with a maximum of 88.860 and a minimum of 70.654 , indicating that listed companies' earnings conferences generally exhibit a high level of scenario disclosure. The mean value of *Tone* is 0.529 , with a minimum of 0.108 , suggesting that the language used by management in earnings conferences tends to be predominantly positive, which is consistent with practical observation. The descriptive statistics of the other variables are generally consistent with prior studies and are therefore not discussed further.

Table 2
Variable definitions.

Variable	Variable definition and explanation
<i>DFeps</i>	$DFeps = (Feps_{cc} - Feps_{sar})/Eps$
<i>Scenario</i>	Level of scenario disclosure in earnings conferences
<i>Size</i>	Natural logarithm of total assets
<i>Lev</i>	Total liabilities/Total assets
<i>Roa</i>	Net profit/Average total assets
<i>Dual</i>	Assigned a value of 1 if the chairman and general manager are the same person, otherwise 0
<i>Insshr</i>	Number of shares held by institutional investors/Total shares outstanding
<i>Top1</i>	Number of shares held by the largest shareholder/Total shares outstanding
<i>State</i>	Assigned a value of 1 if the ultimate controller is state-owned, and otherwise 0
<i>BIG4</i>	Assigned a value of 1 if the audit firm is one of the Big Four, and otherwise 0
<i>Ananum</i>	$\ln(1 + \text{number of tracking analysts})$
<i>Tone</i>	$(\text{Positive words} - \text{Negative words})/(\text{Positive words} + \text{Negative words})$
<i>Quenum</i>	$\ln(1 + \text{number of questions in earnings conferences})$
<i>Lag</i>	$\ln(1 + \text{number of days between earnings conference and annual report disclosure})$
<i>IND FE</i>	Industry fixed effect
<i>Year FE</i>	Year fixed effect

Table 3
Descriptive statistics.

Variable	(1) N	(2) Mean	(3) Sd	(4) Min	(5) P50	(6) Max
<i>Dfeps</i>	5963	-0.110	0.530	-3.260	-0.00780	1.372
<i>Scenario</i>	5963	70.579	7.694	50.860	70.654	88.860
<i>Size</i>	5963	21.991	1.177	20.013	21.797	26.039
<i>Lev</i>	5963	0.354	0.189	0.0416	0.335	0.803
<i>Roa</i>	5963	0.0794	0.0532	-0.0608	0.0723	0.254
<i>Insshr</i>	5963	0.452	0.263	0.0123	0.450	0.959
<i>Dual</i>	5963	0.376	0.484	0	0	1
<i>Top1</i>	5963	0.340	0.141	0.0931	0.325	0.716
<i>State</i>	5963	0.163	0.369	0	0	1
<i>BIG4</i>	5963	0.0481	0.214	0	0	1
<i>Ananum</i>	5963	2.494	0.759	0.693	2.565	3.892
<i>Tone</i>	5963	0.529	0.143	0.108	0.541	0.836
<i>Quenum</i>	5963	3.726	0.719	1.386	3.850	5.100
<i>Lag</i>	5963	2.298	0.588	0.693	2.303	4.522

4. Empirical results

4.1. Baseline regression

Table 4 presents the baseline regression results used to test the main hypothesis of this study. Column (1) reports the results of the univariate regression, showing that *Scenario* is strongly and positively associated with *DFeps*. Column (2) includes the control variables, and the positive relationship remains statistically significant at the 1 % level. Column (3) further reports the results of the two-way fixed effects model, and the coefficient of *Scenario* continues to be positive and significant at the 1 % level. Overall, these results support H1, indicating that a higher level of scenario disclosure in earnings conferences leads to more optimistic market beliefs about the firm's future earnings.

Table 4
Scenario disclosure in earnings conferences and capital market earnings expectations.

Variable	(1) <i>DFeps</i>	(2) <i>DFeps</i>	(3) <i>DFeps</i>
<i>Scenario</i>	0.005*** (5.40)	0.003*** (3.01)	0.003*** (2.87)
<i>Size</i>		0.028*** (3.41)	0.014 (1.48)
<i>Lev</i>		0.048 (1.00)	0.064 (1.16)
<i>Roa</i>		-0.035 (-0.23)	-0.071 (-0.42)
<i>Insshr</i>		0.008 (0.25)	0.017 (0.53)
<i>Dual</i>		-0.025* (-1.70)	-0.025* (-1.67)
<i>Top1</i>		0.056 (1.07)	0.058 (1.03)
<i>State</i>		0.012 (0.60)	0.017 (0.89)
<i>BIG4</i>		-0.045 (-1.33)	-0.036 (-1.27)
<i>Ananum</i>		-0.021** (-2.03)	-0.020* (-1.93)
<i>Tone</i>		-0.031 (-0.64)	-0.022 (-0.46)
<i>Quenum</i>		-0.036*** (-3.41)	-0.012 (-1.08)
<i>Lag</i>		-0.032*** (-2.70)	-0.023* (-1.91)
<i>Constant</i>	-0.449*** (-7.11)	-0.690*** (-3.60)	-0.475** (-2.33)
IND FE	NO	NO	YES
Year FE	NO	NO	YES
Observations	5963	5963	5963
R-squared	0.005	0.016	0.029

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the t values adjusted for firm-level clustered robust standard errors.

4.2. Robustness tests

4.2.1. Excluding the interference of management response length

To further verify that the effect of managerial scenario disclosure in earnings conferences is independent of the mere length of management responses, we conduct the following robustness tests. First, we define *Word* as the natural logarithm of the total number of words in management responses during the earnings conferences and include it as a control variable in the regression. As shown in Column (1) of Table 5, the coefficient of *Scenario* remains significant and positive, while *Word* is statistically nonsignificant. This result suggests that the positive market reaction identified in this study is driven by the degree of scenario disclosure rather than by the length of management responses, and that response length alone does not exert a statistically significant impact on market expectations. Second, to further eliminate the possible influence of response length, *Scenario* is regressed on *Word* and the residuals from this regression are extracted as the net degree of scenario disclosure (*Scenario_resid*). The baseline regression is then re-estimated using *Scenario_resid* as the key explanatory variable. As reported in Column (2) of Table 5, the coefficient of *Scenario_resid* remains significant and positive, providing additional support for the main conclusion.

Table 5
Excluding the interference of response length in earnings conferences.

Variable	(1) <i>DFeps</i>	(2) <i>DFeps</i>
<i>Scenario</i>	0.003*** (2.71)	
<i>Scenario_resid</i>		0.002** (2.54)
<i>Word</i>	0.003 (0.40)	
<i>Size</i>	0.014 (1.49)	0.014 (1.48)
<i>Lev</i>	0.063 (1.16)	0.064 (1.17)
<i>Roa</i>	-0.070 (-0.42)	-0.072 (-0.43)
<i>Insshr</i>	0.017 (0.53)	0.017 (0.52)
<i>Dual</i>	-0.025* (-1.67)	-0.025* (-1.67)
<i>Top1</i>	0.058 (1.03)	0.058 (1.04)
<i>State</i>	0.017 (0.89)	0.017 (0.86)
<i>BIG4</i>	-0.036 (-1.28)	-0.035 (-1.24)
<i>Ananum</i>	-0.020* (-1.93)	-0.020* (-1.91)
<i>Tone</i>	-0.023 (-0.48)	-0.015 (-0.31)
<i>Quenum</i>	-0.012 (-1.02)	-0.015 (-1.30)
<i>Lag</i>	-0.023* (-1.91)	-0.023* (-1.90)
<i>Constant</i>	-0.480** (-2.35)	-0.283 (-1.44)
Firm FE	YES	YES
Year FE	YES	YES
Observations	5963	5963
R-squared	0.029	0.029

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the *t* values adjusted for firm-level clustered robust standard errors.

4.2.2. Replacing the proxy for capital market earnings expectations

To ensure the robustness of the conclusions, we replace the dependent variable with alternative measures of capital market earnings expectations. In Column (1), the earnings expectation indicator is replaced by *DFinance*, defined as the difference between the average analyst forecast of the firm's next-period operating revenue within 60 days after the earnings conference and the average forecast made after the annual report release but before the conference, adjusted by the firm's actual next-period operating revenue. As shown in Column (1) of Table 6, *Scenario* is positive and significant at the 5 % level, confirming the main conclusion of this paper.

Second, a more positive sentiment in analyst reports indicates a more optimistic outlook for a firm's future earnings. This paper measures the positivity of analyst reports by the ratio of positive words to total words and calculates the change in report tone positivity (*Dtone_ratio*). As shown in Column (2) of Table 6, *Dtone_ratio* is positive and significant at the 5 % level, further validating the conclusions of this study.

Table 6
Replacing the proxy for capital market earnings expectations.

Variable	(1) <i>DFincome</i>	(2) <i>Dtone_ratio</i>
<i>Scenario</i>	0.001** (2.05)	0.004** (2.36)
<i>Size</i>	0.001 (0.39)	-0.009 (-0.58)
<i>Lev</i>	0.016 (1.03)	-0.051 (-0.58)
<i>Roa</i>	0.042 (0.91)	-0.626** (-2.40)
<i>Inssh</i>	-0.011 (-1.27)	-0.005 (-0.09)
<i>Dual</i>	-0.001 (-0.14)	0.023 (0.92)
<i>Top1</i>	-0.013 (-0.81)	0.039 (0.44)
<i>State</i>	-0.004 (-0.71)	-0.034 (-0.96)
<i>BIG4</i>	-0.007 (-0.78)	0.074 (1.30)
<i>Ananum</i>	-0.005* (-1.66)	-0.011 (-0.60)
<i>Tone</i>	-0.006 (-0.45)	-0.106 (-1.22)
<i>Quenum</i>	0.001 (0.21)	-0.019 (-0.93)
<i>Lag</i>	-0.002 (-0.78)	0.026 (1.28)
<i>Constant</i>	-0.034 (-0.60)	-0.027 (-0.08)
IND FE	YES	YES
Year FE	YES	YES
Observations	3977	5079
R-squared	0.016	0.018

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the t values adjusted for firm-level clustered robust standard errors.

4.2.3. Excluding samples with long intervals

There exists considerable variation in the interval between the disclosure of annual reports and the holding of earnings conferences among listed companies. Some firms hold their earnings conferences on the same day as the annual report release, while others do so after a longer delay. To eliminate the potential influence of other factors associated with longer intervals between annual report disclosure and the holding of an earnings conference on the regression results, we re-estimate the model using only samples in which the interval between the two events is within 15 days. The results are presented in Table 7. Column (1) reports the univariate regression results, showing that *Scenario* is significantly and positively correlated with *DFeps*. Column (2) reports the results with the control variables, and the significant positive correlation remains. Column (3), which presents the results of the industry and year fixed effects regressions, also shows a consistently significant positive relationship. These findings are consistent with the baseline regression results, confirming the robustness of the conclusions.

4.2.4. Changing the forecast window

This paper also tests the robustness of the regression results using analysts' consensus earnings forecasts within different time windows after earnings conferences. Table 8 presents the results for forecast windows

Table 7

Excluding samples where the interval between annual report disclosure and the holding of an earnings conference exceeds 15 days.

Variable	(1) <i>DFeps</i>	(2) <i>DFeps</i>	(3) <i>DFeps</i>
<i>Scenario</i>	0.004*** (3.95)	0.002** (2.10)	0.002* (1.95)
<i>Size</i>		0.025*** (2.78)	0.011 (1.05)
<i>Lev</i>		0.038 (0.74)	0.052 (0.91)
<i>Roa</i>		0.025 (0.15)	0.011 (0.06)
<i>Inssh</i>		-0.022 (-0.69)	-0.017 (-0.51)
<i>Dual</i>		-0.023 (-1.52)	-0.025 (-1.64)
<i>Top1</i>		0.091 (1.63)	0.093 (1.58)
<i>State</i>		0.014 (0.61)	0.018 (0.86)
<i>BIG4</i>		-0.045 (-1.19)	-0.035 (-1.06)
<i>Ananum</i>		-0.010 (-0.88)	-0.010 (-0.88)
<i>Tone</i>		-0.028 (-0.53)	-0.007 (-0.13)
<i>Quenum</i>		-0.036*** (-3.02)	-0.010 (-0.75)
<i>Lag</i>		0.012 (0.78)	0.014 (0.89)
<i>Constant</i>	-0.369*** (-5.43)	-0.681*** (-3.26)	-0.472** (-2.10)
IND FE	NO	NO	YES
Year FE	NO	NO	YES
Observations	5141	5141	5141
R-squared	0.003	0.010	0.024

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the t values adjusted for firm-level clustered robust standard errors.

of 45 days, 90 days and 120 days following a conference. In all cases, *Scenario* remains significantly and positively correlated with *DFeps*, consistent with the main regression results.

4.2.5. Excluding analysts with business affiliations

Prior research shows that analysts may systematically bias their earnings forecasts due to business affiliations with listed firms (Kolasinski and Kothari, 2008; Mola and Guidolin, 2009; Wu et al., 2013). To ensure that the conclusions of this paper are not affected by affiliated analysts, we exclude analysts who have business relationships with the firms through seasoned equity offerings or rights issues and recalculate *DFeps*. As shown in Column (1) of Table 9, *Scenario* remains significantly and positively correlated with *DFeps*.

4.2.6. Controlling for fixed effects along other dimensions

First, firm fixed effects can capture time-invariant firm characteristics. We replace the industry fixed effects in the baseline regression with firm-level fixed effects, and—as shown in Column (2) of Table 9—*Scenario* remains significantly and positively correlated with *DFeps* at the 5 % level. To control for potential omitted variable bias arising from variations across provinces and industries over time, such as macro factors favoring

Table 8
Changing the forecast window.

Variable	(1) <i>DFeps45</i>	(2) <i>DFeps90</i>	(3) <i>DFeps120</i>
<i>Scenario</i>	0.002*** (2.67)	0.003*** (2.70)	0.002* (1.89)
<i>Size</i>	0.0001 (0.01)	0.022** (2.18)	0.030** (2.48)
<i>Lev</i>	0.058 (1.12)	0.036 (0.62)	-0.020 (-0.30)
<i>Roa</i>	-0.095 (-0.61)	-0.146 (-0.81)	-0.076 (-0.36)
<i>Insshr</i>	0.008 (0.26)	0.020 (0.58)	0.005 (0.12)
<i>Dual</i>	-0.023* (-1.68)	-0.031* (-1.94)	-0.045** (-2.48)
<i>Top1</i>	0.085* (1.65)	0.065 (1.10)	0.099 (1.47)
<i>State</i>	0.009 (0.49)	0.033 (1.59)	0.053** (2.17)
<i>BIG4</i>	-0.039 (-1.42)	-0.023 (-0.76)	0.005 (0.14)
<i>Ananum</i>	-0.009 (-0.86)	-0.031*** (-2.65)	-0.051*** (-3.72)
<i>Tone</i>	-0.021 (-0.46)	-0.014 (-0.28)	0.016 (0.26)
<i>Quenum</i>	-0.010 (-0.88)	-0.020 (-1.56)	-0.020 (-1.35)
<i>Lag</i>	-0.013 (-1.08)	-0.023* (-1.76)	-0.041*** (-2.71)
<i>Constant</i>	-0.178 (-0.91)	-0.641*** (-2.97)	-0.776*** (-2.93)
IND FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	5575	5963	5963
R-squared	0.023	0.038	0.043

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the *t* values adjusted for firm-level clustered robust standard errors.

a particular industry in certain cities, this study further adds province-year fixed effects and industry-year fixed effects to the firm fixed effects model. Columns (3) and (4) of Table 9 show that *Scenario* continues to be significantly and positively associated with *DFeps*, further confirming the robustness of the study's conclusions.

5. Additional tests

5.1. The impact of firm-specific information levels

According to research on situational thinking (Tversky and Kahneman, 1973; Kahneman et al., 1982; Kahneman and Lovallo, 1993), when capital market participants lack the information required to independently evaluate a firm's future, the role of verbal disclosure in filling information gaps by constructing scenario is amplified, making it easier for management to guide market expectations through scenario thinking. Based on this, we further examine how the lack of firm-specific information in the market influences the relationship between scenario disclosure and capital market expectations.

Table 9
Other robustness test.

Variable	(1)	(2)	(3)	(4)
	<i>DFeps</i>	<i>DFeps</i>	<i>DFeps</i>	<i>DFeps</i>
<i>Scenario</i>	0.003*** (2.83)	0.003** (2.41)	0.003** (2.25)	0.003** (2.54)
<i>Size</i>	0.013 (1.45)	0.013 (0.40)	0.011 (0.32)	0.016 (0.46)
<i>Lev</i>	0.064 (1.19)	0.150 (1.43)	0.188* (1.79)	0.116 (1.04)
<i>Roa</i>	-0.079 (-0.48)	-0.532* (-1.80)	-0.479 (-1.52)	-0.622* (-1.93)
<i>Inssh</i>	0.017 (0.52)	-0.034 (-0.33)	-0.036 (-0.35)	-0.078 (-0.72)
<i>Dual</i>	-0.025* (-1.70)	-0.063* (-1.81)	-0.068* (-1.96)	-0.056 (-1.55)
<i>Top1</i>	0.052 (0.94)	0.182 (0.80)	0.109 (0.49)	0.205 (0.92)
<i>State</i>	0.019 (0.97)	-0.126 (-0.92)	-0.155 (-1.10)	-0.231 (-1.59)
<i>BIG4</i>	-0.034 (-1.24)	-0.063 (-1.20)	-0.074 (-1.51)	-0.067 (-1.07)
<i>Ananum</i>	-0.021** (1.99)	-0.044** (-2.57)	-0.048*** (-2.70)	-0.042** (-2.38)
<i>Tone</i>	-0.022 (-0.47)	-0.028 (-0.43)	-0.010 (-0.16)	-0.074 (-1.11)
<i>Quenum</i>	-0.013 (-1.15)	-0.006 (-0.27)	-0.010 (-0.49)	-0.002 (-0.09)
<i>Lag</i>	-0.023* (-1.91)	0.003 (0.18)	0.009 (0.54)	0.002 (0.10)
<i>Constant</i>	-0.452** (-2.25)	-0.476 (-0.68)	-0.402 (-0.53)	-0.514 (-0.69)
IND FE	YES	NO	NO	NO
Firm FE	NO	YES	YES	YES
Year FE	YES	YES	NO	NO
IND-Year	NO	NO	YES	NO
Province-Year	NO	NO	NO	YES
Observations	5955	5264	5230	5172
R-squared	0.030	0.289	0.326	0.343

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the t values adjusted for firm-level clustered robust standard errors.

First, following Yoo (2025), the variable *ASY*—constructed based on the annual average bid-ask spread—is used to quantify the level of information asymmetry and to group the sample. Specifically, the industry-year median of *ASY* is calculated. Firms with *ASY* above the median are classified as the high information asymmetry group, while those with *ASY* at or below the median are classified as the low information asymmetry group. As shown in Columns (1) and (2) of Table 10, the regression coefficient of *Scenario* is significant only in the high information asymmetry group and passes the 5 % level test for differences between groups, indicating that when the market lacks information to assess the firm's future performance, managerial scenario disclosure more strongly increases market expectations of future earnings. Second, analysts with shorter coverage histories have accumulated limited knowledge of and have limited ability to track a firm, putting them at a disadvantage in terms of firm-specific information. Analysts are grouped based on the number of years in which they have published research reports on a given firm, and the earnings forecast change variable *DFeps* is calculated for each group (Mikhail et al., 1997; Bowen et al., 2002). Columns (3) and (4) of Table 10 show the results. *Scenario* is significant only for analysts with shorter coverage histories, and the regression coefficient

Table 10
The effects of firm-specific information levels.

Variable	(1) Low asymmetry <i>DFeps</i>	(2) High asymmetry <i>DFeps</i>	(3) Short coverage <i>DFeps</i>	(4) Long coverage <i>DFeps</i>
<i>Scenario</i>	−0.0003 (−0.20)	0.006*** (2.82)	0.003*** (2.64)	0.001 (0.96)
<i>Size</i>	0.0002 (0.01)	−0.001 (−0.05)	0.005 (0.43)	0.009 (1.01)
<i>Lev</i>	0.088 (0.90)	0.189 (1.58)	0.092 (1.43)	0.052 (0.91)
<i>Roa</i>	0.267 (0.90)	0.060 (0.15)	0.040 (0.21)	−0.189 (−1.15)
<i>Insshr</i>	−0.034 (−0.59)	0.036 (0.56)	0.043 (1.16)	−0.018 (−0.54)
<i>Dual</i>	−0.010 (−0.38)	−0.061* (−1.90)	−0.004 (−0.25)	−0.034** (−2.26)
<i>Top1</i>	0.094 (0.89)	−0.055 (−0.46)	0.038 (0.61)	0.047 (0.83)
<i>State</i>	0.025 (0.71)	0.008 (0.14)	0.009 (0.40)	0.048*** (2.67)
<i>BIG4</i>	−0.056 (−0.78)	0.075 (1.28)	−0.007 (−0.21)	−0.005 (−0.22)
<i>Ananum</i>	−0.018 (−0.85)	−0.029 (−1.21)	−0.024* (−1.96)	−0.025* (−1.95)
<i>Tone</i>	−0.013 (−0.14)	−0.097 (−0.94)	−0.032 (−0.60)	−0.107** (−2.29)
<i>Quenum</i>	−0.019 (−0.81)	−0.002 (−0.07)	−0.001 (−0.05)	−0.025** (−2.20)
<i>Lag</i>	−0.006 (−0.26)	−0.001 (−0.03)	−0.020 (−1.41)	−0.017 (−1.43)
<i>Constant</i>	−0.019 (−0.05)	−0.440 (−0.87)	−0.355 (−1.49)	−0.096 (−0.48)
IND FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	1857	1727	4790	3446
R-squared	0.025	0.046	0.032	0.034
P-value	0.016**		0.086*	

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the t values adjusted for firm-level clustered robust standard errors. The P-values for the test of coefficient differences between groups in the heterogeneity analysis are calculated using Fisher's combination test with 500 sampling iterations.

for the short-coverage group is significantly greater than that for the long-coverage group. This similarly indicates that when the market lacks information to assess a firm's future performance, managerial scenario disclosure more strongly enhances market expectations of future earnings. Overall, these results suggest that firm-specific information affects the impact of scenario disclosure in earnings conferences on market expectations, and that a lack of firm-specific information allows management to use verbal scenario disclosure more effectively to manage market expectations.

5.2. Circumstances under which management uses more scenario language

The preceding results indicate that managerial scenario disclosure in earnings conferences can increase market expectations of a firm's future earnings. In further analysis, this paper explores the circumstances under which management uses more scenario language.

Table 11
The nature of information in earnings conferences and use of scenario language.

Variable	(1) <i>Scenario</i>	(2) <i>Scenario</i>	(3) <i>Scenario</i>	(4) <i>Scenario</i>
<i>Positive_Word</i>	51.347*** (12.44)	47.754*** (11.74)		
<i>Negative_Word</i>	-65.608*** (-11.03)	-60.381*** (-10.50)		
<i>Tone</i>			10.419*** (13.87)	9.446*** (13.01)
<i>Size</i>		0.278 (1.63)		0.292* (1.68)
<i>Lev</i>		0.308 (0.38)		0.129 (0.15)
<i>Roa</i>		-0.344 (-0.15)		-0.987 (-0.42)
<i>Insshr</i>		-0.526 (-0.97)		-0.470 (-0.84)
<i>Dual</i>		-0.067 (-0.27)		0.007 (0.03)
<i>Top1</i>		1.382 (1.54)		1.560* (1.70)
<i>State</i>		-0.497 (-1.30)		-0.562 (-1.44)
<i>BIG4</i>		0.399 (0.60)		0.458 (0.67)
<i>Ananum</i>		0.138 (0.87)		0.156 (0.97)
<i>Quenum</i>		-2.607*** (-12.59)		-2.716*** (-13.03)
<i>Lag</i>		0.293 (1.62)		0.163 (0.88)
<i>Constant</i>	67.100*** (111.12)	69.677*** (19.95)	65.071*** (152.30)	68.292*** (19.58)
IND FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	5963	5963	5963	5963
R-squared	0.208	0.245	0.182	0.222

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses denote the t values adjusted for firm-level clustered robust standard errors.

5.2.1. The nature of information and management's use of scenario language

Managers aim to build a favorable long-term outlook for the firm (Kahn and Rudd, 1999) or demonstrate their capabilities through future-oriented performance (Bochkay et al., 2019). In earnings conferences, management uses scenario narratives to disclose positive information, thereby constructing a favorable future outlook for the firm, boosting investor confidence and enhancing firm valuation. Conversely, using scenario narratives to present negative information would conflict with the objective of managing market expectations. To demonstrate that management employs scenario descriptions primarily for positive information, constructing an optimistic future for information users, this paper further examines how the nature of the information disclosed in earnings conferences affects the degree of scenario disclosure. First, the average proportions of positive words (*Positive_word*) and negative words (*Negative_word*) in earnings conferences are calculated and regressed on the scenario disclosure variable (*Scenario*). In Table 11, Column (1) presents the results without the control variables, where *Positive_word* is significantly and positively associated with *Scenario*, while

Negative_word is significantly and negatively associated with *Scenario*. In Column (2), after including the control variables, *Positive_word* remains significantly and positively associated with *Scenario* at the 1 % level, and *Negative_word* remains significantly and negatively associated with *Scenario* at the 1 % level. These results indicate that positive information is more likely than negative information to be scenario-disclosed. Second, the average net positive tone (*Tone*) of earnings conferences is regressed on *Scenario*. As shown in Columns (3) and (4) of Table 11, regardless of whether the control variables are included, *Tone* is significantly and positively associated with *Scenario* at the 1 % level, indicating that the more positive the information in an earnings conference, the higher the degree of scenario disclosure. Overall, these results suggest that management employs scenario narratives primarily when conveying positive information and constructing optimistic future prospects, thereby reinforcing causal logic and amplifying market optimism. In contrast, scenario narratives are not used when discussing negative information.

Table 12
Capital market pressure and management's use of scenario language.

Variable	(1) <i>Scenario</i>	(2) <i>Scenario</i>	(3) <i>Scenario</i>
<i>Ros_gap</i>	2.750* (1.91)		
<i>Negative_all</i>		0.242** (2.51)	
<i>Negative_org</i>			0.564** (2.26)
<i>Size</i>	0.323* (1.84)	0.249 (1.40)	0.262 (1.48)
<i>Lev</i>	-0.418 (-0.47)	0.420 (0.49)	0.407 (0.47)
<i>Roa</i>	2.777 (0.91)	-0.297 (-0.12)	-0.322 (-0.13)
<i>Insshr</i>	-0.486 (-0.87)	-0.531 (-0.94)	-0.524 (-0.93)
<i>Dual</i>	0.015 (0.06)	0.023 (0.09)	0.017 (0.06)
<i>Top1</i>	1.476 (1.60)	1.671* (1.79)	1.689* (1.80)
<i>State</i>	-0.559 (-1.43)	-0.558 (-1.41)	-0.567 (-1.43)
<i>BIG4</i>	0.488 (0.72)	0.279 (0.41)	0.327 (0.48)
<i>Ananum</i>	0.143 (0.89)	0.137 (0.83)	0.147 (0.89)
<i>Tone</i>	9.405*** (13.02)	9.607*** (12.88)	9.599*** (12.86)
<i>Quenum</i>	-2.709*** (-13.00)	-2.709*** (-12.69)	-2.703*** (-12.66)
<i>Lag</i>	0.176 (0.95)	0.166 (0.88)	0.168 (0.89)
<i>Constant</i>	67.679*** (19.25)	68.830*** (19.35)	68.514*** (19.28)
IND FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	5963	5687	5687
R-squared	0.223	0.225	0.225

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the t values adjusted for firm-level clustered robust standard errors.

Table 13
Scenario disclosure in earnings conference and stock price crash risk.

Variable	(1) <i>FNcskew</i>	(2) <i>FDwol</i>
<i>Scenario</i>	0.005*** (2.96)	0.001* (1.73)
<i>DFeps</i>	0.054** (2.12)	0.020* (1.66)
<i>Size</i>	0.069*** (4.15)	0.035*** (4.39)
<i>Lev</i>	-0.418*** (-4.64)	-0.094** (-2.18)
<i>Roa</i>	-0.959*** (-3.50)	-0.051 (-0.39)
<i>Insshr</i>	-0.131** (-2.41)	0.035 (1.35)
<i>Dual</i>	-0.013 (-0.51)	0.003 (0.26)
<i>Top1</i>	-0.030 (-0.33)	-0.106** (-2.44)
<i>State</i>	-0.045 (-1.25)	-0.029 (-1.62)
<i>BIG4</i>	-0.090 (-1.62)	-0.053* (-1.91)
<i>Ananum</i>	0.027 (1.37)	0.024*** (2.63)
<i>Tone</i>	-0.056 (-0.64)	0.048 (1.17)
<i>Quenum</i>	0.030 (1.31)	-0.009 (-0.89)
<i>Lag</i>	-0.027 (-1.27)	-0.008 (-0.83)
<i>Constant</i>	-2.262*** (-6.06)	-0.976*** (-5.55)
IND FE	YES	YES
Year FE	YES	YES
Observations	5723	5647
R-squared	0.111	0.093

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the *t* values adjusted for firm-level clustered robust standard errors.

5.2.2. Market pressure and management's use of scenario language

First, this paper examines whether a decline in a firm's current fundamentals prompts management to strategically use scenario language to improve market expectations. Following Park (2007) and Li et al. (2018), the median operating profit margin of all firms in the industry in year *t* is used as the expected performance. The difference between expected performance and the firm's actual performance, *ROS_gap*, is calculated, where a larger gap indicates poorer relative performance. As shown in Column (1) of Table 12, the poorer a firm's performance relative to expectations, the more management prefers to use scenario language, suggesting that management strategically employs scenario thinking to improve market expectations during periods of fundamental decline.

Second, media news—representing “opinion leaders” as defined in communication studies—plays a role in conveying opinions and attitudes to the public, potentially shaping market sentiment or even influencing investor behavior (Zhang and Wu, 2021). Media sentiment spreads quickly and widely, often being repeated or emphasized (You and Wu, 2012), thereby affecting market judgments and perceptions of firm performance (Tetlock et al., 2008). Therefore, when media sentiment is negative, management is more likely to use scenario language to enhance market expectations of future earnings. This study measures media sentiment using

online news, specifically calculating the proportion of all negative news (*Negative_all*) and original negative news (*Negative_org*) related to the firm within the 90 days prior to the annual report disclosure. Columns (2) and (3) of Table 12 show that the coefficients of *Negative_all* and *Negative_org* are both significant and positive, indicating that management tends to use scenario language when media sentiment is negative.

In summary, these empirical findings suggest that management may be motivated to manage market expectations through scenario language in earnings conferences, providing valuable guidance for the development of earnings conferences regulations in China.

5.3. Scenario disclosure and stock price crash risk

As previously noted, managerial scenario disclosure in earnings conference functions as an upward market expectation management strategy. This strategy can temporarily boost investor beliefs and generate overly optimistic market expectations. However, if subsequent information or firm performance fails to meet these expectations, negative information is released in a concentrated manner, leading to asymmetric and rapid stock price declines, thereby increasing stock price crash risk. In light of this, the paper further examines the impact of scenario disclosure on stock price crash risk. Following Kim et al. (2011) and Chen et al. (2001), crash risk is calculated over a window from the 5th to the 24th week after the earnings conference. Two variables, *FNskew* and *FDvol*, are constructed and used in the regression of Model (2). *FNskew* measures the skewness of negative returns and *FDvol* measures the ratio of up and down volatility, with higher values indicating greater crash risk. Table 13 reports the effect of scenario disclosure on firm-level crash risk. As shown in Columns (1) and (2), the coefficient of *Scenario* is significant and positive, and *DFeps* is also significant and positive, indicating that scenario disclosure in earnings conferences can mislead market expectations and significantly increase subsequent stock price crash risk.

$$FNskew_{i,t}/FDvol_{i,t} = \alpha + \beta_1 Scenario_{i,t} + \beta_2 DFeps_{i,t} + Controls_{i,t} + INDFE + YearFE + \varepsilon_{i,t} \quad (2)$$

6. Conclusion

The unique Q&A interaction session in earnings conferences breaks the format constraints of periodic reports and ad-hoc reports, enhances the autonomy of management's information disclosure and enables management to engage in oral scenario disclosure. This helps the firm convey a positive image of itself and improve capital market expectations. This paper empirically examines the impact of management's scenario disclosure on market expectations of future firm earnings using earnings conferences transcripts from Chinese listed firms between 2005 and 2021. The study finds that the greater the degree of scenario disclosure, the more optimistic the capital market's expectations of the firm's future earnings. Heterogeneity tests indicate that scenario disclosure has a stronger positive effect on market expectations when firm-specific information is limited. Furthermore, this paper examines the circumstances under which the level of scenario disclosure in language used in earnings conferences is higher and explores the motivations for management's use of scenario language in their responses. The results show that scenario disclosure is more prevalent when management conveys positive (vs. negative) information, when firm performance is poor (vs. good) and when media sentiment is negative (vs. positive), indicating that management indeed uses scenario disclosure to guide market expectations of earnings. Finally, we examine the capital market consequences of scenario oral disclosure in earnings conferences and find that such disclosure increases the risk of stock price crashes in subsequent periods.

Based on the above findings, this paper offers the following implications and recommendations. Earnings conferences, with their real-time interactive format, provide a relatively flexible and unconstrained information disclosure channel. Management can leverage these conferences to construct detailed scenarios that describe corporate plans and influence market expectations of earnings. While this can enhance information transparency in the capital market, management's self-interested exploitation of scenario thinking to manipulate market expectations can further reduce market efficiency. Therefore, regulators should strengthen supervision of and provide clearer guidance for earnings conferences. Specifically, they should prudently define the required content, promote a transparent communication mechanism balancing accuracy, completeness and neutrality and monitor Q&A sessions to minimize manipulative statements by management, thereby

improving market pricing efficiency and reducing systemic risk caused by misleading disclosures. Market participants should recognize the role of scenario language in shaping market expectations and remain cautious about being influenced by overly optimistic narratives. When interpreting information from earnings conferences, investors should consider not only the narrative itself but also the firm's fundamentals and objective financial indicators to form more rational and comprehensive judgments.

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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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Corporate culture and supply chain resilience

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ABSTRACT

Traditional cultural institutions may substantially enhance resilience amid escalating economic uncertainty and geopolitical tensions that amplify vulnerabilities in corporate supply chains. We measure firm-level exposure to Confucian influence based on the number of nearby Confucian temples and find robust evidence that firms with greater exposure exhibit higher supply chain resilience. To address endogeneity concerns, we include granular fixed effects, control for additional variables and implement a propensity score matching procedure and an instrumental variable approach. Our results remain qualitatively unchanged. Exploiting two quasi-natural experiments, we further show that Confucian culture has a muted impact on firms located in regions with historical Manchu garrisons or areas exposed to the Taiping Rebellion. Through mechanism analysis, we reveal that Confucian influence is more pronounced among firms with weaker formal or external governance, slower adaptive evolution or a more opaque information environment. Lastly, heterogeneity tests show that the effect of Confucian culture is stronger on firms with a weaker environmental, social and governance orientation; lower exposure to exotic ideologies; more constrained trade credit financing; or a higher operating risk level. Overall, our study identifies corporate culture as a crucial determinant of resilience and underscores the value of harnessing traditional culture to mitigate operational risks and support long-run sustainability.

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1. Introduction

Firms facing increasing global integration and extensive outsourcing often rely on long-term relationships with a select set of suppliers and customers when reconfiguring their supply chain layouts (McMillan, 1990; Bensaou, 1999), a shift that increases supply chain concentration (Treleven and Bergman Schweikhart, 1988; Choi and Krause, 2006). While a concentrated and centralized supply chain can yield economies of scale, reduce coordination costs and improve procurement efficiency, it also heightens firms' vulnerability to supply chain disruptions (Yang et al., 2012; Chopra and Sodhi, 2014). The resulting losses extend beyond individual focal firms to threaten the stability of the entire real economy (Hendricks and Singhal, 2005; Acemoglu and Tahbaz-Salehi, 2025). Recent geopolitical shocks, particularly the China–U.S. trade war, have further exacerbated supply chain disruptions. As the gap between China and the U.S. is likely to widen further, the world economy is expected to become more contested and fragmented.

The current world order and international environment have exposed the fragilities of supply chain networks, highlighting the need to balance the efficiency gains brought by globalization against increasing supply chain risk (Khan, 2025) and elevating supply chain resilience to a first-order concern. Supply chain resilience refers to a firm's ability to anticipate, adapt to and recover from disruptions while maintaining operational continuity. Such resilience relies on mutual trust and close cooperation among trading partners (Bode et al., 2011; Dubey et al., 2023), as well as on effective supply chain risk management and easy access to low-cost, high-quality inputs (Simchi-Levi et al., 2014). It also requires timely adjustments to restore a stable operating state after disruptions (Ivanov, 2024) and thus mitigate the adverse consequences of unexpected events.

Although corporate culture is an informal institution, it has real impacts on firm behavior. For example, stronger individualism is associated with greater risk-taking (Li et al., 2013), whereas weak integrity norms may lead to operational and financial irregularities (Altamuro et al., 2022). In China, historical Confucian values, the dominant ideology in Imperial China, have persisted and remain influential today (Gu et al., 2024). Prior studies show that Confucianism, which may serve as an alternative governance mechanism in the context of less developed formal institutions, improves information disclosure quality (Zhao et al., 2024), reduces corporate default risk (Zhang et al., 2025a), accelerates integration into social networks (Yan et al., 2024) and alleviates financial constraints (Li et al., 2020; Wei et al., 2023).

In this study, we examine whether and how Confucian culture influences supply chain resilience. Our research question is important for two reasons. First, most of the extant literature either applies analytical models to dynamic adjustments in supply chains (Hu and Kostamis, 2015; Ang et al., 2017) or investigates outcomes and mitigation strategies following external shocks to supply chain networks, such as natural disasters (Barrot and Sauvagnat, 2016; Costello, 2020; Carvalho et al., 2021; Crosignani et al., 2023). In comparison, how supply chain resilience can be strengthened before a disruption, via either formal or informal institutions, remains underexplored. A better understanding of this issue is expected to yield value-relevant implications that can help firms facing disruptions to mitigate losses *ex ante* and accelerate recovery *ex post*. Second, as an informal institution, Confucian culture continuously shapes firms' behavioral patterns (Yao, 2000) and decision-making processes (Fu and Tsui, 2003). If Confucian values can improve supply chain resilience, the benefits would extend beyond the focal firms to a large group of corporate stakeholders, including suppliers, customers, policymakers and regulators, because resilience propagates through supply chains and supports the operational continuity of the real economy.

We apply our research question to a sample of data. Our sample includes a large panel of Chinese firms from 2008 to 2023. One challenge when assessing the influence of Confucian culture on supply chain resilience is the reliable measurement of these two theoretical constructs as firms rarely disclose such information, and both constructs are unobservable to researchers. Following recent research (Jin et al., 2023; Zhang et al., 2025a), we measure a firm's exposure to Confucian culture using the density of Confucian temples in the firm's geographic vicinity. We measure supply chain resilience as the negative value of the deviation between a firm's production volatility and demand volatility (Shan et al., 2014). After controlling for a large set of firm-level characteristics, along with firm and industry-year fixed effects, we find that exposure to Confucian culture improves supply chain resilience. In terms of the economic impact, a one-standard-deviation increase in

our Confucian culture measure is associated with an approximately 10% increase in supply chain resilience relative to the sample standard deviation.

So far, our baseline results indicate that firms with more exposure to Confucian culture exhibit greater supply chain resilience. However, our estimated effects may be biased due to the omission of unobservable covariates, reverse causality or a misspecified functional form of the regression model. To address these endogeneity concerns, we expand the baseline model specification with additional control variables or province fixed effects and re-estimate the model after implementing a propensity score matching (PSM) procedure. The estimated effect of Confucian culture remains positive and significant. We next implement an instrumental variable (IV) approach grounded in the historical diffusion of Confucian values. Specifically, the IVs include the number of chastity memorial arches (Xu et al., 2019; Zhang et al., 2025b), the number of books printed during the Ming dynasty (Gu et al., 2024) and river density. Theoretically, these IVs are historical and geographical features that have influenced the strength and persistence of faith in Confucianism but are plausibly unrelated to modern supply chain management other than through the impact of Confucian values. The results obtained with all IVs reliably show that instrumented Confucian culture continues to have a positive effect on the resilience of firm supply chain.

Given that it is notoriously difficult, if not impossible, to verify the exclusion restriction for the IVs, we exploit two powerful settings that have weakened the impact of Confucian culture: the construction and rebuilding of Manchu cities (Kung and Ma, 2014) and the Taiping Rebellion (Gu et al., 2024). These two quasi-natural experiments can help cross-validate our empirical findings. As expected, we find that the positive relationship between Confucian culture and resilience is muted in regions with historical Manchu garrisons or with high numbers of casualties from the Taiping Rebellion. Taken together, these results lend strong support to a causal interpretation of the positive effect of Confucian culture on supply chain resilience.

We next investigate the economic mechanisms through which Confucian culture promotes supply chain resilience. First, the Confucian virtues of *neixing* (introspective governance) and *shendu* (self-restraint) can curb corporate opportunistic activities (Gu et al., 2024) and unethical behaviors (Chen et al., 2024). By reinforcing self-discipline and mutual obligations along the supply chain, these Confucian norms provide an informal and internal form of governance. Crucially, the governance effect of Confucianism is expected to be stronger when the alternative formal internal control system or external monitoring is weaker. In such situations, firms embedded in a stronger Confucian culture achieve corporate social responsibility (CSR) more consistently (Fu et al., 2022; Cao et al., 2024) and supply chain coordination more effectively (Dai et al., 2021), both of which support stable operations and cushion the supply chain system against disruptions. Consistent with this informal governance mechanism, we find that Confucianism has a stronger effect on the supply chain resilience of firms with greater separation between ownership and control rights and those operating in less competitive product markets.

Second, the Confucian ideology of *zhongyong* (the doctrine of the mean) prizes stability while encouraging adaptive evolution through gradual reform. The Confucian values of *gewuzhizhi* (pursuit of principles), *boxue* (broad learning) and *zhiyi* (critical thinking) cultivate disciplined learning and analytical problem-solving, thus facilitating a positive environment in which firms can proactively pursue adaptive evolution. In our setting, these norms steer firms toward evolutionary activities, enabling their operations to keep pace with market changes (Yan et al., 2021). For firms with weak adaptive capability, Confucian influence may lead managers to prioritize modular upgrades, codify operating routines, improve data capture and adopt advanced technologies (e.g., blockchain) in supply chain management. These practices help strengthen supply chain coordination and production scheduling, reduce variability along the chain and significantly shorten response times when disruptions occur. Using the degree of digital transformation and the number of invention patent grants as two proxies for firms' adaptive capability, we provide evidence supporting this adaptive evolution mechanism. The positive association between Confucian culture and supply chain resilience is stronger for firms with lower levels of digital transformation and for less innovative firms.

Third, the Confucian values of *yi* (righteousness) and *li* (propriety) emphasize ethical integrity, which in turn discourages financial reporting manipulation, promotes timely and transparent communication with stakeholders and reduces information asymmetry along the supply chain. Consistent with this argument, Zhao et al. (2024) find that Confucian culture positively moderates the effect of a firm's business strategy

on its environmental information disclosure. The Confucian emphasis on long-term orientation further motivates firm managers to improve the quality of their disclosures and thus preserve durable cooperative relationships with trading partners. Consequently, the supply chain's capacity to anticipate and absorb shocks is strengthened. If information transparency is the mechanism underlying the main relationship, the effect of Confucian values should be greater for firms with a poorer information environment *ex ante*, as firms that have already adopted high-quality financial reporting practices have little scope for improvement *ex post*. Consistent with this prediction, we find that the positive effect of Confucian culture on supply chain resilience is stronger for firms with poorer earnings quality, which we measure using discretionary accruals, and for firms with a higher stock price crash risk.

Heterogeneity tests help identify conditional relationships between Confucian culture and supply chain resilience that narrow the scope for alternative explanations of our results. These tests also provide additional insights into the mechanisms underlying the causal relationship. We document stronger Confucian influence among firms with poorer environmental, social and governance (ESG) performance, lower exposure to foreign cultural shocks, weaker access to trade credit and higher operating cash flow volatility. Although we cannot rule out alternative explanations with certainty, these analyses considerably assuage concerns about identification and enable us to draw convincing inferences.

We conclude our empirical analyses with a battery of robustness tests. Briefly, we show that the main result holds when we use alternative measures of Confucian culture or supply chain resilience. Our result also is robust to alternative sample selection procedures, such as dropping observations during the 2008 financial crisis and the COVID-19 pandemic period or extending the sample to earlier years. Our result also holds after we exclude firms registered in Xinjiang, Tibet, Ningxia or Qinghai, given that these firms may be heavily affected by other cultures such as Buddhism.

Our study makes several contributions to the literature. We are among the first to provide causal evidence showing that corporate culture affects supply chain resilience and to clarify the mechanisms through which this effect operates. Prior research predominantly concentrates on the effectiveness of formal institutions, such as collaborative structures between firms and their trading partners and trust-based governance models, in mitigating the risk of supply chain disruption (Bode et al., 2011; Dubey et al., 2017; Freund et al., 2022). Recent advances in fintech provide novel pathways for enhancing resilience; for example, big data analytics can be used to improve operational flexibility and predictive responsiveness (Jiang et al., 2024). The literature therefore centers on formal institutional designs and technology adoption while devoting little attention to informal institutional forces such as corporate culture, a gap that is particularly salient in emerging markets with weakly developed formal governance institutions (e.g., laws and regulations) and proprietary core technologies. In the Chinese setting, we show that stronger Confucian influence is associated with more resilient supply chains and that these culturally rooted norms operate through the informal governance, adaptive evolution and information transparency channels. By identifying culture as a key determinant of supply chain resilience, we enrich the literature on corporate governance and supply chain management and elucidate the mechanisms of informal institutions when formal arrangements are weakly developed or technological solutions are likely to be infeasible. Our findings also yield important managerial and policy implications for mobilizing soft cultural capital when designing and implementing resilience strategies.

Our study is also closely related to the literature on the economic impacts of corporate culture, especially the firm-level consequences of Confucian culture. Previous studies chiefly examine outcomes at the focal firm level, including the optimization of cash reserves (Deng and Zeng, 2025), the fulfillment of CSR commitments (Cao et al., 2024; Zhao et al., 2024), the deterrence of misconduct that lowers default risk (Hou et al., 2023; Gu et al., 2024; Zhang et al., 2025a), credit financing behavior (Wei et al., 2023; Yan et al., 2024), corporate climate change awareness (Li et al., 2025) and stock price loss and recovery speed (Zhu et al., 2025). Much less is known about whether and how Confucian culture generates spillovers that operate through cooperative ties with upstream and downstream partners and, in doing so, affect supply chain operations. We contribute to this strand of literature by providing direct evidence that Confucian culture affects corporate supply chain management in this manner and strengthens resilience along the chain. Supply chain resilience arises from collaborative governance among multiple firm stakeholders and relies on managerial expertise and relational capital (Nikookar et al., 2024); given these characteristics, core virtues of Confucianism such as benevolence, righteousness, propriety, wisdom and integrity are particularly relevant. We further enrich the literature by

showing that the effect of Confucian culture on the resilience of the entire supply chain is more salient for firms with poorer financing conditions or more volatile operating performance. Our work thus positions corporate culture as a boundary-spanning informal institution that reshapes supply chain governance, extending the literature on cultural economics from intrafirm outcomes to interfirm, network-level resilience.

The remainder of this paper is arranged as follows. In Section 2, we discuss the theoretical background and develop our hypotheses. Section 3 describes the research design and provides summary statistics. Section 4 presents the empirical results, including the main findings, endogeneity tests, mechanism analyses, heterogeneity tests and robustness checks. Section 5 concludes the work.

2. Theoretical background and hypothesis development

2.1. Theoretical background

Traditional institutional economics emphasizes the impact of formal institutions on firm behavior and economic outcomes. With the emergence of new institutional economics, scholars are focusing on the roles and mechanisms of informal institutions, including culture, ethics and social norms (North, 1990). Through their path dependence and historical continuity, these institutions impart a profound and stable influence on economic behavior. Compared with formal institutions such as laws and contracts, informal institutions are often embedded in social structures. They can substitute for ineffective or incomplete formal institutions and thus have meaningful effects on individual and organizational decisions (Williamson, 2000). In situations characterized by uncertainty due to unexpected shocks, informal institutions provide adaptive flexibility and a basis for coordination via internal norms and behavioral consensus (Helmke and Levitsky, 2012).

Informal institutions also offer a useful theoretical perspective on economic, political and social issues in China (Allen et al., 2005). In situations with poorly developed or enforced formal rules, informal institutions can address these institutional weaknesses, enhance organizational adaptability (Marquis and Tilcsik, 2013) and inform corporate decision-making (Li et al., 2013). As a core component of traditional Chinese culture, Confucianism emphasizes *ren* (benevolence), *yi* (righteousness), *li* (propriety), *zhi* (wisdom) and *xin* (integrity), which shape ethical structures and behavioral norms. In contrast to Western institutional arrangements that emphasize arm's-length transactions, contractual agreements and individual rights and obligations, Confucian culture prioritizes integrity, relationships, collective responsibility and a long-term orientation. These features facilitate the maintenance of cooperative relationships, alleviation of interorganizational frictions and strengthening of trust-based mechanisms in highly uncertain environments (Li et al., 2020).

According to stakeholder theory, firms do not operate in isolation but are embedded in a broad stakeholder network (Freeman, 1984). The Confucian norm that "harmony is the most precious" advocates harmonious relationships and ethical responsibility, thus aligning closely with the stakeholder theory principle of respecting the interests of all parties to achieve long-term goals. In a related vein, social contract theory suggests that while pursuing profits, firms should account for the legitimate rights and interests of their stakeholders to balance their economic goals and social responsibilities (Donaldson and Preston, 1995). Within a supply chain, firms are expected to consider the interests and demands of their trading partners. Confucian culture fosters a normative commitment to integrity and a consultative decision-making orientation, prompting firms to demonstrate a strong sense of responsibility and willingness to coordinate within the supply chain (Cao et al., 2024). As a result, supply chain resilience is enhanced.

From the perspective of agency theory, information asymmetry between firms and their trading partners can lead to adverse selection and moral hazard, both of which can undermine the resilience of firms' supply chains. The formation and stability of a supply chain therefore depends on symmetric information flows and the establishment of trust (Akerlof, 1970; Spence, 1974; Stiglitz, 1985). In practice, however, cognitive biases, delayed or selective disclosure and concealment between firms and their trading partners may lead to inaccurate forecasts and inefficient resource allocation, which ultimately weaken the supply chain's ability to respond to and recover from shocks. Confucian culture can partially mitigate these adverse consequences by reinforcing firms' ethical responsibilities and willingness to share information with stakeholders. For example, honesty and trustworthiness are fundamental principles of Confucian behavioral norms. For firms, these virtues encourage adherence to contractual commitments and high-quality disclosure standards (Zhao et al., 2024).

Such practices enhance transparency, reduce opportunism (Chen et al., 2024; Zhang et al., 2025a) and support more resilient supply chain relationships.

2.2. Hypothesis development

2.2.1. The main effect of Confucian culture on supply chain resilience

Confucianism is a foundational cultural framework that has both shaped Chinese social development for centuries and retains profound social and political salience within contemporary Chinese institutional environments (Angle, 2018), where it continues to affect economic activities and governance systems (Lam, 2003; Alesina et al., 2013). Guiso et al. (2009) show that culture molds the architecture of social trust, which in turn supports the formation and development of transactional relationships across organizational boundaries. Prior studies on supply chain management note that relational governance, built through intensive collaboration and the cultivation of trust-based partnerships, is a key factor in sustaining supply chain operations when disruptions occur (Bode et al., 2011; Dubey et al., 2017). When complemented by long-term relational contracts (Sáenz and Revilla, 2014), such relationships provide an additional layer of resilience that ensures continuity and accelerates post-shock recovery (Jain et al., 2017). Confucianism is directly pertinent here because it deems *xin* (integrity) as the key virtue of its moral system. As an informal institution, this virtue encourages firms to build reputational capital, enhance inter-firm trust and strengthen stakeholders' confidence in the supply chain network (Wei et al., 2023), all of which increase supply chain resilience.

The Confucian virtue of *ren* (benevolence) enhances a firm's social legitimacy (Tsai and Tsai, 2022) and promotes a long-term orientation and a reciprocity norm, which help the firm sustain relationships with key trading partners. By credibly signaling reliability and prosocial intent, benevolence discourages opportunistic behavior and promotes long-term collaboration. These features function as a form of relational governance that lowers contractual frictions and facilitates firms' access to trade credit, as both suppliers and customers are more willing to extend favorable terms to counterparties perceived as more trustworthy and benevolent (Xu and Yang, 2025). As partners come to expect fair deals and predictable conduct, the firm can both deepen its existing relationships and establish new ones. Over time, this process broadens the firm's sourcing and distribution base. It also results in a supply chain network that is more diversified and less exposed to single points of failure, consistent with the evidence that such diversification is associated with shorter recovery cycles following disruptions (Freund et al., 2022). Expanded trade credit capacity and a richer and more diversified partner portfolio increase the working capital slack and operational flexibility, thus providing firms with a liquidity buffer and the substitution options needed to absorb supply chain disruptions while maintaining procurement and production continuity.

Managerial risk aversion also reduces the likelihood of supply chain disruptions by curbing firms' hazardous decisions and reducing exposure to fragile configurations (Simchi-Levi et al., 2014). The Confucian virtue of *li* (propriety) codifies such prudential norms by emphasizing discipline, foresight and order (Chen et al., 2019). Relatedly, the literature shows that Confucian influence is negatively associated with the cost of equity (Tan and Wang, 2023), managerial myopia (Wei et al., 2023) and opportunistic activity (Chen et al., 2025). Anchored in stability and gradual adaptation, the governance philosophy of Confucian culture stresses systemic risk control rather than ad hoc responses. For example, firms subject to stronger Confucian influence are more likely to invest in precautionary slack, formalize coordination protocols and reduce exposure to single-point failures. By lowering the incidence of myopic or opportunistic actions and narrowing information gaps that would otherwise amplify uncertainty, these practices decrease the risk of disruption ex ante and improve recoverability ex post, both of which are aligned directly with the objective of enhancing the firm's supply chain resilience.

From the perspective of contract execution, Confucian culture strengthens both contract execution and relational enforcement in emerging institutional contexts such as China, where formal institutions remain somewhat ineffective. When the legal system and other formal remedies are incomplete, reputation and relationships may serve as alternative enforcement mechanisms (La Porta et al., 2000; Allen et al., 2005). The emphasis in Confucian thought on *ren* (benevolence) and *li* (propriety) provides moral incentives to honor implicit agreements and keep promises, which in turn enhance firms' access to trade credit (Li et al., 2020) and a favorable social reputation. These cultural norms function as informal contract enforcement devices

that can supplement or substitute for legal governance (Shou et al., 2016; Zhang et al., 2020), ensuring the smooth execution of delivery, quality control and payment, even under shocks such as natural disasters. By improving contractual reliability and enforcement, Confucian culture enhances interfirm collaboration and facilitates the recovery of supply chain resilience when formal legal remedies are unavailable or ineffective.

Notably, natural disasters disrupt the logistics, procurement and production processes of supply chains and reduce supply chain efficiency. Prior research shows that firms more strongly oriented toward long-term development are more resilient during crises (Lins et al., 2017; Luo et al., 2024). The long-term value embedded in Confucian culture encourages firms to make strategic choices that favor endurance and adaptation, thereby supporting supply chain resilience. In addition, the emphasis on integrity, benevolence and righteousness strengthens ethical norms (Lam, 2003; Guiso et al., 2009), facilitates stable cooperative relationships with trading partners (Li et al., 2020) and sustains coordination and trust across the supply chain network. The Confucian virtue of *li* (propriety) encourages discipline and orderliness in corporate behavior, enabling firms and their partners to maintain information flows and cooperative routines amid physical disruptions. *Ren* (benevolence) motivates reciprocal support and the shared use of social resources, thus encouraging firms to extend trade credit, inventory reallocation and mutual assistance to affected partners. Such information sharing and mutual assistance reduce opportunistic behavior during disasters, shift priorities toward collective recovery rather than short-term self-interest, mitigate the adverse impacts of disruptions caused by natural disasters and accelerate the restoration of supply chain resilience (Acemoglu and Tahbaz-Salehi, 2025).

Based on these arguments, we frame our main hypothesis as follows:

H1. A firm's exposure to Confucian culture is positively associated with its supply chain resilience.

2.2.2. The moderating effect of formal or external governance

The informal institution-based view of governance systems holds that cultural norms can substitute for formal rules when the latter are poorly developed or weakly enforced. Imprinting theory further suggests that exposure to a strong Confucian influence leaves durable value imprints that guide managerial decision-making over time. In particular, the Confucian virtues of *shendu* (self-restraint) and *neixing* (introspective governance) informally constrain opportunistic behavior when formal governance is limited (Gu et al., 2024) and incentivize managers to prudently optimize supply chain resource allocation. Consistent with this informal governance mechanism, Chen et al. (2024) show that CEOs subject to stronger Confucian influence engage in fewer unethical activities.

Building on this theoretical logic, Confucianism, as an informal institution, can improve the quality of internal governance ex post when formal or external checks and balances are weak ex ante. By reinforcing firms' CSR commitments (Cao et al., 2024) and deepening their collaboration with trading partners (David et al., 2024), Confucian culture restrains managerial opportunism and provides a foundation for stable supply chain operations. From the stakeholders' perspective, stronger internal governance better protects the interests of upstream suppliers and downstream customers, aligns managerial actions with stakeholder expectations and increases stakeholders' willingness to maintain long-term cooperation and provide support when disruptions occur. Because culture-driven discipline is achieved via managerial discretion and informal in nature, its reach and force are greater in firms for which formal or external governance is weaker.

Based on these considerations, we propose the following hypothesis:

H2. The positive effect of Confucian culture on supply chain resilience is more pronounced for firms with weaker formal or external governance.

2.2.3. The moderating effect of adaptive evolution

The capacity for adaptive evolution, such as improving data analytics, refining routines and realigning production processes in response to shocks, is central to supply chain resilience. Digital transformation and technological innovation are the chief vehicles for such adaptation. Advanced technological infrastructure, such as blockchain architectures and big data analytics, can reduce firms' financing costs (Chod et al., 2020), enhance operational adaptability (Cui et al., 2024) and lower business risks faced by suppliers (Li et al., 2024). During shocks such as pandemics and natural disasters, firms with a stronger adaptive capability exhibit greater digital maturity and superior excess returns and profit resilience (Gaspar et al., 2024). Hui and Xie (2024) and Lu

et al. (2024) find that, as an example of adaptive evolution, digital technology can optimize collaboration along the supply chain and improve its resilience.

The Confucian norm of *zhongyong* (the doctrine of the mean) stresses dynamic balance and requires timely adjustment in accordance with spatiotemporal changes. The Confucian values of *gewuzhizhi* (pursuit of principles), *boxue* (extensive learning) and *zhiyi* (critical thinking) cultivate disciplined learning and analytic problem-solving, which support innovation (Dong and Cheng, 2024). All of these ethical precepts create an environment that enables firms to accelerate their adaptive evolution. In line with this view, prior studies link stronger Confucian culture with faster technology adoption (Yan et al., 2024) and deeper digital transformation (Chen et al., 2025). By clarifying informal hierarchies and reducing institutional costs (Chen and Peng, 2024), Confucian culture also reduces coordination frictions, codifies operating routines and improves the reliability of data capture and process execution. These capabilities are particularly consequential when the baseline adaptive capacity is weak. In such settings, each marginal innovation input, modular upgrade and incremental step toward digital transformation yield disproportionately larger gains. In turn, these gains directly bolster supply chain resilience and do so more powerfully when adaptive evolution proceeds slowly, because Confucian culture closes gaps in capability that would otherwise impede technological assimilation and process renewal.

Based on the arguments above, we state our hypothesis as follows:

H3. The positive effect of Confucian culture on supply chain resilience is more pronounced for firms with slower adaptive evolution.

2.2.4. The moderating effect of information transparency

Agency theory posits that information asymmetry exacerbates principal–agent conflicts both within firms (e.g., shareholders versus managers) and across firms' boundaries with external stakeholders (e.g., firms versus suppliers and customers). Monitoring and contracting costs rise when information is opaque, and managers have more room to pursue private benefits and shift the risks to their trading partners. These agency frictions trigger pessimistic market expectations, erode asset values and reduce supply chain stability (Epstein and Schneider, 2008). By contrast, a more transparent information environment tightens monitoring, improves incentive alignment and enables more accurate and timely operating decisions (Zhao, 2025). In a supply chain setting, such an environment reduces inventory and coordination costs, mitigates the bullwhip effect and enhances firms' performance (Chatfield et al., 2004; Li and Lin, 2006; Radhakrishnan et al., 2014).

Confucian ethics, particularly *yi* (righteousness) and *li* (propriety), emphasize integrity, honesty and credible commitment, which in turn encourage timely and candid communication with stakeholders. Confucian culture thus operates as an informal institution that improves disclosure quality and reduces the agency costs of monitoring and bonding (Zhao et al., 2024). The marginal benefit of Confucian values is expected to be greater when baseline information transparency is lower and thus the scope for further improvement is greater. In such situations, the norms of trust and reciprocity embedded in Confucian culture motivate managers to improve their firms' information transparency and thus preserve long-term cooperative relationships with suppliers and customers. These adjustments limit coordination failures, reduce variability and stabilize production scheduling. As a result, corporate supply chain resilience increases.

Based on these arguments, we propose the following hypothesis:

H4. The positive effect of Confucian culture on supply chain resilience is more pronounced for firms with lower information transparency.

3. Research design

3.1. Sample and data

We begin with all A-share firms listed on the Shanghai and Shenzhen stock exchanges from 2008 to 2023. Our sample period starts in 2008 for two reasons. First, the availability of relevant data is limited before 2008. Second, we construct our supply chain resilience measure using information from firms' financial statements, and data before and after 2007 are not directly comparable due to a change in Chinese accounting standards in that year. We exclude firms in the financial industry because they are heavily regulated, and their supply chain

characteristics differ from those of nonfinancial firms. We also exclude firms designated as Special Treatment or Particular Treatment due to their unusual financial conditions. After deleting observations with missing values, we are left with 29,356 firm-year observations corresponding to 2928 unique firms.

The data used to measure firms' exposure to Confucianism, Buddhism and Taoism, as well as data on firms' digital transformation, invention patent grants and ESG ratings, are retrieved from the China Research Data Service Platform database. Historical and geographic variables are sourced from compilations and yearbooks as follows: (i) Counts of chastity memorial arches are obtained from the *History of the Ming Dynasty* and *History of the Qing Dynasty*. (ii) The number of books printed by Ming dynasty printing houses are obtained from *The Chinese History of Printing*, as reported by Chen et al. (2020) and Deng et al. (2024). (iii) River density is obtained from the 2022 *China Water Resources Statistical Yearbook*. (iv) The distribution of Manchu garrisons is obtained from *Research on the Historical Geography of the Manchu Cities in the Qing Dynasty*. (v) Reported casualties of the Taiping Rebellion are obtained from the *History of Chinese Population*. Other firm-level data are obtained from the China Stock Market & Accounting Research (CSMAR) database.

3.2. Dependent variable

Following Shan et al. (2014), we measure a firm's supply chain resilience based on the extent to which fluctuations in production are aligned with fluctuations in demand. Intuitively, the smaller the gap between production volatility and demand volatility, the better the supply chain can reduce mismatches arising from disruptions via flexible adjustments to procurement, production and inventory. We implement this measure using a five-year rolling window so that it reflects not only the degree of matching at a specific point in time but also the dynamic adjustment process after a shock. For example, a disruption may induce a short-run divergence between production and demand. However, the firm may subsequently revise its procurement and production plans such that the two series reconverge and recover in later years, which would reasonably be captured by a five-year window. Conceptually, our measure therefore reflects the capacity of a supply chain to persist, adapt and transform in the face of change. To facilitate interpretation and presentation, we obtain the negative of this volatility ratio and divide it by 100, such that larger values indicate greater supply chain resilience. Formally, our dependent variable is defined as follows:

$$SCR = -\frac{sd(Production)}{sd(Demand)} \div 100 \quad (1)$$

where $sd(\cdot)$ denotes the standard deviation computed over the current and previous four years, $Demand$ represents the sales revenue and $Production$ equals $Demand$ plus the change in net inventories.

3.3. Independent variable

Confucian temples are sites for the veneration and commemoration of Confucius, as such, they embody local adherence to Confucian values. We therefore use the number of Confucian temples near firms to capture firms' exposure to Confucian culture. A stronger Confucian culture is more likely to increase the demand for and construction of Confucian temples, and these architectural carriers in turn help preserve and propagate Confucian values, thus creating a reinforcing cycle of cultural inheritance (Jin et al., 2023). The more Confucian temples, the easier it will be for Confucian culture to be passed down from generation to generation. Hence, regions with a higher density of Confucian temples tend to exhibit stronger religious faith in Confucianism, while firms located in such regions face higher levels of exposure to Confucian values (Chen et al., 2019).

We operationalize a firm's exposure to Confucian culture as the number of Confucian temples located near the firm's registration location (Jin et al., 2023; Huang et al., 2024; Zhang et al., 2025a). For each firm-temple pair, we compute the great-circle distance using the spherical law of cosines, as follows:

$$Distance = \arccos(\cos \beta_1 \times \cos \beta_2 \times \cos(\alpha_1 - \alpha_2) + \sin \beta_1 \times \sin \beta_2) \times R \quad (2)$$

where α_1 (α_2) and β_1 (β_2) respectively denote the longitude and latitude of the firm's registration location (the Confucian temple), and the Earth's radius, R , is approximately 6371.004 km. For each firm, we count

the number of Confucian temples within a 100-km radius of the registration location and define our key independent variable, *Confucianism*, as the natural logarithm of 1 plus this number. A larger value of *Confucianism* indicates a stronger influence of Confucian culture on the firm. Among the 491 Confucian temples that we identify, the most recent temple construction date is 1929 CE. Because the construction of Confucian temples and diffusion of Confucian culture predate our sample period by roughly a century, the exploited geographic variation in Confucian influence is plausibly predetermined with respect to firm-level outcomes such as supply chain resilience.

3.4. Model specification

To assess how Confucian culture affects supply chain resilience, we estimate the following regression model:

$$SCR_{i,t+1} = \beta_0 + \beta_1 \times Confucianism_{i,t} + \gamma' \times Controls_{i,t} + Firm\ FEs + Industry\ by\ year\ FEs + \varepsilon_{i,t+1} \quad (3)$$

where i indexes the firm, t indexes the year and $\varepsilon_{i,t+1}$ is the error term. *SCR* and *Confucianism* are defined earlier, and we impose a one-year lag to avoid simultaneity. We include firm and industry-year fixed effects in the regressions to control for time-invariant firm characteristics and time-varying industry conditions, respectively. Standard errors are clustered at the firm level to correct for error autocorrelation.

With this study, we aim to identify the causal effect of Confucian culture on supply chain resilience. To ensure that this effect is driven by Confucian influence rather than by other correlated firm traits, we control for a large set of firm characteristics, including firm size (*Ln_assets*); firm age (*Ln_firm_age*); financial leverage (*Leverage*); return on assets (*ROA*); book-to-market ratio (*BM*); Tobin's Q (*Tobin_Q*); sales growth rate (*Sales_growth*); cash ratio (*Cash*); property, plant and equipment (*PPE*); capital expenditures (*Capex*); asset liquidity (*Liquidity*); inventory turnover (*Turnover*); financial constraints (*SA_index*, *KZ_index* and *FC_index*); bankruptcy risk (*Z_score*); sales volatility (*Sales_volatility*); information quality (*Info_quality*); institutional ownership (*Inst_ownership*); analyst coverage (*Ln_analyst*); board independence (*Independence*); board size (*Ln_board*); managerial salary (*Ln_mgr_salary*); ownership of the largest shareholder (*Top1*); whether the board chairman also serves as the CEO (*Dual*); and whether the firm is audited by a Big 4 auditing firm (*Big4*). Detailed variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th levels to mitigate the potential impacts of outliers.

3.5. Descriptive statistics

Table 1 presents the descriptive statistics for the main variables used in our study. Our measure of supply chain resilience (*SCR*) has a mean of -0.2002 and a standard deviation of 0.4574 , implying that production fluctuations amount to roughly one-fifth of demand fluctuations on average, with substantial cross-firm variation. The mean and median values of *Confucianism* are 1.7740 and 1.9459 , respectively. The corresponding mean and median values in levels (i.e., without logarithmic transformation) are 6.3105 and 6 (untabulated), respectively, suggesting that there are approximately six Confucian temples within a 100-km radius of the average firm in the sample.

4. Empirical results

4.1. Baseline estimation results

Table 2 reports the results regarding the effect of Confucian culture on supply chain resilience. In Column (1), we include firm and industry-year fixed effects. The coefficient on *Confucianism* is positive and statistically significant at the 10% level. This result suggests that after removing the confounding influences of time-invariant firm characteristics and time-varying industry shocks, firms with greater exposure to Confucian culture exhibit higher supply chain resilience. In Column (2), we include a set of firm-level control variables to

Table 1
Descriptive statistics.

(N = 29,356)	Mean	Std. Dev.	P25	Median	P75
<i>SCR</i>	-0.2002	0.4574	-0.1516	-0.0508	-0.0195
<i>Confucianism</i>	1.7740	0.7308	1.3863	1.9459	2.3979
<i>Ln_assets</i>	22.3657	1.3124	21.4396	22.1889	23.1144
<i>Ln_firm_age</i>	2.3073	0.7264	1.7918	2.4849	2.8904
<i>Leverage</i>	0.4563	0.1966	0.3046	0.4573	0.6058
<i>ROA</i>	0.0552	0.0574	0.0276	0.0503	0.0817
<i>BM</i>	0.6422	0.2500	0.4510	0.6439	0.8322
<i>Tobin_Q</i>	1.9445	1.2015	1.2017	1.5531	2.2170
<i>Sales_growth</i>	0.1618	0.3863	-0.0249	0.1039	0.2594
<i>Cash</i>	0.6556	0.9357	0.1820	0.3476	0.7031
<i>PPE</i>	0.2261	0.1620	0.0978	0.1972	0.3228
<i>Capex</i>	0.0501	0.0474	0.0152	0.0358	0.0700
<i>Liquidity</i>	0.5576	0.2032	0.4138	0.5696	0.7124
<i>Turnover</i>	10.9334	32.4929	2.0204	3.8877	7.5266
<i>SA_index</i>	-3.8230	0.2706	-3.9976	-3.8234	-3.6379
<i>KZ_index</i>	1.3223	2.3567	-0.0552	1.5637	2.9242
<i>FC_index</i>	0.4472	0.2698	0.2089	0.4562	0.6751
<i>Z_score</i>	4.3028	4.7415	1.7327	2.8459	4.8523
<i>Sales_volatility</i>	0.1202	0.1163	0.0499	0.0863	0.1454
<i>Info_quality</i>	0.6157	0.4864	0.0000	1.0000	1.0000
<i>Inst_ownership</i>	0.4788	0.2342	0.3144	0.4997	0.6591
<i>Ln_analyst</i>	1.4105	1.1908	0.0000	1.3863	2.3979
<i>Independence</i>	0.3722	0.0527	0.3333	0.3333	0.4286
<i>Ln_board</i>	2.3904	0.2223	2.3026	2.3979	2.5649
<i>Ln_mgr_salary</i>	14.9754	0.8643	14.4298	14.9790	15.5260
<i>Top1</i>	0.3530	0.1507	0.2339	0.3333	0.4567
<i>Dual</i>	0.2324	0.4223	0.0000	0.0000	0.0000
<i>Big4</i>	0.0680	0.2517	0.0000	0.0000	0.0000

Notes. This table reports the descriptive statistics of main variables for the full set of observations used to estimate the baseline regression (i.e., the second column in Table 2). Variables are defined in Appendix A.

account for the potential confounding effects of observable time-varying firm characteristics. The impact of *Confucianism* remains positive and is significant at the 5% level.¹ Thus, H1 is supported.

4.2. Endogeneity tests

Although our baseline results suggest that firms with greater exposure to Confucian culture exhibit higher supply chain resilience, this finding may be driven by omitted variables, reverse causality or a functional misspecification of the regression model. We conduct the following tests to mitigate these endogeneity concerns.

4.2.1. Controlling for province fixed effects

As our key independent variable is a historical and geographical measure of a firm's exposure to Confucian influence, our results may be driven by omitted location-specific factors. We therefore include province fixed

¹ As firm-level exposure to Confucian culture is expressed as the logarithm of 1 plus the number of Confucian temples near the firm, the marginal change in the independent variable is not naturally interpretable as the growth rate or percentage change of Confucian influence (Cohn et al., 2022). To evaluate the economic significance of our estimates, we re-estimate our model using the raw number of Confucian temples (i.e., without the "logarithm of 1 plus" transformation) as the independent variable. Untabulated results indicate that the coefficient on this raw measure of Confucian culture is 0.0109, which is significant at the 5% level. In terms of economic magnitude, a one-standard-deviation increase in the number of Confucian temples within a 100-km radius of the firm (4.1922, untabulated) corresponds to an increase of 0.0457 (4.1922×0.0109) in supply chain resilience in absolute terms, or a 9.99% increase relative to the sample standard deviation of 0.4574.

Table 2
Confucian culture and supply chain resilience.

	(1)	(2)
	<i>SCR</i>	<i>SCR</i>
<i>Confucianism</i>	0.0738* (1.8143)	0.0954** (2.5704)
<i>Ln_assets</i>		-0.0371*** (-3.4225)
<i>Ln_firm_age</i>		0.0200 (1.1406)
<i>Leverage</i>		0.0101 (0.2444)
<i>ROA</i>		0.0251 (0.3908)
<i>BM</i>		-0.0236 (-0.8057)
<i>Tobin_Q</i>		0.0026 (0.5329)
<i>Sales_growth</i>		0.0171** (2.4321)
<i>Cash</i>		0.0043 (0.9568)
<i>PPE</i>		0.0177 (0.3894)
<i>Capex</i>		0.0289 (0.4440)
<i>Liquidity</i>		-0.1643*** (-3.8969)
<i>Turnover</i>		-0.0000 (-0.2774)
<i>SA_index</i>		-0.1954*** (-2.9035)
<i>KZ_index</i>		-0.0069*** (-3.1433)
<i>FC_index</i>		-0.0092 (-0.4504)
<i>Z_score</i>		-0.0020 (-1.2609)
<i>Sales_volatility</i>		0.0425 (1.2967)
<i>Info_quality</i>		0.0014 (0.1720)
<i>Inst_ownership</i>		-0.0573* (-1.8284)
<i>Ln_analyst</i>		0.0039 (0.9447)
<i>Independence</i>		-0.0716 (-0.8785)
<i>Ln_board</i>		0.0129 (1.0036)
<i>Ln_mgr_salary</i>		0.0168** (2.2889)
<i>Top1</i>		-0.0284 (-0.5015)
<i>Dual</i>		-0.0035 (-0.4176)
<i>Big4</i>		0.0071 (0.1955)

Table 2 (continued)

	(1)	(2)
	SCR	SCR
Observations	31,373	29,140
R-squared	0.6567	0.6737
Firm fixed effects	Yes	Yes
Industry-by-year fixed effects	Yes	Yes
Clustered by	Firm	Firm

Notes. This table reports the OLS regression results. Variables are defined in Appendix A. Robust *t*-statistics listed in parentheses below the point estimates are based on standard errors (SE) clustered along the firm dimension. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

effects in Panel A, Column (1) of Table 3. After removing the effects of any time-invariant provincial heterogeneity, we continue to observe a positive effect of Confucian culture on supply chain resilience, which is significant at the 5% level.

4.2.2. Inclusion of additional control variables

As an alternative check against confounding geographical factors, we replace province fixed effects with four additional geographical controls: an indicator of firms registered in Beijing, Shanghai, Guangzhou or Shenzhen (*City_prov*); an indicator of firms not registered in one of the five autonomous provinces (*Han_prov*); an indicator of firms registered in a coastal province (*Sea*); and an indicator of firms registered in northern China (latitude > 30°N; *North*). Another concern is religious doctrines other than Confucianism, such as Buddhism and Taoism, could influence our results. Currently, there are thousands of Buddhist temples in China but only approximately 400 Confucian temples. To address the potential issue related to the omission of other religious variables, we include the natural logarithm of 1 plus the number of Buddhist temples within a 100-km radius of the firm (*Buddhism*) and an analogous measure for Taoist temples (*Taoism*). Furthermore, the presence of Confucian temples may capture the Confucian emphasis on shaping individuals' behavior through education. Therefore, to tease out the effects of education, we control for the natural logarithm of 1 plus the number of primary and secondary schools in the city where the firm is registered (*Ln_school*) and the natural logarithm of 1 plus the number of higher education institutions in the province where the firm is registered (*Ln_university*).² In Panel A, Column (2) of Table 3, we report the estimates from the specification including these eight additional control variables. The coefficient on *Confucianism* remains positive and significant at the 1% level. The untabulated results show that *Han_prov* loads positively and significantly, the effect of *North* is negative and significant and the coefficients on *City_prov*, *Sea*, *Buddhism*, *Taoism*, *Ln_school* and *Ln_university* are not statistically significant at conventional levels.

4.2.3. Propensity score matching approach

Our regression model delivers unbiased and consistent estimates, assuming that the control variables adequately capture the confounding covariates. However, a nonlinear relationship between the controls and supply chain resilience could induce a specific type of endogeneity bias, namely functional form misspecification. We implement PSM to address this concern. Specifically, we first dichotomize the continuous

² Because latitude–longitude coordinates for schools and higher education institutions are not available, we are unable to calculate the numbers of primary schools, secondary schools and higher education institutions within a 100-km radius of a given firm's registration location. We therefore measure educational infrastructure at the finest available regional levels. Specifically, CSMAR provides city-level counts of primary and secondary schools and province-level counts of higher education institutions.

Table 3
Tests addressing the endogeneity problems.

Panel A. Additional fixed effects and additional control variables						
	(1)		(2)			
	<i>SCR</i>		<i>SCR</i>			
<i>Confucianism</i>	0.0708** (2.0344)		0.1133*** (2.8608)			
Observations	29,140		22,923			
R-squared	0.6760		0.6930			
Control variables	Yes		Yes			
Firm fixed effects	Yes		Yes			
Industry-year fixed effects	Yes		Yes			
Province fixed effects	Yes		No			
Additional control variables	No		Yes			
SE clustered by	Firm		Firm			
Panel B. Propensity score matching approach						
	(1)					
	<i>SCR</i>					
<i>Confucianism</i>	0.0800** (2.1188)					
Observations	21,677					
R-squared	0.6842					
Control variables	Yes					
Firm fixed effects	Yes					
Industry-year fixed effects	Yes					
SE clustered by	Firm					
Panel C. Instrumental variable approach						
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>IV: Ln_paifang</i>		<i>IV: Ln_book</i>		<i>IV: Ln_river</i>	
	<i>Confucianism</i>	<i>SCR</i>	<i>Confucianism</i>	<i>SCR</i>	<i>Confucianism</i>	<i>SCR</i>
<i>Confucianism</i> (instrumented)		0.1304** (2.1208)		0.1422** (1.9846)		0.3274* (1.7960)
<i>Ln_paifang</i>	0.3218*** (9.4633)					
<i>Ln_book</i>			0.1125*** (7.3058)			
<i>Ln_river</i>					1.0603*** (2.7750)	
Observations	29,140	29,140	29,140	29,140	29,140	29,140
R-squared	0.9846	0.0113	0.9828	0.0112	0.9796	0.0027
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered by	Firm	Firm	Firm	Firm	Firm	Firm

Notes. This table reports the OLS regression results. Variables are defined in Appendix A. Robust *t*-statistics listed in parentheses below the point estimates are based on standard errors (SE) clustered along the firm dimension. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

measure of exposure to Confucian culture using the sample median and then match observations with higher exposure to those with lower exposure but similar control variable values. We estimate propensity scores using a logit model that incorporates multidimensional determinants of treatment assignment.³ After matching, we achieve balanced matches for 10,988 high-exposure observations. Covariate balance diagnostics (untabulated) confirm that none of the covariate differences are significant at the 10% level. The regression result based on this matched sample is reported in Panel B of Table 3. The influence of *Confucianism* is positive and significant at the 5% level.⁴

4.2.4. Instrumental variable approach

To address potential endogeneity arising from omitted time-varying factors and reverse causality, we employ an IV approach. Our first instrument is the natural logarithm of 1 plus the number of chastity memorial arches erected during the Ming–Qing period within a 100-km radius of a given firm (*Ln_paifang*) (Xu et al., 2019; Zhang et al., 2025b). These arches were erected explicitly under a Confucian normative order that venerates female chastity (*three obediences and four virtues*) and lifelong marital fidelity and are durable, place-based artifacts that record the historical intensity of Confucian ethical influence. Accordingly, a greater value of *Ln_paifang* should be associated with greater exposure to Confucian culture, thus satisfying the instrument's relevance condition. Equally important for identification is the nature of chastity arches as immobile, pre-industrial relics. These structures neither participate in nor respond to production, logistics or coordination activities and do not directly vary with fluctuations in supply chain conditions. Conditional on our controls and fixed effects, there is no credible channel through which local chastity arches would directly affect supply chain resilience other than via their impact on Confucian culture. Therefore, we expect the exclusion restriction to hold.

Our second instrument is the natural logarithm of 1 plus the number of books printed by Ming dynasty printing houses within a 100-km radius of the firm (*Ln_book*) (Gu et al., 2024). As primary carriers of Confucian doctrine, Confucian classics have expanded access to orthodox texts and deepened the historical imprint of Confucian ethics in local areas (Zhang et al., 2025a). Hence, *Ln_book* should be positively related to the local influence of Confucian culture. In terms of the exclusion restriction, the siting of Ming printing houses was largely governed by paper production feasibility, which depended on the historical availability of bamboo forests and pine wood; these factors are unlikely to affect supply chain resilience today.

The last instrument, *Ln_river*, is defined as the natural logarithm of the aggregate length of rivers whose drainage basins exceed 100 km², normalized by the provincial territorial area. This measure captures the historical intensity of river systems within a province. River basins have long shaped the emergence of early civilizations and influenced both regional economic growth and the diffusion of cultural paradigms. In imperial China, riverine transport was a primary conduit for distributing civil-service examination resources, which underpinned the propagation of Confucian culture. Therefore, provinces with more developed historical river networks plausibly would have experienced stronger and more persistent exposure to Confucian culture, supporting the relevance restriction. Regarding the exclusion restriction, to our knowledge, there is no theoretical or empirical evidence of a direct effect of historical river network development on modern supply chain operations such as production, distribution, logistics or risk management.

The two-stage least squares estimates are shown in Panel C of Table 3. The odd-numbered columns present the first-stage regression results. Consistent with our theoretical expectations, all the IVs are positively and significantly related to *Confucianism*. The even-numbered columns containing the second-stage regression results show that the influences of instrumented *Confucianism* are positive and statistically significant at least at the 10% level.

³ We implement PSM with the following three research design choices. First, we use one-to-one nearest neighbor matching, because the second and third closest matched control firms are more distant from the treatment firm. Using multiple control firms would increase bias in the estimated effect of Confucian influence. Second, to enforce close matches and reduce covariate imbalance, we apply a caliper width of 0.01. Third, we match without replacement, which preserves the representativeness of the control firms and avoids inflating the sampling variance that can arise when a small portion of control firms are repeatedly reused.

⁴ In our regression model with the inclusion of high-dimensional fixed effects, 299 singleton observations are dropped, yielding 21,677 observations as reported in Panel B of Table 3, slightly lower than the matched sample size of 21,976 (10,988 × 2).

4.2.5. Quasi-natural experiment: the construction and rebuilding of Manchu cities

As the exclusion restriction of an IV is inherently difficult to verify, we complement our IV analysis with two quasi-natural experiments to further strengthen the causal identification. First, we exploit historical variation in rebellion intensity, proxied by the spatial distribution of Manchu cities. According to Qing dynasty archival records, the Manchus constructed and rebuilt many cities in regions prone to frequent rebellions, enabling them to garrison the military, quell insurrections and preserve political unity (Lu and Li, 2021). Accordingly, we can use the spatial distribution of Manchu cities as a valid indicator of the intensity of regional rebellion during the Qing period. As the propagation of Confucian teachings and values was seriously constrained in conflict zones, regions that experienced more intense historical unrest should be subsequently less exposed to Confucian culture (Hao and Xue, 2017). We therefore test whether the construction and rebuilding of Manchu cities during the Qing dynasty mutes the effect of a firm's exposure to Confucian culture on its current supply chain resilience.

As our proxy for a firm's exposure to the deterrence of Manchu cities, we develop *Manchu_city*, an indicator variable that equals 1 if the firm is registered in a city with a historically documented Manchu garrison presence, and 0 otherwise. The regression model is:

$$\begin{aligned} SCR_{i,t+1} = & \beta_0 + \beta_1 \times Confucianism_{i,t} \times Manchu_city_{i,t} + \beta_2 \times Confucianism_{i,t} \\ & + \gamma' \times Controls_{i,t} + Firm\ FEs + Industry\ by\ year\ FEs \\ & + Manchu_city\ by\ year\ FEs + \varepsilon_{i,t+1} \end{aligned} \quad (4)$$

where the main effect of *Manchu_city* is subsumed by the *Manchu_city*-year fixed effects, and all other variables are defined as in previous sections. In addition to firm and industry-year fixed effects, we include *Manchu_city*-year fixed effects to further limit the variation to within-Manchu cities in a specific year and alleviate the concern that regions affected by rebellions and their suppression differ systematically from unaffected regions. As shown in Column (1) of Table 4, the effect of the interaction term *Confucianism* \times *Manchu_city* is negative and significant at the 5% level, indicating that the influence of Confucian culture is weakened in regions where its historical penetration was suppressed by rebellions, as reflected by the establishment of Manchu cities.

Table 4
Quasi-natural experiments: The construction and rebuilding of Manchu cities and Taiping Rebellion.

	(1)	(2)
	SCR	SCR
<i>Confucianism</i> \times <i>Manchu_city</i>	-0.1905** (-2.2176)	
<i>Confucianism</i> \times <i>Taiping_city</i>		-0.2684* (-1.7856)
<i>Confucianism</i>	0.1024*** (2.7316)	0.1010*** (2.6827)
Observations	29,140	29,140
R-squared	0.6740	0.6743
Control variables	Yes	Yes
Firm fixed effects	Yes	Yes
Industry-year fixed effects	Yes	Yes
<i>Manchu_city</i> -year fixed effects	Yes	No
<i>Taiping_city</i> -year fixed effects	No	Yes
SE clustered by	Firm	Firm

Notes. This table reports the OLS regression results. Variables are defined in Appendix A. Robust *t*-statistics listed in parentheses below the point estimates are based on standard errors (SE) clustered along the firm dimension. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.2.6. Quasi-natural experiment: the Taiping Rebellion

Having established a causal relationship using Manchu garrison placements as a proxy for the repression of revolts, we leverage the Taiping Rebellion (1850–1864) as another quasi-natural experiment involving a plausibly exogenous cultural disruption (Gu et al., 2024). The Taiping Rebellion, a large-scale sociopolitical movement opposing Qing rule, caused severe population losses (10–30 million deaths) and the widespread destruction of educational infrastructure. These casualties and the dismantling of pedagogical resources are likely to have impaired the transmission of Confucian culture in the affected regions and, consequently, the impact of local Confucian norms. Accordingly, we expect the effect of Confucian culture to be less pronounced in regions that with greater exposure to the Taiping Rebellion. Importantly, the Taiping Rebellion and the construction and rebuilding of Manchu cities are independent sources of exogenous variation in the intergenerational transmission of Confucian culture, enabling us to cross-validate our empirical findings.⁵

We use the following regression model to empirically test our prediction:

$$\begin{aligned} SCR_{i,t+1} = & \beta_0 + \beta_1 \times Confucianism_{i,t} \times Taiping_city_{i,t} + \beta_2 \times Confucianism_{i,t} \\ & + \gamma' \times Controls_{i,t} + Firm\ FEs + Industry\ by\ year\ FEs \\ & + Taiping_city\ by\ year\ FEs + \varepsilon_{i,t+1} \end{aligned} \quad (5)$$

where *Taiping_city* indicates whether casualties due to the Taiping Rebellion in a given city belong to the top quartile or not; the main effect of *Taiping_city* is absorbed by the *Taiping_city*-year fixed effects, and all other variables are defined as in previous sections. The regression result is reported in Column (2) of Table 4. The interaction term *Confucianism* × *Taiping_city* has a negative sign and is statistically significant at the 10% level. Consistent with our expectation, Confucian culture has a muted effect on current supply chain resilience for firms located in regions that historically were more exposed to the Taiping Rebellion.

4.3. Economic mechanisms

4.3.1. Informal governance mechanism

Our main findings indicate that Confucian culture leads to more resilient supply chains. Mechanistically, this outcome could be driven by the poor governance quality of firms with poor supply chain resilience. We first investigate whether the relationship between firms' exposure to Confucian culture and supply chain resilience is less pronounced among firms with stronger alternative formal or external governance mechanisms, as predicted in H2. We use two proxies for the quality of a firm's alternative governance structures. The first proxy, *Separation*, pertains to formal governance and is defined as the deviation between the ownership and control rights of the ultimate controller. Here, a larger deviation implies weaker governance (La Porta et al., 2000) and is often associated with a greater propensity to prioritize short-term interests over sustained supply chain investments (Ersahin et al., 2024). The second proxy, *HHI*, is related to external governance and is defined as the Herfindahl–Hirschman Index, computed at the industry level using firms' main business revenue shares of total industry revenue. A higher *HHI* denotes weaker product market competition and external pressure and monitoring. Taken together, these two measures characterize the strength of the non-cultural governance forces counteracting the informal governance mechanism of Confucian culture.

The regression results are presented in Panel A of Table 5. We conduct a median-split subsample analysis rather than including an interaction term, thus allowing the coefficients on all the regressors and the fixed effects to vary with the moderator and providing greater flexibility for estimation and inference. As reported, the effect of Confucian culture on supply chain resilience is positive and statistically significant in both the high-*Separation* and high-*HHI* subsamples but is not statistically different from zero in the corresponding low subsamples. More importantly, cross-group differences in the coefficient estimates on *Confucianism* are positive and significant at the 5% level. We interpret these findings as indicating that formal or external

⁵ In temporal terms, the construction and rebuilding of Manchu cities were concentrated in the early and middle Qing (i.e., 17th and 18th centuries), whereas the Taiping Rebellion unfolded in the late Qing (i.e., 19th century). Geographically, Manchu cities were broadly distributed across the empire, whereas the Taiping Rebellion was concentrated primarily south of the Yangtze River.

Table 5
Confucian culture and supply chain resilience – The economic mechanisms.

Panel A. Informal governance mechanism				
	(1)	(2)	(3)	(4)
	High <i>Separation</i>	Low <i>Separation</i>	High <i>HHI</i>	Low <i>HHI</i>
	<i>SCR</i>	<i>SCR</i>	<i>SCR</i>	<i>SCR</i>
<i>Confucianism</i>	0.1710***[A] (3.0871)	0.0371[B] (0.8424)	0.1171*[A] (1.9527)	−0.0092[B] (−0.3240)
Observations	13,335	14,159	14,403	14,401
R-squared	0.7036	0.7340	0.7115	0.7334
Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
SE clustered by	Firm	Firm	Firm	Firm
<i>p</i> -value of testing A > B		0.0292**		0.0259**
Panel B. Adaptive evolution mechanism				
	(1)	(2)	(3)	(4)
	Low <i>Digit</i>	High <i>Digit</i>	Low <i>Patent</i>	High <i>Patent</i>
	<i>SCR</i>	<i>SCR</i>	<i>SCR</i>	<i>SCR</i>
<i>Confucianism</i>	0.1674***[A] (2.6266)	0.0109[B] (0.2953)	0.1580***[A] (3.0699)	0.0128[B] (0.7545)
Observations	13,358	12,344	17,927	10,492
R-squared	0.6863	0.8173	0.6733	0.7881
Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
SE clustered by	Firm	Firm	Firm	Firm
<i>p</i> -value of testing A > B		0.0169**		0.0037***
Panel C. Information transparency mechanism				
	(1)	(2)	(3)	(4)
	High <i>DA</i>	Low <i>DA</i>	High <i>Crash</i>	Low <i>Crash</i>
	<i>SCR</i>	<i>SCR</i>	<i>SCR</i>	<i>SCR</i>
<i>Confucianism</i>	0.1500***[A] (3.0159)	0.0086[B] (0.2179)	0.0983***[A] (2.0352)	0.0425[B] (1.2168)
Observations	14,104	14,128	7098	7068
R-squared	0.7014	0.7390	0.7370	0.7359
Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
SE clustered by	Firm	Firm	Firm	Firm
<i>p</i> -value of testing A > B		0.0078***		0.0674*

Notes. This table reports the OLS regression results. Variables are defined in Appendix A. Robust *t*-statistics listed in parentheses below the point estimates are based on standard errors (SE) clustered along the firm dimension. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

governance structures crowd out the marginal value arising from the informal, internal governance effects of Confucianism on supply chain resilience. Thus, H2 is supported.

4.3.2. Adaptive evolution mechanism

We next investigate the role of adaptive evolution capability in a further exploration of the economic mechanism through which exposure to Confucian culture enhances supply chain resilience. In H3, we predict that the positive influence of Confucian culture is stronger for firms with slower adaptive evolution. We use two proxies to measure a firm's adaptive evolution capability. The first proxy is the degree of corporate digital transformation, *Digit*, defined as the number of digitalization-related terms in the firm's annual report. The second proxy is innovation output, *Patent*, defined as the number of invention patent grants. Larger values of *Digit* and *Patent* indicate a larger adaptive evolution capability.

As shown in Panel B of Table 5, the effect of *Confucianism* is positive and significant at the 1% level for firms with slower adaptive evolution, as reflected by either a lower degree of digitalization or fewer patents. In contrast, Confucian culture fails to exert a meaningful impact on firms that exhibit more advanced adaptive evolution. The cross-group differences are positive and significant at least at the 5% level, lending strong support to H3.

4.3.3. Information transparency mechanism

To address the last mechanism, we test H4, which postulates that Confucian culture has a stronger influence on supply chain resilience among firms with lower information transparency ex ante. To empirically test this prediction, we measure information transparency using discretionary accruals calculated according to either the modified Jones model (*DA*) or the stock price crash risk (*Crash*), with greater values of both variables indicating lower information transparency.

We present the regression results in Panel C of Table 5. For firms with lower information transparency (i.e., high-*DA* and high-*Crash* subgroups), the effect of Confucian culture is positive and statistically significant at least at the 5% level, whereas this influence is not statistically significant in the subsamples of firms with higher information transparency. The difference in the coefficient estimates of *Confucianism* across the two subgroups is positive and significant at least at the 10% level, consistent with our prediction in H4.

4.4. Heterogeneity tests

In this section, we examine heterogeneity in the main effect of Confucian culture on supply chain resilience and test the boundary conditions under which its magnitude varies to further bolster the causal interpretation of our findings and rule out alternative explanations.

4.4.1. ESG orientation

A firm's ESG orientation reflects its capacity for sustainable operations. Higher ESG standards increase stakeholders' confidence, promote long-term cooperation and help secure a stable supply of capital, all of which are crucial for supply chain resilience. Confucian values of *neixing* (introspective governance) and a long-term mindset also lay a normative foundation for sustainable supply chain management and, in turn, for strong resilience, suggesting a substitutive effect between Confucian culture and ESG orientation. To quantify firm-level ESG orientation, we use *ESG*, which we define as a firm's ESG rating. We then split the sample into low- and high-*ESG* subsamples using the median value of *ESG*. The regression results in Panel A of Table 6 reveal that Confucian culture has a positive and significant effect on supply chain resilience in the low-*ESG* subsample, whereas the effect is not statistically different from zero in the high-*ESG* subsample. The cross-group difference is positive and significant at the 5% level. By imposing moral discipline and encouraging a long-term orientation, Confucian culture substitutes for weak formal institutions in firms with a low ESG orientation.

4.4.2. Foreign cultural shock

Ideological incompatibility between Confucianism and foreign cultural traditions can reshape firms' value systems and consequently affect their operational decision-making. If Confucianism indeed is the cultural

Table 6
Confucian culture and supply chain resilience – Heterogeneity tests.

Panel A. ESG orientation		
	(1)	(2)
	Low <i>ESG</i>	High <i>ESG</i>
	<i>SCR</i>	<i>SCR</i>
<i>Confucianism</i>	0.1540**[A] (2.3461)	0.0249[B] (0.8790)
Observations	13,917	13,916
R-squared	0.6818	0.7660
Control variables	Yes	Yes
Firm fixed effects	Yes	Yes
Industry-year fixed effects	Yes	Yes
SE clustered by	Firm	Firm
<i>p</i> -value of testing A > B	0.0341**	
Panel B. Foreign cultural shock		
	(1)	(2)
	<i>Foreign</i> = 0	<i>Foreign</i> = 1
	<i>SCR</i>	<i>SCR</i>
<i>Confucianism</i>	0.1010***[A] (2.5950)	−0.0120[B] (−0.2142)
Observations	27,598	1110
R-squared	0.6756	0.9208
Control variables	Yes	Yes
Firm fixed effects	Yes	Yes
Industry-year fixed effects	Yes	Yes
SE clustered by	Firm	Firm
<i>p</i> -value of testing A > B	0.0331**	
Panel C. Trade credit financing		
	(1)	(2)
	Low <i>Finance</i>	High <i>Finance</i>
	<i>SCR</i>	<i>SCR</i>
<i>Confucianism</i>	0.2184***[A] (3.2056)	0.0558[B] (0.8688)
Observations	10,216	10,194
R-squared	0.7287	0.7583
Control variables	Yes	Yes
Firm fixed effects	Yes	Yes
Industry-year fixed effects	Yes	Yes
SE clustered by	Firm	Firm
<i>p</i> -value of testing A > B	0.0408**	

Table 6 (continued)

Panel D. Operating cash flow volatility		
	(1)	(2)
	High <i>CFO_volatility</i>	Low <i>CFO_volatility</i>
	<i>SCR</i>	<i>SCR</i>
<i>Confucianism</i>	0.1455***[A] (2.9387)	0.0405[B] (1.2921)
Observations	14,231	14,177
R-squared	0.6820	0.7855
Control variables	Yes	Yes
Firm fixed effects	Yes	Yes
Industry-year fixed effects	Yes	Yes
SE clustered by	Firm	Firm
<i>p</i> -value of testing A > B	0.0384**	

Notes. This table reports the OLS regression results. Variables are defined in Appendix A. Robust *t*-statistics listed in parentheses below the point estimates are based on standard errors (SE) clustered along the firm dimension. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

norm that drives our results, its effect should be muted when firms are simultaneously exposed to foreign cultures that may direct supply chain operations in different ways. To gauge the degree of foreign cultural penetration, we construct *Foreign*, a dummy variable that equals 1 if at least one director has an overseas educational background, and 0 otherwise. We then split the sample based on this variable. Panel B, Column (1) in Table 6 reports that for firms without overseas-educated directors (*Foreign* = 0), the effect of Confucian culture is positive and significant at the 1% level, whereas for firms with overseas-educated directors (*Foreign* = 1), the effect is not statistically significant. The difference in coefficients between these two subsamples is positive and significant at the 5% level. In a multicultural environment, conflicting cultural values may weaken the influence of Confucian norms, leading to altered operations and stakeholder–management decisions and therefore attenuating the effect of Confucian culture on supply chain resilience.

4.4.3. Trade credit financing

Adequate financial reserves are crucial for maintaining operational continuity, seizing strategic investment opportunities and stabilizing supply chains. Trade credit, which is realized by delaying payments to suppliers and receiving advance payments from customers, is a key component of firms' working capital structure (Lu et al., 2024) and helps stabilize supply chains through strategic working capital optimization (Ersahin et al., 2024). Confucian culture reduces supply chain moral hazard problems by strengthening contractual loyalty (Zhang et al., 2025a), mitigating supply chain operational risk (Yan et al., 2024) and improving firms' creditworthiness (Wei et al., 2023). Under external constraints on trade credit financing, Confucian norms encourage firms' reputation building and cooperative relationships with trading partners. Accrued reputational and social capital alleviate cash shortfalls and reduces the risk of disruption stemming from liquidity stress. These arguments suggest that the incremental effect of Confucian culture should be more pronounced for firms with lower levels of trade credit financing. To test this prediction, we use *Finance* to represent the amount of trade credit financing, defined as the ratio of the sum of accounts payable, notes payable and advances from customers to total assets. We then divide the sample into high- and low-trade-credit subgroups based on the median of *Finance*. The regression results in Panel C of Table 6 show that the impact of Confucian culture is positive and significant at the 1% level in the low-*Finance* subsample but is not significant in the high-*Finance* subsample. The difference in coefficient estimates between the subsamples is positive and significant at the 5% level, suggesting that the marginal contribution of Confucian culture is stronger where trade credit financing is scarcer.

4.4.4. Operating cash flow volatility

A firm's operating cash flow volatility is a proxy for corporate financial stability, reflecting at least in part its supply chain's capacity to withstand shocks. Wild fluctuations in operating cash flows exacerbate the risk of liquidity shortfalls, making it difficult for firms to maintain their working capital investment in core supply chain links such as raw material procurement and production scheduling. Unstable operating cash flows also erode trustworthiness, increase coordination costs and the probability of disruptions and eventually weaken supply chain resilience. In such situations, the Confucian emphasis on long-term orientation and prudence may help firms optimize their inventory buffers and improve their cash flow management. This culturally rooted focus on risk containment and sustainable operations enables firms to better resist the risk of disruption risk, particularly when their operating cash flows are more volatile. We define operating cash flow volatility, *CFO_volatility*, as the standard deviation of operating cash flows scaled by total assets over the current and previous four years. We then split the sample into two subgroups using the median of *CFO_volatility*. Panel D of Table 6 shows that the effect of Confucian culture is positive and significant at the 1% level in the high-*CFO_volatility* subsample but is not significant in the low-*CFO_volatility* subsample. The cross-group difference is positive and significant at the 5% level, consistent with the prediction that Confucian culture has a stronger effect on firms facing greater operating cash flow volatility.

4.5. Robustness tests

To check the sensitivity of our baseline results, we conduct a battery of robustness tests. First, we use alternative measures of supply chain resilience, including the negative value of the gap between a firm's production volatility and demand volatility, computed over a three-year or seven-year window period (*SCR3* or *SCR7*). Although *SCR* is widely accepted and used in the literature, it captures only the amplification ratio between an individual firm's production and demand. It considers neither the amplification ratios of upstream and downstream firms nor the relationship between these ratios. To address this concern, we also calculate the ratio of suppliers' production–demand deviation to customers' production–demand deviation (*SCR3_SC*, *SCR_SC* or *SCR7_SC*) to better reflect the resilience of the entire supply chain.⁶ Second, we construct two alternative measures of a firm's exposure to Confucian culture by counting the number of Confucian temples located within either a 75-km or a 125-km radius centered on the firm's registered location (*Confucianism_75* or *Confucianism_125*). Detailed definitions of these variables are provided in Appendix A. We also use different model specifications to validate our main results. For example, we restrict our sample to firms that exhibit changes in Confucian culture during the sample period, exclude the financial crisis (2008–2009) and COVID-19 pandemic periods (2019–2020), extend the sample period to 2000–2023 and exclude firms registered in Xinjiang, Tibet, Ningxia or Qinghai. The regression results are reported in Table 7. Our baseline finding remains robust to all of these checks.

5. Conclusion

In this research, we provide evidence regarding whether and how a firm's exposure to Confucian culture affects its supply chain resilience. Using a large sample of Chinese A-share listed firms from 2008 to 2023, we document a positive, statistically significant and economically meaningful association between Confucian culture and supply chain resilience, which is robust across alternative specifications and research designs. To address potential endogeneity issues, we include additional fixed effects and control variables, utilize PSM and employ the IV approach. Our results remain qualitatively unchanged. More importantly, by exploiting two quasi-natural experiments that historically curtailed the diffusion of Confucian values, we show that the impact of Confucian culture on current supply chain resilience is attenuated for firms located in regions where Manchu cities were established or in areas exposed to the Taiping Rebellion more than a century ago. We then

⁶ The calculation of *SCR3_SC*, *SCR_SC* and *SCR7_SC* requires data on a firm's five largest suppliers and five largest customers. Because this information is voluntarily disclosed by our sample firms during the sample period, and because most of the disclosed counterparties are private firms, the number of observations is substantially decreased. Therefore, we choose not to use these measures in our baseline model specification.

Table 7
Confucian culture and supply chain resilience – Robustness tests.

Panel A. Alternative measures of supply chain resilience					
	(1)	(2)	(3)	(4)	(5)
	<i>SCR_3</i>	<i>SCR_7</i>	<i>SCR3_SC</i>	<i>SCR_SC</i>	<i>SCR7_SC</i>
<i>Confucianism</i>	0.0992* (1.8219)	0.0643** (2.4418)	0.0583* (1.9507)	0.2517** (2.4992)	0.2314*** (2.7463)
Observations	29,041	29,225	2088	2847	3404
R-squared	0.5340	0.7269	0.4681	0.5599	0.6489
Control variables	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes
SE clustered by	Firm	Firm	Firm	Firm	Firm
Panel B. Alternative measures of Confucian culture					
	(1)	(2)			
	<i>SCR</i>	<i>SCR</i>			
<i>Confucianism_75</i>	0.0913*** (2.9010)				
<i>Confucianism_125</i>		0.1072*** (2.5806)			
Observations	29,140	29,140			
R-squared	0.6736	0.6738			
Control variables	Yes	Yes			
Firm fixed effects	Yes	Yes			
Industry-year fixed effects	Yes	Yes			
SE clustered by	Firm	Firm			
Panel C. Alternative model specifications					
	(1)	(2)	(3)	(4)	
	Keep firms with changes in Confucian culture during the sample period.	Exclude time period during 2008–2009 and 2019–2020.	Extend the sample period to 2000–2023.	Exclude firms registered in Xinjiang, Tibet, Ningxia, or Qinghai.	
	<i>SCR</i>	<i>SCR</i>	<i>SCR</i>	<i>SCR</i>	
<i>Confucianism</i>	0.0852** (2.4298)	0.0749** (2.1013)	0.0731** (2.3615)	0.0974*** (2.6094)	
Observations	6192	22,001	31,195	28,239	
R-squared	0.6581	0.6823	0.6526	0.6732	
Control variables	Yes	Yes	Yes	Yes	
Firm fixed effects	Yes	Yes	Yes	Yes	
Industry-year fixed effects	Yes	Yes	Yes	Yes	
SE clustered by	Firm	Firm	Firm	Firm	

Notes. This table reports the OLS regression results. Variables are defined in Appendix A. Robust *t*-statistics listed in parentheses below the point estimates are based on standard errors (SE) clustered along the firm dimension. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

probe the underlying mechanisms and find empirical evidence consistent with the informal governance, adaptive evolution and information transparency channels. Lastly, through heterogeneity analyses, we find that the main effect is stronger among firms with poorer ESG performance, less exposure to foreign cultural influence, lower levels of trade credit financing and more volatile operating cash flows.

Our findings reposition corporate culture, and especially Confucian values, as a first-order determinant in theories of supply chain resilience. By documenting a causal relation and linking it to three economic mechanisms, we integrate cultural explanations with capability- and institution-based views of resilience.

Our evidence that the influence of Confucian culture is stronger when formal or external governance is weaker and when adaptive capacity is more limited clarifies a substitution logic that soft cultural capital can at least partially compensate for deficits in hard institutional arrangements and technological innovations. We also show that Confucian culture improves information quality and helps mitigate coordination frictions. Based on this important result, we position Confucianism as a mechanism that reduces information asymmetry and transaction costs and integrate Confucian cultural thinking into the agency theory perspective on supply chain management. Taken together, all of our findings provide important theoretical insights into when, why and how cultural endowments translate into improvements in corporate supply chains' operational resilience. The two quasi-natural experiments exploited in our study further show that deeply rooted historical institutions can reshape the outcomes of contemporary firms, thus establishing a bridge between long-run cultural transmission and modern supply chain performance.

Our work also extends the literature on the economic and financial consequences of corporate culture. Prior research has largely emphasized how Confucian culture influences focal firms' cash holdings, responsibility, misconduct and financing policy. In contrast, we show that culturally rooted key virtues of Confucianism (e.g., benevolence, righteousness, propriety, wisdom and integrity) propagate along links between suppliers and customers and thus stabilize coordination and sustain operations. The stronger effects that we document under tighter financing conditions and more volatile operating performance identify culture as an informal institution that reduces agency costs and strengthens governance across the supply chain in environments with poorly developed and/or weakly enforced formal rules or liquidity buffers. Collectively, our research enriches theories of corporate governance and supply chain management by specifying the conditions under which cultural forces substitute for formal contracts; it also motivates comparative inquiries into how distinct cultures might differentially scaffold resilience in their global supply chain networks.

Beyond the theoretical implications discussed above, our findings also have several important practical implications for supply chain management. For example, supplier selection could be informed by profiling the exposure of a firm and its trading partners to Confucian culture. Procurement and risk management teams can shortlist suppliers that are religiously aligned with Confucian values as a form of cultural screening, alongside financial health and quality metrics, especially in environments with relatively weak formal oversight or market discipline. In environments with limited competition, constrained trade credit, opaque information or volatile operating cash flows, managers can draw on corporate culture to optimize supply chain operations. For instance, firm leaders can deploy mentorship and ethics programs to emphasize Confucian values, embed relational contracting and mutual-obligation clauses in supply chain service-level agreements and align managerial compensation with multi-year resilience targets, rather than with single-period cost reductions.

Our study also provides useful insights for investors and policymakers. Equity investors and lenders can include culture-based indicators in their due diligence and pricing models. They also may consider a firm's exposure to supply chains anchored in regions characterized by strong Confucian norms, especially when the firm faces financing constraints or weak formal governance. Local governments and policymakers could promote soft-infrastructure initiatives, such as ethics training and trust-building forums for long-term cooperative behavior, to crowd in the relational capital that we identify here as resilience-enhancing. Regulators can reinforce these initiatives by funding programs that operationalize the Confucian principles of reciprocity, integrity and self-restraint across supplier networks and pairing these with incentive-compatible tools (e.g., tax credits) for firms that verifiably adopt such practices. Treating culture as an asset rather than merely a backdrop can broaden options for deploying supply chains that bend but do not break under stress.

However, several limitations of our study warrant further consideration. First, although we have identified informal governance, adaptive evolution and information transparency as potential mechanisms through which Confucian culture promotes supply chain resilience, the microeconomic and micro-behavioral foundations of managerial decision-making remain only partly understood. Future research could leverage richer and more granular data to analyze managerial judgment and decision-making processes. Second, because we focus exclusively on Confucian culture, we do not examine how other cultures or ideologies, such as Taoism, Buddhism or local ethnic value systems, interact with formal institutional arrangements to influence supply chain operations. Future research that incorporates multidimensional cultural indicators and cross-cultural comparative designs could elucidate the relative effectiveness of distinct cultural paradigms in supply chain risk governance and management. Third, our reliance on production–demand mismatch as a proxy of supply chain

resilience may not fully capture its multidimensional nature. Future studies could use more advanced empirical and modeling techniques to develop richer measures.

To the best of our knowledge, we are among the first researchers to establish a causal link between Confucian culture and firms' supply chain resilience. Given the global diffusion of Confucian ideology and the centrality of culture to economic organizations, we believe that our study marks an important step toward a better understanding of the effects of corporate culture on firms' outcomes and real economies.

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

Dependent variable

Variable	Definition
<i>SCR</i>	$-\frac{sd(Production)}{sd(Demand)} \div 100$, where $sd(\cdot)$ denotes the standard deviation computed over the current and previous four years, <i>Demand</i> is sales revenue, and <i>Production</i> equals <i>Demand</i> plus the change in net inventories.

Independent variable

Variable	Definition
<i>Confucianism</i>	Natural logarithm of one plus the number of Confucian temples within a 100-km radius of the firm's registration location, where the distance between the firm and the Confucian temple is calculated using the spherical law of cosines.

Control variables

Variable	Definition
<i>Ln_assets</i>	Natural logarithm of total assets.
<i>Ln_firm_age</i>	Natural logarithm of one plus the difference between current year and listing year.
<i>Leverage</i>	Total liabilities divided by total assets.
<i>ROA</i>	Sum of total profit and financial expenses, divided by total assets.
<i>BM</i>	Book value of equity divided by market value of equity.
<i>Tobin_Q</i>	Market value of assets divided by book value of assets.
<i>Sales_growth</i>	Operating revenue in the current year minus operating revenue in the previous year, divided by operating revenue in the previous year.

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Variable	Definition
<i>Cash</i>	Cash and cash equivalents divided by current liabilities.
<i>PPE</i>	Net property, plant, and equipment divided by total assets.
<i>Capex</i>	Capital expenditure divided by total assets.
<i>Liquidity</i>	Current assets divided by total assets.
<i>Turnover</i>	Operating costs divided by net inventory.
<i>SA_index</i>	$(-0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age)$, where <i>Size</i> is the natural logarithm of total assets and <i>Age</i> is the difference between current year and founding year.
<i>KZ_index</i>	We construct <i>KZ_index</i> in three steps. First, we compute five ratios: net operating cash flows divided by total assets at the beginning of the year $\left(\frac{CF_{i,t}}{Asset_{i,t-1}}\right)$, cash dividends divided by total assets at the beginning of the year $\left(\frac{Div_{i,t}}{Asset_{i,t-1}}\right)$, cash and cash equivalents divided by total assets at the beginning of the year $\left(\frac{Cash_{i,t}}{Asset_{i,t-1}}\right)$, total liabilities divided by total assets ($Lev_{i,t}$), and Tobin's Q ($Q_{i,t}$). For each year, and using the annual median, we define five indicator variables: if $\frac{CF_{i,t}}{Asset_{i,t-1}}$ is below the median, KZ_1 equals one, and zero otherwise; if $\frac{Div_{i,t}}{Asset_{i,t-1}}$ is below the median, KZ_2 equals one, and zero otherwise; if $\frac{Cash_{i,t}}{Asset_{i,t-1}}$ is below the median, KZ_3 equals one, and zero otherwise; if $Lev_{i,t}$ is above the median, KZ_4 equals one, and zero otherwise; and if $Q_{i,t}$ is above the median, KZ_5 equals one, and zero otherwise. We then calculate <i>KZ</i> as the sum of these five indicator variables. Second, we estimate the following ordered logistic regression: $KZ_{i,t} = \alpha_1 \times \frac{CF_{i,t}}{Asset_{i,t-1}} + \alpha_2 \times \frac{Div_{i,t}}{Asset_{i,t-1}} + \alpha_3 \times \frac{Cash_{i,t}}{Asset_{i,t-1}} + \alpha_4 \times Lev_{i,t} + \alpha_5 \times Q_{i,t}$. Third, <i>KZ_index</i> is the fitted value computed using the estimated coefficients.
<i>FC_index</i>	We construct <i>FC_index</i> in three steps. First, for each year, we standardize firm size, firm age, and cash dividend payout ratio and get the z-score for each variable. We then take the mean of these three standardized variables for each firm and sort firms in ascending order using this composite score. We define a dummy variable <i>QUFC</i> , which equals one for firms in the bottom tercile of this composite score, and zero otherwise. Second, we estimate a logit model for the probability of being financially constrained: $QUFC_{i,t} = \alpha_0 + \alpha_1 \times Size_{i,t} + \alpha_2 \times Lev_{i,t} + \alpha_3 \times \frac{Dividends_{i,t}}{Assets_{i,t}} + \alpha_4 \times MB_{i,t} + \alpha_5 \times \frac{NWC_{i,t}}{Assets_{i,t}} + \alpha_6 \times \frac{EBIT_{i,t}}{Assets_{i,t}} + \varepsilon_{i,t}$, where <i>Size</i> is natural logarithm of total assets, <i>Lev</i> is total liabilities divided by total assets, <i>Divideneds</i> is cash dividends, <i>MB</i> is the market-to-book ratio, <i>NWC</i> is the net working capital and <i>EBIT</i> is earnings before interest and tax. Third, we compute the fitted probability and use it as a continuous measure of financing constraints, denoted as <i>FC_index</i> .
<i>Z_score</i>	$Z_score = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$, where X_1 is working capital divided by total assets, X_2 is accumulated retained earnings divided by total assets, X_3 is earnings before interest and tax divided by total assets, X_4 is market value of equity divided by book value of debt, and X_5 is operating revenue divided by total assets.
<i>Sales_volatility</i>	Standard deviation of operating revenue divided by total assets computed over the current and previous four years.

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Variable	Definition
<i>Info_quality</i>	The Shanghai and Shenzhen stock exchanges evaluate the accounting information disclosure quality of listed firms regarding the following six aspects: authenticity, accuracy, completeness, timeliness, fairness, and compliance. The evaluation results are categorized into four grades: excellent, good, qualified, and unqualified. <i>Info_quality</i> is a dummy variable equal to one if the firm is rated as good or excellent, and zero otherwise.
<i>Inst_ownership</i>	Sum of shares owned by institutional investors as a percentage of total shares outstanding.
<i>Ln_analyst</i>	Natural logarithm of one plus the number of analysts following the firm.
<i>Independence</i>	Proportion of independent directors on the board.
<i>Ln_board</i>	Natural logarithm of one plus the number of board directors.
<i>Ln_mgr_salary</i>	Natural logarithm of one plus the total compensation of senior managers, excluding allowances.
<i>Top1</i>	Proportion of shares owned by the largest shareholder.
<i>Dual</i>	A dummy variable equal to one if the board chairman also serves as the CEO, and zero otherwise.
<i>Big4</i>	A dummy variable equal to one if the audit is provided by the Big4 audit firm, and zero otherwise.

Other variables

Variable	Definition
<i>City_prov</i>	A dummy variable equal to one if the firm is registered in Beijing, Shanghai, Guangzhou, or Shenzhen, and zero otherwise.
<i>Han_prov</i>	A dummy variable equal to one if the firm is not registered in one of the five autonomous regions (i.e., Inner Mongolia Autonomous Region, Guangxi Zhuang Autonomous Region, Tibet Autonomous Region, Xinjiang Uygur Autonomous Region, and Ningxia Hui Autonomous Region), and zero otherwise.
<i>Sea</i>	A dummy variable equal to one if the firm is registered in a coastal province (i.e., Guangdong Province, Fujian Province, Zhejiang Province, Shanghai Municipality, Jiangsu Province, Shandong Province, Tianjin Municipality, Hebei Province, Hainan Province, Guangxi Zhuang Autonomous Region, and Hong Kong Special Administrative Region), and zero otherwise.
<i>North</i>	A dummy variable equal to one if the latitude of the firm's registration location is greater than 30°N, and zero otherwise.
<i>Buddhism</i>	Natural logarithm of one plus the number of Buddhist temples within a 100-km radius of the firm's registration location, where the distance between the firm and the Buddhist temple is calculated using the spherical law of cosines.
<i>Taoism</i>	Natural logarithm of one plus the number of Taoist temples within a 100-km radius of the firm's registration location, where the distance between the firm and the Taoist temple is calculated using the spherical law of cosines.
<i>Ln_school</i>	Natural logarithm of one plus the number of primary and secondary schools in the city where the firm is registered.

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Variable	Definition
<i>CFO_volatility</i>	Standard deviation of operating cash flows divided by total assets computed over the current and previous four years.
<i>SCR3</i>	$-\frac{sd(Production)}{sd(Demand)} \div 100$, where $sd(\cdot)$ denotes the standard deviation computed over the current and previous two years, <i>Demand</i> is sales revenue, and <i>Production</i> equals <i>Demand</i> plus the change in net inventories.
<i>SCR7</i>	$-\frac{sd(Production)}{sd(Demand)} \div 100$, where $sd(\cdot)$ denotes the standard deviation computed over the current and previous six years, <i>Demand</i> is sales revenue, and <i>Production</i> equals <i>Demand</i> plus the change in net inventories.
<i>SCR3_SC</i>	$-\frac{\frac{sd(Production_{sup})}{sd(Demand_{sup})}}{\frac{sd(Production_{cus})}{sd(Demand_{cus})}} \div 100$, where $sd(\cdot)$ denotes the standard deviation computed over the current and previous two years, <i>Demand_{sup}</i> (<i>Demand_{cus}</i>) is the average sales revenue of the firm's five largest suppliers (customers), and <i>Production_{sup}</i> (<i>Production_{cus}</i>) equals the average of sales revenue plus the change in net inventories for the firm's five largest suppliers (customers).
<i>SCR_SC</i>	$-\frac{\frac{sd(Production_{sup})}{sd(Demand_{sup})}}{\frac{sd(Production_{cus})}{sd(Demand_{cus})}} \div 100$, where $sd(\cdot)$ denotes the standard deviation computed over the current and previous four years, <i>Demand_{sup}</i> (<i>Demand_{cus}</i>) is the average sales revenue of the firm's five largest suppliers (customers), and <i>Production_{sup}</i> (<i>Production_{cus}</i>) equals the average of sales revenue plus the change in net inventories for the firm's five largest suppliers (customers).
<i>SCR7_SC</i>	$-\frac{\frac{sd(Production_{sup})}{sd(Demand_{sup})}}{\frac{sd(Production_{cus})}{sd(Demand_{cus})}} \div 100$, where $sd(\cdot)$ denotes the standard deviation computed over the current and previous six years, <i>Demand_{sup}</i> (<i>Demand_{cus}</i>) is the average sales revenue of the firm's five largest suppliers (customers), and <i>Production_{sup}</i> (<i>Production_{cus}</i>) equals the average of sales revenue plus the change in net inventories for the firm's five largest suppliers (customers).
<i>Confucianism_75</i>	Natural logarithm of one plus the number of Confucian temples within a 75-km radius of the firm's registration location, where the distance between the firm and the Confucian temple is calculated using the spherical law of cosines.
<i>Confucianism_125</i>	Natural logarithm of one plus the number of Confucian temples within a 125-km radius of the firm's registration location, where the distance between the firm and the Confucian temple is calculated using the spherical law of cosines.

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Putting firms in the spotlight: does the mismatch between words and actions or suspicions of greenwashing drive stock risk premiums?



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ABSTRACT

Prior studies define corporate greenwashing as inconsistent and exaggerated environmental disclosures compared with actual practices. This study explores how the stock market identifies and penalizes greenwashing risks, focusing on mismatches between companies' words and actions and suspicions of greenwashing. Using data from non-financial Chinese A-share firms that publish CSR reports (2008–2021), we test the stock risk premium effects of greenwashing suspicions, while textual evidence of greenwashing amplifies negative reactions, but does not directly increase premiums. The mechanism analysis reveals that exposure to reputational risk, financial misallocation, and information frictions drive premium increases. Heterogeneity analysis indicates that external pollution shocks, internal financial regulations, and corporate strategies affect the amount of premiums. Moreover, firms mimic their peers' disclosure formats to reduce their environmental information risks, which triggers a transmission of greenwashing and exacerbates systemic risks. Contrary to the view that heavily polluting firms are major greenwashers, low-polluting firms bear higher greenwashing risk premiums because investors already consider the environmental risks of heavily polluting firms. This study measures the likelihood of greenwashing by integrating its motives, expressions, and behaviors, thus offering policy insights for green finance and corporate environmental disclosure frameworks.

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1. Introduction

Over the past few decades, global capital markets have deeply integrated environmental, social, and governance (ESG) standards into their investment decision-making systems, and corporate environmental information disclosure has become a key channel for stakeholders to assess enterprises' sustainable development capabilities (Starks, 2023). However, greenwashing—the inconsistency between enterprises' exaggerated commitments to green actions in their written disclosures and their actual environmental practices—continues to erode the credibility of the information disclosed (Lyon and Montgomery, 2015). This mismatch between words and actions renders ESG ratings ineffective, distorts investor valuations, and undermines the implementation effect of green finance policies in the market. From a practical perspective, although the total number of global greenwashing cases decreased by 12 % in 2024¹ (with a 20 % decrease in Europe and a 4 % decrease in the UK) due to the strengthening of government supervision and the introduction of relevant laws, the number of high-risk greenwashing cases still increased by more than 30 %. This contrast clearly highlights the repetitiveness and arduousness of addressing the greenwashing issue. In addition, the greenwashing problem in the U.S. and Canada is showing a worsening trend, which is a potential important driver of the ESG resistance movement represented by the U.S. market (Nchako and Benjamin, 2025).

International academic research on greenwashing has mainly focused on policy analysis, greenwashing motives, and its economic consequences. Despite the abundance of research findings, three key gaps still persist and hinder the capital market's understanding of corporate greenwashing. First, some empirical studies have yielded mixed results and contradictory conclusions (e.g., Testa et al., 2018; Walker and Wan, 2012), which interferes with the market's exploration of the underlying value of ESG and its recognition of greenwashing risks. Second, studies have conflated the antecedents and key characteristics of greenwashing, failing to clearly distinguish between enterprises' motives for manipulating their disclosures and their actual observable behaviors (Free et al., 2024). Third, investors' decision-making logic is ambiguous. Textual disclosures are often proactive and concealed, making it difficult for the capital market to directly identify the existence of greenwashing (Kim and Lyon, 2015). However, few studies have explored how the interaction between greenwashing and fraudulent corporate motives affects pricing outcomes.

The development stage, market characteristics, and policy uniqueness of China's A-share market make it a favorable setting for greenwashing research. Unlike the environmental information disclosure requirements of the Hong Kong (China)² and U.S. markets,³ which focus on top-level design, investor protection, and corporate strategy, the corporate environmental information disclosure framework for the A-share market is still undergoing gradual improvement. In terms of disclosure systems, environmental information disclosure in the A-share market is led by the China Securities Regulatory Commission (CSRC), which adheres to the principle of "encouragement as the main approach and mandatory requirements as supplementary measures." The proportion of third-party assurance is low, and enterprises have significant autonomy in deciding whether to disclose information and how to do so (Marquis and Qian, 2014; Shi et al., 2023). In terms of disclosure content, the CSRC, the People's Bank of China, and the Ministry of Ecology and Environment have different priorities with respect to environmental accounting information. This has led to fragmented and complex disclosure content by enterprises, with many failing to disclose environmental costs and business issues related to climate change. From a market perspective, the "Greenwashing List" published annually since 2009 by China's *Southern Weekend* has exposed the greenwashing practices of 151 enterprises. These listed enterprises are concentrated in industries subject to high environmental regulatory pressure, intense market competition, or strong social attention, such as energy, pharmaceuticals, electronics, and daily necessities. Furthermore, the

¹ Source: <https://www.reprisk.com/insights/news-and-media-coverage/reprisk-data-shows-decrease-in-greenwashing-for-first-time-in-six-years-but-severity-of-incidents-is-on-the-rise>.

² Sources: The Stock Exchange of Hong Kong Limited (HKEX) Corporate Governance Code and Environmental, Social and Governance (Climate Information Disclosure) Guidelines 2021, and HKEX Environmental, Social and Governance Reporting Guidelines 2025.

³ Sources: Regulation S-K, Regulation S-X, *Staff Accounting Bulletins* (SAB) of the U.S. Securities and Exchange Commission (SEC), *Financial Reporting Releases* (FRR), *Statement of Financial Accounting Standards No. 5: Accounting for Contingencies* (FASB), *Introduction to Environmental Accounting* (EPA).

market exhibits a phenomenon analogous to Gresham's Law, where inferior entities crowd out superior ones in the context of green disclosure. Based on the above discussion, certain issues in the A-share market have enabled some enterprises to "avoid substantive issues and focus on trivial ones" to control disclosure content. These enterprises may engage in rent-seeking and fraudulent practices, and use inappropriate means to manipulate or conceal information related to environmental fraud, to evade their responsibilities or exaggerate their environmental image.

However, faced with the potential risk of greenwashing, does the capital market engage in suspicious pricing or behavioral pricing?

From the perspective of practical foundations, to identify corporate value and green governance risks, rational investors represented by institutional investors or analysts⁴ will analyze the current financial status and financing progress of enterprises (Fan et al., 2024). In addition, they will interpret environmental regulations related to core business operations and reasonably assess the credibility of accounting information and the likelihood of its manipulation, which helps analysts adjust their asset pricing. Furthermore, analysts will interpret publicly disclosed cases of greenwashing, thereby deepening their understanding of corporate greenwashing behavior. Therefore, in reality, the capital market's pricing of greenwashing risks focuses simultaneously on suspicions of greenwashing and on the greenwashing act itself, and may place greater emphasis on determining suspicions of greenwashing, being more lenient toward companies with weaker greenwashing suspicions.

From a theoretical perspective, based on the efficient market hypothesis, principal-agent theory, and information asymmetry theory, agents may manipulate disclosed environmental information in the pursuit of short-term benefits. Moreover, publicly disclosed greenwashing information is assumed to be rationally priced by the market. Therefore, by the time investors recognize greenwashing practices, stock prices have already fluctuated, failing to achieve the goal of ex-ante risk avoidance. From a psychological standpoint, investors may overestimate greenwashing behavior due to overconfidence, or overreact to potential greenwashing risks due to loss aversion. These emotional and psychological biases lead to price distortions. Thus, from an economic theory perspective, due to market efficiency, pricing based solely on greenwashing behavior may not prevent risks. From a psychological theory perspective, suspicious pricing or behavioral pricing alone may lead to distorted outcomes. Rational investors must pay close attention to both suspicions of greenwashing and acts of greenwashing committed by companies, and achieve reasonable risk management through the synergistic effect of the two.

To quantify the authenticity of green accounting information, based on multi-condition effectiveness theory and multiple signals theory, we construct a greenwashing suspicion index to represent dynamic changes in investor decision-making (Pástor et al., 2021). Combined with the greenwashing causality framework proposed by Xie et al. (2024), greenwashing focuses on three types of entities: institutions, organizations, and individuals. It is generated by the interaction of multiple factors, including external institutional pressure, social pressure, stakeholder pressure, and internal profit motives, as well as corporate characteristics. Therefore, the capital market's assessment of suspicions of corporate greenwashing must also consider multiple perspectives to avoid over-identification due to a single factor. Focusing on the causes and manifestations of greenwashing, we set the suspicion threshold for greenwashing based on four indicators: internal corporate financing risk, bankruptcy risk, external soft regulatory pressure from stock exchanges, and environmental penalty deterrence. When a company exhibits high leverage manipulation, high internal bankruptcy costs, and is not subject to soft stock exchange regulation or weak external environmental penalty deterrents, it is considered suspected of greenwashing. Such companies are more likely to engage in greenwashing to alleviate internal and external operational contradictions, reduce governance costs, and ease financing constraints. These samples are assigned a value of 1, while their opposites are assigned a value of 0. The greenwashing suspicion

⁴ RepRisk has identified five key factors for monitoring greenwashing risks, divided into two perspectives. From the perspective of causes, these factors include the importance of ESG and financial stability, corporate competitiveness and reputation, the transparency of information disclosure and accountability systems, and the intensity of regulatory scrutiny. From the perspective of outcomes, the objective is to prevent the misallocation of capital due to greenwashing. Therefore, to characterize suspicions of corporate greenwashing, this paper integrates factors from the perspective of causes with the specific conditions of the Chinese market and existing research frameworks for measurement. Data source: <https://www.reprisk.com/regulatory-hub/esg-topics/regulatory-briefing-greenwashing>.

indicator presented in this paper is reliable, and its results are closely linked to “greenness.” When enterprises individually meet these four conditions, their greenwashing behaviors all increase,⁵ which is analogous to the research findings of Berrone et al. (2017) and Chen et al. (2024).

This study is based on the theoretical premise that “corporate behavior is socially irresponsible only when observers perceive it as irresponsible,” exploring the market consequences and transmission mechanisms generated by suspicions of corporate greenwashing and evidence of greenwashing. By identifying suspicions of greenwashing among non-financial enterprises listed on the Chinese A-share market from 2008 to 2021 and analyzing their CSR reports to obtain textual evidence of greenwashing, we find that (1) investors’ decision-making focuses more on suspicions of greenwashing than on inconsistencies between enterprises’ actions and statements. Although textual greenwashing is not directly captured by the market, the embellishment of disclosures amplifies suspicions of greenwashing, raising doubts among investors about corporate environmental performance. (2) The imitation of textual disclosures among companies exacerbates the spread of greenwashing within industries and regulatory regions, transforming individual greenwashing into industry-wide greenwashing. This reduces investors’ sensitivity to greenwashing and is not conducive to preventing systemic financial risks. (3) Air pollution shocks, internal corporate financial regulations, and strategic risks all impact the risk premium of greenwashing.

Unlike previous studies, this paper makes the following key contributions:

(1) In terms of research methodology, this paper characterizes suspicions of corporate greenwashing from four perspectives: financing constraints, bankruptcy costs, soft regulation by stock exchanges, and the deterrent effect of environmental penalties. In addition, it integrates Python-based text analysis to obtain textual evidence of greenwashing, thereby correcting the error of prior studies that conflate the antecedents and manifestations of greenwashing. This approach effectively analyzes the actual process of investors’ risk avoidance regarding greenwashing and assesses the market’s tolerance for greenwashing behavior. (2) Regarding the research perspective, this paper explicitly distinguishes the three causal stages of greenwashing behavior: antecedents, expressions, and economic risks. Furthermore, it estimates the heterogeneous impacts from the perspective of differences between domestic and international environmental information disclosure frameworks and proposes corresponding policy recommendations. (3) In terms of mechanisms and further research, suspicions of greenwashing magnify reputational risk, information frictions, and financial misallocation. Moreover, unlike previous studies, this paper finds that heavily polluting companies are not the primary targets of greenwashing, as their non-green attributes have already been considered by investors. In contrast, as low-polluting companies have better control over their information disclosure, the risk premium associated with greenwashing is more pronounced.

The remainder of this paper is structured as follows. Section 2 outlines the institutional background of environmental information disclosure in the Chinese A-share market. Section 3 reviews the literature and conducts a theoretical analysis. Section 4 details the research design (core variables, model setting, sample selection). Section 5 presents the empirical results (baseline regressions, robustness tests, endogeneity). Section 6 explores the underlying mechanisms via the three aforementioned channels. Section 7 conducts a heterogeneity analysis. Section 8 further examines the differences in risk premium related to greenwashing (heavily/slightly polluting firms) and its contagion effects. Finally, Section 9 summarizes the findings and offers policy recommendations.

2. Institutional background

The institutional issues underlying governance deficiencies are the source of greenwashing risks. Clarifying the interconnections between institutional arrangements at the stock exchange, government, financial institution, and corporate levels can help understand corporate motives for greenwashing, greenwashing behaviors, and their economic consequences.

The encouragement of disclosure and the soft-law regulatory norms of stock exchanges and the CSRC currently constitute the main institutional characteristics of environmental information disclosure in China. In 2002, the CSRC issued the “Corporate Governance Guidelines for Listed Companies,” which proposed

⁵ Relevant results are presented in Appendix Section 3.

requirements for the disclosure of corporate green information. In 2006 and 2008, the Shenzhen Stock Exchange and the Shanghai Stock Exchange respectively encouraged listed companies to publish ESG annual reports. In 2011, the Shenzhen Stock Exchange revised the “Measures for the Assessment of Information Disclosure Work of Listed Companies,” incorporating the disclosure of ESG reports into the assessment system for listed companies to strengthen the incentives for listed companies to disclose ESG information. Subsequently, the framework for environmental accounting information continued to be refined.⁶ Until 2021, the revision of the “Content and Format of Annual Reports” became an important vehicle for China’s environmental accounting disclosure rules, initially forming a disclosure model that combines mandatory disclosure, “disclose or explain,” and encourages disclosure. Nevertheless, statistics from the Zhongchengxin Green Finance ESG Ratings database show that from 2022 to 2024, the sustainability information disclosure rate of listed companies was still below 40 %. The standardization of environmental information disclosure and the correlation between business and environmental risks still exist. Companies can still control the content of their disclosure and fail to fulfill their environmental and social responsibilities.

Companies reluctant to engage in green governance prefer to exploit the loopholes of environmental information disclosure systems to manipulate their disclosures to obtain more financing support or reduce their environmental governance costs. In 2012, the China Banking Regulatory Commission issued the “Green Credit Guidelines” to strengthen the constraints imposed on financial institutions regarding corporate environmental risks. For companies with negative environmental governance, the “Green Credit Guidelines” restrict their investment behavior, reduce their financing channels, and lead to a lack of long-term financial support when they engage in green innovation. In 2019, China further issued the “Green Industry Guidance Catalog”,⁷ which distinguishes green industries, clarifies industry boundaries, and strengthens financing constraints on non-green companies. As a result, non-green companies find it difficult to obtain green financing support under the supervision of professional financial institutions. To meet regulatory requirements and external financing needs, companies are resorting to opportunistic practices of embellishing their environmental information to ease the pressure they face regarding green financing.

However, companies’ inappropriate disclosure of environmental information and financial fraud related to their business and financing activities are likely to attract the attention of regulatory authorities. Similar to the U.S.,⁸ China’s annual report inquiry mechanism is based on an administrative penalty system and an express information disclosure system. In 2002, the CSRC proposed “non-punitive regulatory measures” for the first time. In 2013 and 2014, the Shanghai Stock Exchange and the Shenzhen Stock Exchange respectively implemented an express information disclosure system,⁹ thereby eliminating pre-approval of information disclosure and conducting post-event supervision through methods such as issuing inquiry letters. After 2014, the soft regulatory system of inquiry letters was formally clarified. Inquiry letters are issued directly by the stock exchange and relate to the quality of information disclosure, such as business activities, violations, and environmental protection measures, with the aim of improving the transparency of corporate accounting information.

⁶ In 2017, the CSRC revised the *Contents and Format of Annual Reports*. In 2018, it revised the *Guidelines for Corporate Governance of Listed Companies*, forming a preliminary framework for ESG information disclosure. In 2020, the Shenzhen Stock Exchange revised the *Assessment Measures for Information Disclosure of Listed Companies*, formally adopting the concept of ESG information.

⁷ In 2023, the *Green Industry Guidance Catalogue* (2023 Edition) (draft for comment) was expanded from the original six categories to seven categories: energy conservation and carbon reduction, environmental protection, resource recycling, clean energy, ecological protection, restoration and utilization, green modernization of infrastructure, and green services. *The Green and Low-Carbon Transformation Industry Guidance Catalogue* (2024 Edition), published in 2024, added key elements such as low-carbon industrial transformation and production digital intelligence.

⁸ In 2002, following the Enron scandal, the U.S. enacted the Sarbanes–Oxley Act of 2002. Section 408 of the Act mandates that the SEC review the annual reports of listed companies every three years to ensure compliance with SEC disclosure requirements and Generally Accepted Accounting Principles. If the SEC identifies potential issues in a company’s accounting information disclosure, it will issue an inquiry letter to the company, requiring supplementary accounting information and even demanding a restatement or revision of the report.

⁹ A comprehensive institutional arrangement whereby listed companies and other entities, in accordance with the requirements of the relevant business rules of stock exchanges, directly submit their proposed disclosure announcements to designated official websites or specified media for release, with the exchanges conducting post-event supervision.

Soft regulation is accompanied by environmental punishments, which are also the most basic means of combating environmental violations, to encourage companies to comply with the law and implement environmental governance actions. In 2015, the newly revised “Environmental Protection Law of the People’s Republic of China” was officially implemented, greatly increasing the cost of environmental violations and requiring a combination of “punishments and education,” to deter and educate companies that have not been punished and to alleviate the limitations of government regulatory resources and information asymmetry. As a result, the combination of strong regulatory deterrence through environmental punishments and stock exchanges’ soft regulatory system of annual report review forms an interrelated regulatory system.

From an institutional perspective, disclosure frameworks, financing guidelines, market competition, and regulation and punishments are interrelated. The imperfections of the disclosure framework offer opportunities for corporate greenwashing behavior. Companies use greenwashing to alleviate their financing constraints, gain unfair competitive advantages in the market, reduce operational pressures, and thus achieve better financial optimization and market performance with relatively minor greenwashing accounting fraud. However, the soft regulatory system of stock exchanges and the legal punishment system regulate companies’ financial information, environmental governance actions, and environmental information disclosure, thereby alleviating the information asymmetry between investors and companies. Faced with potential “greenwashing bubbles,” investors evaluate suspicions of corporate greenwashing, measure the market’s tolerance for greenwashing behavior, and assess the risks.

3. Literature review and theoretical analysis

3.1. Literature review

Corporate greenwashing behavior is the result of the interplay of multiple factors. From the perspective of policy systems and macro-governance, flaws in information disclosure systems, environmental taxes (Hu et al., 2023), and environmental subsidies (Chen et al., 2024) are all important factors that induce corporate greenwashing. The decoupling between the Chinese government’s emission reduction requirements and companies’ operational restrictions exacerbates the occurrence of greenwashing. Based on signaling theory, public perception of environmental information and social media attention (Zhang et al., 2024) support the embellishment of corporate environmental information. Pressure from customers and industry associations often encourages greenwashing (Sun et al., 2024). From the perspective of corporate management and operations, the functional diversity of the executive team (Zhang et al., 2023) and managerial overconfidence (Wang et al., 2024) both exacerbate the degree of greenwashing. To alleviate financing constraints, the institutional link between banks’ credit decisions and corporate environmental performance increases the level of risk-taking by non-green firms, which is also an important cause of greenwashing (Fan et al., 2021).

In terms of economic consequences, greenwashing behavior severely affects companies’ business strategies and exacerbates social inequalities (Shen et al., 2023). Consumers lose confidence in companies exposed for greenwashing, and these companies’ market share is affected. Negative information spreads quickly and widely, while the cost of repairing reputation is high and the effect limited (Seele and Gatti, 2017). Second, companies that engage in greenwashing face legal and regulatory risks, including high fines, litigation, and even market exclusion. Investor confidence in such companies also declines, and exposure to greenwashing can lead to significant stock price fluctuations and weakened market tolerance. Finally, greenwashing behavior results in ineffective management of core environmental and climate issues. As companies do not focus on their core business, capital allocation is diverted, hindering the achievement of sustainable development goals.

Due to the opaque nature of greenwashing, previous studies have used different methods to measure greenwashing. Huang and Watson (2015) measured the extent of selective disclosure (reporting good news but not bad news) and manipulative expression (inconsistency between words and actions) from four dimensions: governance and structure, processes and controls, inputs and outputs, methods and compliance. Some scholars have measured greenwashing through differences in ESG ratings from Bloomberg, Huazheng ESG ratings, and Wind ESG ratings, or through textual analysis of the frequency of environmental words (Zhang et al., 2024). However, all of these greenwashing indicators have issues: (1) differences in measurement scales and

focal points of ESG ratings cause scoring biases; (2) corporate social responsibility (CSR) reports may already be the result of manipulation, making it difficult for word frequency analysis to accurately measure the level of greenwashing; and (3) investors cannot fully understand corporate greenwashing through comprehensive analysis of indicators and textual reading. Therefore, existing greenwashing indicators are not based on the investors' perspective and do not reflect the process by which capital markets identify potential greenwashing risks.

3.2. Theoretical analysis

With the emergence of new models and business formats, greenwashing has gradually evolved from its initial form as a simple corporate marketing strategy into a phenomenon known as “green fraud” (Lyon and Montgomery, 2015). This transformation is driven by economic incentives within capital markets, where companies disseminate false information and conceal their negative environmental performance. In a broader context, the concept of “risk premium” pertains to the decisions made by firms in their quest to “maximize their own interests” while considering increasing levels of current or anticipated risks. These decisions aim to achieve a balance between returns and risks in the market (Pástor et al., 2021). To prevent corporate greenwashing behavior from causing environmental damage, which in turn affects companies' operating conditions and profitability levels and increase their exposure to risk, investors may demand higher risk premiums for stock prices based on the market information they obtain (Edmans et al., 2017). Based on this argument, we propose the following theoretical hypotheses.

3.2.1. Corporate reputation risk

Based on the media information function hypothesis, social media attention to companies can also be a potential factor in exposing greenwashing behavior. Media reports, as an important source of information for investors and regulators, shift their focus from greenwashing behavior itself to the entire company. Furthermore, negative news tends to disclose risks concerning listed companies, severely damaging their social image and reducing their credibility and reliability. As borrowers, companies exposed to negative news will face the high cost of loan interruptions (Houston and Shan, 2022). Faced with uncertainty about the potential impact of such news on their operations, companies may choose to remain silent or avoid disclosing (Bond and Zeng, 2022). As a result, companies engaging in greenwashing may do everything they can to conceal their negative information, weaken investors' risk perception, and increase their exposure to reputational risk. Once a company is in financial distress or faces financing constraints, investors will have serious doubts about the information it discloses, thereby increasing their risk premium.

3.2.2. Investor information friction and decision risk

Corporate greenwashing behavior significantly increases stock risk premiums by exacerbating information frictions. Information frictions refer to the situation in which market participants cannot accurately assess the true value of assets due to information distortion or asymmetry, which significantly raises the cost of capital (Edmans et al., 2017). Greenwashing behavior distorts investors' perception of companies' environmental risks by providing false or misleading information about environmental performance, increasing the complexity of investment decisions and the probability of investment errors (Dyck et al., 2019). This further undermines market efficiency (Krueger et al., 2020), exacerbates general market uncertainty, and increases risk exposure. In addition, greenwashing behavior undermines investor confidence, and investor skepticism increases risk premiums (Hong et al., 2019). Therefore, greenwashing behavior subjects investors to strong information frictions, leading to inefficient decision-making and prompting the market to demand higher risk premiums.

3.2.3. Market financial mismatch risk

Greenwashing exacerbates the information asymmetry between companies and investors, preventing investors from accurately assessing companies' environmental risks and long-term value (Du, 2015). This information asymmetry may lead investors to misallocate their funds to companies engaging in greenwashing rather

than those with genuine sustainable development capabilities, thereby distorting the resource allocation efficiency of the capital market (Chen et al., 2018). This exacerbates financial inequalities in the market, distorts investment decisions, and disrupts market order. More seriously, the transmission of greenwashing behavior weakens capital pricing efficiency, triggering systemic risks and reducing the market's ability to self-correct resource allocation deviations (Delmas and Montes-Sancho, 2010). As a result, substantial evidence of greenwashing and suspicions of greenwashing will expose risks, leading investors to demand higher risk premiums.

In summary, this paper proposes the following benchmark regression hypothesis:

H1: Capital markets simultaneously assess suspicions of greenwashing and related behaviors and demand a higher risk premium.

The hypotheses for the mechanism analysis are as follows:

H2: Corporate greenwashing behavior increases the risk of reputational damage, leading investors to demand a higher risk premium.

H3: The spread of misleading information and the friction caused by corporate greenwashing behavior are inevitable, which weakens the efficiency of market investments and increases the level of risk premiums.

H4: Corporate greenwashing behavior exacerbates financial misallocation, leads to price distortions, and increases the level of risk premiums (Fig. 1).

4. Research design

4.1. Model

To examine the impact of corporate greenwashing behavior on stock risk premiums, we construct the following regression model for analysis:

$$\text{rmrf}_{i,t} = \alpha_0 + \alpha_1 \text{GTE}_{i,t} \times \text{Motivation}_{i,t} + \alpha_2 \text{GTE}_{i,t} + \alpha_3 \text{Motivation}_{i,t} + \alpha_4 \text{Controls}_{i,t} + \sum \text{year} + \sum \text{firm} + \varepsilon_{i,t} \quad (1)$$

We focus on α_1 , while simultaneously analyzing the individual impacts of α_2 and α_3 . This model verifies the capital market's identification of greenwashing risks through the combined results of greenwashing suspicions and textual evidence of greenwashing. Here, $\text{rmrf}_{i,t}$ represents the risk premium, $\text{GTE}_{i,t}$ indicates the textual evidence of greenwashing, $\text{Motivation}_{i,t}$ denotes suspicions of greenwashing, and Controls represents the control variables. The regression results are fixed at the year-firm level, and $\varepsilon_{i,t}$ is the residual term. In this model, the subscript i corresponds to the i -th company, and the subscript t corresponds to the t -th year. The specific measurement methods for the variables are detailed in Sections 4.2–4.5.

4.2. Explanatory variable

4.2.1. Suspicions of greenwashing (motivation)

When a company is suspected of greenwashing, investors will reprice its stock and adjust their asset portfolios to protect themselves against potential crash risks. Understanding the motivations behind sustainable finance requires clarifying investors' financial and green preferences. We use the revealed preference method (Pástor et al., 2021) to simulate the dynamic process of investors questioning corporate greenwashing. Based on multi-condition validity theory and multiple signals theory, we conduct an in-depth analysis of suspicions of corporate greenwashing from four perspectives, namely financing risk, bankruptcy risk, soft regulation by stock exchanges, and environmental penalty deterrence, to better understand its information disclosure behavior (Kim and Lyon, 2015). We then construct the dummy variable *Motivation*:

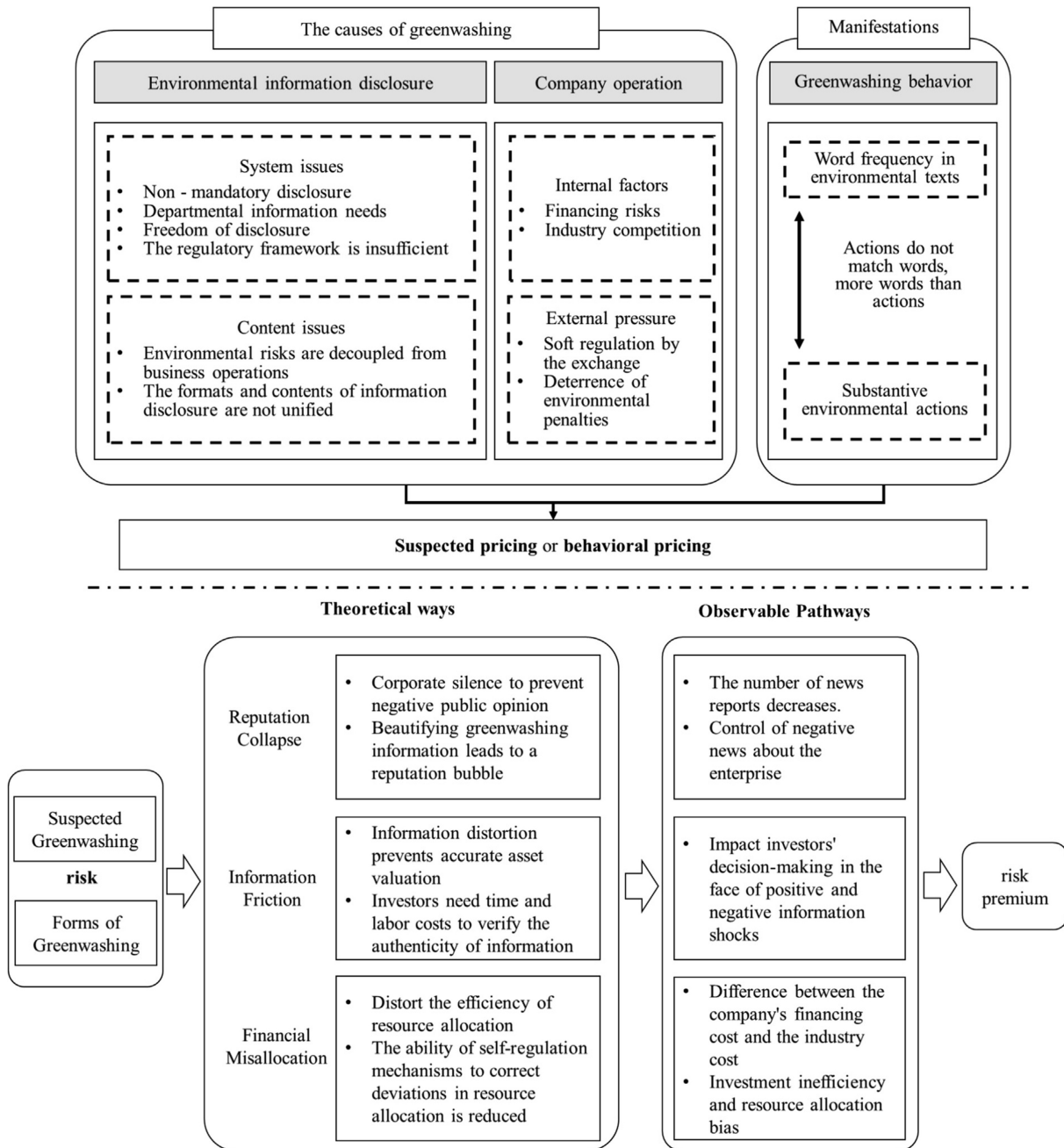


Fig. 1. Process for identifying suspected greenwashing and risk transmission mechanism.

Financing Risk (FC): Professional financial institutions, such as banks, are very sensitive to corporate greenwashing. Their tightening of credit for companies practicing greenwashing increases their financing difficulties (Houston and Shan, 2022). Companies are motivated to reduce their financial leverage to enhance their on-balance-sheet financing capacity and obtain more credit resources. However, in the short term, it is difficult for companies to achieve substantial deleveraging by reducing their liabilities or increasing their equity. Off-balance-sheet liabilities or disguised debt–equity swaps are more feasible, and leverage manipulation can improve financing capacity (Landsman et al., 2008). Additionally, the identification and response of financial

institutions to greenwashing behavior may exacerbate corporate financing constraints, prompting companies to adopt more covert financial measures to address their short-term funding pressures (Bond and Zeng, 2022). The leverage manipulation indicator has a stronger explanatory power than financing constraint indicators such as KZ, reflecting the financing difficulties of companies and amplifying the divergence between funding pressure and book leverage. We select leverage manipulation as a proxy for financing constraints (Levm), assigning a value of 1 to companies above the 50th percentile, indicating high-leverage manipulation firms, and 0 otherwise.

$$\text{Levm} = \frac{\text{Debtb_total}_{i,t} + \text{Debt_ob}_{i,t} + \text{Debt_nsrd}_{i,t}}{\text{Assetb_total}_{i,t} + \text{Debt_ob}_{i,t}} - \text{LEVB}_{i,t} \quad (2)$$

Here, Levm represents the degree of leverage manipulation, Debtb_total is the total book value of liabilities, Debt_ob is the total off-balance-sheet liabilities, Debt_nsr is the total level of disguised debt–equity swaps, Asset_total is the total book value of assets, and LEVB is the book leverage ratio.

Bankruptcy Risk (BC): Financial distress is a significant driver of information embellishment by companies (Liao et al., 2019). Companies operating in highly concentrated industries face higher costs when attempting to overcome financial difficulties (Purnanandam, 2008). At the same time, in highly competitive environments, the quality of information disclosed by companies can influence their competitive position within the industry (He and Tian, 2013). To comprehensively consider the costs of financial distress and market competition pressure, we use the Herfindahl–Hirschman Index (HHI) of the industry in which the company operates to measure the cost of overcoming financial distress. A high HHI (above the 75th percentile) indicates a highly concentrated industry, while a low HHI (below the 25th percentile) represents a highly competitive environment. Companies belonging to these two intervals are assigned a greenwashing suspicion value of 1, and otherwise 0. This approach ensures uniformity of measurements.

Soft Regulation by Stock Exchanges (SR): After considering the deterrent effect of strict regulation, we use inquiry letters related to annual reports as a soft regulatory measure for corporate information disclosure. Although inquiry letters do not carry punitive consequences, their mandatory response and public disclosure attributes enable regulation to combat financial fraud through signal transmission mechanisms, external audit mechanisms (Lyon and Maxwell, 2011), and improvements in internal controls (Liao et al., 2019). Soft regulation typically involves stock exchanges directly issuing inquiry letters to companies about their annual reports. If a company receives an inquiry letter from the stock exchange in a given year, it is considered to be subject to soft regulation from that year onward (Liao et al., 2023), leading to self-regulation and a reduction in suspicions of greenwashing. Specifically, companies subject to soft regulation are assigned a greenwashing suspicion value of 0 for the current year and all subsequent years, while those not subject to soft regulation are assigned a value of 1.

Deterrence of Environmental Penalties (DEP): Environmental regulations have always been a directional indicator for information disclosure (Huang, 2021). Soft regulation provides guidance for strict regulation, and environmental penalties imposed by regulatory authorities directly deter other companies in the same locality, thus standardizing corporate behavior (Long et al., 2025). Therefore, we posit that if a company is subject to environmental penalties during year N, then during that same year, companies in the same industry and prefecture-level city will standardize their environmental practices, enhance environmental awareness, and take concrete actions to comply with regulatory inspections. Consequently, the suspicion of greenwashing is assigned a value of 0, and otherwise 1. The industry classification follows China’s 2012 *Guidelines for the Classification of Listed Companies by Industry*.

Based on the previous analysis, when all four conditions are met simultaneously, a company is considered highly suspected of greenwashing (Motivation):

$$\text{Motivation} = \text{FC} \times \text{BC} \times \text{DEP} \times \text{SR} \quad (3)$$

4.2.2. Greenwashing Textual Evidence (GTE)

Drawing on the approach of Zhang et al. (2024), we conduct a detailed verification of the method and results of word frequency extraction. The process is as follows: CSR reports are used as the data pool to extract environmental textual information. Based on government documents such as the “Environmental Pro-

tection Law of the People's Republic of China" and the "Measures for the Administration of Enterprise Environmental Information Disclosure," words related to green and low-carbon initiatives, ecological environment, and pollution control are extracted. Combining these words with environmental keywords from the literature, an environmental information lexicon is created, resulting in 1597 environmental keywords.¹⁰ Using web scraping technology, CSR reports are obtained from the CNINFO website. These reports are converted to text format using the pdfplumber module, and the environmental keyword lexicon is added to a custom dictionary. The jieba module is then used for precise word segmentation of the reports. We remove words of length 1 and modal particles, calculate the total frequency of words in the reports, and extract the frequency of environmental textual information disclosed by companies based on the environmental keyword lexicon. The ratio of the frequency of disclosed words to the total frequency of words is used to measure the volume of textual disclosure (eword). Subsequently, we examine the indicators of substantive disclosure by companies. After assigning values to each indicator, we obtain the substantive disclosure score (escore). The specific measurement method is detailed in Appendix 4. To eliminate the influence of the scale, the Z-Score standardization method is applied to standardize the volume of textual disclosure and the substantive disclosure score (Yu et al., 2020). Textual evidence of corporate greenwashing (GTE) is then calculated.

$$\text{eword} = \frac{\text{The frequency of environmental terms disclosed in CSR reports}}{\text{The total word frequency in the reports.}} \quad (4)$$

$$\text{GTE} = \frac{\overline{\text{eword}}_{i,t} - \overline{\text{eword}}_i}{\text{sd}(\overline{\text{eword}}_{i,t})} - \frac{\overline{\text{escore}}_{i,t} - \overline{\text{escore}}_i}{\text{sd}(\overline{\text{escore}}_{i,t})} \quad (5)$$

Here, $\overline{\text{eword}}$ and $\overline{\text{escore}}$ represent the annual means of the volume of textual disclosure and the volume of substantive disclosure, respectively, while $\text{sd}(\overline{\text{eword}}_{i,t})$ and $\text{sd}(\overline{\text{escore}}_{i,t})$ are their standard deviations. The GTE indicator measures whether a company engages in substantial greenwashing by calculating the deviation between its environmental information disclosure and its concrete environmental actions.

In summary, the $\text{GTE} \times \text{Motivation}$ index considers both the existence of embellishment of companies' environmental information and their motivation for greenwashing, representing the manifestation of greenwashing. At this point, the measurement of the greenwashing manifestation index satisfies the requirement that "corporate behavior is socially irresponsible only to the extent that observers perceive it as irresponsible" (Seele and Gatti, 2017; Testa et al., 2018; Wang et al., 2024).

We also analyze the greenwashing situation in various industries, and the specific values are shown in Table 1. (1) The industry where greenwashing is most severe is that of water conservancy, environment, and public facility management, with a mean value of 1.4709. In contrast, the accommodation and catering industry has the lowest level of greenwashing, with a mean value of -0.5170 , which is determined by its operational characteristics. (2) Research generally suggests that heavily polluting companies¹¹ engage more in greenwashing than the industry average (Zhang et al., 2023). However, our findings are not entirely consistent with this view. The mean levels of greenwashing for the mining and manufacturing industries are both below 0, at -0.0498 and -0.1386 , respectively, indicating limited scope for greenwashing in these sectors. The greenwashing situation in the electric power industry is relatively serious (mean = 0.7820), but compared with the water conservancy and agriculture/forestry industries, it remains within an acceptable range. Additionally, there is significant variation in the level of greenwashing among heavily polluting companies. The mining industry has a large standard deviation in information disclosure (1.4804), which may be due to a lack of clarity in the information disclosure framework. Therefore, further analysis is needed regarding greenwashing in heavily polluting industries and the resulting stock market reactions.

¹⁰ Chinese vocabulary and phrases are relatively unique, with several terms expressing the same meaning. However, these terms are typically translated into a single expression in English. The Chinese version of the environmental lexicon can be obtained upon request from the author.

¹¹ Based on China's "Classification and Management Catalog of Environmental Verification for Listed Companies," "Guidelines for Environmental Information Disclosure of Listed Companies," and "Guidelines for the Classification of Listed Companies by Industry," we define companies in the mining (industry codes: B06, B07, B08, B09), manufacturing (industry codes: C17, C19, C22, C25, C26, C28, C29, C30, C31), and electric power and thermal production and supply (industry code: D44) industries as polluting companies.

Table 1
Industry-specific textual greenwashing intensity.

	Mean	Min	Max	SD	50 %
Agriculture, Forestry, Animal Husbandry, and Fishery	0.6911	-1.2011	3.2093	0.9290	0.5552
Mining Industry	0.0203	-4.4577	3.5555	1.4804	0.2028
Manufacturing Industry	-0.1314	-4.6927	4.6363	1.1241	-0.1052
Electric Power Industry	0.8604	-2.9682	4.0039	1.0931	0.8447
Construction Industry	-0.1694	-3.5850	3.3087	1.1367	-0.1297
Wholesale and Retail Trade	0.0397	-2.7309	4.0909	0.9031	-0.1013
Transportation, Storage, and Postal Services	-0.0353	-2.3736	3.9706	0.9854	-0.0297
Accommodation and Catering Services	-0.5170	-2.6237	1.6045	1.0606	-0.2928
Information Transmission, Software, and Information Technology Services	0.1272	-2.5755	1.8266	0.7081	0.1446
Real Estate Industry	0.0833	-2.9061	3.0555	0.8360	0.0704
Leasing and Business Services	0.0552	-2.3995	4.6465	0.8513	0.1788
Scientific Research and Technical Services	0.2417	-2.2279	2.1375	0.8762	0.1116
Water Conservancy, Environment, and Public Facility Management	1.4709	-4.0256	4.1681	1.2894	1.5875
Education	-0.0675	-0.4516	0.1697	0.2205	-0.0987
Health and Social Work	-0.2890	-1.6535	1.4120	0.6801	-0.2130
Culture, Sports, and Entertainment Industry	0.1234	-1.3484	2.2060	0.5204	0.0926
Heavily Polluting Mining Industry	-0.0498	-4.4577	3.5555	1.4982	0.1123
Heavily Polluting Manufacturing Industry	-0.1386	-4.6927	4.2251	1.1928	-0.1484
Heavily Polluting Electric Power Industry	0.7820	-2.8810	3.1220	1.0087	0.7911

4.3. Dependent variable

The difference between the annual return of individual stocks, considering cash dividend reinvestment, and the risk-free rate is the dependent variable in this study (Bolton and Kacperczyk, 2021). The annual return of individual stocks, considering cash dividend reinvestment, is expressed by the following formula, where $P_{i,t}$ represents the daily closing price of the corresponding company on the last trading day of year t , adjusted for cash dividend reinvestment, while $rf_{i,t}$ represents the risk-free rate of return:

$$\text{rmrf}_{i,t} = \left(\frac{P_{i,t}}{P_{i,t-1}} - 1 \right) - rf_{i,t} \quad (6)$$

4.4. Control variables

Following Xu et al. (2020) and Liao et al. (2023), we control for factors that may affect returns and risks at the operational and governance levels. In terms of operational characteristics, the control variables include firm size, intangible asset ratio, gross profit margin, overall tax rate, corporate investment ratio, Tobin's Q, and listing age. For the governance characteristics, the control variables include ownership concentration and the proportion of independent directors.

4.5. Sample selection and data sources

Our sample includes all non-financial A-share companies¹² that publish CSR reports from 2008 to 2021. All samples whose reports are in image or scanned format that cannot be processed by the algorithm are excluded. All samples with missing data for the key variables are also removed. Due to the risk of delisting, ST and *ST companies are further excluded. To avoid the impact of extreme values on our empirical results,

¹² The industry classification refers to the "Guidelines for the Classification of Industries of Listed Companies" revised by the CSRC in 2012.

all continuous variables are winsorized at the top and bottom 1 %. The final sample consists of 7357 observations. The CSR reports come from the CNINFO website, corporate financial information is obtained from the CSMAR database, and data on environmental penalties are sourced from the Peking University Law Information Database (Table 2).

The descriptive statistics of the main variables are presented in Table 3. The maximum value of textual greenwashing (GTE) is 4.6465, indicating that some enterprises engage in greenwashing practices. Additionally, the results for the four indicators measuring suspicions of corporate greenwashing are as follows: 3311 companies have financing constraints (high leverage manipulation), 6678 companies are not subject to soft regulation, 3863 companies face high market competition and high costs of financial distress, and 6878 com-

Table 2
Variable definitions.

	Variable	Definition
Explanatory Variable	Motivation	A binary variable indicating the “suspicion threshold” of greenwashing
	GTE	Textual evidence of greenwashing
Dependent Variable	rmrf	Stock risk premium without considering the reinvestment of cash dividends
Control Variables	Lnsiz	Firm size
	Ocr	Ownership concentration ratio
	Idr	Proportion of independent directors
	GrossProfit	Gross profit margin on sales
	Intangible	Proportion of intangible assets
	CTR	Composite tax rate
	Invest	Proportion of corporate investments
	TobinQ	Tobin’s Q
Other Variables	ListAge	Years since listing
	eword escore	Ratio of the frequency of environmental words to the total frequency of words Score of substantial environmental information

Table 3
Descriptive statistics.

Variable	Mean	SD	Min	Max
num	170.9450	180.6975	0.0000	2787.00
mw	3.9138	1.5848	0.5021	9.0567
mr	9.9776	6.4159	1	32
GTE	0.0044	1.1065	-4.6927	4.6465
GTE1	-0.0046	1.1068	-4.6800	4.6365
GTE2	-0.0003	0.2283	-0.9877	0.9012
GTE3	-0.0108	1.1065	-4.7069	4.6293
rmrf	10.1664	50.6284	-89.119	509.551
rmrf1	10.0947	50.3734	-88.960	509.551
Lnsiz	13.8391	1.4170	11.1363	19.0462
Ocr	54.4656	16.3139	19.0100	92.8000
Idr	37.8693	7.2303	25.0000	60.0000
GrossProfit	0.2854	0.1743	-0.0606	0.8712
Intangible	0.0461	0.0528	0.0000	0.3823
CTR	0.0383	0.0439	-0.0512	0.2728
Invest	0.0674	0.0760	0.0000	1.0893
TobinQ	1.8625	1.2843	0.0000	15.6067
ListAge	2.3749	0.7752	0.0000	3.3673

panies are not within the scope of environmental penalty deterrence. Only companies that meet all four conditions are considered suspected of greenwashing, resulting in a total of 1301 samples.

5. Empirical results

5.1. Baseline regression results

In Table 4, column (1) indicates that companies suspected of greenwashing raise doubts among investors in the market and generate a risk premium of 3.4981, which is significant at the 5 % level. Column (2) considers only textual evidence of corporate greenwashing. The results show that the greenwashing behavior of some companies in their written disclosures remains within the market's acceptable range. As long as the internal and external conditions of a company are favorable, the risks associated with greenwashing decrease, which is consistent with the findings of Testa et al. (2018). Column (3) considers both the motivation for corporate greenwashing and its evidence, namely the manifestation of greenwashing. We find that the embellishment of corporate textual information has no significant impact on the risk premium, but amplifies suspicions of greenwashing, creating a negative feedback effect. As a result, the impact of greenwashing suspicions on the risk premium reaches 3.9786, which is statistically significant at the 5 % level. Under the combined effect

Table 4
Baseline regression results.

	(1) rmrf	(2) rmrf	(3) rmrf
GTE × Motivation			2.6789** (2.0693)
GTE		0.3181 (0.5247)	-0.0889 (-0.1395)
Motivation	3.4981** (2.0232)		3.9786** (2.2534)
Lnsiz	-1.7014 (-0.9252)	-1.6593 (-0.8989)	-1.7658 (-0.9587)
Ocr	0.1376 (1.5424)	0.1388 (1.5450)	0.1366 (1.5261)
Idr	0.0677 (0.7716)	0.0672 (0.7675)	0.0722 (0.8248)
GrossProfit	26.4416*** (2.6632)	25.7724*** (2.6008)	26.7077*** (2.6907)
Intangible	-44.6787* (-1.8505)	-45.7749* (-1.9022)	-45.7657* (-1.8997)
CTR	89.0735** (2.4445)	89.6297** (2.4610)	89.5786** (2.4597)
Invest	31.6327** (2.5730)	31.3408** (2.5430)	31.7683*** (2.5837)
TobinQ	22.3773*** (14.9666)	22.4536*** (14.9955)	22.3828*** (14.9686)
ListAge	-6.8064*** (-2.8525)	-6.5879*** (-2.7582)	-6.8952*** (-2.8912)
_cons	-12.9082 (-0.4731)	-13.3666 (-0.4884)	-11.9352 (-0.4363)
Adj R ²	0.4684	0.4680	0.4686
Year-fixed	Yes	Yes	Yes
Firm-fixed	Yes	Yes	Yes
N	7357	7357	7357

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

of greenwashing suspicions and textual evidence of greenwashing, corporate greenwashing behavior is exposed and captured by investors, leading to a 2.6789% increase in the risk premium. Furthermore, we confirm that identifying suspicions of greenwashing is a crucial step for investors to detect greenwashing-related information, which amplifies market sensitivity to corporate information manipulation. This, in turn, exposes corporate greenwashing and leads investors to demand a higher risk premium.

5.2. Robustness tests

This section conducts a series of robustness tests from three perspectives: indicator measurement, control variables, and placebo tests. These results consistently support our baseline results, indicating that our conclusions are robust. The results are detailed in Appendix 5.

Indicator Measurement: The measures for embellishment of environmental information and the risk premium are revised. (1) The measurement of disclosure of substantial environmental information is modified by excluding the disclosure of negative environmental events to calculate textual evidence of greenwashing (GTE1), which is then multiplied by suspicions of greenwashing (Motivation). (2) The range standardization method is applied to standardize the volume of substantial environmental information disclosure and the volume of textual environmental disclosure, after which textual evidence of greenwashing (GTE2) is calculated. GTE2 is then multiplied by suspicions of greenwashing (Motivation). (3) To account for the impact of non-essential keywords on the results, keywords that appear less than 10 times in corporate environmental reports are removed and the third measure of textual evidence of greenwashing (GTE3) is calculated. (4) To further verify the reliability of the greenwashing manifestation index, we continue to use inter-institutional rating differences as a method for identifying greenwashing. The differences between Bloomberg ESG ratings and Huazheng ESG ratings (GWL_HZ) and between Bloomberg ESG ratings and Wind ESG ratings (GWL_Wind) are used as measures. (5) We use the difference between the annual stock return, excluding cash dividend reinvestment, and the risk-free rate (rmrf1).

Control Variables: Corporate greenwashing behavior varies according to industry characteristics and is also influenced by regional regulatory dynamics. We investigate this phenomenon by adjusting the fixed effects, control variables, and sample period. (1) To control for the impact of unobservable factors that change over time, we control for individual-year-industry-city fixed effects. (2) Control variables such as board size (board), separation of ownership and control (Separate), financial leverage (FL), and operating expense ratio (Ofee) are added as indicators of corporate management. (3) Considering that the stock price of the previous year may affect the stock price of the current year, we include the stock price of the previous period as a control variable to further examine the risk premium generated by greenwashing. When the risk premium level of the previous year is added, investors demand a higher risk premium for suspicions of greenwashing in the current period, and the pricing of greenwashing behavior becomes less obvious. (4) As enterprises in the water conservancy, environmental protection, and public facility management sectors use a large number of environmental terms in their information disclosures, this can lead to misinterpretation of textual evidence of greenwashing and affect the results. Therefore, in the robustness test, all enterprises in these sectors are excluded for the regression analysis. (5) Stock returns are closely related to market cycles. In 2008 and 2015, the Chinese stock market experienced significant fluctuations. By excluding the market shocks that occurred during these two years, we identify the risk premium level of corporate greenwashing.

5.3. Endogeneity tests

In this section, we use the instrumental variable (IV) method and the difference-in-differences (DID) approach to address endogeneity issues arising from omitted variables or bidirectional causality.

We use the IV approach to address endogeneity. Greenwashing behavior and corporate stock risk premiums may have a bidirectional causal relationship: greenwashing is essentially incomplete information disclosure. If investors fail to promptly detect corporate greenwashing, it can lead to market mispricing. At the same time, stakeholders may tolerate superficial information disclosure, thereby allowing companies to profit from greenwashing and strengthening their incentive to engage in such behavior. Studies have used the mean of related variables within the same industry or region as IVs (Breuer et al., 2018). Some scholars have used infor-

Table 5
Endogeneity tests.

Variable	(1) First stage GTE × Motivation	(2) Second stage rmrf
IV	0.009*** (3.229)	
GTE × Motivation		82.944* (1.676)
Observations	5996	5996
Control	YES	YES
Year-fixed	YES	YES
Firm-fixed	YES	YES
F-test		10.35
P-value		0.0013
LM-value		10.43

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

mation disclosure lagged by one period (Siddique et al., 2021), selected the average quality of information disclosure in the first period of the industry (Larcker and Rusticus, 2010), or referred to Angrist and Krueger (1991) by introducing the interaction term between annual dummy variables and original variables as IVs. Although these variables meet the requirements for IVs, issues remain regarding the assumption of exogeneity. For example, information disclosure may have long-term effects on stock prices, and lagged terms may directly affect stock returns. The average quality of information disclosure, as an external environmental factor, may directly influence corporate stock returns without affecting the quality of information disclosure. Therefore, the IVs used in previous studies do not fully exclude the interference of relevance and exclusivity.

To address this issue, we abandon the above approaches and construct a new IV from the perspective of regulatory oversight by the CSRC¹³ and corporate internal controls (Liao et al., 2019). The IV construction process is as follows: First, the distance between the primary business location of each company and the local CSRC office is calculated. Given China's vast territory and the significant differences between provinces, some companies are located extremely far from their local CSRC offices. Therefore, this distance is logarithmically transformed to mitigate the impact of extreme cases. Next, we obtain the DIB internal control index, which is an authoritative and comprehensive measure of corporate internal controls. Companies with an Enterprise Internal Control (EIC) score below the 25th percentile are considered to have internal control deficiencies (assigned a value of 1, and otherwise 0). Given the lag in internal control reporting, the EIC variable is lagged by one period and multiplied by the distance variable to obtain our IV.

$$IV_{i,t} = \text{Distance}_i \times \text{EIC}_{i,t} \quad (7)$$

This IV satisfies both the requirements of relevance and exogeneity. In terms of **relevance**, the regulation of listed companies across regions is primarily managed by the CSRC, notably through random inspections, the periodic publication of regulatory updates, and the enforcement of administrative measures. Due to differences in regulatory accessibility caused by geographical distance, companies located farther from local CSRC offices are subject to less frequent and weaker regulatory oversight, which makes them more inclined to disguise their operations to evade supervision (Chen et al., 2018). Additionally, companies with weak internal controls have poor management capabilities and are more likely to have gaps in information disclosure (Larcker and Rusticus, 2010). Our above results suggest that investors are more likely to identify suspicions of greenwashing than inconsistencies between companies' words and actions. Therefore, the farther a company is from the CSRC office and the weaker its internal controls, the more pronounced its tendency to engage

¹³ The CSRC oversees 31 province-level regulatory bureaus, five regulatory bureaus in cities with independent planning status, and two commissioner offices. Each regulatory bureau oversees companies within its jurisdiction, including through random inspections and compliance assessments, thus exerting a strong regulatory influence on companies in its region.

in greenwashing, satisfying the relevance condition. In terms of **exclusivity**, the distance between a company and the CSRC office is a geographical indicator and typically does not directly affect stock valuation. The DIB internal control index used in this paper is an external agency rating, which satisfies the exogeneity condition. Therefore, the interaction term between these two variables does not directly influence stock market returns and risks, thus satisfying the exclusivity condition.

The regression results of our IV are reported in Table 5. Column (1) shows the first-stage regression results, indicating that weak CSRC oversight and poor internal controls significantly exacerbate greenwashing behavior (0.009). Based on the second-stage regression results, the underidentification test significantly rejects the null hypothesis of underidentification, and the F-statistic of the weak instrument test exceeds the critical value of 15 % of the Stock–Yogo weak identification test, indicating no issues of underidentification or weak instruments. After addressing endogeneity, the results in column (2) still support the finding that the manifestation of greenwashing increases stock risk premiums, confirming the robustness of our baseline regression results.

To further mitigate omitted variable bias and exogenous policy shocks, we perform two DID tests, the results of which support our baseline regression findings. Specific details are provided in Appendix 6.

6. Mechanism tests

Based on our previous in-depth analyses, suspicions of greenwashing and greenwashing behavior jointly affect risk premiums and reputational risks. However, by analyzing corporate greenwashing, investors can identify the divergence between enterprises' beautified information disclosure and their true environmental management, as well as detect hidden risks. At the investor level, the existence of greenwashing exacerbates information frictions and decision-making risks: investors need time and money to revalue assets and adjust their investment portfolios, leading to decision-making inefficiencies (Krueger et al., 2020). In terms of financial misallocation, the concealment of environmental information causes disordered resource allocation and weakens the market's self-regulating capabilities. After revealing suspicions and evidence of greenwashing, the unfair allocation of resources caused by information disclosure issues not only intensifies financial risks but also triggers reactions from the capital market.

To test the above mechanisms, we construct the following model. Here, $Med_{i,t}$ represents the mechanism variable, β_1 indicates the extent to which the manifestation of greenwashing behavior affects the mechanism variable, and β_2 and β_3 represent the impacts of textual greenwashing and suspicions of greenwashing on the mechanism variable, respectively. Our coefficient of interest is β_1 .

Table 6
Corporate reputation risk.

	(1) CRR_TB	(2) CRR_OB	(3) CRR_TN _{t+2}	(4) CRR_Baidu
GTE × Motivation	−16.9264* (−1.8211)	−2.1967* (−1.7827)	−0.0395* (−1.6833)	−0.0233* (−1.6518)
GTE	2.1283 (0.3928)	−0.1644 (−0.1780)	−0.0066 (−0.6152)	0.0013 (0.1563)
Motivation	5.5451 (0.7608)	1.4559 (1.0327)	−0.0076 (−0.2238)	−0.0026 (−0.1247)
_cons	−604.1677** (−2.3518)	−151.3284*** (−3.5728)	0.4370 (0.5217)	4.3386*** (6.4663)
Adj R ²	0.6960	0.8234	0.8416	0.9369
Year-fixed	YES	YES	YES	YES
Firm-fixed	YES	YES	YES	YES
Control	YES	YES	YES	YES
N	7320	7320	4916	3444

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

$$\text{Med}_{i,t} = \beta_0 + \beta_1 \text{GTE}_{i,t} \times \text{Motivation}_{i,t} + \beta_2 \text{GTE}_{i,t} + \beta_3 \text{Motivation}_{i,t} + \sum_{i=1}^n \gamma_i \text{Controls}_{i,t} + \sum \text{year} + \sum \text{firm} + \varepsilon_{it} \quad (8)$$

(1) Corporate Reputation Risk (CRR): Media reports draw public attention to enterprises and fulfill the function of social supervision, thereby enhancing public sensitivity to information (Ang et al., 2021). Enterprises may remain silent or even control negative information to regulate social emotions and interfere with the capital market's review of enterprises and asset pricing. We identify this mechanism using proxy variables such as the total number of negative news reports about the enterprise (CRR_TB), the number of original negative news reports (CRR_OB), the logarithm of the total number of media news reports about the enterprise during the year (CRR_TN), and the logarithm of the number of Baidu searches for the enterprise during the year (CRR_Baidu). As shown in Table 6, we find that enterprises tend to remain silent and reduce news exposure, with coefficients of -0.0395 and -0.0233 , both significant at the 10 % level. Additionally, enterprises that engage in greenwashing choose to manipulate negative information to weaken public perception of their true environmental behavior, with coefficients of -16.9264 and -2.1967 , significant at the 1 % level. Such behavior alleviates the problem of banks tightening credit to enterprises following negative news. However, due to suspicions of greenwashing, investors still rightly doubt the image of these enterprises. Increased exposure to reputational risk leads the market to demand higher risk premiums for stocks.

(2) Information Friction and Decision Risk: Behavioral finance suggests that investors' attention is limited and that, due to time and effort constraints, they can only focus on essential information. However, the presence of greenwashing behavior interferes with investors' decision-making processes. Institutional investors, who are typically more professional and have stronger supervisory and governance motivations than other investors, are more suitable for measuring information frictions based on the dispersion of their attention when making investments. We follow Kempf et al. (2017) and construct an investor attention distraction indicator as a proxy for the information friction index. The degree of information friction caused by positive and negative shocks is calculated separately. Given the lag in information disclosure, the information friction index is lagged by one period before being incorporated into the regression model.

The regression results are shown in Table 7. Greenwashing behavior does indeed lead to information frictions, complicating investors' decision-making process and affecting their investment efficiency, with a coefficient of 0.0883 , significant at the 10 % level. Furthermore, we analyze the interference caused by positive and

Table 7
Information friction and decision risk.

	(1) distraction _{t+1}	(2) distraction_pos _{t+1}	(3) distraction_neg _{t+1}
GTE × Motivation	0.0883* (1.8852)	0.0189 (0.6688)	0.0727* (1.9437)
GTE	-0.0184 (-0.6862)	-0.0201 (-1.1065)	0.0019 (0.0989)
Motivation	0.0105 (0.1612)	-0.0006 (-0.0146)	0.0030 (0.0619)
_cons	1.6178 (1.5142)	0.9410 (1.5234)	0.7478 (0.9570)
Adj R ²	0.5471	0.4826	0.6508
Year-fixed	YES	YES	YES
Firm-fixed	YES	YES	YES
Control	YES	YES	YES
N	5850	5850	5850

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 8
Financial mismatch risk.

	(1) FMR	(2) INE _{t+3}	(3) Overinvest _{t+3}
GTE × Motivation	0.0304** (1.9652)	0.0028** (2.5324)	0.0017* (1.9472)
GTE	-0.0189** (-2.1420)	-0.0001 (-0.1327)	-0.0002 (-0.4616)
Motivation	0.0613*** (2.5813)	0.0016 (1.1871)	-0.0007 (-0.7427)
_cons	1.7320*** (4.9913)	0.0377 (1.1196)	0.0392 (1.4491)
Adj R ²	0.3194	0.8183	0.8596
Year-fixed	YES	YES	YES
Firm-fixed	YES	YES	YES
Control	YES	YES	YES
N	7217	3618	3618

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

negative information shocks on decision-making. The results in Table 7 show that the presence of greenwashing behavior makes investors more hesitant in the face of negative information, leading to inefficient decision-making, with a coefficient of 0.0727, significant at the 10 % level. Investor inefficiency and disorder in information acquisition lead investors to demand higher risk premiums from companies.

(3) Financial Mismatch Risk (FMR): The financial mismatch burden level is used to measure credit mismatch, which corresponds to the deviation between a company's cost of capital and the average cost of capital in its industry. A larger deviation indicates a higher degree of credit mismatch borne by the company. This measurement approach facilitates the study of resource allocation efficiency at the company level. Here, FMR_{ipt} represents the degree of financial mismatch faced by company i in year t , R_{pt} denotes the average cost of capital for industry p in year t , I represents corporate interest expenses, L represents liabilities, and A represents accounts payable. Furthermore, companies with a degree of mismatch above the 50th percentile are assigned a value of 1, while those with a degree below the 50th percentile are assigned a value of 0, to examine the probability that greenwashing leads to financial mismatch.

$$FMR_{ipt} = \frac{I_{ipt}/(L_{ipt} - A_{ipt}) - R_{pt}}{R_{pt}} \quad (9)$$

In addition, financial mismatch is reflected in corporate investment inefficiency. We adopt the method proposed by Richardson (2006) to estimate normal investment levels, then we use the residuals of the model to measure inefficient resource allocation (INE). Furthermore, overinvestment (Overinvest) can be decomposed in the model for identification.

The results are reported in Table 8. Due to information asymmetry in the market, corporate greenwashing behavior increases the probability of financial mismatches, with a coefficient of 0.0304, significant at the 5 % level. Furthermore, corporate financial mismatch is reflected in reduced investment efficiency, with a coefficient of 0.0028, significant at the 5 % level. The main reason lies in overinvestment, leading to resource waste and misuse, with a coefficient of 0.0017, significant at the 1 % level. The market's self-regulation mechanism cannot alleviate short-term resource mismatch issues, exacerbating inequalities between companies and increasing exposure to credit risk. This accentuates the risk premium effect of greenwashing on stocks.

7. Heterogeneity analysis

7.1. Pollution shocks

Air pollution has long been a subject of public concern. In February 2012, the Ministry of Environmental Protection of China issued the newly revised *Ambient Air Quality Standards* (GB 3095-2012), which, for the first time, included PM2.5 in the monitoring framework. After 2013, exceedances of PM2.5 measurement limits were observed in various regions, making air pollution a trending topic of widespread public attention. Notably, air pollution has constrained China's economic development and has had adverse repercussions on workers' health. Regions with higher pollution levels face a brain drain crisis, which reduces the productive capacity of enterprises (Fu et al., 2021). This has led to heightened risk expectations among capital market participants regarding firms operating in these areas (Krueger et al., 2020). The impact of pollution has increased regulatory pressure at the regional level, prompting firms to adopt greener and more environmentally friendly practices. Consequently, this has mitigated the premium effects associated with greenwashing (Berrone et al., 2017). To examine the impact of air pollution shocks on exposure to the risk associated with greenwashing, we use annual peak levels of PM2.5 at the regional level as an observation metric. Regions with peak PM2.5 levels exceeding the mean ($PM2.5 > 50$) are classified as heavily polluted, while others are categorized as lightly polluted areas. The advantage of this metric lies in the fact that annual PM2.5 peaks do not reflect the long-term pollution conditions of a region. However, the public and regulatory authorities exhibit heightened sensitivity to annual PM2.5 peaks compared with average values, leading to larger adjustments in environmental regulations.

To test the above conjecture, we conduct grouped regression analyses. The results in Table 9 show that in regions with higher pollution shock intensity, exposure to the risk associated with greenwashing is mitigated. This can be attributed to two factors: first, pollution shocks reduce firms' motivation to optimize their textual disclosures to showcase their environmental actions, as even limited environmental efforts cannot align with the severe pollution levels in the region; second, public scrutiny and pressure from environmental regulators force firms to shift their operational models, thereby reducing their risk exposure, as indicated by the coeffi-

Table 9
Heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
	Air pollution Strong rmrf	Weak rmrf	Internal financial regulation Yes rmrf	No rmrf	Strategic risk High rmrf	Low rmrf
GTE × Motivation	-0.3711 (-0.2149)	6.1758*** (2.6505)	1.2504 (0.8468)	7.0446*** (2.5934)	4.0025* (1.8877)	0.4904 (0.2475)
GTE	0.3954 (0.4308)	-0.6963 (-0.6587)	0.3896 (0.5285)	-0.0382 (-0.0262)	-1.1415 (-1.2936)	1.7172 (1.5147)
Motivation	-0.2347 (-0.1117)	11.0081*** (3.1190)	3.4561 (1.5218)	7.8260** (2.0327)	4.8973* (1.8628)	3.9906 (1.4873)
_cons	-87.7368** (-2.4230)	2.0609 (0.0414)	-10.6129 (-0.3073)	-24.9733 (-0.3639)	12.6273 (0.3502)	-90.0232* (-1.7925)
Adj R ²	0.4924	0.4474	0.4734	0.4777	0.4650	0.4838
Intergroup heterogeneity	6.547*** (0.000)		5.794* (0.070)		-3.512** (0.030)	
Control	YES	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES	YES
Firm-fixed	YES	YES	YES	YES	YES	YES
N	3961	3228	5355	1827	3950	3038

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

cient of -0.3711 , which is not statistically significant. However, in regions with low pollution levels, exposure to the risk associated with greenwashing persists, with a coefficient of 6.1758 , which is statistically significant at the 1 % level. The bootstrap method reveals a between-group heterogeneity P-value of 0.000 , indicating that weaker pollution shocks result in higher risk premiums associated with greenwashing.

7.2. Internal financial regulation

Executives with a financial background typically have a better understanding of risk management and information disclosure, enabling them to more accurately assess the potential financial and reputational risks associated with greenwashing, thereby mitigating those risks (Larcker and Rusticus, 2010). In the capital market, individuals with extensive financial expertise are more familiar with market dynamics and investor expectations. They are likely to increase corporate value through genuine environmental performance rather than deceptive practices, thus reducing the risk of investor distrust and the legal repercussions stemming from greenwashing (Edmans et al., 2017). In terms of strategic planning, financially oriented executives are likely to prioritize long-term financial stability, favoring the implementation of sustainable environmental strategies rather than relying on greenwashing for short-term gains (Bénabou and Tirole, 2010). We divide firms into two groups based on whether they have executives with a financial background and we conduct separate regressions for each group.

The results in columns (3) and (4) of Table 9 indicate that firms with financially oriented executives can reduce their exposure to the risk associated with greenwashing to a level acceptable to investors. Although the premium is positive (1.2504), it is not statistically significant. In contrast, firms without such executives are more exposed to the risk associated with greenwashing, leading the market to demand higher risk premiums, as reflected by the coefficient of 7.0446 , which is statistically significant at the 1 % level. Additionally, we use the bootstrap method to test between-group heterogeneity, yielding a P-value of 0.070 . This suggests that weaker internal financial regulation results in higher risk premiums associated with greenwashing.

7.3. Strategic risk

According to upper echelons theory, managers' characteristics determine their behaviors and strategic choices, which in turn influence their organization's goals, actions, and outcomes (Hambrick and Mason, 1984). CSR activities can be understood as strategic resource allocation decisions within a business model. When CSR activities are meticulously designed and executed for strategic business purposes, they can provide a competitive advantage. Allocating resources to initiatives that enhance the business model while addressing social issues is a very effective business strategy. However, greenwashing, often seen as a form of CSR misconduct, is largely driven by managerial decisions. Strategic short-termism may lead firms to engage in greenwashing, exposing them to increased risks of penalties and operational challenges in the future (Lyon and Montgomery, 2015).

Following Hu et al. (2023), we calculate the proportion of the frequency of "short-term horizon" words relative to the total frequency of words in the Management Discussion and Analysis section using a dictionary-based method. This proportion is then multiplied by 100 to obtain the managerial myopia index. A higher value of this index indicates greater managerial short-termism. Firms are grouped based on their myopia level, with those above the 50th percentile classified as presenting a higher strategic risk and the others as presenting a lower strategic risk. As shown in columns (5) and (6) of Table 9, managerial myopia increases a firm's strategic risk, as short-term focused managers tend to overlook the long-term consequences of greenwashing. Consequently, the market demands higher risk premiums, with a coefficient of 4.0025 , which is statistically significant at the 10 % level. In contrast, firms with well-planned strategic management are better able to control risks, optimize resource allocation, and support genuine green initiatives. This conclusion is further validated by between-group heterogeneity tests, yielding a P-value of 0.030 .

Table 10
Grouped regression based on companies' pollution attributes.

	(1) Heavily polluting rmrf	(2) Slightly polluting rmrf
GTE × Motivation	−0.4363 (−0.2018)	3.7393** (2.3928)
GTE	1.0545 (0.9116)	−0.1503 (−0.1951)
Motivation	−4.0499 (−1.0785)	5.5827*** (2.8161)
_cons	−11.4593 (−0.2129)	−11.0228 (−0.3512)
Adj R ²	0.5092	0.4655
Intergroup heterogeneity	4.176*** (0.000)	
Year-fixed	YES	YES
Firm-fixed	YES	YES
Control	YES	YES
N	1415	5942

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

8. Further research

8.1. Limitations of greenwashing in heavily polluting industries

Heavily polluting enterprises are under close scrutiny by various stakeholders regarding how they are improving their pollution emissions. Currently, China is experiencing rapid development in the field of green finance. Whether in the bond market, the stock market, or the credit market, there is a growing preference for investment in green enterprises (low-pollution firms) (Zhang et al., 2023). Due to the inherently “polluting” nature of their production and operations, heavily polluting enterprises lack the opportunity to engage in greenwashing and cannot use such tactics to present themselves as environmentally friendly (Testa et al., 2018). At the same time, in terms of information disclosure by heavily polluting enterprises, China explicitly established disclosure standards for these firms in 2015. As a result, their disclosure frameworks are relatively standardized, leaving limited room for greenwashing. This finding has already been validated in Section 3.2.2, Table 1.

In summary, our findings differ from those of previous studies. The environmental problems of heavily polluting enterprises are already taken into account by investors and are reasonably priced, leaving little room for significant suspicions of greenwashing. Consequently, their exposure to the risk associated with greenwashing is not pronounced. Using a regression analysis grouped by firms' pollution attributes, the results in Table 10 indicate that heavily polluting enterprises do not exhibit significant premiums related to greenwashing. This suggests that these firms' efforts to optimize their environmental information disclosure remain within the limits of investor tolerance. In contrast, low-polluting enterprises show a notably high greenwashing premium, with a coefficient of 3.7393, which is statistically significant at the 5 % level.

To further validate the risk premium effects of greenwashing in heavily polluting enterprises, we conduct a separate analysis focused on heavily polluting firms in China. In 2010, China issued the *Environmental Information Disclosure Guidelines for Listed Companies*, which identified 16 heavily polluting industries. We select firms from these 16 industries between 2011 and 2020 as our research sample, excluding companies with

Table 11
Risk premium for greenwashing by heavy polluting enterprises.

	(1) Baseline rmrf	(4) RF rmrf	(5) NNET rmrf	(6) lassoCV rmrf	(7) GradBoost rmrf
GWL	0.0840 (0.8138)	0.041 (0.093)	-0.008 (0.079)	0.066 (0.116)	0.089 (0.086)
_cons	-538.34* (-1.861)	0.781 (1.426)	0.077 (1.633)	0.140 (1.558)	0.177 (1.446)
Adj R ²	0.3201				
Control	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES
Firm-fixed	YES	YES	YES	YES	YES
N	658	658	658	658	658

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

abnormal financial data or serious data deficiencies, resulting in a final sample of 658 firms. We categorize greenwashing levels into four major frameworks: governance and structure, inputs and outputs, processes and controls, and compliance and practices. From these frameworks, we derive 20 indicators to construct a corporate greenwashing index.¹⁴ This index can appropriately amplify the extent of corporate greenwashing,¹⁵ and its calculation formula is as follows:

$$\text{Selective disclosure GWLS} = 100 \times (1 - \text{Number of disclosed items/items to be disclosed})$$

$$\text{Express manipulation GWLE} = 100 \times (\text{Symbolic disclosure/disclosed})$$

$$\text{Degree of greenwashing GWL} = \sqrt{\text{GWLS} \times \text{GWLE}}$$

(10)

Furthermore, we conduct linear regression tests and causal inference analyses using double/debiased machine learning (DDML) to examine the relationship between greenwashing by heavily polluting companies and stock risk premiums, with the following objectives: (1) to mitigate regular bias in the estimation results and ensure the absence of bias in the treatment effect estimator in small samples; (2) given that we identify endogeneity between greenwashing and premiums in previous tests, the use of DDML can help address this endogeneity issue and improve the precision of our tests; and (3) based on the previous analysis, heavily polluting companies have limited room for greenwashing. Therefore, to verify their marginal premium levels, it is necessary to better understand the non-linear characteristics of the sample. As shown in Table 11, the linear regression coefficient is positive (0.0840) but not significant. Subsequently, we use various algorithms, including random forest (RF), neural network (NNET), lasso regression with cross-validation (lassoCV), and gradient boosting (GradBoost), for DDML regression analysis. The results indicate that greenwashing by heavily polluting enterprises does not generate significant risk premiums. Even if heavily polluting enterprises engage in greenwashing, investors do not accept such “green declarations.” The non-green attributes of heavily polluting enterprises are difficult to alter, and their potential environmental risks have been incorporated into the pricing process, resulting in an insignificant risk premium effect.

¹⁴ We use a method of averaging multiple scores to reduce errors and repeatedly review and evaluate results that deviate significantly from the norm to ensure the reliability of the scoring.

¹⁵ For example, failure to disclose the volume of wastewater treated is considered descriptive manipulation, and failure to report at least 20 indicators is perceived as selective disclosure. These aspects cannot be assessed through a text-based word frequency analysis.

8.2. Imitation of greenwashing

Interorganizational imitation represents a widespread mode of organizational behavior. Whether in strategic corporate decisions such as innovation, investment, and financing, or in the selection of institutions such as auditors, the phenomenon of interorganizational imitation is widely observed. Aerts et al. (2006), in their study of large companies in Canada, France, and Germany, found significant evidence of imitation in the process of disclosing environmental information. When disclosure objectives are ambiguous, organizational technologies are difficult to understand, or uncertainties arise due to environmental changes, organizations may stabilize their legitimacy by imitating the behaviors of other firms. Based on our previous analysis, greenwashing information amplifies risk exposure. Faced with the uncertainty of choosing which topics to disclose, the management of listed companies may naturally resort to imitating other firms (Bond and Zeng, 2022). Specifically, if a listed company does not engage in imitation but rather discloses risk topics that other companies have not mentioned, investors are likely to perceive these new risk topics as unknown risk factors. From a heterogeneity perspective, the disclosure of unknown risk factors increases investors' risk perception.

To examine whether corporate greenwashing behavior exhibits contagion and imitation effects, we redefine the variable Motivation^N. Specifically, if a company operates in the same industry as another company suspected of greenwashing in the current year (Motivation = 1), then Motivation¹ = 1, and otherwise 0. Similarly, if a company is located in the same city and operates in the same industry as another company suspected of greenwashing in the current year, then Motivation² = 1, and otherwise 0. Additionally, samples where Motivation = 1 are excluded from the analysis.

$$GTE_{i,t} = \gamma_0 + \gamma_1 \text{Motivation}_{i,t}^n + \gamma_2 \text{Controls}_{i,t} + \sum \text{year} + \sum \text{firm} + \varepsilon_{i,t} \quad (11)$$

$$\begin{aligned} \text{rmrf}_{i,t} = & \delta_0 + \delta_1 GTE_{i,t} \times \text{Motivation}_{i,t}^n + \delta_2 GTE_{i,t} + \delta_3 \text{Motivation}_{i,t} + \delta_4 \text{Controls}_{i,t} + \sum \text{year} \\ & + \sum \text{firm} + \varepsilon_{i,t} \end{aligned} \quad (12)$$

As shown in column (1) of Table 12, corporate greenwashing behavior does indeed exhibit contagion and imitation effects, with imitation occurring more rapidly among firms in the same industry. The coefficient for imitation identified in the current period is 0.0657, which is significant at the 10 % level. However, when the characteristic of being located in the same city is included, the imitation effect of firms gradually emerges over time. As shown in column (5) of Table 12, the imitation coefficient becomes 0.1 after a three-period lag, which is statistically significant at the 10 % level. From the perspectives of imitation channels and targets, firms in the same industry often face common industrial economic policies, business conditions, technological environments, and growth opportunities, and thus exhibit a high degree of comparability between them (Liao et al., 2019). The external policy environment for firms within the same industry but in different years may vary. Imitating the information disclosed by peers in the same industry and year may represent a safer and more effective social reference path. Furthermore, to reduce the sensitivity of regulatory authorities to greenwashing between firms in the same industry and city, imitation tends to be delayed but more pronounced. When firms face similar regulatory systems and policy guidance, imitators consequently devote more space in their risk information disclosures to discussing risk topics already disclosed by their local peers.

We confirm that greenwashing behavior exhibits a contagion effect, but its impact on risk premiums is more complex, for the following possible reasons: (1) there may be a lag effect in the imitation of corporate greenwashing, and investors may take time to recognize the contagion of behavior between firms (Marquis and Toffel, 2020); and (2) there are significant disparities in regulatory policies, enforcement intensity, and regulatory approaches between different cities. The geographical distribution of Chinese listed companies is uneven, with some regions having a higher concentration of listed firms and stronger regulatory pressure, leading to substantial heterogeneity in the extent of greenwashing contagion (Wang et al., 2024). We also analyze the market response to the imitation of greenwashing in the capital market. As shown in columns (1) and (3) of Table 13, the imitation of greenwashing does not produce a significant premium effect during the current period. The coefficient for the premium effect of intra-industry imitation is -1.6396, while the coefficient for imitation within the same city and industry is 1.7234. These results indicate that investors are not highly sensitive to the concealment of information. After lagging the textual evidence of greenwashing (GTE) and poten-

Table 12
The imitation of greenwashing.

	(1) GTE	(2) GTE	(3) GTE	(4) GTE	(5) GTE
Motivation ¹	0.0657* (1.6866)				
Motivation ²		-0.0100 (-0.2530)			
Motivation ² _{t-1}			-0.0151 (-0.3075)		
Motivation ² _{t-2}				0.0823 (1.5173)	
Motivation ² _{t-3}					0.1000* (1.6741)
_cons	-0.3338 (-0.4051)	-0.3367 (-0.4087)	-0.3631 (-0.3397)	-0.5457 (-0.4630)	-0.6424 (-0.4649)
Adj R ²	0.5562	0.5559	0.5748	0.5877	0.6057
Control	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES
Firm-fixed	YES	YES	YES	YES	YES
N	6059	6059	4468	3714	3098

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 13
The risk premium of greenwashing imitation.

	(1) rmrf	(2) rmrf	(3) rmrf	(4) rmrf	(5) rmrf
GTE × Motivation ¹	-1.6390 (-1.3307)				
GTE _{t-1} × Motivation ¹ _{t-1}		2.2447* (1.7441)			
GTE × Motivation ²			1.7234 (1.3674)		
GTE _{t-1} × Motivation ² _{t-1}				1.2660 (0.8679)	
GTE _{t-2} × Motivation ² _{t-2}					-2.8316* (-1.7705)
_cons	-7.2511 (-0.2400)	-38.4982 (-1.0277)	-8.7460 (-0.2892)	-35.4859 (-0.9545)	-22.1306 (-0.5191)
Adj R ²	0.4732	0.4525	0.4731	0.4524	0.3914
Year-fixed	YES	YES	YES	YES	YES
Firm-fixed	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES
N	6059	4468	6059	4468	3714

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

tial imitation motives (Motivationⁿ) separately by one period, we find that the stock risk premium becomes significantly evident. The premium effect of intra-industry imitation is 2.2447, which is significant at the 1 % level. However, there is no significant premium associated with the transmission of the imitation of green-

Table 14
Industry-wide greenwashing and risk premium.

	(1) industry_GTE	(2) rmrf	(3) rmrf	(4) rmrf	(5) rmrf	(6) rmrf
GTE	0.1173*** (9.3422)					
industry_GTE		0.5229 (0.3659)				
industry_GTE _{t-1}			-3.3875* (-1.9067)			
industry_GTE _{t-2}				-1.7092 (-1.0095)		
industry_GTE _{t-3}					-0.0800 (-0.0422)	
industry_GTE _{t-4}						6.4913*** (2.9948)
_cons	-0.0414 (-0.1852)	-13.4442 (-0.4917)	-31.5570 (-0.9906)	-25.6632 (-0.6988)	0.2090 (0.0044)	26.2317 (0.4446)
Adj R ²	0.7119	0.4680	0.4575	0.3857	0.4046	0.4005
Control	YES	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES	YES
Firm-fixed	YES	YES	YES	YES	YES	YES
N	7357	7357	5850	4973	4259	3565

Note: The t values in brackets are adjusted by clustering the robustness standard errors; *, **, and *** represent significance at the 10 %, 5 %, and 1 % levels, respectively.

washing within the same city and industry. The most likely explanation is that regional regulations control imitation behavior in greenwashing.

The imitation and contagion effects of individual companies' greenwashing behavior can evolve into industry-wide greenwashing. To examine this potential impact, we conduct further analyses: first, we calculate the annual mean level of greenwashing for each industry; second, we observe the relationship between industry greenwashing and risk transmission.

$$\text{industry_GTE}_{i,t} = \varphi_0 + \varphi_1 \text{GTE}_{i,t} + \varphi_2 \text{Controls}_{i,t} + \sum \text{year} + \sum \text{firm} + \varepsilon_{i,t} \quad (13)$$

$$\text{rmrf}_{i,t} = \omega_0 + \omega_1 \text{industry_GTE}_{i,t} + \omega_2 \text{Controls}_{i,t} + \sum \text{year} + \sum \text{firm} + \varepsilon_{i,t} \quad (14)$$

As shown in Table 14, we find that corporate greenwashing drives industry greenwashing, with a coefficient of 0.1173, which is statistically significant at the 1 % level. However, the market seems insensitive to collective greenwashing behavior. On the contrary, in the short term (with a one-period lag), the market exhibits a relatively positive attitude toward greenwashing, as evidenced by a decline in risk premiums, with a coefficient of -3.3875, significant at the 10 % level. It is only after a longer period (with a four-period lag) that corporate environmental issues gradually come to light, leading to a significant increase in market risk premiums, reaching 6.4913, which is statistically significant at the 1 % level. This demonstrates that corporate greenwashing evolves into industry-wide greenwashing, and that the market's delayed reaction to industry dynamics is detrimental to corporate sustainability and the mitigation of systemic social risks.

9. Conclusions

Environmental accounting information is an essential component of corporate reports published by listed companies and is of considerable importance to investors who wish to understand companies' environmental actions. This paper explores the impact of corporate greenwashing on stock risk premiums by analyzing the process from the identification of suspicions of greenwashing, through the use of obscure textual expressions, to the gradual manifestation of behaviors. Based on data from non-financial A-share listed companies from

2008 to 2021, the study finds that, first, investors' decision-making focuses more on suspicions of greenwashing than on inconsistencies between companies' words and actions. Although textual greenwashing is not directly detected, it amplifies suspicions of greenwashing by embellishing disclosed information, thereby raising doubts among investors about the environmental performance of enterprises. Second, our analysis of observable pathways reveals that suspicions of greenwashing increase firms' exposure to reputational risk, investor information friction, and financial misallocation. As a result, the capital market demands a higher risk premium. Third, the heterogeneity analysis indicates that the impact of corporate greenwashing on stock risk premiums is more pronounced when firms are subject to severe air pollution shocks, lack internal financial supervision, and exhibit short-term strategic thinking. Fourth, the greenwashing behavior of individual enterprises can be imitated by other firms in the same region or industry, leading to industry-wide greenwashing, which is detrimental to resolving systemic financial risks. Moreover, contrary to previous studies that have suggested that heavily polluting enterprises are the primary targets of greenwashing, we find that such enterprises have more comprehensive disclosure frameworks and that their "non-green" attributes are well known to the capital market. In contrast, low-polluting enterprises exhibit a stronger tendency and a higher risk of greenwashing, with fewer information disclosure constraints.

Based on our hypotheses and research findings, we propose the following policy recommendations:

(1) **Investor Vigilance:** Investors should not only listen to companies' statements but also closely observe their actions. This approach will enable them to better detect concealed and embellished disclosures, thereby preventing them from being misled by extensive but potentially misleading environmental disclosures.

(2) **Structured Improvement of Corporate Disclosure Systems:** It is essential to refine corporate information disclosure frameworks to reduce the possibilities for manipulation in the disclosure process. A unified disclosure framework could help create a cohesive and integrated market in China. Furthermore, as greenwashing behavior is often imitated by numerous firms, a standardized disclosure framework would effectively curb such imitations, thereby enhancing market sensitivity to deceptive information.

(3) **Mitigating Suspicions of Greenwashing:** Reducing suspicions of greenwashing is also a crucial element in the fight against environmental deception. This can be achieved by optimizing the financing environment and support for enterprises. For firms genuinely committed to the green transformation, it is essential to introduce and refine fiscal and tax incentives and financial support mechanisms. These measures should lower their financing costs and promote sustainable development. For firms suspected of greenwashing, regulatory and disclosure requirements should be strengthened, and financing costs should be increased to ensure that market resources are more effectively allocated to firms taking concrete environmental action.

(4) **Strengthening Penalties for Environmental Violations and Market Feedback Mechanisms:** Government departments should establish a public platform to expose environmental violations, to raise awareness among the public and investors about the environmental behavior of companies. In addition to legal sanctions, companies guilty of environmental violations should face market-based penalties, such as restrictions on government procurement or access to green credit. Encouraging and supporting third-party environmental organizations and the media to monitor and expose corporate environmental behavior will help build a socially collaborative environmental regulatory system.

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. 1. Differences in Information Disclosure Frameworks across Markets

Encouraged disclosure and soft-law regulations from stock exchanges and the China Securities Regulatory Commission (CSRC) are the primary institutional features of China's current environmental information disclosure system. In 2002, CSRC introduced the Guidelines for Corporate Governance of Listed Companies, which frameworkly proposed requirements for corporate green information disclosure. In 2006 and 2008, the Shenzhen Stock Exchange (SZSE) and the Shanghai Stock Exchange (SSE) respectively encouraged listed companies to disclose ESG annual reports. In 2011, SZSE revised the Assessment Measures for Information Disclosure of Listed Companies, incorporating ESG report disclosure into the evaluation system for listed companies to strengthen incentives for ESG information disclosure. Since then, the environmental accounting information framework has continued to improve,¹⁶ until the 2021 revision of the Contents and Format of Annual Reports became a key carrier of China's environmental accounting information disclosure rules, initially forming a disclosure model combining mandatory disclosure, "explain if not disclosed," and encouraged disclosure. Nevertheless, statistics from the CCX Green Gold ESG Ratings database show that the sustainability information disclosure rate of listed companies remained below 40 % from 2022 to 2024.

Table A1

Differences in information disclosure frameworks across markets.

	Specific Content
China A-share Market	<ol style="list-style-type: none"> 1. Pollution emission parameters. 2. Construction, operation, environmental assessment, and administrative licensing of pollution prevention facilities. 3. Self-monitoring, emergency plans, and administrative penalty situations. 4. Carbon emissions and quota clearance status. 5. Environmental management administrative licenses, environmental protection taxes, pollution insurance coverage, and environmental credit ratings. 6. Encouraged disclosure of environmental protection information on resources, verification status, tripartite certification, etc.
United States	<ol style="list-style-type: none"> 1. Corporate carbon emission information, carbon emissions of suppliers and partners. 2. Climate risks and opportunities. 3. Climate and environment-related strategies, business models, and expected impacts. 4. Physical, liability, and transition risks related to climate change. 5. Environmental management structure, environmental costs, liabilities, and risks. 6. Greenhouse gas emission parameters. 7. Pollution emission verification, governance objectives. 8. Emission volumes of toxic substances and waste.
Hong Kong, China	<p>The focus is on distinguishing between mandatory disclosure requirements and "explain if not disclosed" provisions:</p> <ol style="list-style-type: none"> 1. Regulatory framework, senior management and ESG supervision 2. Types and quantities of pollution emissions, compliance plans, and governance processes 3. Resource usage volumes, optimization objectives, and implementation processes 4. Impacts of business activities on natural resources 5. Climate change and business value 6. Environmental and social risks in supply chain management 7. Greenhouse gas emissions 8. Climate risks and opportunities

¹⁶ In 2017, the China Securities Regulatory Commission (CSRC) revised the Contents and Format of Annual Reports, and in 2018, CSRC revised the Guidelines for Corporate Governance of Listed Companies, forming a preliminary framework for ESG information disclosure. In 2020, the Shenzhen Stock Exchange (SZSE) revised the Assessment Measures for Information Disclosure of Listed Companies, formally adopting the concept of ESG information.

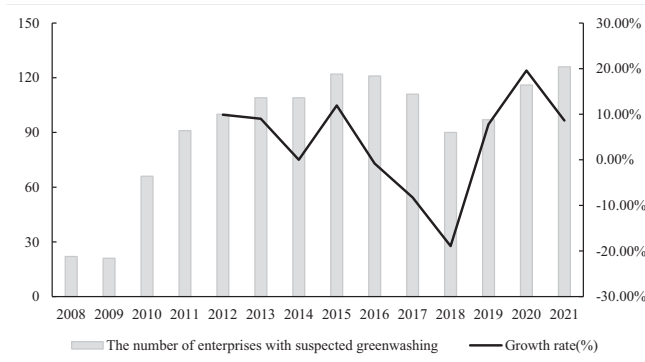


Fig. A1. Annual Changes in the Number of Samples of Enterprises Suspected of Greenwashing.

2. Analysis of correlations for samples suspected of greenwashing

Based on Fig. A1 and in conjunction with policy dynamics,¹⁷ it can be seen that from 2011 to 2015, the number of enterprises suspected of greenwashing gradually increased, but the growth rate slowed down. This is attributed to the macroeconomic regulation after the financial crisis. Furthermore, during the period of 2015–2019, the number of relevant enterprises showed a decreasing trend. However, affected by the 2019 pandemic, business operations stagnated, and the number of enterprises in operational difficulties and thus potentially suspected of greenwashing increased again. It can be concluded that the number of enterprises suspected of greenwashing is related to the macroeconomic development situation. In the subsequent empirical process, we controlled for individual and year fixed effects to further stabilize the research results.

3. The “green” relevance of the “greenwashing suspicion” indicator

The “greenwashing suspicion” characterizes a situation faced by enterprises, which is highly correlated with their “greenness.” In this paper, the measurement of greenwashing suspicion adopts four dimensions: financing constraints, bankruptcy risk, soft regulation by stock exchanges, and deterrence of environmental penalties. An enterprise is considered to have greenwashing suspicion only when all four indicators meet the criteria simultaneously. The purpose of corporate greenwashing is not necessarily limited to manipulating their own green risks. If enterprises face overall financing constraints or industry competition, they may also choose to falsely promote social responsibility through greenwashing to optimize their reputation and seek support from capital markets.

To verify the strong correlation between financing constraints, industry competition, soft regulation by stock exchanges, environmental penalty deterrence, and “greenwashing,” we regressed these four indicators as explanatory variables against the core dependent variable GTE. The results are shown in Table A2: When any one of the four conditions exists individually, it increases the likelihood of corporate greenwashing. However, judging greenwashing suspicion based on a single indicator may lead to over-identification, so some results are not significant. By contrast, when all four indicators are present simultaneously, enterprises face a critical dilemma, which highlights the existence of greenwashing. Additionally, we regressed Motivation

¹⁷ In 2006 and 2008, the Shenzhen Stock Exchange (SZSE) and the Shanghai Stock Exchange (SSE) respectively encouraged listed companies to disclose ESG annual reports. In 2011, the SZSE revised the Assessment Measures for Information Disclosure of Listed Companies. Therefore, before 2011, based on the preliminary requirements of the environmental information disclosure framework, the number of enterprises within the sample disclosing CSR reports increased rapidly, and the sample of enterprises suspected of greenwashing also increased rapidly simultaneously.

against the greenwashing index calculated from institutional ESG ratings [using differences between Bloomberg ESG ratings and China Securities Index (HZ) ESG ratings (GWL_HZ), as well as between Bloomberg ESG ratings and Wind ESG ratings (GWL_Wind)]. The results consistently show a positive correlation, further validating the association between the four indicators and “greenwashing.”

Table A2

The green-relatedness of greenwashing suspect indicators.

	(1) GTE	(2) GTE	(3) GTE	(4) GTE	(5) GTE	(6) GWL_HZ	(7) GWL_Wind
FC	0.1225*** (3.7709)						
SR		0.0054* (1.8992)					
BC			0.0069 (0.1768)				
DEP				0.0673 (1.5102)			
Motivation					0.0569* (1.8285)	0.0321 (0.5900)	0.1170* (1.8909)
_cons	-0.2603 (-0.3621)	-0.3852 (-0.529)	-0.3871 (-0.532)	-0.4336 (-0.593)	-0.3961 (-0.545)	-1.3193 (-1.1542)	0.3514 (0.1950)
Adj R ²	0.4523	0.5391	0.4235	0.4287	0.3708	0.3934	0.4088
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7357	7357	7357	7357	7357	4841	2183

Note: The t values in brackets are adjusted by clustering robustness standard error; *, ** and *** represent significance levels of 10 %, 5 % and 1 %, respectively.

To better support the results of this paper, we consider different scenarios here: (1) When only financing constraints and bankruptcy risk exist ($FB = FC \times BC$), the premium situation of enterprises' greenwashing ($FB \times GTE$); (2) When financing constraints, bankruptcy risk, and soft regulatory measures of exchanges are considered ($FBS = FC \times BC \times SR$), the degree of greenwashing premium of enterprises ($FBS \times GTE$); (3) When financing constraints, bankruptcy risk, and deterrence of environmental penalties are considered ($FBD = FC \times BC \times DEP$), the degree of greenwashing premium of enterprises ($FBD \times GTE$); (4) All four conditions are satisfied (benchmark regression results).

As shown in Table A3, we found that all decomposed indicators of greenwashing suspicion have an impact on risk premiums. Moreover, as the restrictive conditions become stricter, the premiums brought by greenwashing gradually increase, which once again verifies the reliability of these four indicators.

Table A3
Risk premium test of sub-indicators of greenwashing suspicions.

	(1) rmrf	(2) rmrf	(3) rmrf	(4) rmrf
FB × GTE	2.0620** (2.4527)			
FBS × GTE		2.5745** (2.0789)		
FBD × GTE			2.1732** (2.0322)	
Motivation × GTE				2.6789** (2.0693)
GTE	0.1148 (0.1593)	-0.0808 (-0.1270)	0.0548 (0.0775)	-0.0889 (-0.1395)
FB	0.7006 (0.7321)			
FBS		5.0365*** (2.9478)		
FBD			1.7117 (1.3586)	
Motivation				3.9786** (2.2534)
_cons	-13.8719 (-0.5077)	-11.7239 (-0.4285)	-13.1908 (-0.4826)	-11.9352 (-0.4363)
Adj R ²	0.4684	0.4689	0.4680	0.4686
Control	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes
Firm-fixed	Yes	Yes	Yes	Yes
N	7357	7357	7357	7357

Note: The t values in brackets are adjusted by clustering robustness standard error; *, ** and *** represent significance levels of 10 %, 5 % and 1 %, respectively.

In addition, by analyzing the publicly disclosed cases of corporate greenwashing by Southern Weekly since 2009, existing studies have found that greenwashing companies are mainly distributed across industries such as energy (17.11 %), chemicals (14.47 %), electronics (10.53 %), consumer goods (32.89 %), and pharmaceuticals (9.21 %). The most prominent characteristics of these companies are high environmental regulatory pressure, intense market competition, and severe financial issues. Therefore, we have chosen to capture a broader range of corporate issues to refine the depiction of greenwashing suspicion.

4. The characterization method of *escore* in the Greenwashing Textual Evidence (GTE) indicator

This paper uses the ratio of environmental word frequency to total word frequency of enterprises to characterize “what enterprises say about the environment,” and uses their substantive environmental achievements to characterize “what enterprises do for the environment.” The difference between the two after standardization is taken as the index of corporate greenwashing behavior. The following table shows the basis for our characterization of “what enterprises do for the environment.” Due to its lengthy content, Table A4 is placed in the Appendix.

Table A4
Measurement criteria for substantive environmental information.

	Substantive Environmental Information Indicators	Valuation Criteria
Reliability	Whether the CSR report is prepared with reference to GRI standards	1 if GRI is referenced, 0 otherwise
	ISO14001 certification	1 if certified, 0 otherwise
	Reliability Whether the auditor is from one of the Big Four accounting firms	1 if yes, 0 otherwise
	Whether the report has been verified by a third-party organization	1 if verified, 0 otherwise
	Honors or awards received by the company in environmental protection	1 if received, 0 otherwise
Specificity	Compliance status of pollutant emissions	1 if disclosed, 0 otherwise
	Work safety situation	1 if disclosed, 0 otherwise
	Disclosure of environmental negative events (3 types): sudden environmental accidents, environmental violations, environmental complaint cases	1 if disclosed, 0 otherwise. Value range [0, 3]
	Company's participation in environmental special activities and other social welfare activities	1 if disclosed, 0 otherwise
	Company's establishment of a major environmental emergency response mechanism	1 if disclosed, 0 otherwise
	Specificity "Three Simultaneities" system	1 if implemented, 0 otherwise
	Implementation status of clean production	1 if disclosed, 0 otherwise
	Disclosure of pollutant emissions (6 types): wastewater, COD, SO ₂ , CO ₂ , smoke and dust, industrial solid waste	0 if not disclosed, 1 if qualitatively disclosed, 2 if quantitatively disclosed. Value range [0, 12]
	Disclosure of pollutant treatment (5 types): waste gas, wastewater, smoke and dust, noise and light pollution, solid waste	0 if not disclosed, 1 if qualitatively disclosed, 2 if quantitatively disclosed. Value range [0, 10]

5. Robustness test

Indicator Measurement: The measurement of environmental information embellishment and risk premium is revised. (1) The substantive environmental information disclosure system is modified by excluding the disclosure of negative environmental events to calculate textual greenwashing evidence (GTE1). This is then multiplied by greenwashing suspicion (Motivation). (2) The range standardization method is applied to standardize the volume of substantive environmental information disclosure and environmental textual disclosure, after which textual greenwashing evidence (GTE2) is calculated. This is then multiplied by greenwashing suspicion (Motivation). (3) To account for the impact of non-essential keywords on the results, keywords with a frequency of less than 10 in corporate environmental information disclosure are removed, and textual greenwashing evidence (GTE3) is recalculated. (4) To further verify the reliability of the greenwashing manifestation index, this paper continues to use inter-institutional rating differences as a method for identifying greenwashing. The differences between Bloomberg ESG ratings and Huazheng ESG ratings (GWL_HZ) and between Bloomberg ESG ratings and Wind ESG ratings (GWL_Wind) are used as measures. (5) The difference between the annual stock return excluding cash dividend reinvestment and the risk-free rate (rmrf1) is used. The results are shown in Table A5.

Table A5
Replace index measurement.

	(1) rmrf	(2) rmrf	(3) rmrf	(4) rmrf	(5) rmrf	(6) rmrf1
GTE1 × Motivation	2.6124** (2.0168)					
GTE2 × Motivation		14.0719** (2.2451)				
GTE3 × Motivation			2.6933** (2.0778)			
GWL_HZ				1.4999** (2.1777)		
GWL_Wind					3.6800** (2.3315)	
GTE × Motivation						2.6673** (2.0785)
GTE						-0.0141 (-0.0222)
GTE1	-0.0854 (-0.1339)					
GTE2		-0.4403 (-0.1381)				
GTE3			-0.0867 (-0.1361)			
Motivation	3.9900** (2.2566)	4.0566** (2.2901)	4.0223** (2.2714)			3.9080** (2.2219)
_cons	-11.9681 (-0.4375)	-11.9102 (-0.4353)	-11.9199 (-0.4356)	34.7685 (0.9640)	447.9999*** (4.0620)	-11.1588 (-0.4090)
Adj R ²	0.4686	0.4687	0.4686	0.3865	0.4801	0.4687
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	7357	7357	7357	4841	2183	7357

Note: The t values in brackets are adjusted by clustering robustness standard error; *, ** and *** represent significance levels of 10 %, 5 % and 1 %, respectively.

Additionally, this paper replaces the dependent variable with Cumulative Abnormal Return (CAR), but the results are not significant. The reason is that greenwashing by companies is an issue of information disclosure, and there are potential greenwashing imitation behaviors as well as industry-wide greenwashing phenomena. This implies the presence of systematic risks. Therefore, the Cumulative Abnormal Return (CAR) may include systematic risk components that have not yet been identified in this paper. As shown in the Table A6, the occurrence of such systematic risks renders the excess returns no longer applicable.

Table A6
The impact of greenwashing on cumulative abnormal returns (CAR).

	(1) CAR	(2) CAR _{t+1}	(3) CAR _{t+2}
GTE × Motivation	−0.0005 (−0.1329)	−0.0031 (−0.5759)	0.0038 (0.6723)
GTE	−0.0003 (−0.1150)	−0.0028 (−0.9934)	0.0014 (0.4438)
Motivation	0.0058 (0.9981)	−0.0171** (−2.3221)	−0.0031 (−0.4333)
_cons	1.0625*** (11.8358)	0.7560*** (8.6672)	0.0236 (0.2015)
Adj R ²	0.1719	0.1255	0.0736
Control	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes
Firm-fixed	Yes	Yes	Yes
N	7214	5850	4259

Note: The t values in brackets are adjusted by clustering robustness standard error; *, ** and *** represent significance levels of 10 %, 5 % and 1 %, respectively.

This paper found that corporate greenwashing has industry-specific attributes, where enterprises within the same industry may mimic each other, leading to industry-wide greenwashing issues. Therefore, based on the characteristics of industry competition, we ultimately selected the Herfindahl-Hirschman Index (HHI) to better reflect the industry pressure faced by enterprises and the likelihood of greenwashing. Of course, the Z-Score indicator is also a valid measurement method. Here, we replaced HHI with Z-Score for a substitution test: enterprises with a Z-Score below 2.67 are deemed to have greenwashing suspicions, assigned a value of 1 for ZS. A total of 3825 such samples were screened, indicating that these enterprises may face certain bankruptcy risks. This process yields a new greenwashing suspicion index, Motivation_z. The regression results are shown in the Table A7, the adjusted interaction term remains significant, with a coefficient of 1.6105, significant at the 5 % level:

$$\text{Motivation}_z = \text{FC} \times \text{SR} \times \text{DEP} \times \text{ZS}$$

Table A7
Change the measurement method of greenwashing suspicion.

	(1) rmrf	(2) rmrf	(3) rmrf
GTE × Motivation _z			1.6105** (2.1433)
GTE	0.3181 (0.5247)		0.2370 (0.3900)

Table A7 (continued)

	(1) rmrf	(2) rmrf	(3) rmrf
Motivation_z		−3.3944 (−1.3748)	−3.5074 (−1.4061)
_cons	−13.3666 (−0.4884)	−15.2277 (−0.5561)	−14.8726 (−0.5421)
Adj R ²	0.4487	0.5398	0.4789
Control	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes
Firm-fixed	Yes	Yes	Yes
N	7357	7357	7357

Note: The t values in brackets are adjusted by clustering robustness standard error; *, ** and *** represent significance levels of 10 %, 5 % and 1 %, respectively.

Control Variables: Corporate greenwashing behavior varies by industry characteristics and is also influenced by regional regulatory dynamics. This paper further investigates this phenomenon by adjusting control variables, sample periods, and fixed effects. (1) To control for the impact of unobservable factors that change over time, this paper controls for individual-year-industry-city fixed effects. (2) Control variables such as board size (board), separation of ownership and control (Separate), financial leverage (FL), and operating expense ratio (Ofee) are added as indicators of corporate management. (3) Considering that the stock price of the previous year may affect the stock price of the current year, this paper includes the stock price of the previous period as a control variable to further examine the risk premium generated by greenwashing. When the risk premium level of the previous year is added, investors demand a higher risk premium for greenwashing suspicions in the current period, and the pricing of greenwashing behavior becomes less evident. (4) Since enterprises in the water conservancy, environmental protection, and public facility management sectors use a large number of environmental terms in their information disclosure, this may lead to a “misjudgment” of greenwashing textual evidence and affect the sample results. Therefore, in the robustness test, samples from enterprises in these sectors are excluded for regression analysis. (5) Stock returns are closely related to market cycles. In 2008 and 2015, China’s stock market experienced significant fluctuations. By excluding the market shocks of these two years, this paper identifies the risk premium level of corporate greenwashing. All robustness test results are presented in the Appendix Table A8.

Table A8
Control variables.

	(1) rmrf	(2) rmrf	(3) rmrf	(4) rmrf	(5) rmrf
GTE × Motivation	3.5085** (2.1380)	2.6379** (2.0184)	2.4182 (1.5757)	2.6323** (2.0240)	3.0459** (2.1635)
GTE	0.1814 (0.1991)	−0.0848 (−0.1332)	−0.3212 (−0.4380)	−0.0167 (−0.0256)	0.0078 (0.0113)
Motivation	5.1986**	3.7771**	5.9916***	4.0105**	4.2496**

(continued on next page)

Table A8 (continued)

	(1) rmrf	(2) rmrf	(3) rmrf	(4) rmrf	(5) rmrf
L.rmrf	(2.0741)	(2.1456)	(2.9747) −0.2674*** (−17.9724)	(2.2564)	(2.2566)
_cons	27.9166 (0.6715)	17.9673 (0.5290)	−66.5714** (−2.0158)	−10.5210 (−0.3752)	−17.8800 (−0.6281)
Adj R ²	0.4518	0.4692	0.5015	0.4684	0.4386
Control	Yes	Add	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	Yes
Firm-fixed	Yes	Yes	Yes	Yes	Yes
City-fixed	Yes	No	No	No	No
Industry-fixed	Yes	No	No	No	No
N	4930	7357	5850	7268	6665

Random Sampling Test: To examine whether the regression results are influenced by random factors or omitted variables and to avoid the impact of unobservable factors on the baseline regression analysis, this paper assumes the Motivation variable as an exogenous quasi-natural experiment. Companies are randomly sampled to represent a fictional treatment group, and the coefficient of corporate greenwashing on stock risk premiums is estimated through regression. The reliability of the conclusions is judged based on the baseline regression coefficients obtained from the placebo test. The process is repeated 1000 times, resulting in 1000 sets of regression coefficients and assumed values, respectively. The kernel density distributions are depicted in the Fig. A2. The mean is close to zero, and the coefficients deviate significantly from the mean, aligning with the expectations of the placebo test. Therefore, the estimation results are not biased due to omitted variables. The external shock test in this research further confirms the robustness of the conclusion that greenwashing by firms leads to stock risk premiums.

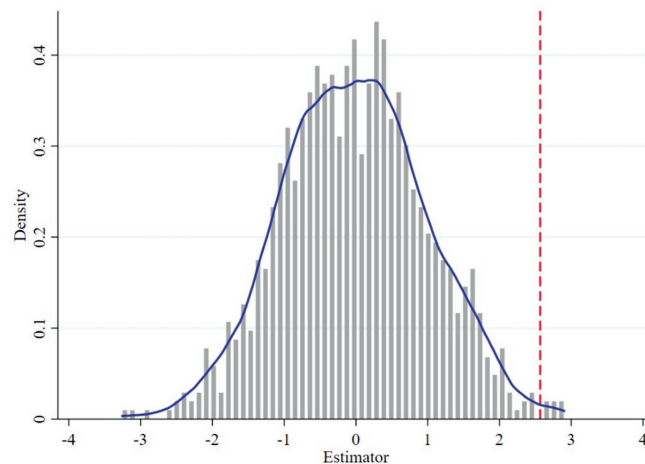


Fig. A2. Random Sampling Test.

6. Endogeneity test

To further address endogeneity issues, this paper designs a Difference-in-Differences (DID) approach to test the reliability of the results. First, companies with substantive disclosure levels below the 50th percentile of the industry are assumed to potentially engage in greenwashing and are assigned a value of 1, while others are assigned 0. The greenwashing suspicion variable Motivation (1 for companies with greenwashing suspicion, 0 otherwise) from the previous analysis is also retained, completing the DID1 design. As shown in Table A9, the risk premium brought by corporate greenwashing behavior is further validated, with a coefficient of 6.4635, significant at the 5% level. After propensity score matching (PSM), the conclusion remains robust, with a coefficient of 8.2099, significant at the 1% level.

The intensification of corporate financing constraints increases bankruptcy costs and compliance costs. Under the deterrence of penalties, capital flexibility is low, and liquidity risks are exacerbated. This paper further considers potential greenwashing risks under policy impacts. China introduced the *Green Credit Guidelines* in 2012, which institutionally links banks' credit decisions with enterprises' environmental performance and information compliance, guiding the allocation of bank credit funds. This enables green enterprises to obtain credit support more easily than non-green enterprises, while strengthening professional compliance supervision of relevant enterprises.

Based on *China's Green Industry Guidance Catalog* (2019), this paper manually classifies green and non-green industries according to the main business of each company in the sample. Non-green enterprises suspected of greenwashing are set as the experimental group (treat = 1), while enterprises without greenwashing suspicion are set as treat = 0; the period before the policy is post = 0, and the period after the policy is post = 1; the interaction term DID2 is calculated as the explanatory variable. Non-green enterprises with greenwashing suspicion face financing risks. As analyzed earlier, financing constraints may further lead to increased financial costs and rising bankruptcy risks, while regulatory inquiry letters and regional penalty deterrence also increase enterprises' compliance costs and financial pressures. Therefore, we argue that such enterprises found a speculative opportunity to alleviate financing constraints after the policy was promulgated. However, due to the existence of greenwashing suspicion, the market remains sensitive to the greenwashing practices of non-green enterprises.

As shown in Table A9: after propensity score matching, the greenwashing suspicion of non-green enterprises significantly increases the risk premium, with a coefficient of 10.4582, which is statistically significant at the 10% level. This indicates that the speculative financing behavior of non-green enterprises is often a key focus for investors and one of the factors that manifest corporate greenwashing. Moreover, due to the special identity of these enterprises, greenwashing suspicions are amplified, leading to demands for higher risk premiums.

Table A9
Endogeneity test.

	(1)	(2)	(3)	(4)
	DID1		DID2	
	rmrf	rmrf	rmrf	rmrf
DID1	6.4635** (2.5235)	8.2099*** (2.7480)		
DID2			1.5770 (0.6020)	10.4582* (1.7594)

(continued on next page)

Table A9 (continued)

	(1)	(2)	(3)	(4)
	DID1		DID2	
	rmrf	rmrf	rmrf	rmrf
_cons	-13.2474 (-0.4832)	-74.6498* (-1.7116)	-13.3144 (-0.4871)	-160.4077 (-1.4341)
Adj R ²	0.4687	0.4759	0.4680	0.4904
Control	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES
Firm-fixed	YES	YES	YES	YES
N	7357	2910	7357	805

Note: The t values in brackets are adjusted by clustering robustness standard error; *, ** and *** represent significance levels of 10 %, 5 % and 1 %, respectively.

7. Further Research – Greenwashing by Heavy Pollution Enterprises

This paper further validates the greenwashing behaviors of heavy pollution enterprises and capital market reactions by newly constructing a greenwashing index for heavy pollution enterprises:

Table A10
Greenwashing by heavy pollution enterprises.

	Mean	Sd	Min	Max	25 %	50 %	75 %
GWL	55.6531	18.5848	0.0000	97.4679	43.4122	54.7723	67.0820
GWLS	53.4000	17.7054	0.0000	95.0000	40.0000	55.0000	65.0000
GWLE	60.8929	23.9650	0.0000	100.0000	42.8571	62.5000	77.7778

The statistical results in Table A10 reveal that the mean green performance score across firms is 55.6531, with a median of 54.7723. This indicates that greenwashing behavior still exists to some extent in heavily polluting industries, but there is considerable variation in green performance among companies, as reflected by a standard deviation of 18.5848.

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Can digital innovation be a new driver of corporate sustainability?



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ABSTRACT

Digital innovation enables firms to build competitive advantages and achieve sustainability. Based on data from Chinese A-share listed firms from 2014 to 2023, we explore the impact of digital innovation on corporate sustainability and the moderating effect of economic policy uncertainty. We find that digital innovation promotes corporate sustainability, with increasing economic policy uncertainty strengthening this effect. In mechanism tests, this effect occurs by improving management efficiency and mitigating managerial myopia. Heterogeneity analyses indicate that digital innovation has a greater positive effect on sustainability for firms with stronger green transformation capabilities and those facing greater marketization. Analysis of different digital innovation patents shows that utility model and invention patents contribute to corporate sustainability, unlike design patents. These findings highlight the effect of digital innovation on corporate sustainability and offer valuable insights for firms seeking to balance innovation, competitiveness and long-term sustainability.

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1. Introduction

Digital innovation drives progress by generating new products, services and business paradigms (Yoo et al., 2010; Abrell et al., 2016), serving as a fundamental mechanism for the continuous evolution of the digital economy (Svahn et al., 2017). As a critical driver of organizational transformation and competitive advantage (Sestino et al., 2020), this innovation paradigm substantially enhances corporate performance while upgrading operational processes and the user experience (Jahanmir and Cavadas, 2018). Effective digital innovation strategies help mitigate information asymmetry (Nambisan et al., 2019; Di Vaio et al., 2021), lower commu-

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nication and coordination costs (Adner et al., 2019), expand financing opportunities (Babilla, 2023) and optimize resource allocation and operational efficiency (Liu et al., 2023), thereby strengthening corporate resilience (Zhang et al., 2024a) and increasing firm value (Acemoglu and Restrepo, 2019). Moreover, the 70th session of the United Nations General Assembly adopted the 2030 Agenda for Sustainable Development, which calls on all member states to adopt sustainable production patterns and promote sustainable economic growth. Firms, serving as both the foundation and principal catalyst for achieving national high-quality development, must urgently prioritize the implementation of comprehensive sustainability strategies. Amid escalating international trade tensions, recurring natural disasters and the persistent threat of a global economic downturn, advanced sustainable development enables firms to more effectively adapt to increasingly complex and volatile environments. This, in turn, facilitates the flexible restructuring of organizational systems, the enhancement of management efficiency and the formulation of long-term strategic plans (Zhou et al., 2022; Liu and Cao, 2025). These outcomes collectively support the maintenance and expansion of market share in the face of fierce competition, thereby contributing to the sustainable development of the national economy and society. In the context of the current volatile international economic environment, can digital innovation serve as an intelligent engine to achieve corporate sustainability? This study aims to explore whether and how digital innovation affects corporate sustainability. It also investigates the underlying mechanisms by which digital innovation affects corporate sustainability and examines how these effects vary in different contexts, emphasizing perspectives related to accounting information processing and financial decision-making optimization. The findings provide empirical evidence and micro-level insights that can help global firms to achieve high-quality development and enhance their sustainability in the digital economy.

Economic policy uncertainty exerts a considerable influence on firms' daily investment decisions and operational activities (Wen et al., 2021). Currently, the whole world is going through a critical phase of economic structural transformation and upgrading, with firms facing an increasingly complex and demanding external environment. Frequent adjustments to economic policies, driven by factors such as international trade frictions, extreme climate events and information security risks, have further increased economic policy uncertainty (Ologeanu-Taddei et al., 2025). During periods of economic policy tightening, firms are exposed to a highly volatile and unpredictable external environment. In this context, firms that actively engage in digital innovation benefit from greater technological first-mover advantages and development potential, enabling them to more effectively identify and capitalize on emerging opportunities (Ologeanu-Taddei et al., 2025). Specifically, by integrating technologies such as artificial intelligence, big data and cloud computing (Wang and Zhu, 2025), digital innovation enables firms to efficiently integrate, filter and refine information from multiple sources, thereby alleviating the information overload caused by economic policy uncertainty. Digital assets can be conceptualized as "exploratory options" (Trigeorgis, 1996), which provide firms with strategic flexibility and enhance their adaptability to uncertain environments (Nambisan et al., 2019), ultimately improving management efficiency. Meanwhile, digital innovation accelerates the iterative upgrading of products and production factors, fosters the creation of new knowledge and facilitates the identification of emerging opportunities (Liu et al., 2023). These dynamics help mitigate short-sighted managerial behavior and enable firms to plan their operations and make strategic decisions from a long-term perspective, thereby fostering sustainable development.

Based on the above analysis, this study explores the impact of digital innovation on corporate sustainability and the moderating role of economic policy uncertainty, using a sample of Chinese A-share listed firms from 2014 to 2023. The findings indicate that a higher level of digital innovation significantly promotes corporate sustainability, and that increased economic policy uncertainty strengthens this positive effect. These main results remain robust after conducting multiple rounds of endogeneity and robustness tests. The mechanism tests reveal that digital innovation facilitates corporate sustainability by improving management efficiency and reducing managerial myopia. The heterogeneity tests indicate that the positive impact of digital innovation on corporate sustainability is more pronounced for firms with greater green transformation capabilities and for those operating in regions with higher marketization. Furthermore, the analysis of the different types of digital innovation patents shows that utility model and invention patents have a significant and positive impact on corporate sustainability, while design patents have no statistically significant correlation with corporate sustainability.

We focus on Chinese firms for three reasons. First, as the world's largest emerging economy, China faces a critical sustainability paradox. Over the past three decades, while experiencing unprecedented GDP growth, China has suffered severe ecological costs, including deteriorating air and water quality and the overexploitation of non-renewable resources (Wang et al., 2023b). This structural tension between economic expansion and environmental constraints highlights the urgent need for institutional innovation, specifically for strategies that reconcile growth objectives with ecological balance. The unsustainable nature of resource-dependent development is forcing Chinese firms to shift from an extensive model based on scale and speed to a new development paradigm focused on longevity and high-quality growth. According to *Fortune* magazine, the average lifespan of small and medium-sized firms in China is only 2.5 years, while conglomerate firms only survive 7 to 8 years. This is significantly shorter than in the United States, where firms typically survive about 10 times longer, and represents only 50–60 % of the average lifespan observed among OECD member countries in the European Union. Therefore, compared with developed economies, China faces a more pressing imperative to accelerate its transition to sustainable development.

Second, the extremely competitive market environment has not only increased the survival pressures for Chinese firms (Zhou et al., 2022) but has also exacerbated deficiencies in technological innovation and managerial competencies. These compounded challenges erode core competitive advantages, compromising firms' ability to adapt to rapid market transformations and technological disruptions (Lara and Salas-Vallina, 2017). Consequently, the Chinese government is actively promoting the principle that “science and technology constitute the primary productive forces, and innovation serves as the fundamental driver of development,” while expediting the implementation of its innovation-driven development strategy. Currently, Chinese firms' level of digital innovation remains at an emerging exploratory phase, with substantial heterogeneity observed in implementation outcomes across firms. As such, China offers an ideal institutional context for conducting a natural experiment to examine the digital innovation–sustainability nexus in emerging economies, while providing policy implications transferable to other developing economies navigating similar sustainability transitions.

Third, China's economic system combines dominant public ownership with diversified ownership structures, with the government playing a key role in resource allocation (Zhao and Su, 2022), which contrasts sharply with developed economies like the United States, where market mechanisms predominantly determine resource distribution (Wen et al., 2021). Due to stronger administrative intervention and shorter policy transmission mechanisms characteristic of its institutional environment, Chinese firms experience more pronounced effects of economic policy uncertainty, particularly in the current international economic environment characterized by escalating trade tensions between China and the United States and evolving tariff barrier policies. Building on this institutional distinctiveness, we examine how economic policy uncertainty moderates the relationship between digital innovation and corporate sustainability in the Chinese context.

This study contributes to the literature in the following ways. First, we offer new perspectives and strategic directions to advance corporate sustainability. Studies primarily examine the effects of digital technologies (Mubarak et al., 2021), green innovation (Aftab et al., 2022), corporate governance (Buchetti et al., 2024) and government governance (Luo and Xu, 2024) on corporate sustainability. To date, research on the potential pathways to achieving corporate sustainability from the perspective of digital information processing has been limited. This study examines how digital innovation influences corporate sustainability in the context of economic policy instability. Our findings offer empirical evidence on how firms can attain sustainable development amid complex and turbulent operating conditions.

Second, this study deepens our understanding of how digital innovation shapes corporate sustainability. Corporate sustainability reflects the integrated outcome of coordinated development between economic and environmental performance (Wang and Kang, 2024). Research suggests that as digital innovation becomes more deeply integrated, firms see improvements in both their economic performance (Babilla, 2023; Chen et al., 2023; Liu et al., 2023) and environmental performance (Chen and Hao, 2022; Huang et al., 2023b; Li et al., 2024; Wang and Yang, 2024). However, studies have not yet fully elucidated the intrinsic mechanisms through which digital innovation drives corporate sustainability. To address this gap, we systematically unpack the “black box” of how digital innovation promotes corporate sustainability by enhancing manage-

ment efficiency and mitigating managerial myopia. Furthermore, we clarify the mechanism through which digital innovation affects corporate sustainability in the context of economic policy uncertainty. These insights have important implications for firms aiming to strengthen their coping strategies and adaptive capabilities during periods of external turbulence, thereby improving their sustainability.

Third, this study extends the boundary conditions under which digital innovation affects corporate sustainability by examining the heterogeneous effects of firms' green transformation capabilities and regional marketization. The capacity for green transformation constitutes a critical pathway to achieving synergistic improvements in economic and environmental performance (Liu and Cao, 2025), while a robust market environment facilitates optimal resource allocation and serves as a key external driver for digital innovation (Liu et al., 2023). Consequently, examining the heterogeneous roles of these factors in promoting corporate sustainability through digital innovation is of considerable importance. Our results reveal that firms with stronger green transformation capabilities and higher levels of regional marketization can leverage digital innovation strategies to more effectively promote sustainability. These findings provide empirical evidence for firms to design digital innovation strategies aligned with their characteristics and external environments, and offer practical guidance to governments to steer firms toward high-quality development.

2. Literature review and hypothesis development

2.1. Literature review

Digital innovation is a central mechanism through which organizations leverage digital technologies to develop new products, services and business models. It enhances overall organizational performance and drives comprehensive improvements in production processes, operational workflows and user experience (Yoo et al., 2010; Bharadwaj et al., 2013; Abrell et al., 2016). In the digital era, digital innovation is widely recognized as the main driver of the continued development of the digital economy and plays a critical role in organizational transformation and the development of core competitive advantages (Svahn et al., 2017; Sestino et al., 2020).

Sustainability reflects the integrated goal of firms to achieve balanced economic and environmental growth (Wang and Kang, 2024). Research on the effects of digital innovation on corporate sustainability largely examines its impact on either economic or environmental performance. Economically, digital innovation helps enhance total factor productivity by optimizing resource allocation (Chen et al., 2023) and improving marginal resource efficiency as well as overall production capacity (Nucci et al., 2023). Digital innovation also strengthens operational efficiency and firms' adaptability in competitive environments (Liu et al., 2023), producing incremental gains in financial performance (Babilla, 2023). Additionally, Jardak and Ben Hamad (2022) argue that although substantial initial investments in digital innovation may temporarily reduce profits, long-term economic performance improves steadily as information systems mature and internal capabilities are integrated.

Environmentally, digital innovation has become a crucial technological pillar for corporate green transformation (Huang et al., 2023b). Chen and Hao (2022) note that by implementing digital innovation strategies and leveraging big data analytics alongside intelligent sensing systems to establish efficient environmental monitoring mechanisms, firms can significantly enhance their precision management capabilities in energy consumption and carbon emissions, thereby advancing clean production and low-carbon operational objectives. Concurrently, as the digital infrastructure continues to mature (Svahn et al., 2017), the transparency and traceability of firms' environmental data are steadily improving. This effectively improves firms' environmental, social and governance (ESG) performance (Huang et al., 2023b) and enhances both the quantity and quality of green innovations (Wang and Yang, 2024). Digital innovation also broadens the channels of corporate engagement with external stakeholders, reinforces the fulfillment of social responsibilities and shapes a positive corporate image (Li et al., 2024). Furthermore, by leveraging its advantages in information processing efficiency and cost control, digital innovation effectively mitigates uncertainties in green investment, thereby bolstering firms' sustained investment capacity and strategic commitment to green technology R&D and energy-saving upgrades (Wang et al., 2024).

The literature highlights that economic and environmental benefits together form the foundational pillars of corporate sustainability (Wang and Kang, 2024). However, prior studies mainly investigate the effects of digital innovation on either economic or environmental benefits, which limits the comprehensive understanding of the mechanisms through which digital innovation fosters corporate sustainability. Moreover, most research focuses on relatively stable economic contexts, overlooking how the relationship between digital innovation and corporate sustainability develops under conditions of high external uncertainty. From the perspective of management efficiency and managerial myopia, we systematically investigate how digital innovation fosters corporate sustainability amid economic policy uncertainty, providing empirical evidence to guide firms in the effective implementation of digital innovation and the strengthening of their sustainable development capabilities in uncertain environments.

2.2. Hypothesis development

2.2.1. Digital innovation and corporate sustainability

Based on information processing theory, a firm fundamentally functions as an information processing system. Its operational efficiency depends on its ability to acquire, transmit, interpret and integrate information (Galbraith, 1973). To achieve goal alignment and operational efficiency, firms must enhance their information processing capabilities through structural design and technological applications, thereby addressing increasing task complexity and decision-making demands. As a core element of the new generation of technological transformation, digital innovation substantially strengthens firms' information processing capabilities by integrating tools such as artificial intelligence, big data and cloud computing. This integration accelerates responsiveness to external changes, optimizes internal resource allocation and increases overall management efficiency. Simultaneously, by improving information visualization and traceability, digital innovation enhances internal transparency and governance quality while reducing the information burden on management in the face of external uncertainties. As a result, it mitigates the information asymmetry between management teams and external investors, reinforces oversight mechanisms and accountability and systematically curbs managerial short-termism. Consequently, digital innovation supports decision-making that aligns more closely with shareholder interests and long-term firm value. Overall, digital innovation promotes sustainable corporate development through its dual function of enhancing management efficiency and alleviating managerial myopia.

First, digital innovation can significantly improve management efficiency, which in turn promotes corporate sustainability. According to information processing theory, firms must align task complexity with their information processing capabilities to effectively manage increasing decision-making demands and coordination challenges (Galbraith, 1973). In highly dynamic and uncertain task environments, firms face increased information processing demands. By integrating technologies such as artificial intelligence, big data and cloud computing, digital innovation markedly strengthens firms' ability to process complex and diverse information (Tanaka et al., 2020). This alleviates their information overload and processing costs, enhances their responsiveness to external changes and improves their decision-making quality, thereby significantly increasing management efficiency (Nambisan et al., 2019; Di Vaio et al., 2021). Moreover, by blurring the boundaries between internal functions and external networks, digital innovation mitigates information silos and enhances firms' ability to coordinate information and allocate resources amid increased task uncertainty (Hu et al., 2022; Hu and Ma, 2023). This reduces coordination costs in cross-level communication and interdepartmental collaboration (Hui et al., 2024), thereby establishing a critical foundation for improved management efficiency (Adner et al., 2019). Finally, digital innovation improves the timeliness and transparency of information disclosure and process control, strengthening firms' ability to perceive and respond to potential operational risks (Huang et al., 2023b). It further enables firms to establish intelligent management systems, eliminate redundant processes and resource waste, reduce process control and environmental governance costs and achieve a cost-efficient, green and streamlined operating model. The green transformation outcomes of digital innovation also enhance firms' reputation and public recognition, thereby attracting new customers and partners. Furthermore, digital innovation produces synergistic effects that facilitate the optimization of management processes and enhance cross-level coordination efficiency (Cheng and Wu, 2024). Consequently, by strengthening firms' information processing structures and capabilities, digital innovation enables flexible and highly

efficient management in complex and volatile environments. This minimizes managerial losses caused by redundant resource allocation and delayed responses, thus laying a solid foundation for corporate sustainability.

Second, digital innovation can effectively absorb uncertainty by enhancing firms' information processing capabilities, thereby mitigating managerial myopia and promoting corporate sustainability. Based on information processing theory, organizations operate as information processing systems whose decision-making efficiency depends on the implementation of mechanisms adapted to the complexity of their decision-making environment. This requirement becomes particularly salient in the presence of information asymmetry or governance blind spots, necessitating effective structures for information acquisition, transmission and integration (Galbraith, 1973). Managerial myopia often arises from a structural imbalance between information processing capacity and supervisory demands, which constrains firms' ability to absorb external uncertainties. By strengthening their capabilities to collect, process, disseminate and interpret information, digital innovation enables firms to transform complex and fragmented data into reliable decision-making inputs, thereby improving their ability to absorb uncertainty (Teece et al., 2016). Indeed, digital innovation enhances the quality and relevance of raw data for decision-making through information visualization, structuring and traceability. Real-time acquisition and analysis of critical information from market, policy and technological environments (Goldfarb and Tucker, 2019) allow firms to mitigate external shocks and better adapt to dynamic conditions. Moreover, increased information transparency and accountability enhance the observability of management's long-term goal-oriented behavior, which reduces monitoring difficulties and agency costs. This constrains managerial incentives to sacrifice sustainability for short-term performance gains. Furthermore, by optimizing information processing mechanisms (Wang et al., 2023a), digital innovation reduces external investors' cognitive uncertainty regarding management's strategic decisions and long-term intentions in uncertain environments. This fosters greater investor tolerance for short-term performance volatility and strengthens their understanding of and support for new strategic initiatives. As a result, firms benefit from lower financing costs and reduced managerial conservatism due to career concerns, thereby reducing the governance costs associated with deviations from long-term value creation. Ultimately, digital innovation empowers management teams to pursue long-term, sustainability-oriented strategies in a more rational and resolute manner (Guo et al., 2023), laying a solid foundation for sustained corporate growth.

Based on the above analysis, digital innovation enhances management efficiency and empowers firms to achieve sustainable development. It also mitigates managerial myopia, thereby laying a solid foundation for firms' long-term sustainability. Therefore, we propose the following hypothesis:

Hypothesis 1. *Ceteris paribus*, digital innovation contributes to corporate sustainability.

2.2.2. *The moderating role of economic policy uncertainty*

From the perspective of dynamic capabilities, firms constantly identify opportunities, integrate resources and reconfigure their internal capabilities to maintain their competitive advantage in the face of rapid environmental changes and high uncertainty (Teece et al., 1997). Under high economic policy uncertainty, digital innovation, through the integration of advanced technologies such as big data, artificial intelligence and the Internet of Things (Liang et al., 2022), enhances management efficiency, curbs managerial myopia and strengthens firms' dynamic capabilities to navigate environmental changes, thereby supporting sustainable development. By enabling real-time data collection and intelligent analysis, digital innovation reduces information asymmetry and overload arising from policy changes and market volatility (Wang and Zhu, 2025), thus improving firms' adaptability to information complexity and boosting management efficiency. Additionally, the generative nature of digital innovation accelerates product iteration and facilitates the identification of new opportunities (Yoo et al., 2012; Liu et al., 2023). This process transforms environmental uncertainty into innovative momentum, thereby mitigating managerial myopia and promoting long-term strategic decision-making. Consequently, in environments characterized by high economic policy uncertainty, digital innovation effectively enhances firms' strategic flexibility and dynamic capabilities, providing strong support for sustainable development.

First, under high economic policy uncertainty, digital innovation significantly enhances management efficiency, thereby creating effective pathways for corporate sustainability. High economic policy uncertainty

often coincides with increased information complexity and environmental volatility (Huang et al., 2024), intensifying the role of digital innovation in information integration and dynamic response (Nambisan et al., 2019). By improving information processing and knowledge integration, digital innovation accelerates information acquisition and circulation, increases sensitivity to external changes (Wang and Zhu, 2025), mitigates information overload and asymmetry (Wang et al., 2023a) and enhances management efficiency. Digital assets serve as exploratory options (Trigeorgis, 1996), offering firms the flexibility to pursue future expansion, transformation or reinvestment opportunities while converting information complexity into a strategic decision space. This, in turn, strengthens their ability to navigate uncertainty. By bolstering information processing capabilities, digital innovation optimizes decision-making quality and leverages strategic flexibility, improving firms' adaptability to uncertain environments (Nambisan et al., 2019). This allows firms to defer irreversible investment decisions during periods of policy uncertainty, rapidly scale digital applications when conditions mature and flexibly adjust their technology strategies or organizational models in response to external shocks, thereby reinforcing strategic resilience. Differences in resources and adaptive capacity between firms generate heterogeneous performance under economic policy uncertainty (He et al., 2020). Technology-intensive firms possess strong digital absorption and transformation capabilities, enabling them to adapt quickly to policy changes. In contrast, traditional manufacturing firms have relatively limited flexibility and technological absorptive capacity (Lou et al., 2022). Nevertheless, all firms can leverage digital innovation to enhance their management efficiency. Technology-intensive firms convert external uncertainties into opportunities for technological and organizational innovation, while traditional manufacturing firms exploit low-cost, exploratory trial-and-error mechanisms, conducting small-scale reversible tests to anticipate and adjust technologies and processes (Fichman and Kemerer, 1997). These practices help to optimize management systems and improve operational efficiency. Consequently, in a context of high economic policy uncertainty, digital innovation provides firms with greater strategic latitude and managerial flexibility, ultimately strengthening their capacity for sustainable development.

Second, under high economic policy uncertainty, digital innovation can more effectively mitigate managerial myopia, thereby promoting corporate sustainability. Although increased economic policy uncertainty heightens operational risks, it simultaneously creates significant growth opportunities (Wan et al., 2024). In this context, firms leverage the generative nature of digital innovation to capture and exploit these opportunities (Yoo et al., 2012), reducing managerial myopia and supporting sustainable development. As digital innovation capabilities advance, firms accelerate product iteration and the renewal of factors of production, generating new knowledge and uncovering new opportunities (Liu et al., 2023). This process enables managers and external investors to better appreciate the strategic value of digital innovation under uncertain policy conditions. Motivated by operational stability and long-term value creation, they tend to abandon short-term decision-making and adopt digital innovation strategies to strengthen their competitiveness (Guo et al., 2023). Moreover, differences in operational resilience and dynamic adaptability lead firms to respond differently to economic policy uncertainty (He et al., 2020). Technology-intensive firms, with a greater capacity to bear risks, undertake more innovative initiatives amid elevated policy uncertainty (Lou et al., 2022). In contrast, traditional manufacturing firms, constrained by high fixed costs and limited flexibility, often exhibit strategic hesitation under uncertain conditions (Bloom, 2009). Nevertheless, in all industries, digital innovation mitigates managerial myopia and supports corporate sustainability. For technology-intensive firms, the flexibility and investment options offered by digital innovation reinforce their confidence in their ability to seize opportunities through forward-looking, long-term decisions (Lou et al., 2022). For traditional manufacturing firms, data-driven tools generated by digital innovation facilitate scenario analysis and option evaluation, reducing short-termism caused by policy uncertainty (Babu et al., 2024). Consequently, by identifying new opportunities in turbulent environments through digital innovation, firms can prevent myopic decision-making driven by short-term gains, thereby advancing their sustainable development.

Based on the above analysis, under conditions of high economic policy uncertainty, digital innovation can more effectively enhance management efficiency and mitigate managerial myopia. This, in turn, generates greater development opportunities for firms, supporting continuous value creation and promoting sustainable development. Therefore, we propose the following hypothesis:

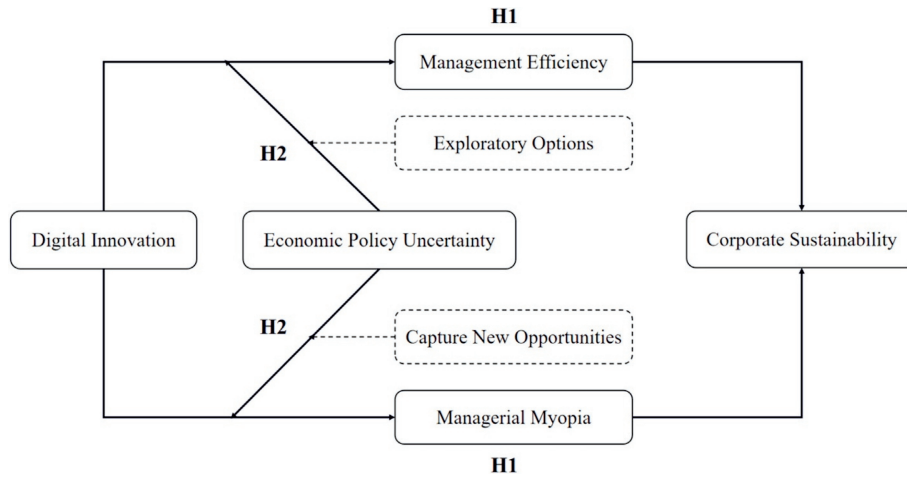


Fig. 1. Conceptual framework.

Hypothesis 2. *Ceteris paribus*, high economic policy uncertainty strengthens the positive effect of digital innovation on corporate sustainability.

Fig. 1 illustrates the conceptual framework of this study.

3. Sample and variables

3.1. Sample

We use a sample of Chinese A-share listed firms from 2014 to 2023. In November 2013, the 18th CPC National Congress placed technological innovation at the core of national development, designating it as a strategic driver of social productivity and overall national strength. Subsequently, the 2014 Academician Conference of the Chinese Academy of Sciences and the Chinese Academy of Engineering reinforced the commitment to a distinctively Chinese innovation model and urged faster adoption of an innovation-driven development strategy to bolster sustainable national growth. Therefore, we take 2014 as the starting point for our sample period. We exclude (1) firms in the financial and insurance sectors; (2) firms in serious financial distress, including ST and *ST firms; and (3) firms with missing data and those delisted during the sample period. Our final sample includes 16,533 firm-year observations from 3526 firms.

To reduce the influence of extreme values on the regression results, we winsorize all continuous variables at the upper and lower 1% levels. The data on digital innovation and financial data come from the Chinese Research Data Services (CNRDS) platform. The data relating to the economic policy uncertainty index come from the website <https://www.policyuncertainty.com>, while other data come from the China Stock Market and Accounting Research database.

3.2. Variables

3.2.1. Corporate sustainability

Following Wang and Kang (2024), we measure corporate sustainability (*Sdl*) using a dual performance framework that integrates financial and environmental performance. We measure financial performance by return on equity (*Roe*) and environmental performance using the natural logarithm (*LnE*) of the environmental score provided by the Huazheng ESG rating system. According to organizational ambidexterity theory, firms must achieve balanced and synergistic development in both dimensions to adapt to environmental changes and maintain their competitiveness (Gibson and Birkinshaw, 2004). Accordingly, *Sdl* captures a firm's ability to achieve a dynamic balance and create synergistic value between its financial and environmental per-

formance under resource constraints. It reflects the firm's ability to simultaneously pursue economic and environmental objectives through strategic adjustments and capability restructuring in complex external environments with constrained internal resources. The calculation proceeds as follows: First, we standardize financial and environmental performance to ensure that their values are between 0 and 1. Subsequently, we transform the standardized financial performance (Roe) and environmental performance (LnE) values into our dual performance measure (Sdl) using Eq. (1). $1 - |Roe - LnE|$ represents the equilibrium between a firm's financial and environmental performance. If a firm compromises its environmental performance to maximize its profits, this value approaches 0. The term $\sqrt{Roe \times LnE}$ captures the synergistic effect between financial and environmental performance, illustrating how their simultaneous improvement contributes positively to corporate sustainability. Sdl ranges from 0 to 1, with higher values indicating better balance and stronger synergy between economic and environmental performance, and thus reflecting greater corporate sustainability.

$$Sdl = \left[(1 - |Roe - LnE|) \times \sqrt{Roe \times LnE} \right] / 1 \quad (1)$$

3.2.2. Digital innovation

We measure corporate digital innovation across quantitative and qualitative dimensions. Following Hu and Ma (2023), we assess the quantitative dimension of digital innovation based on the number of digital innovation patent applications filed by firms. Based on the *Classification of Digital Economy and Its Core Industries (2021)* issued by the National Bureau of Statistics of China, which identifies 22 core digital economy subcategories,¹ we apply the pre-trained SBERT model in Python to compute the textual similarity between patent abstracts and category descriptions. To improve identification accuracy, we combine manual verification with segment-level accuracy evaluation. For each category, we establish a corresponding similarity threshold and retain patents exceeding that threshold. This approach ensures systematic coverage and precision in the identification of digital innovation patents. Specifically, (1) we adopt SBERT to compute the cosine similarity between patent abstracts filed and published by listed firms on the CNRDS platform from 2014 to 2023 and the 22 core digital economy category descriptions. The similarity scores range from 0 to 1, with higher values indicating a greater likelihood that the patent belongs to the corresponding category. (2) Considering the heterogeneity of similarity distributions across categories, we manually evaluate and segment accuracy rates to determine appropriate thresholds, retaining patents exceeding those thresholds as digital innovation patents. (3) We match the identification results at the firm-year level and construct the annual digital innovation quantity indicator ($DinI$) by taking the natural logarithm of 1 plus the total number of digital innovation patent applications identified for each firm.

Following Wu and Zhong (2023), we measure the quality of digital innovation using the knowledge breadth of digital innovation patents, which reflects the technological complexity and diversity of knowledge they embody. We adopt the Herfindahl–Hirschman Index (HHI) approach to calculate the distribution of each digital innovation patent across classification codes at the main group level of the International Patent Classification (IPC), as shown in Eq. (2):

$$Kb = 1 - \sum \alpha^2 \quad (2)$$

where α represents the proportion of patents within each main group and Kb captures the overall knowledge breadth of a patent. A higher Kb value suggests broader coverage of knowledge domains, greater complexity in technology combinations and better innovation quality. As design patents follow a distinct IPC system, we follow Wu and Zhong (2023) and exclude design patents, retaining only invention and utility model digital innovation patents. We then use the median method to aggregate the knowledge breadth of these patents

¹ The 22 subcategories are as follows: 0101 Computers; 0102 Communication and Radar Equipment; 0103 Digital Media Devices; 0104 Smart Devices; 0105 Electronic Components and Equipment; 0106 Other Digital Products; 0201 Digital Product Wholesale; 0202 Digital Product Retail; 0203 Digital Product Leasing; 0204 Digital Product Maintenance; 0301 Software Development; 0302 Telecommunications, Broadcasting and Satellite Transmission Services; 0303 Internet-Related Services; 0304 Information Technology Services; 0305 Other Digital Technologies; 0401 Internet Platforms; 0402 Internet Wholesale and Retail; 0403 Internet Finance; 0404 Digital Content and Media; 0405 Information Infrastructure; 0406 Data Resources and Property Rights Trading; 0407 Other Digital Factors.

at the firm level. After applying a natural logarithmic transformation, we construct the annual digital innovation quality indicator ($Din2$) for each firm.

3.2.3. Economic policy uncertainty

Following Lou et al. (2022), we measure economic policy uncertainty using the index developed by Baker et al. (2016). This index is constructed through the text analysis of policy-related reports, in which predetermined keywords such as “economy,” “policy,” “legislation” and “uncertainty” are used to conduct text mining on the *South China Morning Post*. The number of articles containing these keywords are divided by the total number of articles published in a given month to obtain the monthly economic policy uncertainty index. Following Lou et al. (2022), we compute the arithmetic mean of the monthly indices and divide it by 100 to generate our measure of economic policy uncertainty (Epu).

3.2.4. Control variables

Following Li et al. (2024) and Wang and Kang (2024), we use a set of variables to control for factors that may affect corporate sustainability. Specifically, we include firm size ($Size$), measured as the natural logarithm of total assets at the end of the year; firm age (Age), measured by the natural logarithm of the number of years since the firm’s establishment; financial leverage (Lev), defined as the ratio of total liabilities to total assets at the end of the year. Profitability (Roa), measured by the ratio of net profit to total assets; inventory ratio (Inv), measured as the proportion of inventory to total assets at the end of the year; R&D intensity (RD), measured by the ratio of R&D expenditure to operating revenue; ownership of the largest shareholder ($Top1$), measured by the proportion of shares held by the largest shareholder; CEO duality ($Dual$), assigned a value of 1 if the board chair also serves as CEO, and 0 otherwise; and firm growth ($Grow$), measured by the growth rate of operating income. Furthermore, we include firm ($Firm$) and year ($Year$) fixed effects to absorb confounding factors that remain constant over time or across firms. Table 1 provides detailed definitions of the variables.

3.3. Empirical models

We use Eqs. (3) and (4) to examine the effect of digital innovation on corporate sustainability (Sdl) and the moderating role of economic policy uncertainty:

$$Sdl = \alpha_0 + \alpha_1 Din_{i,t} + \sum \alpha_j Controls_{i,t} + \sum Year + \sum Firm + \varepsilon_{i,t} \quad (3)$$

$$Sdl = \beta_0 + \beta_1 Din_{i,t} + \beta_2 Epu_{i,t} + \beta_3 Din_{i,t} \times Epu_{i,t} + \sum \beta_j Controls_{i,t} + \sum Year + \sum Firm + \mu_{i,t} \quad (4)$$

Table 1
Variable definitions.

Symbols	Variables	Variable measurement
Sdl	Corporate sustainability	Calculated using Eq. (1).
$Din1$	Quantity of digital innovation	The natural logarithm of the number of digital innovation patent applications plus one.
$Din2$	Quality of digital innovation	The natural logarithm of the total knowledge breadth of invention and utility model digital innovation patents.
Epu	Economic policy uncertainty	The arithmetic means of annual economic policy uncertainty divided by 100.
$Size$	Firm size	The natural logarithm of total assets at the end of the year.
Age	Firm age	The natural logarithm of the number of years since the firm’s establishment.
Lev	Financial leverage	The ratio of total liabilities to total assets at the end of the year.
Roa	Profitability	The ratio of net profit to total assets.
Inv	Inventory ratio	The proportion of inventory to total assets at the end of the year.
RD	R&D intensity	The ratio of R&D expenditure to operating revenue.
$Top1$	Ownership of the largest shareholder	The proportion of shares held by the largest shareholder.
$Dual$	CEO duality	A value of 1 if the board chair also serves as CEO, and 0 otherwise.
$Grow$	Firm growth	Growth rate of operating income.

where Din denotes digital innovation, measured by its quantity ($Din1$) and quality ($Din2$); $Controls$ denotes the set of control variables; and ε and μ are the random disturbance terms.

4. Empirical results

4.1. Descriptive statistics

Table 2 reports the descriptive statistics of all variables. The mean and minimum values of Sdl are 0.255 and 0.025, respectively, suggesting a relatively low overall level of corporate sustainability in our sample. The mean (standard deviation) values of $Din1$ and $Din2$ are 0.988 (1.054) and 0.441 (0.281), respectively, indicating a substantial variation in both the quantity and quality of digital innovation across our sample firms. The mean value of Epu is 1.460. Additionally, the descriptive statistics of the other variables are consistent with prior studies.

4.2. Correlation analysis

Table 3 presents the Pearson correlation matrix for the main variables. $Din1$ and $Din2$ demonstrate statistically significant positive correlations with Sdl , providing preliminary evidence that digital innovation enhances corporate sustainability. Most of the control variables are significantly correlated with Sdl , indicating that we select effective control variables. The correlation coefficients between the control, independent and dependent variables are all within reasonable ranges. The maximum value of the variance inflation factor (VIF) is 2.01, with a mean value of 1.28, which is much smaller than the critical value of 10, suggesting that there is no serious multicollinearity problem between our variables.

4.3. Baseline regression results

Table 4 summarizes the baseline regression results. Columns (1) and (2) control only for firm ($Firm$) and year ($Year$) fixed effects, showing that the coefficients of $Din1$ and $Din2$ are both significant at the 1% level. Columns (3) and (4) present the results with all control variables included. The coefficients of $Din1$ and $Din2$ remain statistically significant at the 1% level. These results indicate that both the quantity and quality of digital innovation have a significant positive impact on corporate sustainability. From an economic perspective, a one standard deviation increases in the quantity of digital innovation corresponds to an average improvement of 1.370% (0.013×1.054) in corporate sustainability, equivalent to 5.373% ($1.370\%/0.255$) of the sample

Table 2
Descriptive statistics.

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Sdl	16,533	0.255	0.051	0.025	0.226	0.257	0.285	0.527
$Din1$	16,533	0.988	1.054	0.000	0.000	0.693	1.609	6.863
$Din2$	16,533	0.441	0.281	0.000	0.240	0.500	0.625	0.943
Epu	16,533	1.460	0.191	1.250	1.321	1.436	1.506	1.852
$Size$	16,533	22.270	1.247	19.640	21.380	22.060	22.920	26.440
Age	16,533	2.953	0.297	1.946	2.773	2.996	3.178	3.638
Lev	16,533	0.392	0.188	0.049	0.241	0.385	0.527	0.925
Roa	16,533	0.048	0.058	-0.375	0.018	0.045	0.078	0.254
Inv	16,533	0.127	0.089	0.000	0.067	0.111	0.167	0.778
RD	16,533	0.062	0.073	0.000	0.031	0.044	0.070	2.175
$Top1$	16,533	0.330	0.144	0.076	0.219	0.308	0.422	0.757
$Dual$	16,533	0.331	0.471	0.000	0.000	0.000	1.000	1.000
$Grow$	16,533	0.150	0.311	-0.653	-0.012	0.109	0.253	3.273

Table 3
Correlation analysis.

	<i>Sdl</i>	<i>Din1</i>	<i>Din2</i>	<i>Epu</i>	<i>Size</i>	<i>Age</i>	<i>Lev</i>	<i>Roa</i>	<i>Inv</i>	<i>RD</i>	<i>Top1</i>	<i>Dual</i>	<i>Grow</i>
<i>Sdl</i>	1.000												
<i>Din1</i>	0.018**	1.000											
<i>Din2</i>	0.062***	-0.044***	1.000										
<i>Epu</i>	0.102***	0.026***	0.425***	1.000									
<i>Size</i>	-0.166***	0.176***	0.064***	0.002	1.000								
<i>Age</i>	0.036***	-0.014*	0.201***	0.131***	0.194***	1.000							
<i>Lev</i>	0.088***	0.099***	0.028***	-0.017**	0.530***	0.146***	1.000						
<i>Roa</i>	-0.809***	-0.063***	-0.055***	-0.064***	-0.063***	-0.095***	-0.399***	1.000					
<i>Inv</i>	-0.001	0.016**	-0.015**	-0.030***	0.002	0.042***	0.211***	-0.067***	1.000				
<i>RD</i>	0.164***	0.165***	0.015**	0.077***	-0.227***	-0.122***	-0.269***	-0.068***	-0.121***	1.000			
<i>Top1</i>	-0.142***	-0.002	-0.007	-0.031***	0.162***	-0.044***	0.035***	0.123***	0.007	-0.200***	1.000		
<i>Dual</i>	0.013	0.018**	0.015*	0.025***	-0.211***	-0.114***	-0.141***	0.053***	-0.018**	0.152***	-0.031***	1.000	
<i>Grow</i>	-0.277***	-0.014*	-0.077***	-0.129***	0.008	-0.113***	0.032***	0.295***	0.044***	-0.059***	-0.013	0.032***	1.000

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 4
Baseline regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>
<i>Din1</i>	0.019*** (3.01)		0.013*** (3.49)		0.013*** (3.46)	
<i>Din2</i>		0.065*** (3.87)		0.028*** (2.96)		0.031*** (3.29)
<i>Epu</i>					-0.621*** (-2.95)	-0.621*** (-2.96)
<i>Din1</i> × <i>Epu</i>					0.018** (2.40)	
<i>Din2</i> × <i>Epu</i>						0.116*** (2.87)
<i>Size</i>			-0.016 (-1.14)	-0.013 (-0.95)	-0.016 (-1.11)	-0.014 (-0.98)
<i>Age</i>			0.059 (0.78)	0.051 (0.67)	0.057 (0.76)	0.051 (0.67)
<i>Lev</i>			-0.483*** (-9.84)	-0.484*** (-9.86)	-0.483*** (-9.84)	-0.483*** (-9.84)
<i>Roa</i>			-7.572*** (-48.91)	-7.571*** (-48.92)	-7.570*** (-48.89)	-7.570*** (-48.92)
<i>Inv</i>			-0.106 (-1.56)	-0.108 (-1.59)	-0.108 (-1.58)	-0.106 (-1.55)
<i>RD</i>			-0.254* (-1.96)	-0.251* (-1.95)	-0.254** (-1.96)	-0.254** (-1.97)
<i>Top1</i>			-0.002 (-0.03)	-0.001 (-0.02)	-0.001 (-0.02)	-0.001 (-0.01)
<i>Dual</i>			0.003 (0.34)	0.003 (0.33)	0.003 (0.33)	0.003 (0.32)
<i>Grow</i>			-0.014 (-1.51)	-0.014 (-1.55)	-0.014 (-1.54)	-0.014 (-1.56)
<i>_cons</i>	2.489*** (177.30)	2.488*** (183.00)	3.370*** (10.19)	3.336*** (10.09)	4.142*** (16.90)	4.115*** (16.79)
<i>Firm</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	16,533	16,533	16,533	16,533	16,533	16,533
<i>Adj. R²</i>	0.044	0.044	0.640	0.640	0.640	0.640

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the *t*-values adjusted for firm-level clustered robust standard errors.

mean of corporate sustainability. Similarly, a one standard deviation increase in the quality of digital innovation leads to an average increase of 0.787 % (0.028 × 0.281), representing 3.085 % (0.787 %/0.255) of average sustainability. These results suggest that digital innovation has both statistically and economically significant effects on corporate sustainability, thereby supporting H1. Therefore, a greater quantity and better quality of digital innovation enable firms to integrate diverse technologies more effectively, thereby enhancing their responsiveness to changes in the external environmental and their decision-making quality. These improvements help to strengthen management efficiency (Nambisan et al., 2019; Tanaka et al., 2020), which, in turn, promote corporate sustainability. Furthermore, digital innovation reshapes information generation and processing mechanisms, thereby strengthening firms' information processing capabilities and facilitating their ability to absorb external uncertainty (Teece et al., 2016). This process mitigates managerial myopia and, consequently, enhances corporate sustainability.

Columns (5) and (6) show that the coefficients of *Din1* × *Epu* and *Din2* × *Epu* are 0.018 and 0.116, respectively, both significant at the 5 % level. These results suggest that stronger economic policy uncertainty

strengthens the positive effect of digital innovation on corporate sustainability. From an economic perspective, a one unit increase in economic policy uncertainty, accompanied by a one percentage point increase in the quantity and quality of corporate digital innovation, corresponds to respective increases of 0.018 % and 0.116 % in corporate sustainability, thereby confirming H2. Therefore, in the face of high economic policy uncertainty, digital innovation enhances firms' environmental adaptability by leveraging their strategic flexibility enabled by advanced information processing capabilities and digital assets, thereby improving management efficiency (Nambisan et al., 2019). Moreover, digital innovation facilitates the continuous iteration and upgrading of innovative products (Yoo et al., 2012), enabling firms to identify and capture emerging opportunities in dynamic environments (Liu et al., 2023). By mitigating managerial myopia and discouraging short-term profit-seeking behavior, digital innovation promotes corporate sustainability during period of increased economic policy uncertainty.

4.4. Endogeneity tests

4.4.1. Heckman two-stage model

We use the Heckman two-stage model to mitigate endogeneity caused by potential sample self-selection bias. In the first stage, following Huang et al. (2023a), we set "whether the firm engages in digital innovation" (*Din_dum*) as the dependent variable and use the average level of digital innovation (*Ipedt*) among the sample firms within the same industry and province in the same year as the exogenous variable. As firms located in the same province share similar digital technology resources and environmental conditions, a certain degree of convergence exists in the levels of digital innovation of firms operating in the same industry. Therefore, industry-level digital innovation within the same province is significantly correlated with digital innovation of individual firms, satisfying the relevance condition. Moreover, a firm's sustainability is mainly determined by internal factors such as resource endowment, strategic choices and managerial decisions. It does not exhibit a direct or necessary causal relationship with the overall level of digital innovation in its industry or province (Huang et al., 2023a), thereby fulfilling the exogeneity requirement. Column (1) of Table 5 shows that the regression coefficient of *Ipedt* is positive and significant at the 1 % level, confirming the validity of our exogenous variable. In the second-stage regression, we incorporate the previously derived inverse Mills ratio (*Imr*) into Eq. (3). Columns (2) and (3) of Table 5 show that the regression coefficients of *Din1* and *Din2* remain significant and positive, confirming the robustness of our main conclusion.

4.4.2. Instrumental variable approach

We use the instrumental variable approach to mitigate potential endogeneity concerns caused by reverse causality, omitted variable bias and measurement error. Following Zhang et al. (2024b), we construct our instrumental variable (*IV*) as the interaction between the spherical distance from each firm's location to Hangzhou and the annual indicator variable. As one of the core hubs of China's digital economy, Hangzhou concentrates a high density of leading internet platform firms, advanced technological resources and innovation networks. Owing to the strong spatial spillover effects of digital factors, cities near Hangzhou are likely to benefit from spillovers in digital infrastructure, talent and knowledge, thereby enhancing firms' digital innovation capabilities. This satisfies the relevance condition for the instrumental variable. Meanwhile, the spherical distance between each firm's location and Hangzhou represents an exogenous geographic characteristic. Given that this distance is independent of economic and social factors and has no direct link with corporate sustainability, it satisfies the exogeneity requirement. As the spherical distance represents cross-sectional variation, we incorporate the annual variable to construct an interaction term suitable for the two-stage instrumental variable regression. The first-stage regression results, reported in Columns (4) and (6) of Table 5, reflect that the coefficient of *IV* is significant and positive, which aligns with our expectations. The Wald F-statistics of 59.29 and 352.17 exceed the critical threshold of 10, indicating that our instrumental variable does not suffer from weak instrument bias. The second-stage regression results in Columns (5) and (7) of Table 5 demonstrate that the coefficients of *Din1* and *Din2* remain positive and significant at least at the 5 % level, confirming the robustness of our baseline results.

Table 5
Endogeneity test results.

Variables	Heckman two-stage model			Instrumental variable approach				DID model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Din_dum</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Din1</i>	<i>Sdl</i>	<i>Din2</i>	<i>Sdl</i>	<i>Sdl</i>
<i>Ipedt</i>	1.329*** (58.83)							
<i>Din1</i>		0.009** (2.35)			0.141*** (2.72)			
<i>Din2</i>			0.030*** (3.16)				0.127** (2.07)	
<i>IV</i>				1.723*** (7.70)		2.322*** (18.77)		
<i>Treat × Post</i>								0.063*** (5.51)
<i>Size</i>	0.132*** (11.42)	-0.020 (-1.40)	-0.019 (-1.34)	0.197*** (8.86)	-0.046*** (-3.41)	0.003 (0.38)	-0.015* (-1.78)	-0.042*** (-3.44)
<i>Age</i>	0.125*** (3.24)	0.054 (0.72)	0.046 (0.61)	-0.348** (-2.23)	0.111* (1.72)	0.139*** (2.74)	0.030 (0.51)	-0.004 (-0.06)
<i>Lev</i>	0.191** (2.29)	-0.488*** (-9.97)	-0.489*** (-10.01)	-0.119 (-1.49)	-0.485*** (-14.86)	-0.027 (-1.03)	-0.486*** (-16.17)	-0.443*** (-10.34)
<i>Roa</i>	0.081 (0.34)	-7.567*** (-48.86)	-7.565*** (-48.87)	-0.224 (-1.41)	-7.588*** (-117.61)	-0.127** (-2.47)	-7.586*** (-127.77)	-7.665*** (-49.60)
<i>Inv</i>	-0.292** (-2.28)	-0.090 (-1.32)	-0.087 (-1.27)	-0.239* (-1.69)	-0.090 (-1.56)	-0.058 (-1.27)	-0.106** (-2.03)	-0.179*** (-2.82)
<i>RD</i>	1.916*** (9.39)	-0.279** (-2.16)	-0.284** (-2.21)	0.309* (1.81)	-0.308*** (-4.40)	0.053 (0.94)	-0.264*** (-4.06)	-0.282** (-2.16)
<i>Top1</i>	0.114 (1.42)	-0.007 (-0.10)	-0.007 (-0.11)	-0.060 (-0.43)	-0.004 (-0.06)	-0.052 (-1.14)	-0.003 (-0.05)	-0.043 (-0.66)
<i>Dual</i>	0.046* (1.93)	0.002 (0.24)	0.002 (0.22)	-0.023 (-1.12)	0.011 (1.29)	-0.007 (-1.03)	0.006 (0.72)	0.007 (0.80)
<i>Grow</i>	-0.182*** (-4.80)	-0.010 (-1.02)	-0.009 (-0.93)	-0.029 (-1.36)	-0.005 (-0.57)	-0.001 (-0.18)	-0.013 (-1.59)	-0.014 (-1.61)
<i>Imr</i>		-0.047*** (-3.44)	-0.057*** (-4.24)					
<i>_cons</i>	-4.430*** (-17.16)	3.507*** (10.61)	3.520*** (10.65)	-2.557*** (-4.28)	3.781*** (13.89)	-0.175 (-0.90)	3.396*** (15.20)	4.110*** (13.84)
<i>Firm</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	16,533	16,533	16,533	14,777	14,777	14,777	14,777	16,533
<i>Adj. R²/</i>	0.224	0.640	0.640	0.046	0.606	0.381	0.641	0.682
Pseudo R ²								
<i>Wald Chi2</i>				59.29		352.17		

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses denote the *t*-values adjusted for firm-level clustered robust standard errors.

4.4.3. Exogenous policy shock

Following Xiao et al. (2024), we use the policy shock of the digital transformation of state-owned enterprises (SOEs) for robustness testing to address potential endogeneity resulting from omitted variables. In 2020, the State-owned Assets Supervision and Administration Commission issued the *Notice on Accelerating the Digital Transformation of State-owned Enterprises*, requiring SOEs to expedite their digital transformation. This policy is directly linked to digital innovation, providing new opportunities for firms to pursue digital upgrading and high-quality development (Zhou and Chen, 2023). Moreover, as the implementation of national policies is largely exogenous to firms, the policy shock satisfies the exogeneity assumption. Thus, we develop a difference-in-differences (DID) model to examine the impact of digital innovation on corporate

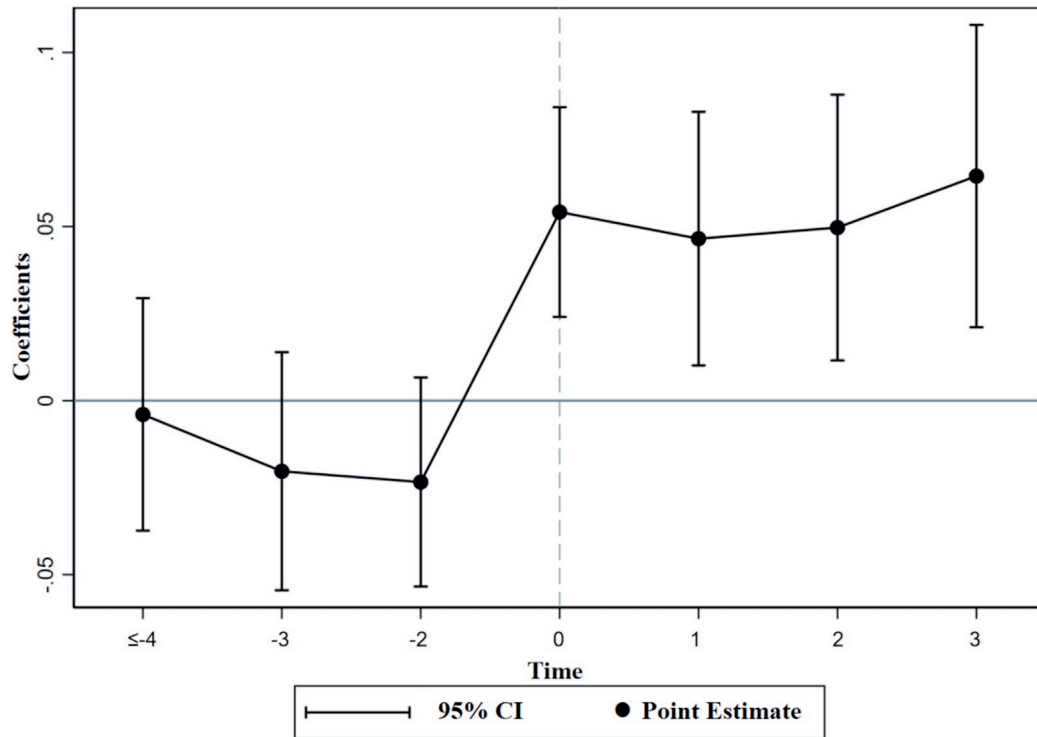


Fig. 2. Parallel trend test results.

sustainability. SOEs engaged in digital innovation are assigned to the treatment group, while the remaining firms constitute the control group. The variable *Treat* distinguishes the groups, and *Post* identifies the policy implementation period (equal to 1 for 2020 and after, and 0 for 2014–2019).

The prerequisite for conducting a DID regression analysis is that the treatment and control groups follow parallel trends prior to policy implementation. To verify this assumption, we follow Jacobson et al. (1993) and examine the trends of both groups before and after the policy intervention. Nonsignificant regression coefficients before the policy shock would imply comparable trends between the two groups, thereby validating the parallel trend assumption. Given the relatively small sample size for the 2014–2015 period, we aggregate observations from the 4 years before the implementation of the policy (2014–2015) into period -4 , enabling an examination of trends over a period from 4 years before the policy's enactment in 2020 until the end of the observation window. Using the year before the policy (2019) as the baseline, we test the annual changes before and after the implementation of the policy. The results in Fig. 2 show that the regression coefficients for all pre-policy years are not statistically significant. In contrast, beginning in 2020, firms in the treatment group show a significant improvement in corporate sustainability relative to the control group. These results confirm the absence of systematic differences between the two groups prior to the policy shock, thereby satisfying the parallel trend assumption.

4.5. Robustness checks

4.5.1. Alternative measure of the independent variable

We use an alternative measure of the independent variable to mitigate the adverse impact of variable measurement bias on our regression results. Following Zheng and Zhuang (2024), we perform a text analysis of *DI*. We calculate the frequency of keywords across three digital innovation dimensions, namely products, processes and business models, and then rerun our regression analyses. Columns (1) and (2) of Table 6 reveal that

Table 6

Robustness checks results: Re-measurement of independent variable, and one-period lagged independent and control variables.

Variables	Re-measurement of independent variable		One-period lagged independent and control variables			
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>
<i>DI</i>	0.183*** (2.74)	0.183*** (2.75)				
<i>Din1</i>			0.025*** (3.91)		0.024*** (3.86)	
<i>Din2</i>				0.039** (2.41)		0.042*** (2.59)
<i>Epu</i>		-0.736*** (-3.80)			2.037** (2.24)	2.086** (2.28)
<i>DI</i> × <i>Epu</i>		0.239*** (2.86)				
<i>Din1</i> × <i>Epu</i>					0.042*** (2.96)	
<i>Din2</i> × <i>Epu</i>						0.261*** (3.00)
<i>Size</i>	-0.016 (-1.29)	-0.016 (-1.27)	0.178*** (7.23)	0.181*** (7.42)	0.178*** (7.27)	0.180*** (7.39)
<i>Age</i>	0.099 (1.56)	0.098 (1.55)	0.035 (0.26)	0.003 (0.02)	0.032 (0.23)	0.006 (0.05)
<i>Lev</i>	-0.472*** (-10.99)	-0.472*** (-11.02)	-0.404*** (-5.57)	-0.406*** (-5.57)	-0.406*** (-5.59)	-0.405*** (-5.56)
<i>Roa</i>	-7.792*** (-51.43)	-7.788*** (-51.38)	-2.000*** (-11.93)	-1.994*** (-11.82)	-2.002*** (-11.93)	-1.997*** (-11.84)
<i>Inv</i>	-0.104 (-1.61)	-0.107* (-1.65)	-0.344*** (-3.25)	-0.343*** (-3.21)	-0.347*** (-3.27)	-0.336*** (-3.14)
<i>RD</i>	-0.342** (-2.24)	-0.346** (-2.28)	0.561* (1.86)	0.564* (1.91)	0.561* (1.85)	0.560* (1.92)
<i>Top1</i>	-0.006 (-0.09)	-0.003 (-0.05)	-0.271** (-2.28)	-0.305*** (-2.60)	-0.271** (-2.28)	-0.310*** (-2.65)
<i>Dual</i>	-0.002 (-0.23)	-0.002 (-0.24)	-0.004 (-0.23)	-0.006 (-0.35)	-0.004 (-0.25)	-0.006 (-0.34)
<i>Grow</i>	-0.012 (-1.39)	-0.012 (-1.41)	-0.128*** (-6.73)	-0.138*** (-7.19)	-0.127*** (-6.69)	-0.138*** (-7.17)
<i>_cons</i>	3.287*** (10.14)	4.199*** (19.29)	-0.984* (-1.68)	-0.946 (-1.62)	-4.061** (-2.23)	-4.073** (-2.23)
<i>Firm</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	16,373	16,373	10,997	10,997	10,997	10,997
<i>Adj. R²</i>	0.668	0.668	0.132	0.137	0.133	0.138

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses denote the *t*-values adjusted for firm-level clustered robust standard errors.

the regression coefficients of *DI* and *DI* × *Epu* remain significant and positive, further validating our hypotheses.

4.5.2. One-period lagged independent and control variables

Given the lagged effects of digital innovation, we lag the independent and control variables by one period. The results in Columns (3)–(6) of Table 6 are consistent with our baseline regression results.

4.5.3. Including industry fixed effects

To mitigate potential omitted variable bias, particularly endogeneity arising from unobservable heterogeneity at the industry level, we include industry (*Industry*) fixed effects, along with firm and year fixed effects. This approach systematically accounts for the influence of industry-specific, time-varying confounding factors. The results in Columns (1)–(4) of Table 7 remain consistent with our baseline regression results.

4.5.4. Alternative measure of the dependent variable

Given the potential measurement bias of the dependent variable, following Ain et al. (2022), we use the Van Hoorn sustainable growth model as specified in Eq. (5) to construct a corporate sustainability indicator (*Sgr*) and rerun our regression analyses. The results in Columns (5)–(8) of Table 7 are consistent with our baseline regression findings, confirming the robustness of our conclusions.

Table 7

Robustness checks results: Including industry fixed effect, and re-measurement of dependent variable.

Variables	Including industry fixed effect				Re-measurement of dependent variable			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sgr</i>	<i>Sgr</i>	<i>Sgr</i>	<i>Sgr</i>
<i>Din1</i>	0.013*** (3.48)		0.013*** (3.45)		0.004** (2.15)		0.004* (1.92)	
<i>Din2</i>		0.027*** (2.93)		0.031*** (3.25)		0.014** (2.17)		0.016** (2.46)
<i>Epu</i>			-0.632*** (-2.98)	-0.633*** (-3.00)			-0.133 (-1.02)	-0.136 (-1.04)
<i>Din1</i> × <i>Epu</i>			0.019** (2.52)				0.012** (2.38)	
<i>Din2</i> × <i>Epu</i>				0.112*** (2.81)				0.053** (2.11)
<i>Size</i>	-0.017 (-1.17)	-0.014 (-0.98)	-0.016 (-1.15)	-0.014 (-1.01)	-0.035*** (-6.68)	-0.034*** (-3.27)	-0.035*** (-3.32)	-0.035*** (-3.28)
<i>Age</i>	0.067 (0.89)	0.060 (0.78)	0.066 (0.87)	0.060 (0.78)	0.049 (1.39)	0.045 (0.99)	0.048 (1.05)	0.045 (0.99)
<i>Lev</i>	-0.486*** (-10.03)	-0.487*** (-10.05)	-0.486*** (-10.03)	-0.486*** (-10.03)	0.715*** (37.21)	0.715*** (23.09)	0.716*** (23.09)	0.715*** (23.09)
<i>Roa</i>	-7.590*** (-49.49)	-7.589*** (-49.49)	-7.588*** (-49.47)	-7.589*** (-49.49)	2.210*** (46.28)	2.209*** (31.70)	2.211*** (31.68)	2.210*** (31.71)
<i>Inv</i>	-0.110 (-1.60)	-0.111 (-1.62)	-0.111 (-1.63)	-0.108 (-1.57)	0.175*** (5.42)	0.174*** (4.31)	0.175*** (4.31)	0.176*** (4.34)
<i>RD</i>	-0.274** (-2.15)	-0.272** (-2.14)	-0.274** (-2.16)	-0.274** (-2.16)	0.032 (0.48)	0.034 (0.46)	0.031 (0.42)	0.033 (0.44)
<i>Top1</i>	-0.005 (-0.07)	-0.004 (-0.06)	-0.004 (-0.06)	-0.004 (-0.06)	-0.137*** (-4.29)	-0.137** (-2.39)	-0.137** (-2.39)	-0.137** (-2.39)
<i>Dual</i>	0.002 (0.25)	0.002 (0.23)	0.002 (0.24)	0.002 (0.23)	-0.007 (-1.36)	-0.007 (-1.09)	-0.007 (-1.10)	-0.007 (-1.09)
<i>Grow</i>	-0.016* (-1.75)	-0.017* (-1.79)	-0.016* (-1.78)	-0.017* (-1.81)	0.025*** (5.07)	0.025*** (3.98)	0.024*** (3.95)	0.025*** (3.96)
<i>_cons</i>	3.236*** (9.56)	3.206*** (9.47)	4.020*** (16.11)	4.004*** (16.05)	0.513*** (3.65)	0.500** (2.17)	0.676*** (3.93)	0.671*** (3.92)
<i>Industry</i>	Yes	Yes	Yes	Yes	No	No	No	No
<i>Firm</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	16,533	16,533	16,533	16,533	14,497	14,497	14,497	14,497
<i>Adj. R²</i>	0.642	0.642	0.642	0.642	0.264	0.264	0.265	0.265

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the *t*-values adjusted for firm-level clustered robust standard errors.

Table 8
Robustness checks results: Excluding high-tech firms and specific years.

Variables	Excluding high-tech firms				Excluding specific years			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>
<i>Din1</i>	0.015** (2.13)		0.016** (2.17)		0.019*** (3.82)		0.017*** (3.50)	
<i>Din2</i>		0.048*** (2.69)		0.058*** (3.15)		0.029** (2.39)		0.035*** (2.82)
<i>Epu</i>			-1.429*** (-3.64)	-1.425*** (-3.61)			-0.719*** (-3.08)	-0.696*** (-2.99)
<i>Din1</i> × <i>Epu</i>			0.036** (2.47)				0.023** (2.18)	
<i>Din2</i> × <i>Epu</i>				0.263*** (2.97)				0.204*** (4.19)
<i>Size</i>	0.021 (0.86)	0.023 (0.94)	0.022 (0.88)	0.023 (0.91)	-0.025 (-1.56)	-0.022 (-1.37)	-0.024 (-1.53)	-0.023 (-1.43)
<i>Age</i>	0.186 (1.36)	0.170 (1.24)	0.182 (1.33)	0.172 (1.25)	0.115 (1.34)	0.104 (1.20)	0.112 (1.31)	0.106 (1.22)
<i>Lev</i>	-0.599*** (-6.50)	-0.596*** (-6.47)	-0.599*** (-6.50)	-0.594*** (-6.41)	-0.492*** (-8.05)	-0.492*** (-8.05)	-0.492*** (-8.05)	-0.491*** (-8.02)
<i>Roa</i>	-8.518*** (-29.72)	-8.514*** (-29.67)	-8.512*** (-29.67)	-8.511*** (-29.74)	-7.714*** (-41.29)	-7.714*** (-41.27)	-7.711*** (-41.27)	-7.712*** (-41.31)
<i>Inv</i>	0.087 (0.65)	0.092 (0.70)	0.089 (0.67)	0.100 (0.76)	-0.103 (-1.21)	-0.109 (-1.27)	-0.107 (-1.26)	-0.101 (-1.18)
<i>RD</i>	-0.883*** (-3.10)	-0.870*** (-3.03)	-0.876*** (-3.09)	-0.884*** (-3.09)	-0.157 (-1.40)	-0.156 (-1.39)	-0.155 (-1.39)	-0.159 (-1.43)
<i>Top1</i>	-0.156 (-1.29)	-0.160 (-1.32)	-0.156 (-1.29)	-0.156 (-1.29)	0.011 (0.12)	0.013 (0.15)	0.012 (0.13)	0.014 (0.16)
<i>Dual</i>	-0.026 (-1.35)	2.317*** (3.50)	2.312*** (3.49)	4.097*** (10.08)	4.088*** (10.15)	0.003 (0.24)	0.003 (0.24)	0.003 (0.24)
<i>Grow</i>	-0.021 (-1.21)	-0.021 (-1.21)	-0.021 (-1.23)	-0.021 (-1.23)	0.001 (0.11)	0.000 (0.00)	0.001 (0.10)	-0.0003 (-0.03)
<i>_cons</i>	2.317*** (3.50)	2.312*** (3.49)	4.097*** (10.08)	4.088*** (10.15)	0.340*** (9.33)	0.338*** (9.23)	0.430*** (15.16)	0.425*** (14.95)
<i>Firm</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	4785	4785	4785	4785	11,479	11,479	11,479	11,479
<i>Adj. R²</i>	0.634	0.634	0.634	0.635	0.633	0.632	0.633	0.633

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses denote the *t*-values adjusted for firm-level clustered robust standard errors.

$$Sgr = Npm \times Rr \times (1 + Em) / [1/Tat - Npm \times Rr \times (1 + Em)]. \quad (5)$$

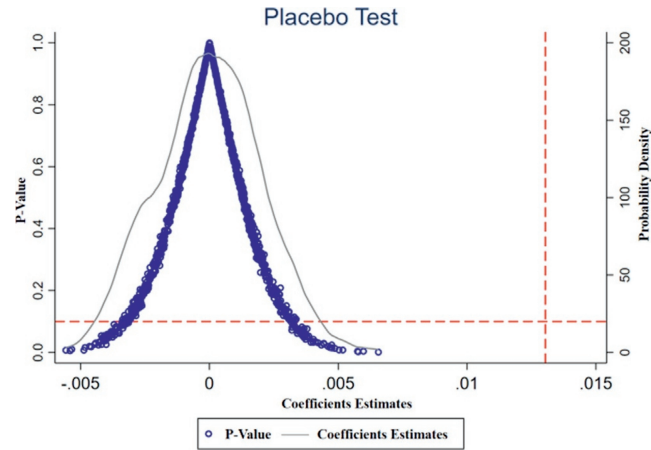
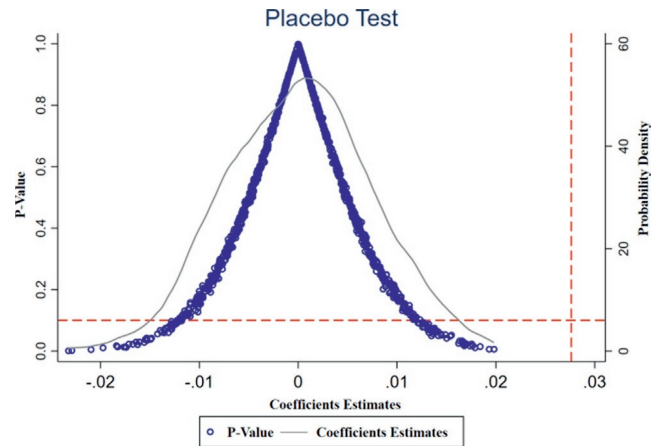
where *Npm*, *Rr*, *Em* and *Tat* respectively represent net profit margin, earnings retention ratio, equity ratio and total asset turnover rate.

4.5.5. Excluding high-tech firms

Given that high-tech firms typically exhibit high levels of digital innovation and distinctive business models, we conduct a new regression analysis after excluding these firms. The results in Columns (1)–(4) of Table 8 are consistent with our baseline regression results in Table 4, demonstrating the robustness of our findings.

4.5.6. Excluding specific years

To mitigate the influence of exceptional external events on our regression results, we remove the years that were significantly affected by major economic events during our research period, as follows: (1) 2015, which was affected by systemic volatility (in June and July 2015, the Chinese A-share market experienced a period

Fig. 3. Placebo test results (*Din1*).Fig. 4. Placebo test results (*Din2*).

of systemic volatility, characterized by more than 1000 listed firms experiencing maximum declines in 16 trading days); and (2) 2020 and 2021, which were influenced by the COVID-19 pandemic. The results in Columns (5)–(8) of Table 8 further support our hypotheses.

4.5.7. Placebo test

To verify that our baseline regression results are not due to chance, we conduct a placebo test. We randomly assign *Din1*, *Din2* and their interaction terms to the sample firms to generate simulated variables (*Din1_random*, *Din2_random*, *Din1* × *Epu_random* and *Din2* × *Epu_random*), and perform 1000 random iterations. Figs. 3–6 show that the regression coefficients of these 1000 iterations cluster around 0, with most of the absolute values being lower than those reported in Columns (3)–(6) of Table 4. Only a negligible number of *p*-values are less than 0.1. These results reveal that digital innovation genuinely enhances corporate sustainability and that greater economic policy uncertainty strengthens this positive relationship, confirming the robustness of our baseline results.

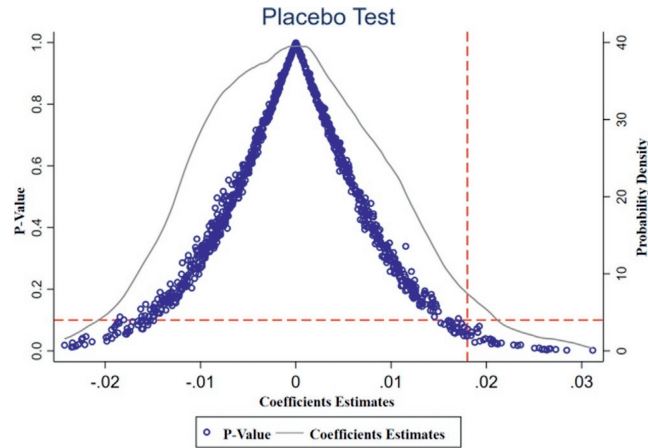


Fig. 5. Placebo test results ($Din1 \times Epu$).

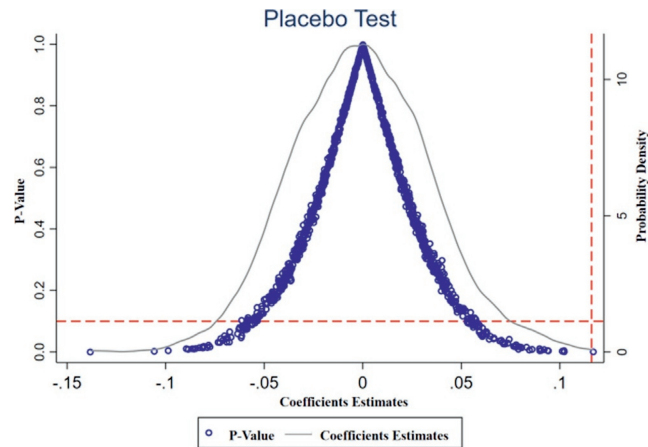


Fig. 6. Placebo test results ($Din2 \times Epu$).

5. Further analysis

5.1. Mechanism test

The previous analysis suggests that digital innovation improves corporate sustainability by enhancing management efficiency and mitigating managerial myopia. Following Wang et al. (2023a), we use the grouped regression method to validate the effectiveness of this mechanism. We predict that digital innovation will further improve the sustainability of firms with lower management efficiency and stronger managerial myopia.

5.1.1. Management efficiency mechanism

Following Sun et al. (2024), we measure management efficiency ($Meff$) using the residuals from the regression specified in Eq. (6). We then perform grouped regression analyses based on the annual industry averages of $Meff$. Table 9 shows that the coefficients of $Din1$ and $Din2$ are significant and positive in the group with lower management efficiency, but not significant in the group with higher management efficiency. These results indicate that digital innovation promotes corporate sustainability by improving management efficiency.

Table 9
Mechanism test results.

Variables	Higher management efficiency		Lower management efficiency		Higher managerial myopia		Lower managerial myopia	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>
<i>Din1</i>	0.008 (1.368)		0.010** (2.063)		0.012** (2.40)		0.007 (1.62)	
<i>Din2</i>		0.015 (0.964)		0.027** (2.148)		0.034** (2.30)		-0.004 (-0.43)
<i>Size</i>	-0.027 (-1.457)	-0.026** (-2.022)	-0.036** (-2.376)	-0.033** (-2.173)	-0.044** (-1.99)	-0.041* (-1.86)	-0.033*** (-3.31)	-0.032** (-2.02)
<i>Age</i>	0.078 (0.732)	0.072 (0.786)	0.021 (0.238)	0.019 (0.219)	-0.132 (-1.13)	-0.135 (-1.16)	0.100 (1.41)	0.098 (1.15)
<i>Lev</i>	-0.461*** (-6.308)	-0.462*** (-9.680)	-0.490*** (-8.894)	-0.491*** (-8.930)	-0.486*** (-6.22)	-0.488*** (-6.28)	-0.426*** (-11.91)	-0.427*** (-7.88)
<i>Roa</i>	-7.309*** (-32.879)	-7.311*** (-83.352)	-8.466*** (-41.093)	-8.459*** (-41.049)	-8.465*** (-36.47)	-8.468*** (-36.50)	-7.701*** (-104.06)	-7.703*** (-41.18)
<i>Inv</i>	-0.127 (-1.208)	-0.128 (-1.550)	-0.073 (-0.744)	-0.078 (-0.802)	-0.077 (-0.64)	-0.082 (-0.68)	-0.142** (-2.39)	-0.144** (-2.07)
<i>RD</i>	-0.095 (-1.053)	-0.093 (-1.050)	-0.469** (-2.498)	-0.461** (-2.450)	-0.771*** (-2.65)	-0.769*** (-2.66)	-0.026 (-0.30)	-0.022 (-0.20)
<i>Top1</i>	0.035 (0.364)	0.034 (0.418)	0.095 (1.063)	0.093 (1.043)	-0.089 (-0.78)	-0.080 (-0.71)	-0.058 (-0.98)	-0.059 (-0.80)
<i>Dual</i>	0.004 (0.270)	0.004 (0.345)	0.003 (0.269)	0.003 (0.268)	0.006 (0.43)	0.005 (0.39)	0.008 (0.85)	0.008 (0.69)
<i>Grow</i>	-0.028* (-1.844)	-0.028** (-2.335)	-0.005 (-0.481)	-0.005 (-0.481)	0.003 (0.17)	0.002 (0.12)	-0.019** (-2.00)	-0.019* (-1.79)
<i>_cons</i>	3.494*** (7.835)	3.486*** (10.069)	3.921*** (9.872)	3.860*** (9.689)	4.570*** (8.96)	4.513*** (8.90)	3.634*** (13.39)	3.619*** (9.82)
<i>Firm</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	9330	9330	7203	7203	5098	5098	11,435	11,435
<i>Adj.R²</i>	0.619	0.619	0.722	0.722	0.827	0.827	0.637	0.637

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the *t*-values adjusted for firm-level clustered robust standard errors.

$$Mcost = \alpha_0 + \alpha_1 Asset + \alpha_2 Employee + \alpha_3 Profitup + Year + Industry + \varepsilon \quad (6)$$

where *Mcost*, *Asset* and *Employee* refer to management expenses, total assets and number of employees, respectively, while *Profitup* is the ratio of operating costs to operating revenue. After taking the natural logarithm of these variables and accounting for firm and year effects, we assess management efficiency (*Meff*) based on regression residuals, with smaller residuals indicating greater efficiency.

5.1.2. Managerial myopia mechanism

Following Guo et al. (2023), we construct a lexicon of “short-term perspective” terms and perform a textual analysis of the Management Discussion and Analysis (MD&A) sections in the annual reports of listed firms. Managerial myopia (*Myopia*) is quantified by multiplying the proportion of these terms in the MD&A by 100, with higher values indicating a stronger tendency toward short-termism. We then conduct a grouped regression analysis based on the industry-year mean of *Myopia*. Table 9 reveals that when managerial myopia is stronger, the coefficients of *Din1* and *Din2* are significant and positive, while they are not statistically significant when managerial myopia is weaker. These results indicate that digital innovation mitigates managerial myopia and thus enhances corporate sustainability.

5.2. Heterogeneity tests

5.2.1. Heterogeneous effect of firms' green transformation capabilities

The green transformation represents a crucial pathway for firms to integrate low-carbon development principles into their operations and serves as an effective strategy for balancing economic performance with environmental protection (Liu and Cao, 2025). Robust green transformation capabilities strengthen the generative nature of digital innovation (Yoo et al., 2012) and encourage firms to improve their energy efficiency and management effectiveness, thus establishing a solid foundation for sustainable development (Arfi et al., 2018). Furthermore, firms with strong green transformation capabilities actively embrace green development principles and obtain policy subsidies and incentives that provide financial support for digital innovation. Such financial and institutional support helps firms to enhance the information integration function of digital innovation (Nambisan et al., 2019) and improves the visualization and traceability of multidimensional information, thereby strengthening shareholder oversight. Additionally, cultivating a green image helps firms build reputational capital and gain investor trust (Cheng and Wu, 2024). This, in turn, reduces external pressure on management, discourages short-term decision-making and thus fosters corporate sustainability. Therefore, digital innovation should have a more pronounced effect on promoting sustainable development in firms with stronger green transformation capabilities.

Following Cheng and Wu (2024), we apply textual analysis to quantify the frequency of 113 keywords related to five dimensions, namely public advocacy initiatives, strategic concepts, technological innovation, pollution control and monitoring management in the annual reports of publicly listed firms. We use the natural logarithm of keyword frequency plus 1 as a proxy to quantify firms' green transformation capabilities (*Gretrans*). We then perform a grouped regression based on the industry-year mean to examine the heterogeneous effect of green transformation capabilities on the relationship between digital innovation and corporate sustainability. Firms above the median are classified as the "high capability" group, while those below the median are designated as the "low capability" group. Table 10 shows that for firms with stronger green transformation capabilities, the coefficients of *Din1* and *Din2* are significant and positive, while they are not significant for firms with weaker green transformation capabilities. These findings suggest that digital innovation has a greater positive effect on the sustainability of firms with stronger green transformation capabilities, in line with our expectations.

5.2.2. Heterogeneous effect of regional marketization

The impact of digital innovation on corporate sustainability may depend on regional marketization. Higher marketization improves resource allocation, thereby encouraging firms to leverage digital innovation tools to enhance their management efficiency and support sustainable development. Moreover, regions with higher levels of marketization offer more abundant technological resources for digital innovation (Liu et al., 2023), which strengthens firms' innovation capabilities and promotes their sustainable development. Therefore, regional marketization is expected to influence the relationship between digital innovation and corporate sustainability.

We adopt the marketization index to measure regional marketization (*Market*). We perform regression analyses by grouping firms based on the industry-year median of the marketization index to examine the heterogeneous effects of regional marketization on the relationship between digital innovation and corporate sustainability. Firms above the median are classified as the "high marketization" group, while those below the median are designated as the "low marketization" group. Table 10 shows that the coefficients of *Din1* and *Din2* are significant and positive for firms facing higher marketization levels, but not significant for firms facing lower marketization levels. These results indicate that higher marketization enhances the positive impact of digital innovation on corporate sustainability, consistent with our expectations.

5.3. The impact of different types of digital innovations on corporate sustainability

Digital innovation patents include three categories: invention patents, utility model patents and design patents. We investigate the effects of these three types of patents on corporate sustainability. Table 11 shows

Table 10
Heterogeneity test results.

Variables	Higher capability	Lower capability	Higher capability	Lower capability	Higher marketization	Lower marketization	Higher marketization	Lower marketization
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)
<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>
<i>Din1</i>	0.013** (2.227)	0.004 (0.941)	0.047*** (3.161)	0.012 (1.150)	0.014*** (2.821)	0.008 (1.314)	0.034*** (2.690)	0.022 (1.621)
<i>Din2</i>	-0.076*** (-3.632)	0.012 (0.782)	-0.074*** (-3.529)	0.013 (0.844)	-0.030 (-1.538)	-0.016 (-0.891)	-0.027 (-1.398)	-0.015 (-0.821)
<i>Size</i>	0.053 (0.508)	0.003 (0.034)	0.041 (0.392)	0.000 (0.003)	0.024 (0.234)	0.178 (1.645)	0.172 (1.594)	0.172 (1.594)
<i>Age</i>	-0.439*** (-6.409)	-0.573*** (-10.067)	-0.440*** (-6.391)	-0.574*** (-10.118)	-0.470*** (-6.680)	-0.489*** (-7.393)	-0.473*** (-6.719)	-0.488*** (-7.381)
<i>Lev</i>	-7.835*** (-36.022)	-7.947*** (-39.455)	-7.843*** (-36.061)	-7.945*** (-39.496)	-7.611*** (-38.453)	-7.682*** (-31.716)	-7.618*** (-38.485)	-7.674*** (-31.767)
<i>Roa</i>	-0.253** (-2.386)	0.051 (0.582)	-0.249** (-2.338)	0.049 (0.567)	-0.209** (-2.321)	0.048 (0.478)	-0.210** (-2.336)	0.048 (0.476)
<i>Inv</i>	-0.611*** (-3.091)	-0.117 (-1.106)	-0.627*** (-3.192)	-0.116 (-1.096)	-0.239 (-1.078)	-0.118 (-1.401)	-0.241 (-1.091)	-0.115 (-1.360)
<i>RD</i>	-0.041 (-0.377)	0.038 (0.467)	-0.035 (-0.327)	0.038 (0.467)	-0.019 (-0.220)	-0.038 (-0.362)	-0.016 (-0.181)	-0.038 (-0.362)
<i>Top1</i>	-0.001 (-0.045)	0.015 (1.296)	0.001 (0.059)	0.015 (1.277)	0.004 (0.293)	0.010 (0.711)	0.004 (0.331)	0.010 (0.688)
<i>Dual</i>	0.005 (0.258)	-0.006 (-0.490)	0.004 (0.222)	-0.005 (-0.481)	0.004 (0.297)	-0.027* (-1.943)	0.003 (0.281)	-0.027** (-1.967)
<i>Grow</i>	4.733*** (9.897)	2.930*** (7.621)	4.714*** (9.857)	2.921*** (7.625)	3.765*** (8.721)	3.059*** (6.448)	3.729*** (8.622)	3.044*** (6.454)
<i>_cons</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Firm</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	8038	8495	8038	8495	9379	7154	9379	7154
<i>Adj. R²</i>	0.470	0.513	0.470	0.513	0.672	0.634	0.671	0.634
<i>Chow Test</i>	30.13***		39.38***		15.06***		16.82***	

Note: ***, **, * and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the *t*-values adjusted for firm-level clustered robust standard errors.

Table 11
Impacts of different types of digital innovation on corporate sustainability.

Variables	(1)	(2)	(3)
	<i>Sdl</i>	<i>Sdl</i>	<i>Sdl</i>
<i>faming</i>	0.009*** (2.83)		
<i>shiyong</i>		0.006** (2.04)	
<i>waiguan</i>			0.004 (1.34)
<i>Size</i>	-0.006 (-0.46)	-0.005 (-0.42)	-0.005 (-0.38)
<i>Age</i>	0.033 (0.50)	0.031 (0.47)	0.029 (0.45)
<i>Lev</i>	-0.559*** (-12.86)	-0.558*** (-12.85)	-0.559*** (-12.85)
<i>Roa</i>	-8.031*** (-59.38)	-8.029*** (-59.30)	-8.028*** (-59.21)
<i>Inv</i>	-0.097 (-1.62)	-0.098 (-1.64)	-0.098 (-1.63)
<i>RD</i>	-0.235*** (-2.87)	-0.230*** (-2.81)	-0.228*** (-2.77)
<i>Top1</i>	-0.023 (-0.37)	-0.023 (-0.37)	-0.023 (-0.36)
<i>Dual</i>	0.007 (0.81)	0.007 (0.81)	0.006 (0.76)
<i>Grow</i>	-0.007 (-0.83)	-0.006 (-0.80)	-0.006 (-0.82)
<i>_cons</i>	3.265*** (11.28)	3.264*** (11.26)	3.264*** (11.28)
<i>Firm</i>	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes
<i>N</i>	16,533	16,533	16,533
<i>Adj. R²</i>	0.706	0.706	0.706

Note: ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively. The values in parentheses denote the *t*-values adjusted for firm-level clustered robust standard errors.

that invention and utility model patents have a significant and positive effect on corporate sustainability, while design patents exhibit no statistically significant effect. This difference is likely to arise from inherent variations in technological complexity, functional innovation and information processing requirements among these patent types. Invention and utility model patents generally exhibit high technical complexity (Higham et al., 2021). They require the integration of cross-disciplinary knowledge, the coordination of information across multiple domains and advanced information processing in product design, performance optimization and production. These capabilities generate substantial economic benefits and support corporate sustainability. In contrast, design patents emphasize aesthetic appearance, with information processing demands largely limited to perceptual and stylistic combinations. They impose lower requirements for cross-knowledge integration and complex technical reasoning (Menell and Corren, 2021), which makes it difficult to achieve meaningful functional innovations or establish long-term competitive advantages. Furthermore, design patents are closely linked to consumer preferences, have short life cycles and are subject to frequent updates. These characteristics reduce their ability to contribute to sustained corporate performance (Andersson et al., 2023). Their technological impacts on sustainability objectives such as energy conservation, emissions reduction and resource efficiency are limited and may even be negative if environmentally harmful materials are used (Demirel and Kesidou, 2019). Additionally, owing to the limited protection provided by the intellectual property system and the weak enforcement of related laws, firms have difficulty establishing strong technological

barriers or monopolistic advantages through these patents (Gallini, 2002; Bessen and Meurer, 2009), which further reduces their ability to promote corporate sustainability. Consequently, the positive effect of digital innovation on corporate sustainability primarily comes from invention and utility model patents that exhibit higher technical sophistication and functional value. To achieve long-term sustainable development goals, firms pursuing digital innovation should prioritize functional and technical enhancements, strengthen their core R&D capabilities and seek synergistic improvements in their environmental, social and economic performance.

6. Conclusion and discussion

6.1. Conclusions

This study investigates the role of digital innovation in encouraging corporate sustainability, providing valuable insights into how technological advances reshape sustainability imperatives. By analyzing data from Chinese A-share listed firms from 2014 to 2023, we show that digital innovation significantly promotes corporate sustainability. Moreover, the positive effect of digital innovation is more pronounced when economic policy uncertainty intensifies. The mechanism tests demonstrate that digital innovation fosters corporate sustainability by enhancing management efficiency and alleviating managerial myopia. The heterogeneity tests indicate that the effect of digital innovation on corporate sustainability is more pronounced for firms with stronger green transformation capabilities and for those located in regions with higher marketization. Finally, our analysis of the different types of digital innovation patents reveals that, compared with design patents, utility model and invention patents significantly promote corporate sustainability.

6.2. Theoretical contributions

This study makes significant contributions to the field in several aspects. First, this study introduces a new perspective and strategic orientation to promote corporate sustainability. While the literature has extensively explored the impact of factors such as digital technologies (Mubarak et al., 2021), green innovation (Aftab et al., 2022), corporate governance (Buchetti et al., 2024) and government governance (Luo and Xu, 2024) on corporate sustainability, no studies have systematically examined its mechanisms from the perspective of digital innovation. Moreover, we extend the theoretical discussion of Teece et al. (1997) on the mechanisms through which firms sustain their competitive advantage in dynamic environments. To elucidate how digital innovation enhances corporate sustainability during external turbulence, we incorporate the strengthening effect of economic policy uncertainty. The results challenge prior studies (Geng et al., 2023) that posit that economic policy uncertainty suppresses firms' digital innovation output and R&D investments, thus impeding their long-term development. Therefore, our study not only offers a new theoretical perspective for subsequent research but also provides a solid theoretical foundation for firms to develop effective response strategies and optimize innovation pathways in complex and dynamic environments.

Second, drawing on information processing theory (Galbraith, 1973), this study develops our theoretical understanding of how digital innovation drives corporate sustainability. Prior studies show that digital innovation improves both economic performance (Babilla, 2023; Chen et al., 2023; Liu et al., 2023) and environmental performance (Chen and Hao, 2022; Huang et al., 2023b; Li et al., 2024; Wang and Yang, 2024). Our study demonstrates that, in complex international economic environments, digital innovation enhances management efficiency and mitigates managerial myopia by improving firms' information processing capacity and their ability to absorb uncertainty. These enhancements facilitate simultaneous improvements in economic and environmental performance, thereby promoting corporate sustainability. While Zhou et al. (2025) demonstrate that innovation in artificial intelligence primarily enhances corporate governance and social outcomes without significantly promoting environmental performance, we reveal that digital innovation produces synergistic gains across both economic and environmental dimensions. This distinction highlights the critical role of digital innovation in strengthening firms' ability to collect, analyze and apply complex environmental and

operational information. Consequently, firms can effectively convert their informational advantages into concrete results that support sustainable development. These findings provide a new theoretical perspective on how digital innovation fosters corporate sustainability under economic policy uncertainty, open up new research directions and propose actionable insights for firms aiming to optimize innovation strategies and achieve sustainable development in complex environments.

Third, from the two crucial perspectives of corporate green transformation capabilities and regional marketization, this study extends the theoretical boundary conditions of the effect of digital innovation on corporate sustainability. As demonstrated by Liu and Cao (2024), robust green transformation capabilities constitute an effective strategic mechanism for simultaneously enhancing economic performance and environmental protection. By examining the heterogeneous effects of green transformation capabilities and regional marketization, our study uncovers the mechanisms through which digital innovation fosters corporate sustainability in diverse organizational and institutional contexts. The results corroborate those of Liu and Cao (2025), demonstrating that strong green transformation capabilities are an effective strategic pathway to simultaneously enhance economic performance and environmental protection, and confirm the findings of Liu et al. (2023) by demonstrating that regions with higher levels of marketisation offer more abundant technological resources and institutional support for digital innovation. These findings deepen our theoretical understanding of how digital innovation promotes corporate sustainability and offer valuable guidance for policymakers and managers for designing sustainable development strategies and optimizing governance practices.

6.3. *Practical implications*

Firms should fully acknowledge the strategic value of digital innovation to enhance their management efficiency and alleviate managerial myopia. They should prioritize the advanced information processing capabilities provided by high-tech invention and utility model patents in the field of digital innovation. Firms should embed digital innovation throughout the entire process of decision-making, planning, execution and monitoring. Strengthening the intelligent construction of accounting information systems and promoting deep integration of management systems with digital technologies can enhance information quality and resource allocation efficiency. By enhancing cross-departmental collaboration to track corporate dynamics in real time and respond quickly, firms can strengthen their adaptability to complex information environments. Especially during periods of high economic policy uncertainty, firms should exploit the strategic flexibility offered by digital assets to improve their resilience in complex environments. Simultaneously, developing their green transformation capabilities by optimizing their energy structures, promoting green manufacturing, enhancing technological innovation and refining institutional mechanisms will allow firms to maintain strategic robustness amid policy fluctuations and market changes. This integrated approach can cultivate competitive advantages and ultimately support high-quality, sustainable development.

With regard to external investors, during periods of high economic policy uncertainty, it is crucial to fully understand the complex risks and pressures that management faces when implementing new strategies and pursuing high-value digital innovation. For firms with strong green transformation capabilities and operating in regions with high levels of marketization, investors should be patient. By providing financial and technical support, investors can help management alleviate internal and external pressures, reduce managerial myopia and focus on long-term initiatives. Especially during periods of high economic policy uncertainty, investors must maintain their confidence in digital innovation projects. Given the limited impact of design digital innovation patents on corporate sustainability, investors should prioritize supporting invention and utility model patents. This approach can prevent the premature reduction of R&D budgets in the pursuit of short-term profits, thereby protecting firms' long-term competitive advantage.

From the government's perspective, firms with strong green transformation capabilities should benefit from comprehensive policy subsidies and preferential measures. This support can help enhance their digital innovation capacity, expand opportunities for experimentation and sustainably stimulate innovative activity. In the context of high economic policy uncertainty, the government should implement stable digital infrastructure policies. Initiatives such as tax credits for cloud migration can help reduce the short-term costs and risks asso-

ciated with corporate digital innovation. At the same time, the government should lead efforts to establish and maintain a stable and predictable market environment by improving market oversight and intellectual property protection systems. This would foster an innovation-friendly climate, protect market order and ensure fair competition, thereby preserving firms' innovative achievements. By raising marketization levels and strengthening regional innovation effects, firms can access a wider range of technological resources, supporting sustainable development.

6.4. Limitations and future research

This study has several limitations that warrant further investigation in future research. First, our keyword database is based on the *Classification of Digital Economy and Its Core Industries (2021)* and we use pre-trained language models such as SBERT and Python programming to identify digital innovation patents. Although this approach broadens the coverage of core content in the traditional digital economy through semantic similarity matching, it does not fully capture certain emerging digital industries, such as generative artificial intelligence, blockchain and quantum computing. Given the rapid evolution of digital technologies, the existing lexicon has limitations both in terms of coverage and dynamic updating, potentially underestimating the true contribution of emerging technologies to corporate digital innovation. We call for future research to adopt patent citation network methodologies to capture disruptive digital innovations more comprehensively and quickly. By constructing and analyzing citation networks between patents, this approach could reveal cross-domain technological integration and knowledge flows, systematically tracks high-impact patents and their diffusion pathways and enable the early identification of emerging technologies located at critical intersections of knowledge. Additionally, patents primarily reflect technological outputs rather than organizational adoption and often overlook process innovations and business model innovations that affect internal corporate management. Although we use keyword frequency from corporate annual reports across three dimensions (i.e., products, processes and business models) to measure digital innovation in robustness tests, future research could incorporate advanced text analysis methods to explore the multidimensional role of digital innovation within firms, from both a technological and strategic perspective, thereby enhancing the robustness of our findings. Second, we examine the moderating effect of economic policy uncertainty on the relationship between digital innovation and corporate sustainability, as well as the heterogeneous effects of green transition capabilities and marketization. Future research could expand our analytical framework to include additional internal corporate characteristics and external environmental factors, thereby deepening our understanding of the boundary conditions of the effect of digital innovation on corporate sustainability.

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Declaration of competing interest

The authors confirm that there are no relevant financial or non-financial competing interests to report.

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