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China Journal of Accounting Research



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Production and hosting by Elsevier

Radarweg 29, 1043 NX Amsterdam, The Netherlands

ISSN 1755-3091

© China Journal of Accounting Research

Founded by Sun Yat-sen University and City University of Hong Kong

Sponsored by: 
广州注册会计师协会

Published quarterly in March, June, September, and December

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CHINA JOURNAL OF ACCOUNTING RESEARCH

Volume 19/1 (2026)

Available online at www.sciencedirect.com

ScienceDirect



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Sustained learning and corporate ESG practices: evidence from returnee CEOs in China



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ARTICLE INFO

Article history:

Received 16 August 2025

Accepted 26 December 2025

Available online 16 January 2026

Keywords:

Returnee CEOs

ESG mandates

ESG performance

International knowledge transfer

ABSTRACT

This study explores a new channel through which environmental, social and governance (ESG) reporting mandates implemented in one country can influence firms' ESG performance in another country, focusing on returnee CEOs in China who studied or worked abroad. We find that compared with Chinese firms led by returnee CEOs from countries without ESG mandates or Chinese CEOs with no foreign experience, firms managed by returnee CEOs from countries with ESG mandates implemented *after their return* show improved ESG performance. Therefore, returnee CEOs' sustained attention to foreign regulatory environments has a lasting impact on their decision-making, particularly in relation to ESG practices. Additionally, we find that the influence of foreign ESG reporting mandates on Chinese firms' ESG performance is stronger when mandates originate from countries with strong investor protection, when firms are audited by reputable auditors, when they generate more sales in foreign markets and when they have foreign subsidiaries. Our findings reveal how CEOs' foreign relationships and networks can transcend geographical boundaries, shape individual behaviors and decisions and enhance ESG practices.

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1. Introduction

In recent years, international talent migration has become increasingly common, with many skilled professionals choosing to return to their home countries after gaining education or work experience abroad (Giannetti et al., 2015; Quan et al., 2023). These returnee executives are considered crucial channels for international knowledge transfer, often bringing valuable technical expertise, diverse global perspectives and advanced management practices that can positively affect firms in their home country (Liu et al., 2010). The literature highlights the positive influence of returnee CEOs on various corporate outcomes, including financial performance, innovation and governance (Wang et al., 2022; Zhou et al., 2022; Quan et al., 2023). These studies typically focus on how the skills and knowledge acquired *during* a CEO's time abroad influence the firm's behavior *after* their return.

However, a significant gap remains. Most studies treat the characteristics of foreign host countries as static factors observed *before or during* returnee CEOs' overseas experiences. The possibility that *subsequent* institutional developments in these host countries—changes that occur *after* the CEO returns home—continue to shape their decision-making is often overlooked. This static view neglects the dynamic and lasting nature of international networks and social ties.

The global emphasis placed on environmental, social and governance (ESG) issues provides an ideal setting to investigate this sustained influence. In recent decades, numerous countries have introduced ESG reporting mandates, creating a natural experiment to test whether returnee CEOs remain attentive to policy developments in their former host countries. In contrast, China's ESG disclosure regime has historically been less developed and applies to a smaller subset of firms (Chen et al., 2018),¹ making it a context where foreign policy signals can be particularly influential.

This study investigates a new channel for international policy diffusion: the ongoing connection between returnee CEOs and their former host countries. We argue that due to global embeddedness (Granovetter, 1985),² returnee CEOs maintain professional and personal networks that keep them informed of major regulatory changes, such as the introduction of ESG mandates, even after their return to China. According to upper echelons theory (Hambrick and Mason, 1984), returnee CEOs' values, experiences and external foci directly influence their strategic choices. When a major economy where a CEO once lived or worked implements a stringent ESG mandate, it signals a shift in global norms and stakeholder expectations. Through their sustained networks, returnee CEOs become aware of this shift and are motivated to internalize these evolving standards, translating them into improved ESG practices within their Chinese firms to maintain their legitimacy on the global stage and leverage their international connections.

To isolate this “sustained learning” effect, we focus specifically on CEOs who returned to China *before* their host countries enacted ESG reporting mandates. This design allows us to test whether the *subsequent* introduction of such policies abroad influences the ESG performance of the firms they lead in their home country. We use a sample of Chinese listed firms from 2009 to 2020 to examine the impact of the subsequent introduction of ESG reporting mandates in the foreign host countries where returnee CEOs once studied or worked on the ESG performance of the Chinese firms they lead after returning to China. We find that returnee CEOs who returned to China prior to the implementation of ESG reporting mandates in the foreign countries where they studied or worked continue to be significantly influenced by these policies after their enactment, driving improvements in the ESG performance of the firms they lead in China. This finding is consistent with our conjecture that even after returning to their home countries, returnee CEOs continue to monitor and draw insights from the policy development of the countries or regions where they studied or worked. These CEOs not only integrate foreign policy ideals into their decision-making but also serve as key channels for the transfer of cross-border policy trends. Through their cross-cultural experiences and global perspectives, they introduce

¹ Although China implemented mandatory corporate social responsibility (CSR) disclosure in 2008, this mandate applies only to a relatively small subset of firms listed on Chinese stock exchanges (Chen et al., 2018).

² Global embeddedness or network theory suggests that individuals who have lived or worked in foreign countries often maintain an ongoing connection to those countries, particularly in terms of monitoring policy changes and institutional developments, through personal and professional networks that persist beyond their physical presence (Granovetter, 1985).

international policy trends and more advanced practices into domestic firms, thereby driving substantial progress in corporate ESG practices.

Furthermore, given that various factors may influence the decision-making and ESG performance of the firms they lead,³ we examine whether these factors moderate the relationship between foreign ESG reporting mandates and the ESG performance of firms led by returnee CEOs. We find that the positive effect is more pronounced when the host country where the CEO gained experience abroad has stronger institutional frameworks, characterized by stronger investor protection. The impact is also more significant when firms are audited by more reputable auditors, when they generate more sales in foreign markets and when they have foreign subsidiaries.

This study contributes to the literature in several ways. First, the literature mostly focuses on the immediate impact of CEOs' foreign experience on the financial and non-financial outcomes of the firms they lead. However, limited attention has been paid to how developments in the foreign countries where CEOs gained their international experience may continue to influence their decision-making and strategic choices when returning to their home country. Our findings confirm that returnee CEOs act as conduits for cross-border policy trends. The implementation of ESG mandates in their former host countries leads to a significant improvement in the ESG performance of their Chinese firms. This effect is stronger when the host country has stronger institutions (e.g., better investor protection), when the firm is audited by a Big 4 auditor and when the firm has greater exposure to foreign markets through sales or subsidiaries.

Second, this study introduces a new channel through which ESG policies in one country can influence corporate ESG performance in another. Although most studies on the transnational diffusion of policies focus on channels such as multinational corporations and international mergers and acquisitions (Ellis et al., 2017), our study extends these approaches by emphasizing the role of CEOs in driving the harmonization of improved ESG practices. Specifically, it explores how returnee CEOs, although not directly subject to foreign ESG reporting mandates, continue to monitor and internalize ESG developments in the countries where they studied or worked, thereby bringing global ESG standards into their domestic firms over time.

Thus, this study contributes to the literature by being among the first to demonstrate that the institutional characteristics of a foreign host country can influence returnee CEOs' decisions *after* their return, highlighting a dynamic and ongoing process of international learning. It also identifies a new, individual-driven channel for the transnational diffusion of ESG policies, complementing existing channels such as multinational corporations. Finally, it expands our understanding of the determinants of corporate ESG performance by showing that domestic firms can be shaped by regulatory changes in other countries through the personal networks of their leaders.

Finally, this study sheds light on the impact of foreign ESG reporting mandates on the ESG performance of domestic firms. In recent years, researchers have examined the factors that influence the ESG engagement or ESG performance of companies from different perspectives, including economic development (Ren et al., 2023), the implementation of reforms or government regulations (Liao et al., 2021; Wang et al., 2024; Xin et al., 2025), audit committee characteristics (Pozzoli et al., 2022), board structure (Husted and de Sousa-Filho, 2019; Liao et al., 2021), environmental risk (Du et al., 2024), CEO characteristics (Chen et al., 2023; Park et al., 2023) and institutional investors (Liu et al., 2023). However, the literature on the relationship between foreign ESG reporting mandates and the ESG performance of domestic firms is limited. Therefore, this study enriches the ESG literature by showing that the ESG performance of firms in one country can be shaped by the ESG reporting mandates of other countries. This finding is consistent with global network theory, which suggests that once an individual has lived in a country, its developments, policy changes and direction become an integral part of their ongoing interest. Even after returning home, the ties with this place (whether professional or personal) remain, and what happens there continues to matter (Granovetter, 1985).

The remainder of this paper is organized as follows. Section 2 provides a literature review and develops our hypotheses. Section 3 describes the sample and research design. Section 4 presents our main empirical results and additional analyses. Section 5 concludes the paper.

³ These factors include the characteristics of the foreign host country, the approach by which foreign ESG reporting mandates are implemented, the characteristics of their Chinese firm and the personal characteristics of the CEO (e.g., Liao et al., 2021; Park et al., 2023; Xin et al., 2025; see also Tsang et al., 2023 for a literature review).

2. Literature review and hypothesis development

2.1. Determinants of ESG performance

Prior research has examined a wide range of country-level and firm-level factors that influence ESG performance. For example, in terms of country-level institutional factors, Wang (2023) examines the impact of ESG disclosure regulations on banks and their transmission effects through the lending channel, focusing on U.S. firms borrowing from non-U.S. banks. The results show that borrowers exposed to these regulations improve their environmental and social performance following the disclosure mandate. Zhou et al. (2024) use a sample of Chinese firms to investigate the influence of specialized bankruptcy courts on corporate ESG performance and find that the establishment of such courts leads to improvements in corporate ESG performance. Similarly, You (2024) analyzes how social responsibility standards shape CSR practices through the influence of political leaders, corporate executives, employees and the public. The results show that firms headquartered in cities with stronger social responsibility standards tend to have higher ESG scores, even after controlling for various demographic, regional and economic factors.

In terms of firm-level variables, Burke (2022) conjectures that the media can affect public opinion on ESG issues and finds that coverage of negative ESG issues in prominent media outlets is more likely to result in CEO dismissal. In a follow-up paper, Long et al. (2024) use a sample of Chinese listed firms and find that negative sentiment in stock message boards prompts firms to engage in ESG greenwashing. Dyck et al. (2019) assess whether shareholders can drive the environmental and social performance of firms worldwide and find that across 41 countries, institutional ownership is positively associated with firms' environmental and social performance. Derchi et al. (2021) and Cohen et al. (2023) find that the use of CSR-linked compensation contracts for executive officers promotes CSR performance.

2.2. Managerial foreign experience

Since the implementation of China's Open Door Policy in 1978, there has been a rapid increase in the number of Chinese individuals studying or working abroad. Correspondingly, the migration of international talent has seen significant growth (Harrington and Seabrooke, 2020). Unlike the traditional brain drain, a growing number of skilled professionals are choosing to return to their home countries, contributing to what is often referred to as "brain gain" or "brain circulation" (Giannetti et al., 2015; Quan et al., 2023). Upper echelons theory posits that the values and experiences of executives influence the strategies and outcomes of the firms they lead (Hambrick and Mason, 1984). As such, a vast literature has explored the impact of executives' international experience on firm performance.⁴ In addition, studies suggest that executives' foreign experience can have an impact on firms' non-financial performance.⁵ This talent mobility is particularly beneficial for developing countries, as returnees are essential vectors for the transfer of knowledge, skills and innovative practices from abroad (Lin et al., 2016).

Compared with the development of ESG in developed countries, the perception of environmental management, social responsibility and sustainability is relatively low in China (Wong et al., 2010; Weber, 2014; Zhang et al., 2022; Li et al., 2025). Because most returnees come from developed countries or regions, they are likely to have learned ESG concepts and techniques and to be influenced by ethical organizational climate stemming through their experience abroad (Quan et al., 2023). Additionally, foreign experience can improve CEOs'

⁴ Returnee executives have generally acquired academic knowledge through education and/or technical training abroad, and they may have also gained practical business skills by working in a foreign business environment. Most of the literature suggests that the knowledge and skills acquired overseas by returnee executives can bring advanced management experience to the firms they lead, thereby improving their corporate governance (Iliev and Roth, 2018), financial performance (Carpenter et al., 2001; Dai and Liu, 2009; Le and Kroll, 2017; Miletkov et al., 2017; Liu et al., 2019), investment efficiency (Dai et al., 2018), internationalization (Mohr and Batsakis, 2019; Zhou et al., 2022), mergers and acquisitions (Xie and Wang, 2022), dividend payouts (Tao et al., 2022), initial public offering (IPO) valuation (Cumming et al., 2015) and financial reporting quality (Shan et al., 2023).

⁵ For example, Slater and Dixon-Fowler (2009) find that due to their enhanced capabilities, global network, awareness of societal stakeholders and personal values, CEOs' international experience improves their firms' CSR performance. Wang et al. (2022) and Quan et al. (2023) find that CEOs' foreign experience is positively associated with corporate green innovation.

ability to deal with complex issues and information (Slater and Dixon-Fowler, 2009; Quan et al., 2023). Learning theory suggests that when individuals face new, contradictory and meaningful environments, they are motivated to learn and adapt to those environments because of cognitive dissonance (Kolb, 1984). Therefore, the overseas environment can stimulate executives to learn and thus improve their general competence, including their creativity, problem-solving, leadership and information processing (Endicott et al., 2003; Suutari and Mäkelä, 2007; Quan et al., 2023).

To achieve sustainability, CEOs must focus on multiple areas simultaneously, such as environmental protection, social responsibility, corporate governance and financial performance (Ahn, 2022). Their enhanced ability to process complex information allows returnee CEOs to better target the achievement of sustainability as a company goal. In addition to enhancing their competencies, returnee CEOs' foreign experience may influence their cognitive orientation (Ricks et al., 1990; Hermann and Datta, 2005; Slater and Dixon-Fowler, 2009). For example, Slater and Dixon-Fowler (2009) document that CEOs with foreign experience are more aware of stakeholders than those without such experience. Through their exposure to different value systems and institutional environments, returnee CEOs develop a global mindset, increased empathy and a sense of responsibility and respect for others. Moreover, returnee CEOs have broader international social networks than local CEOs, giving them access to important resources and timely information and increasing opportunities to share their knowledge with others (Liu et al., 2010; Hao et al., 2019; Quan et al., 2023).

2.3. Hypothesis development

Global embeddedness theory (Granovetter, 1985) posits that individuals who have lived or worked abroad become embedded in transnational networks. These networks, composed of former colleagues, mentors, alumni and business partners, are not broken upon returning home (Conyon et al., 2019). Instead, they serve as essential channels for a continuous exchange of information. Returnee CEOs are thus likely to remain attentive to major developments, including regulatory changes such as the introduction of ESG mandates, in their former host countries. This is not merely a passive awareness; these CEOs have a vested interest in the regulatory climate of the countries where they maintain professional ties and where their firms might seek future opportunities, financing or partnerships.

Upper echelons theory (Hambrick and Mason, 1984) argues that executives' experiences and perspectives shape their strategic choices. For a returnee CEO, a new ESG mandate in a country such as the United States or the United Kingdom is not just foreign news; it is a signal from a familiar institutional environment. They are better equipped to interpret the significance of this mandate, understanding it as a response to investor pressure, a shift in consumer preferences or an emerging global standard. This interpretation, facilitated by their unique experiential perspective, leads them to view enhanced ESG performance as a strategic imperative for their firm's long-term competitiveness, risk management and access to global capital.

The interaction between sustained awareness, facilitated by international networks, and strategic interpretation, derived from prior experience abroad, establishes a mechanism whereby advances in ESG practices in foreign countries where returnee CEOs have studied or worked continue to shape their decisions and strategies upon returning to their home country.⁶ Therefore, based on this discussion, we predict that returnee CEOs are likely to improve their firms' ESG performance following the implementation of ESG reporting mandates in the foreign countries where they studied or lived. Thus, we state our first hypothesis as follows:

HI: Compared with firms led by returnee CEOs from foreign countries without ESG reporting mandates or by local CEOs, firms led by returnee CEOs from countries with ESG mandates implemented after their return show improved ESG performance following the implementation of ESG reporting mandates.

Country-level institutions vary significantly between countries (La Porta et al., 1998; La Porta et al., 2000). The literature suggests that strategic perspectives and decisions relating to ESG criteria vary according to the level of economic and institutional development (Julian and Ofori-Dankwa, 2013; Garcia and Orsato, 2020). For example, firms in developed countries or countries with stronger institutions, such as greater accountability

⁶ This can occur through both informal channels (professional social media, personal communications, alumni networks) and formal channels (monitoring international business news, reports from institutions in their former host countries). This ensures that they are aware of major policy changes such as the enactment of ESG mandates.

and lower levels of corruption, are associated with better CSR performance and higher levels of CSR disclosure (Ioannou and Serafeim, 2012; Cahan et al., 2016).

Furthermore, institutions in countries where returnees have gained experience abroad can influence returnees' ethics, behaviors and norms through international knowledge transfer (Zhang et al., 2018; Zhang et al., 2022; Quan et al., 2023), which may have a differential impact on ESG criteria. Supporting this view, Xu and Hou (2021) find that CEOs with foreign experience in developed countries, such as European countries and the United States, have a stronger effect on CSR than those with foreign experience in less developed countries. Zhang et al. (2022) show that Chinese managers who return from developed countries often adopt corporate philanthropy practices that are common in developed countries. Wang et al. (2022) and Quan et al. (2023) suggest that CEOs with foreign experience in developed countries can improve corporate green innovation. Dai et al. (2018) find that foreign experience in countries with effective governance and low corruption levels has significant marginal effects on improving the efficiency of investments in the home country.⁷

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

H2: The effect of ESG reporting mandates in foreign countries on the ESG performance of Chinese firms managed by returnee CEOs varies according to the characteristics of the host countries where they gained their foreign experience.

3. Data, sample and research design

3.1. Data sample and selection

We begin with all Chinese listed firms between 2009 and 2020.⁸ All financial variables, CEO characteristics and firm characteristics are obtained from the China Stock Market & Accounting Research (CSMAR) database. Data on corporate ESG performance are collected from Sino-Securities Index Information Service (Shanghai) Co. Ltd. via the Wind database. After excluding financial firms and observations with missing variables, our final sample contains 21,921 firm-year observations. We then collect CEO background information from the CSMAR database and manually verify CEOs' foreign experience. Following the literature (e.g., Giannetti et al., 2015; Yuan and Wen, 2018; Liao et al., 2022), we define foreign experience as study or work experience outside mainland China mentioned in CEO biographies in annual reports.

Panel A of Table 1 presents the distribution of returnee CEOs by country or region. Column (1) shows the countries where returnee CEOs gained their foreign experience. Column (2) reports the year in which foreign ESG reporting mandates are first implemented (*Foreign ESG Mandate*) by country or region, and columns (3) and (4) present the number and percentage of returnee CEOs, respectively. The results show a total of 395 returnee CEOs in our sample from countries or regions where ESG reporting mandates are implemented after their return to China and from countries where no ESG reporting mandates are implemented before or after their return. The largest number of returnee CEOs are from the United States (n = 120), representing 30.38 % of all returnee CEOs, followed by 24.05 % from Hong Kong and 10.63 % from the United Kingdom.

Panel B reports the number of CEOs and the number of observations in the treatment and control groups. In column (1), there are 211 returnee CEOs in the treatment group, which includes firms managed by returnee CEOs from foreign countries where ESG reporting mandates are implemented after their return to China. In column (2), there are 184 returnee CEOs in the first control group, which includes firms managed by returnee CEOs from foreign countries where no ESG reporting mandates are implemented before or after their return to China. In column (3), there are 5782 local CEOs in the second control group, which includes firms managed

⁷ Similarly, Yuan and Wen (2018) suggest that managers who gain foreign experience in the United States tend to be more influential and innovative than those who have foreign experience in other countries or regions. Duan et al. (2020) find that firms managed by returnee CEOs from more advanced legal institutions are more likely to undertake foreign IPOs. Wen et al. (2020) document that directors from countries with better investor protection are more likely to reduce corporate tax avoidance. Hao et al. (2021) show that the positive relationship between foreign culture and corporate transparency is stronger when directors have foreign experience in more incorruptible countries or regions. Liao et al. (2022) suggest that corporate transparency is higher for firms with returnee directors who have gained experience in countries with higher transparency standards.

⁸ We choose this sample period because the ESG data start in 2009.

Table 1
Distribution of CEOs.

Panel A

(1) Country	(2) Initial Year of Foreign ESG Reporting Mandates	(3) Number of Returnee CEOs	(4) % of Returnee CEOs
1 Afghanistan	n.a.	1	0.25
2 Algeria	n.a.	1	0.25
3 Australia	2003	7	1.77
4 Belgium	2009	1	0.25
5 Brazil	n.a.	1	0.25
6 Canada	2004	4	1.01
7 Denmark	2016	1	0.25
8 Ethiopia	n.a.	2	0.51
9 France	2001	3	0.76
10 Gambia	n.a.	1	0.25
11 Germany	2016	7	1.77
12 Hong Kong (China)	2015	95	24.05
13 India	2015	2	0.51
14 Indonesia	2012	2	0.51
15 Iran	n.a.	2	0.51
16 Italy	2016	2	0.51
17 Japan	n.a.	22	5.57
18 Kazakhstan	n.a.	1	0.25
19 Kenya	n.a.	1	0.25
20 Korea	n.a.	3	0.76
21 Kuwait	n.a.	1	0.25
22 Macao (China)	n.a.	9	2.28
23 Mauritania	n.a.	1	0.25
24 Netherlands	2016	6	1.52
25 Nigeria	n.a.	1	0.25
26 Russian Federation	n.a.	2	0.51
27 Singapore	2016	24	6.08
28 Sri Lanka	n.a.	1	0.25
29 Sultan	n.a.	2	0.51
30 Sweden	2016	1	0.25
31 Switzerland	n.a.	2	0.51
32 Taiwan (China)	2019	14	3.54
33 Thailand	n.a.	8	2.03
34 United Arab Emirates	n.a.	1	0.25
35 United Kingdom	2013	42	10.63
36 US	n.a.	120	30.38
37 Venezuela	n.a.	1	0.25
Total		395	100.00

Panel B

(1) Treatment # of CEOs	N	(2) Control 1 # of CEOs	N	(3) Control 2 # of CEOs	N	(4) Control 3 # of CEOs	N	(5) Control 4 # of CEOs	N
211	794	184	580	5782	20,333	97	214	6063	21,127

This table reports the distribution of CEOs. Panel A reports the distribution of Chinese returnee CEOs from different countries. Column (1) shows the countries where returnee CEOs gained foreign experience. Column (2) reports the initial year of foreign ESG reporting mandates (*Foreign ESG Mandate*) by each country, and columns (3) and (4) present the number and percentage of returnee CEOs from foreign countries where ESG reporting mandates are implemented after their return to China and from foreign countries where no ESG reporting mandates are implemented. Panel B reports the number of CEOs and the number of observations of the treatment and control groups. In column (1), the treatment firms represent firms managed by returnee CEOs from foreign countries where ESG reporting mandates are implemented after their return to China. Column (2) shows the first control group, which includes firms managed by returnee CEOs from foreign countries where no ESG reporting mandates are implemented before or after their return to China. Column (3) shows the second control group, which includes firms managed by local CEOs (i.e., CEOs with no foreign experience). Column (4) shows the third control group, which includes firms managed by all CEOs not included in the treatment sample (i.e., first control sample + second control sample + CEOs returned from foreign countries where ESG reporting mandates are implemented before their return to China).

by local CEOs (i.e., CEOs with no foreign experience). In column (4), there are 6063 CEOs in the third control group, which includes firms managed by all CEOs not included in the treatment sample (i.e., first control sample + second control sample + returnee CEOs from foreign countries where ESG reporting mandates are implemented before their return to China).

3.2. Research design

As ESG reporting mandates are initiated in different countries and in different years, we use the staggered difference-in-differences (DID) model to test our main hypothesis:

$$ESG\ Perf_{i,t} = \alpha_{i,t} + \beta Foreign\ ESG\ Mandate_{i,t} + \gamma Control_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t} \quad (1)$$

where i and t indicate the firm and the year, respectively. The dependent variable $ESG\ Perf$ represents the ESG performance of firms measured using the Sino-Securities Index ESG rating system, which is divided into nine levels (i.e., “C,” “CC,” “CCC,” “B,” “BB,” “BBB,” “A,” “AA” and “AAA”). Following prior studies (Feng et al., 2022; Jiang et al., 2022), C–AAA levels are assigned scores of 1–9, respectively. $Foreign\ ESG\ Mandate$ is the independent variable, which is an indicator variable set to 1 for all years following the introduction of ESG reporting mandates in the foreign host country where the company’s returnee CEO lived or studied.

$Controls$ is a vector of control variables. Following prior studies (Feng et al., 2022; Mu et al., 2023; Wang, 2023; Wang et al., 2023; Krueger et al., 2024), we control for the following CEO and firm characteristics: CEO gender ($Gender$), CEO age (Age), CEO tenure ($Tenure$), an indicator variable set to 1 if the chair of the board and the CEO are the same person ($Duality$), firm size ($Size$), leverage ($Leverage$), profitability (ROA), the total number of directors ($Directors$), the ratio of independent directors ($Independence$), the natural logarithm of the number of analysts following a firm ($LnAnalyst$), other receivables divided by total assets ($Receivables$), the logarithm of the year in which the firm was established ($Firm\ age$), the percentage of shares held by the largest shareholder ($Top1$), the ratio of shares held by the 2nd–5th largest shareholders to the shares held by the largest shareholder ($EquityBalance$), the proportion of foreign sales ($ForeignSale$), the ratio of fixed assets ($Fixed\ assets$), the ratio of advertising expenses ($Advertising$), the ratio of net cash flows (CFO), the revenue growth rate ($Growth$) and an indicator variable set to 1 if the auditor is a Big 4 auditor ($Big4$). δ_i and θ_t are firm and year indicators, respectively.⁹

Panel A of Table 2 presents the summary statistics of the key variables. For example, $ESG\ Perf$ has a mean of 4.092 and a standard deviation of 1.100, indicating that the ESG ratings of the sample firms vary greatly. The mean value of $Foreign\ ESG\ Mandate$ is 0.022, indicating that 2.2 % of the firms are managed by returnee CEOs from foreign countries with ESG reporting mandates implemented after their return. Other variables are comparable to previous findings in the literature (e.g., Feng et al., 2022; Mu et al., 2023; Wang et al., 2023). We present a Pearson correlation matrix in Panel B. As shown in the table, there is a positive correlation between $Foreign\ ESG\ Mandate$ and $ESG\ Perf$, significant at the 1 % level. This finding preliminarily supports $H1$, predicting a positive association between returnee CEOs from foreign host countries with ESG reporting mandates implemented after their return and corporate ESG performance in their home country. Other characteristics are generally consistent with the literature (e.g., Jiang et al., 2022; Luo et al., 2023).

Table 3 presents the results of the univariate tests. We define the treatment firms as those managed by returnee CEOs from foreign countries where ESG reporting mandates are implemented after their return to China (column (1)). To address potential sample selection bias, we define the control firms in four ways: firms managed by returnee CEOs from foreign countries where no ESG reporting mandates are implemented before or after their return to China (column (2)); firms managed by local CEOs (i.e., CEOs with no foreign experience) (column (3)); firms managed by returnee CEOs from foreign countries with ESG reporting mandates implemented before their return to China (column (4)); and firms managed by all CEOs not included in the treatment sample (i.e., first control sample + second control sample + third control sample + returnee CEOs from foreign countries where ESG reporting mandates are implemented before their return to China) (column (5)). The mean values of the variables for the treatment and control firms are presented in Table 3. We conduct

⁹ The definitions of all variables are summarized in Appendix A. All of the continuous variables are winsorized at the 1st and 99th percentiles. To adjust for possible cross-sectional and serial correlations, standard errors are clustered at the firm level.

Table 2
Summary statistics.

Panel A Summary statistics	N	Mean	Std	25th	Median	75th																
<i>ESG Perf</i>	21,921	4.096	1.101	3	4	5																
<i>Foreign ESG Mandate</i>	21,921	0.022	0.146	0	0	0																
<i>Gender</i>	21,921	0.941	0.237	1	1	1																
<i>Age</i>	21,921	49.574	6.466	46	50	54																
<i>Tenure</i>	21,921	3.512	3.606	1	2	5																
<i>Duality</i>	21,921	0.219	0.413	0	0	0																
<i>Size</i>	21,921	22.331	1.305	21.412	22.167	23.087																
<i>Leverage</i>	21,921	0.459	0.206	0.299	0.458	0.616																
<i>ROA</i>	21,921	0.036	0.057	0.013	0.034	0.063																
<i>Directors</i>	21,921	10.315	2.683	9	10	12																
<i>Independence</i>	21,921	0.372	0.052	0.333	0.333	0.417																
<i>LnAnalystist</i>	21,921	1.455	1.187	0	1.386	2.485																
<i>Receivables</i>	21,921	0.017	0.026	0.003	0.008	0.018																
<i>Firm age</i>	21,921	2.800	0.382	2.565	2.833	3.045																
<i>Top1</i>	21,921	35.608	15.124	23.610	33.740	46.120																
<i>EquityBalance</i>	21,921	0.648	0.569	0.203	0.479	0.934																
<i>ForeignSale</i>	21,921	0.111	0.193	0	0.005	0.139																
<i>Fixed assets</i>	21,921	0.232	0.171	0.097	0.199	0.332																
<i>Advertising</i>	21,921	0.072	0.324	0	0	0																
<i>CFO</i>	21,921	0.048	0.071	0.009	0.047	0.090																
<i>Growth</i>	21,921	0.161	0.428	-0.032	0.095	0.247																
<i>Big4</i>	21,921	0.066	0.248	0	0	0																
Panel B Correlation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
<i>1 ESG Perf</i>																						
<i>2 Foreign ESG Mandate</i>	<i>0.03</i>																					
<i>3 Gender</i>	<i>-0.01</i>	<i>-0.03</i>																				
<i>4 Age</i>	<i>0.06</i>	<i>-0.02</i>	<i>0.04</i>																			
<i>5 Tenure</i>	<i>0.06</i>	<i>0.04</i>	<i>0.02</i>	<i>0.28</i>																		
<i>6 Duality</i>	<i>-0.03</i>	<i>0.04</i>	<i>0.01</i>	<i>0.17</i>	<i>0.13</i>																	
<i>7 Size</i>	<i>0.26</i>	<i>0.01</i>	<i>0.05</i>	<i>0.13</i>	<i>0.06</i>	<i>-0.13</i>																
<i>8 Leverage</i>	<i>-0.05</i>	<i>-0.03</i>	<i>0.03</i>	<i>0.01</i>	<i>0.01</i>	<i>-0.11</i>	<i>0.45</i>															
<i>9 ROA</i>	<i>0.22</i>	<i>-0.02</i>	<i>-0.02</i>	<i>0.02</i>	<i>0.01</i>	<i>0.05</i>	<i>0.02</i>	<i>-0.38</i>	<i>1</i>													
<i>10 Directors</i>	<i>-0.02</i>	<i>-0.01</i>	<i>0.05</i>	<i>0.03</i>	<i>-0.08</i>	<i>-0.13</i>	<i>0.22</i>	<i>0.13</i>	<i>-0.07</i>													
<i>11 Independence</i>	<i>0.08</i>	<i>0.03</i>	<i>-0.05</i>	<i>0.01</i>	<i>0.00</i>	<i>0.09</i>	<i>0.04</i>	<i>0.01</i>	<i>-0.02</i>	<i>-0.26</i>												
<i>12 LnAnalystist</i>	<i>0.27</i>	<i>-0.02</i>	<i>0.01</i>	<i>0.02</i>	<i>0.04</i>	<i>0.02</i>	<i>0.40</i>	<i>-0.02</i>	<i>0.40</i>	<i>0.04</i>	<i>0.00</i>											
<i>13 Receivables</i>	<i>-0.08</i>	<i>0.01</i>	<i>0.01</i>	<i>-0.03</i>	<i>-0.00</i>	<i>-0.03</i>	<i>0.04</i>	<i>0.21</i>	<i>-0.17</i>	<i>0.02</i>	<i>0.03</i>	<i>-0.09</i>										
<i>14 Firm age</i>	<i>-0.03</i>	<i>0.03</i>	<i>-0.02</i>	<i>0.12</i>	<i>0.11</i>	<i>-0.07</i>	<i>0.15</i>	<i>0.12</i>	<i>-0.10</i>	<i>0.07</i>	<i>-0.00</i>	<i>-0.20</i>	<i>0.07</i>									
<i>15 Top1</i>	<i>-0.01</i>	<i>0.01</i>	<i>0.03</i>	<i>-0.14</i>	<i>-0.06</i>	<i>0.22</i>	<i>0.05</i>	<i>0.12</i>	<i>0.01</i>	<i>0.05</i>	<i>0.12</i>	<i>-0.08</i>	<i>-0.16</i>									

(continued on next page)

Table 2 (continued)

Panel B Correlation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
16 <i>EquityBalance</i>	-0.02	0.02	-0.02	0.01	0.02	0.07	-0.06	-0.10	0.01	0.04	-0.03	0.03	0.01	0.03	-0.66							
17 <i>ForeignSale</i>	-0.00	0.02	-0.02	-0.00	0.02	0.09	-0.07	-0.01	-0.05	0.00	0.01	-0.07	-0.07	-0.05	0.06							
18 <i>Fixed assets</i>	-0.05	-0.04	0.03	0.04	0.02	-0.07	0.05	0.03	-0.09	0.11	-0.05	0.01	-0.21	-0.05	0.06	-0.04	0.04					
19 <i>Advertising</i>	-0.03	0.01	0.02	0.02	0.02	0.00	0.01	0.00	0.01	0.01	0.01	-0.01	-0.03	0.07	-0.02	0.00	0.01	0.01				
20 <i>CFO</i>	0.09	0.00	-0.01	0.05	0.03	0.00	0.04	-0.19	0.39	0.02	-0.01	0.22	-0.16	-0.02	0.08	0.01	0.03	0.24	0.02			
21 <i>Growth</i>	-0.01	-0.01	-0.01	-0.04	-0.05	0.02	0.05	0.05	0.20	0.01	0.00	0.11	0.01	-0.04	0.02	0.04	-0.00	-0.07	0.01	0.02		
22 <i>Big4</i>	0.11	0.01	0.01	0.05	-0.01	-0.06	0.36	0.09	0.05	0.08	0.05	0.19	0.01	0.00	0.15	-0.01	-0.02	0.03	0.00	0.06	-0.01	

This table reports the summary statistics of the key variables in the sample from 2009 to 2020 for a total of 21,921 firm/year observations. The mean, standard deviation, median, and 25th and 75th percentile values are presented. All variables are defined in Appendix A.

This table presents the Pearson's correlations for the sample used in the regression analyses. All variables are defined in Appendix A. All of the continuous variables are winsorized at the 1st and 99th percentiles. Bold values indicate correlations that are statistically significant at the 10% level or higher.

Table 3
Univariate test results.

	(1) Treatment Sample		(2) Control Sample 1		(3) Control Sample 2		(4) Control Sample 3		(5) Control Sample 4					
	<i>firms managed by returnee CEOs from foreign countries with no ESG reporting mandates implemented before or after their return</i>	<i>returnee CEOs from foreign countries with no ESG reporting mandates implemented before or after their return</i>	<i>firms managed by local CEOs from foreign countries with no ESG reporting mandates implemented before their return to China</i>	<i>firms managed by local CEOs from foreign countries with no ESG reporting mandates implemented before their return to China</i>	<i>firms managed by local CEOs with ESG reporting mandates implemented before their return to China</i>	<i>firms managed by local CEOs with ESG reporting mandates implemented before their return to China</i>	<i>firms returned from foreign countries with ESG reporting mandates implemented before their return to China</i>	<i>firms returned from foreign countries with ESG reporting mandates implemented before their return to China</i>	<i>firms managed by all CEOs from foreign countries with ESG reporting mandates implemented before their return to China</i>	<i>firms managed by all CEOs from foreign countries with ESG reporting mandates implemented before their return to China</i>				
	N	Mean	N	Mean	Difference (1) - (2)	t-value	N	Mean	Difference (1) - (3)	t-value				
	(1)	(2)	(3)	(4)	(3)	(4)	(5)	(4)	(4)	(5)				
<i>ESG Perf</i>	794	4.29	580	4.08	0.21	3.48***	20,333	4.08	0.21	5.07***	21,127	4.09	0.20	4.97***
<i>Gender</i>	794	0.91	580	0.95	-0.04	-2.73***	20,333	0.94	-0.03	-3.90***	21,127	0.94	-0.03	-3.81***
<i>Age</i>	794	49.12	580	48.24	0.88	1.90*	20,333	49.64	-0.52	-2.24**	21,127	49.59	-0.47	-2.11**
<i>Tenure</i>	794	3.98	580	3.68	0.30	1.42	20,333	3.50	0.48	3.71***	21,127	3.49	0.49	3.81***
<i>Duality</i>	794	0.31	580	0.27	0.04	1.50	20,333	0.21	0.10	6.21***	21,127	0.22	0.09	6.13***
<i>Size</i>	794	22.41	580	22.36	0.05	0.60	20,333	22.32	0.09	1.60	21,127	22.71	-0.3	-3.03***
<i>Leverage</i>	794	0.44	580	0.43	0.01	1.25	20,333	0.46	-0.02	-2.75***	21,127	0.46	-0.02	-2.68***
<i>ROA</i>	794	0.03	580	0.04	-0.01	-2.28**	20,333	0.04	-0.01	-1.08*	21,127	0.04	-0.01	-1.26
<i>Directors</i>	794	10.14	580	10.03	0.11	0.73	20,333	10.33	-0.19	-1.97*	21,127	10.17	-0.03	-1.86*
<i>Independence</i>	794	0.38	580	0.37	0.01	2.72***	20,333	0.37	0.01	4.02***	21,127	0.38	0	3.89***
<i>LnAnalyst</i>	794	1.53	580	1.74	-0.21	-3.15***	20,333	1.44	0.09	2.12**	21,127	1.45	0.08	1.81*
<i>Receivables</i>	794	0.02	580	0.02	0.00	1.74*	20,333	0.02	0.00	1.03	21,127	0.02	0.00	1.08
<i>Firm age</i>	794	2.78	580	2.75	0.03	1.14	20,333	2.80	-0.02	-1.82*	21,127	2.88	-0.1	-1.89**
<i>Top1</i>	794	37.16	580	32.95	4.21	4.82***	20,333	35.61	1.55	2.69***	21,127	37.75	-0.59	-0.56
<i>EquityBalance</i>	794	0.63	580	0.82	-0.19	-5.30***	20,333	0.64	-0.01	-0.85	21,127	0.69	-0.06	-1.51
<i>ForeignSale</i>	794	0.13	580	0.18	-0.05	-3.32***	20,333	0.11	0.02	3.04***	21,127	0.17	-0.04	-2.30**
<i>Fixed assets</i>	794	0.21	580	0.21	0.00	0.64	20,333	0.23	-0.02	-4.12***	21,127	0.21	0	0.37
<i>Advertising</i>	794	0.10	580	0.05	0.05	2.71***	20,333	0.07	0.03	2.56**	21,127	0.02	0.08	3.00***
<i>CFO</i>	794	0.05	580	0.06	-0.01	-1.97*	20,333	0.05	0.00	0.49	21,127	0.06	-0.01	-2.53**
<i>Growth</i>	794	0.14	580	0.16	-0.02	-1.09	20,333	0.16	-0.02	-1.54	21,127	0.16	-0.02	-1.56
<i>Big4</i>	794	0.13	580	0.10	0.03	1.73*	20,333	0.61	-0.48	-7.54***	21,127	0.14	-0.01	-0.59

This table reports the results of univariate tests. In column (1), the treatment firms (i.e., Treatment Sample) represent firms managed by returnee CEOs from foreign countries where ESG reporting mandates are implemented after their return to China. In column (2), the first control sample (1) represents firms managed by returnee CEOs from foreign countries where no ESG reporting mandates are implemented before or after their return to China. In column (3), the second control sample (2) represents firms managed by local CEOs (i.e., CEOs with no foreign experience). In column (4), the third control sample (3) represents firms managed by returnee CEOs from foreign countries where ESG reporting mandates are implemented before their return to China. In column (5), the fourth control sample (4) represents firms managed by all CEOs not included in the treatment sample (i.e., first control sample + second control sample + third control sample). Two-tailed t-tests are performed to analyze the mean differences between the two groups of firms. All variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

two-tailed t-tests of the mean differences between the two groups and report the t-statistics in Table 3. The results indicate that the mean value of *ESG Perf* is significantly higher for the treatment firms than for the control firms, significant at the 1 % level in all columns. In terms of firm characteristics, the treatment firms have more female CEOs, more independent directors and a higher percentage of shares held by the largest shareholder than do the control firms.

4. Empirical analysis

4.1. Main tests

We present the results of Eq. (1) in Table 4. The treatment group consists of firms managed by returnee CEOs from foreign countries with ESG reporting mandates implemented after their return to China, while the control firms include firms managed by returnee CEOs from foreign countries with no ESG reporting mandates implemented before or after their return to China, firms managed by local CEOs, firms managed by returnee CEOs from foreign countries with ESG reporting mandates implemented before their return to China and firms managed by all CEOs excluding the treatment sample (columns (1)–(4), respectively). The results show that the coefficients of *Foreign ESG Mandate* are positive and significant at the 1 % level in all columns. The economic effect is also significant. For example, the coefficient of *Foreign ESG Mandate* in column (1) indicates that, on average, for each standard deviation increase in *Foreign ESG Mandate*, the average *ESG Perf* increases by 6.04 % ($0.452 \times 0.147/1.100$) standard deviations. *Size* is positively related to ESG performance in all columns, while the coefficients of *Leverage* and *Directors* are negative and statistically significant. These results are generally consistent with previous findings from ESG research in China (e.g., Liu et al., 2023; Mu et al., 2023; Wang et al., 2023). Overall, our findings in Table 4 support *H1*, predicting a positive relationship between *Foreign ESG Mandate* and *ESG Perf*.

4.2. Robustness tests

4.2.1. Parallel trend assumption

A common assumption in the DID method is the parallel trend assumption, which posits that firms in the treatment and control groups should follow parallel trends in the absence of treatment. This implies that in the absence of foreign ESG reporting mandates, the evolution of ESG performance from before to after the implementation period of foreign ESG reporting mandates in the treatment firms should be the same as the evolution of ESG performance from before to after the pseudo-implementation period of foreign ESG reporting mandates in the control firms.

To validate the parallel trend assumption, we estimate the following equation:

$$ESG\ Perf_{i,t} = \alpha_{i,t} + \sum_{\tau \in [-5,5]} \beta_{\tau} Foreign\ ESG\ Mandate_{i,\tau} + \gamma Control_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t} \quad (2)$$

where *Foreign ESG Mandate*_{*i,τ*} indicates year *τ*, relative to the introduction of foreign ESG reporting mandates in year *t* = 0, and four or more years before (*t* ≤ −4) or after (*t* ≥ +4) the introduction of a mandate are grouped together.

The results are shown in Table 5, and the coefficients and corresponding confidence intervals of *Foreign ESG Mandate*_{*i,τ*} are plotted in Fig. 1. The results show no significant difference between the treatment and control firms before the introduction of foreign ESG reporting mandates, which validates the parallel trend assumption. However, ESG performance shows an almost upward trend in the years following the introduction of ESG reporting mandates.

4.2.2. Fixed effects

To mitigate omitted variable bias, we estimate models that include industry, CEO and Year × Industry fixed effects. The results are reported in Table 6. In Panels A, B, C and D, the control firms are firms managed by returnee CEOs from foreign countries with no ESG reporting mandates implemented before or after their return to China, firms managed by local CEOs, firms managed by returnee CEOs from foreign countries with

Table 4

ESG reporting mandates of foreign countries and ESG performance of Chinese firms.

$Y = ESG\ Perf$	(1) Benchmark	(2) Control Sample 1	(3) Control Sample 2	(4) Control Sample 3
Foreign ESG Mandate	0.452*** (3.94)	0.238*** (3.56)	0.314** (2.03)	0.239*** (3.65)
<i>Gender</i>	-0.477 (-1.62)	0.051 (1.05)	0.563*** (2.77)	0.021 (0.45)
<i>Age</i>	-0.008 (-0.57)	0.001 (0.50)	0.002 (0.10)	0.000 (0.24)
<i>Tenure</i>	-0.002 (-0.09)	0.010*** (3.14)	-0.028 (-1.21)	0.009*** (2.82)
<i>Duality</i>	-0.033 (-0.21)	-0.099*** (-3.40)	-0.167 (-0.92)	-0.093*** (-3.23)
<i>Size</i>	0.199* (1.82)	0.207*** (8.65)	0.189 (1.30)	0.202*** (8.40)
<i>Leverage</i>	-1.318*** (-3.37)	-0.787*** (-8.69)	-0.750 (-1.61)	-0.784*** (-8.80)
<i>ROA</i>	0.470 (0.70)	0.963*** (4.98)	0.933 (1.09)	0.990*** (5.27)
<i>Directors</i>	-0.021* (-1.70)	-0.014*** (-4.40)	-0.016 (-1.22)	-0.014*** (-4.55)
<i>Independence</i>	-0.976 (-0.90)	1.394*** (6.16)	0.079 (0.05)	1.389*** (6.23)
<i>LnAnalysist</i>	0.055 (1.43)	0.067*** (6.15)	0.064 (1.27)	0.067*** (6.19)
<i>Receivables</i>	-0.145 (-0.12)	-1.172*** (-3.18)	-0.537 (-0.34)	-1.175*** (-3.25)
<i>Firm age</i>	0.203 (0.48)	-0.160 (-1.16)	0.323 (0.54)	-0.132 (-0.99)
<i>Top1</i>	-0.011 (-1.46)	-0.002 (-0.95)	-0.005 (-0.69)	-0.002 (-0.94)
<i>EquityBalance</i>	-0.125 (-0.99)	-0.132*** (-3.87)	-0.113 (-0.82)	-0.120*** (-3.57)
<i>ForeignSale</i>	-0.243 (-0.92)	-0.093 (-0.97)	-0.007 (-0.03)	-0.125 (-1.33)
<i>Fixed assets</i>	0.137 (0.25)	0.068 (0.64)	-0.009 (-0.01)	0.097 (0.92)
<i>Advertising</i>	0.032 (0.46)	-0.059 (-1.54)	0.061 (0.87)	-0.050 (-1.27)
<i>CFO</i>	-0.278 (-0.73)	-0.372*** (-3.44)	-0.347 (-0.89)	-0.357*** (-3.36)
<i>Growth</i>	-0.050 (-0.77)	-0.060*** (-4.04)	-0.072 (-0.93)	-0.064*** (-4.35)
<i>Big4</i>	0.353 (1.32)	-0.014 (-0.18)	0.760*** (4.48)	0.008 (0.11)
Year&Firm FE	YES	YES	YES	YES
N	1374	21,127	1008	21,921
Adj. R ²	0.698	0.588	0.723	0.589

This table presents the effects of ESG reporting mandates implemented in a foreign country (*Foreign ESG Mandate*) after returnee CEOs' return to China on the ESG performance of the Chinese firms they lead (*ESG Perf*). All variables are defined in Appendix A. Firm and year fixed effects are included in all regressions. The t-statistics are presented below the coefficients in parentheses calculated based on standard errors clustered by firm. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 5
Dynamic tests.

$Y = ESG\ Perf$	(1)	(2)	(3)	(4)
Benchmark	Control	Control	Control	Control
	Sample 1	Sample 2	Sample 3	Sample 4
<i>pre3</i>	0.178 (1.51)	-0.010 (-0.10)	0.260 (1.65)	-0.019 (-0.19)
<i>pre2</i>	0.041 (0.33)	0.008 (0.09)	0.097 (0.52)	0.007 (0.07)
<i>pre1</i>	0.109 (0.77)	-0.066 (-0.63)	0.277 (1.31)	-0.067 (-0.66)
Foreign ESG Mandate Year	0.309** (2.00)	0.154 (1.56)	0.497* (1.97)	0.167* (1.71)
<i>post1</i>	0.455*** (3.12)	0.267*** (2.84)	0.748*** (2.88)	0.288*** (3.20)
<i>post2</i>	0.510*** (3.53)	0.258** (2.36)	0.776*** (2.78)	0.295*** (2.87)
<i>post3</i>	0.426*** (3.36)	0.274** (2.28)	0.762*** (2.75)	0.330*** (3.18)
<i>post4</i>	0.380*** (3.09)	0.238** (2.40)	0.599** (2.06)	0.223*** (3.05)
Control Variables	YES	YES	YES	YES
Year&Firm FE	YES	YES	YES	YES
N	1374	21,127	1008	21,921
Adj. R ²	0.698	0.588	0.729	0.590

This table presents the results examining the parallel trend assumption. The dependent variable is corporate ESG performance (*ESG Perf*). The independent variables are individual year indicators (relative to the year in which *Foreign ESG Mandate* is implemented, year $t = 0$). All variables are defined in Appendix A. Firm and year fixed effects are included in all regressions. The t-statistics are presented below the coefficients in parentheses calculated based on standard errors clustered by firm. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

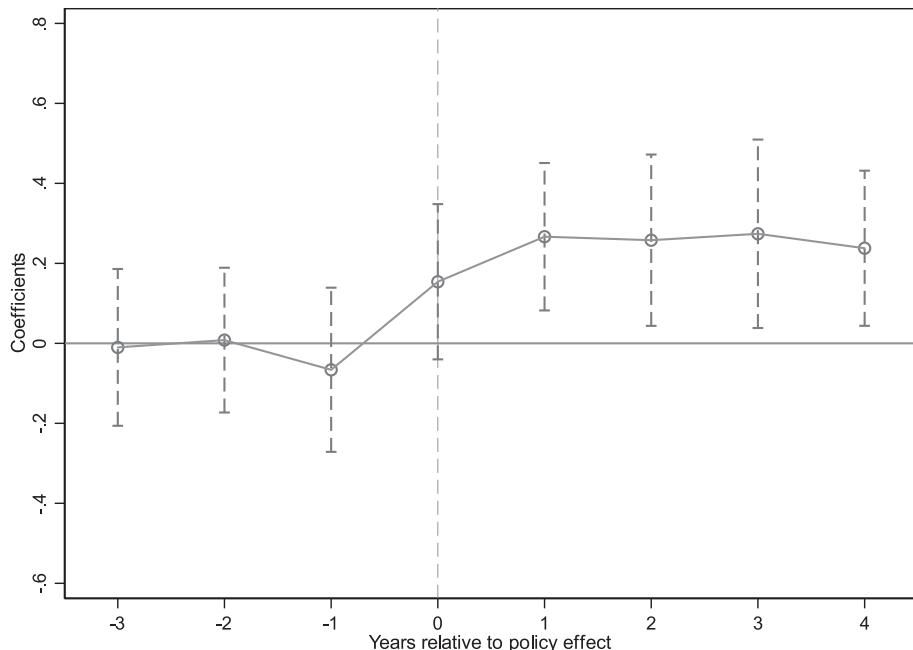


Fig. 1. ESG reporting mandates implemented in foreign countries after returnee CEOs' return to China and the ESG performance of Chinese firms: The x-axis represents the year relative to the first year in which an ESG reporting mandate is implemented in a foreign country. The y-axis is based on the regression results in Table 5, column (2). The dashed line indicates 95% confidence intervals.

Table 6
Fixed effects.

Panel A: Returnee CEOs from foreign countries where ESG reporting mandates are implemented after their return vs. returnees CEOs from foreign countries where no ESG reporting mandates are implemented before or after their return (Control sample 1)

<i>Y = ESG Perf</i>	(1)	(2)	(3)	(4)	(5)
Foreign ESG Mandate	0.450*** (3.85)	0.413*** (3.23)	0.429*** (3.32)	0.353** (2.54)	0.266* (1.67)
Control Variables	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES		
Industry FE	YES		YES		
CEO FE		YES	YES		YES
Year × Industry FE				YES	YES
N	1374	1374	1374	1374	1374
Adj. R ²	0.703	0.714	0.717	0.740	0.790

Panel B: Returnee CEOs from foreign countries where ESG reporting mandates are implemented after their return vs. their local (i.e., non-returnee) counterparts (Control sample 2)

<i>Y = ESG Perf</i>	(1)	(2)	(3)	(4)	(5)
Foreign ESG Mandate	0.236*** (3.52)	0.361*** (3.41)	0.370*** (3.45)	0.253*** (3.84)	0.356*** (3.26)
Control Variables	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES		
Industry FE	YES		YES		
CEO FE		YES	YES		YES
Year × Industry FE				YES	YES
N	21,127	21,127	21,127	21,127	21,127
Adj. R ²	0.590	0.698	0.699	0.598	0.729

Panel C: Returnee CEOs from foreign countries where ESG reporting mandates are implemented after their return vs. return after ESG mandate (Control sample 3)

<i>Y = ESG Perf</i>	(1)	(2)	(3)	(4)	(5)
Foreign ESG Mandate	0.325*** (3.03)	0.401** (2.38)	0.423** (2.39)	0.340*** (2.74)	0.380* (1.72)
Control Variables	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES		
Industry FE	YES		YES		
CEO FE		YES	YES		YES
Year × Industry FE				YES	YES
N	1008	1008	1008	1008	1008
Adj. R ²	0.300	0.738	0.742	0.600	0.796

Panel D: Returnee CEOs from foreign countries where ESG reporting mandates are implemented after their return vs. all other CEOs (Control sample 3)

<i>Y = ESG Perf</i>	(1)	(2)	(3)	(4)	(5)
Foreign ESG Mandate	0.236*** (3.60)	0.363*** (3.30)	0.372*** (3.33)	0.250*** (3.90)	0.356*** (3.25)
Control Variables	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES		
Industry FE	YES		YES		
CEO FE		YES	YES		YES
Year × Industry FE				YES	YES

(continued on next page)

Table 6 (continued)

Panel D: Returnee CEOs from foreign countries where ESG reporting mandates are implemented after their return vs. all other CEOs (Control sample 3)

<i>Y = ESG Perf</i>	(1)	(2)	(3)	(4)	(5)
N	21,921	21,921	21,921	21,921	21,921
Adj. R ²	0.591	0.725	0.726	0.600	0.731

This table presents the results of robustness tests. The dependent variable is firms' ESG performance (*ESG Perf*). All variables are defined in Appendix A. The t-statistics are presented below the coefficients in parentheses calculated based on standard errors clustered by firm. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

ESG reporting mandates implemented before their return to China and firms managed by all CEOs excluding the treatment sample, respectively. The coefficients of *Foreign ESG Mandates* in all columns are still positive and statistically significant after controlling for industry fixed effects (column (1)), CEO fixed effects (column (2)), industry and CEO fixed effects (column (3)), Year \times Industry fixed effects (column (4)) and CEO and Year \times Industry fixed effects (column (5)). Overall, the results in Table 6 indicate that our baseline results are robust and are unlikely to be driven by unobservable CEO variables or by unobservable industry-related economic factors.¹⁰

4.3. Further analysis

As discussed before, institutions in different countries may influence the ESG practices of returnee CEOs in various ways. We therefore use two measures of country-level institutions to examine whether the positive relationship between *Foreign ESG Mandate* and *ESG Perf* varies with the institutions of returnee CEOs' foreign host countries (*H2*).

We choose the following measures: (1) a pair of indicator variables, *Foreign ESG Mandate with Investor Protection_high* (*Foreign ESG Mandate with Investor Protection_low*), equal to 1 for all years following the introduction of ESG reporting mandates in the country where the returnee CEO lived or studied and this country has a high (low) level of investor protection, and 0 otherwise; and (2) another pair of indicator variables, *Foreign ESG Mandate with Protection of Minority Shareholders_high* (*Foreign ESG Mandate with Protection of Minority Shareholders_low*), equal to 1 for all years following the introduction of ESG reporting mandates in the country where the returnee CEO lived or studied and this country has a high (low) level of minority shareholder protection, and 0 otherwise.

The results are presented in Table 7. As shown in columns (1) and (2), the coefficients of *Foreign ESG Mandate with Investor Protection_high* and *Foreign ESG Mandate with Protection of Minority Shareholders_high* are positive and significant at the 1 % level. However, the coefficients of *Foreign ESG Mandate with Protection of Minority Shareholders_low* are not significant. Although the coefficient of *Foreign ESG Mandate with Investor Protection_low* is positive and significant, it is significantly smaller than the coefficient of *Foreign ESG Mandate with Investor Protection_high*. The results indicate that the treatment firms managed by returnee CEOs from host countries with stronger investor and minority shareholder protection tend to exhibit higher ESG performance than those managed by returnee CEOs from host countries with weaker investor and minority shareholder protection. Overall, the results in Table 7 support *H2*, showing that the positive relationship between returnee CEOs from foreign countries with ESG reporting mandates and their firms' ESG performance is more pronounced for returnee CEOs from host countries with stronger institutions than for those from host countries with weaker institutions.

¹⁰ In untabulated robustness tests, we exclude from our sample all cross-listed firms (e.g., A+H shares) to ensure that our results are not confounded by the different regulatory pressures these firms face. Our main finding, which shows that *Foreign ESG Mandate* positively affects *ESG Perf*, remains statistically significant and qualitatively unchanged.

Table 7

Foreign ESG reporting mandates, institutions of foreign countries, and ESG performance of Chinese firms.

<i>Y = ESG Perf</i>	(1)	(2)
Foreign ESG Mandate with Investor Protection_high	0.908*** (2.71)	
Foreign ESG Mandate with Investor Protection_low	0.225*** (3.34)	
Foreign ESG Mandate with Protection of Minority Shareholders_high		0.241*** (3.57)
Foreign ESG Mandate with Protection of Minority Shareholders_low		-0.052 (-1.29)
Tests of diff. in coefficients (p-value)	0.046	0.000
Control	YES	YES
Year&Firm	YES	YES
N	21,127	21,127
Adj. R ²	0.591	0.591

This table presents the roles of country-level institutions in the effect of foreign ESG reporting mandates implemented after returnee CEOs' return to China on the ESG performance of Chinese firms. The control sample is firms managed by local CEOs. The dependent variable in all columns is firms' ESG performance (*ESG Perf*). Country-level institutional variables are *Foreign ESG Mandate with Investor Protection_high* (*low*) and *Foreign ESG Mandate with Protection of Minority Shareholders_high* (*low*). All variables are defined in Appendix A. The control variables are included in all regressions but are not reported for simplicity. The t-statistics are presented under the coefficients in parentheses calculated based on standard errors clustered by firm. *, **, and *** indicate significance at the 10 %, 5 % and 1 % levels, respectively.

As globally recognized audit and consulting firms, the Big 4 provide professional governance reviews, compliance assessments and improvement recommendations, helping companies establish more robust governance frameworks to ensure adequate oversight and accountability at all levels (Fang et al., 2018). As the Big 4 are synonymous with high-quality corporate governance, companies that hire them are typically more focused on enhancing their governance practices. Good corporate governance is closely linked to strong ESG performance, as effective governance structures facilitate the fulfillment of ESG responsibilities. Therefore, we examine whether international Big 4 auditors can moderate the relationship between foreign ESG reporting mandates and corporate ESG performance in the home country.

Foreign ESG Mandate_Big4 is an indicator variable equal to 1 if a treatment firm is audited by a Big 4 auditor and 0 otherwise. *Foreign ESG Mandate_NonBig4* is an indicator variable equal to 1 if a treatment firm is not audited by a Big 4 auditor and 0 otherwise. The results are presented in column (1) of Table 8, and the coefficients of *Foreign ESG Mandate_Big4* and *Foreign ESG Mandate_NonBig4* are positive and significant. However, a test of the difference between the two coefficients indicates that the coefficient of *Foreign ESG Mandate_Big4* is significantly larger than that of *Foreign ESG Mandate_NonBig4*, implying that the ESG performance of the treatment firms audited by Big 4 auditors is significantly higher than that of the treatment firms not audited by Big 4 auditors.

Globally, and especially in developed markets, companies are facing increasingly stringent ESG requirements. Many international investors and regulatory bodies mandate that firms adhere to high standards in ESG practices. ESG performance has become a key criterion for global investors, consumers and other stakeholders when evaluating firms. To keep their stakeholders satisfied, companies are motivated to adopt proactive ESG strategies. As a result, companies with larger foreign sales are likely to exhibit higher levels of ESG performance. By demonstrating a strong commitment to ESG, companies can not only enhance their brand value in international markets but also build trust with consumers and investors. Thus, we next examine whether foreign sales can moderate the relationship between foreign ESG reporting mandates and corporate ESG performance in the home country. We create two indicator variables, *Foreign ESG Mandate_ForeignSale_high* and *Foreign ESG Mandate_ForeignSale_low*, equal to 1 if the proportion of foreign sales of a treatment firm is above and below the median value, respectively, and 0 otherwise.

Table 8

Foreign ESG reporting mandates, auditor choice/foreign sales/overseas subsidiaries of Chinese firms, and ESG performance of the firms.

<i>Y = ESG Perf</i>	(1)	(2)	(3)
<i>Foreign ESG Mandate_Big4</i>	0.468*** (3.70)		
<i>Foreign ESG Mandate_NonBig4</i>	0.209*** (2.85)		
<i>Foreign ESG Mandate_ForeignSale_high</i>		0.345*** (4.39)	
<i>Foreign ESG Mandate_ForeignSale_low</i>		0.125 (1.31)	
<i>Foreign ESG Mandate_WithOverseasSub</i>			0.303** (1.99)
<i>Foreign ESG Mandate_WithoutOverseasSub</i>			0.006 (0.05)
Tests of diff. in coefficients (p-value)	0.071	0.051	0.590
Year&Firm FE	YES	YES	YES
Control	YES	YES	YES
N	21,127	21,127	21,127
Adj. R ²	0.588	0.588	0.590

This table reports the roles of auditor choice and foreign sales in the effect of foreign ESG reporting mandates implemented after returnee CEOs' return to China on the ESG performance of Chinese firms. The control sample is firms managed by local CEOs. The dependent variable is firms' ESG performance (*ESG Perf*). The cross-sectional variables examined are *Foreign ESG Mandate_Big4*, *Foreign ESG Mandate_NonBig4*, *Foreign ESG Mandate_ForeignSale_high*, and *Foreign ESG Mandate_ForeignSale_low*, *Foreign ESG Mandate_WithOverseasSub*, and *Foreign ESG Mandate_WithoutOverseasSub*. All variables are defined in Appendix A. The control variables are included in all regressions but are not reported for simplicity. The t-statistics are presented under the coefficients in parentheses and are calculated using standard errors clustered by firm. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

The results are presented in column (2) of Table 8. The coefficient of *Foreign ESG Mandate_ForeignSale_high* is positive and significant, but the coefficient of *Foreign ESG Mandate_ForeignSale_low* is not significant. The difference between the two coefficients is statistically significant, indicating that the ESG performance of the treatment firms with higher foreign sales is significantly higher than that of the treatment firms with lower foreign sales.

Similarly, we examine whether connections to foreign markets can moderate the relationship between foreign ESG reporting mandates and corporate ESG performance in the home country. We create two additional indicator variables, *Foreign ESG Mandate_WithOverseasSub* and *Foreign ESG Mandate_WithoutOverseasSub*, equal to 1 for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO leads a firm with overseas subsidiaries, and 0 otherwise. The results reported in column (3) of Table 8 indicate that the ESG performance of the treatment firms with foreign subsidiaries is significantly higher than that of the treatment firms without foreign subsidiaries.

Following the literature (Aggarwal et al., 2005; Leuz and Wysocki, 2016), we next examine how the relationship between foreign ESG reporting mandates and corporate ESG performance is moderated by the institution issuing these mandates and by implementation requirements. Following Krueger et al. (2024), we create the following indicator variables: (1) mandates are issued by the stock exchange (*Foreign ESG Mandate Issued by Stock Exchange*); (2) mandates are issued by a government institution (*Foreign ESG Mandate Issued by Government Institution*); (3) mandates are implemented on a full-compliance basis (*Foreign ESG Mandate Comply*); (4) mandates are implemented on a comply-or-explain basis (*Foreign ESG Mandate Comply or Explain*); (5) mandates are implemented all at once (*Foreign ESG Mandate All at Once*); and (6) mandates are implemented one by one (*Foreign ESG Mandate Gradual*).

The results are shown in Table 9. The coefficients of *Foreign ESG Mandate Issued by Stock Exchange*, *Foreign ESG Mandate Issued by a Government Institution*, *Foreign ESG Mandate Comply* and *Foreign ESG Mandate Comply or Explain* are all positive and significant, indicating that ESG performance can be improved

Table 9

Foreign ESG reporting mandates, ESG implementation approach/institutions of foreign countries, and ESG performance of Chinese firms.

<i>Y = ESG Perf</i>	(1)	(2)	(3)
<i>Foreign ESG Mandate Issued by Stock Exchange</i>	0.213** (2.53)		
<i>Foreign ESG Mandate Issued by Government Institution</i>	0.286** (2.24)		
<i>Foreign ESG Mandate Comply</i>		0.294** (2.53)	
<i>Foreign ESG Mandate Comply or Explain</i>		0.204** (2.29)	
<i>Foreign ESG Mandate All at Once</i>			0.275*** (3.29)
<i>Foreign ESG Mandate Gradual</i>			0.189 (1.56)
Tests of diff. in coefficients (p-value)	0.629	0.534	0.556
Control	YES	YES	YES
Year&Firm FE	YES	YES	YES
N	21,127	21,127	21,127
Adj. R ²	0.588	0.588	0.588

This table presents the cross-sectional variation in the effect of foreign ESG reporting mandates implemented after returnee CEOs' return to China on the ESG performance of Chinese firms. The control sample is firms managed by local CEOs. The dependent variable is firms' ESG performance (*ESG Perf*). The cross-sectional variables examined are *Foreign ESG Mandate Issued by Stock Exchange*, *Foreign ESG Mandate Issued by Government Institution*, *Foreign ESG Mandate Comply*, *Foreign ESG Mandate Comply or Explain*, *Foreign ESG Mandate All at Once*, and *Foreign ESG Mandate Gradual*. All variables are defined in Appendix A. The control variables are included in all regressions but are not reported for simplicity. The t-statistics are presented under the coefficients in parentheses and are calculated using standard errors clustered by firm. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

regardless of the issuing body of the mandates and their implementation requirements. Moreover, although the coefficient of *Foreign ESG Mandate All at Once* is significant and that of *Foreign ESG Mandate Gradual* is not significant, there is no significant difference between the two coefficients.

As previously discussed, an executive's background and individual characteristics can influence their attention to issues such as social responsibility, environmental protection and corporate governance. These factors can, in turn, influence their firm's strategic decisions and resource allocation in these areas, ultimately affecting its ESG performance. Therefore, we examine whether CEO characteristics can affect the relationship between foreign ESG reporting mandates and corporate ESG performance.

We create three sets of indicator variables: (1) *Foreign ESG Mandate with male CEO* (*Foreign ESG Mandate with female CEO*), equal to 1 if the CEO of a treatment firm is a man (a woman) and 0 otherwise; (2) *Foreign ESG Mandate with older CEO* (*Foreign ESG Mandate with younger CEO*), equal to 1 if the age of the CEO of a treatment firm is above (below) the median value and 0 otherwise; and (3) *Foreign ESG Mandate with long-tenured CEO* (*Foreign ESG Mandate with short-tenured CEO*), equal to 1 if the tenure of the CEO of a treatment firm is above (below) the median value and 0 otherwise. The results are presented in Table 10. In all columns, the differences between the coefficients are not significant, indicating that CEO characteristics do not have a significant impact on the relationship between foreign ESG reporting mandates and corporate ESG performance in the home country.

5. Conclusion

This study provides robust evidence that the cross-border influence of ESG policies extends beyond direct regulatory jurisdictions through the unique channel of returnee CEOs. We demonstrate that the ESG performance of Chinese firms improves significantly following the implementation of ESG reporting mandates in the

Table 10

Foreign ESG reporting mandates, CEO characteristics, and ESG performance of Chinese firms.

<i>Y = ESG Perf</i>	(1)	(2)
<i>Foreign ESG Mandate with male CEO</i>	0.325*** (3.96)	
<i>Foreign ESG Mandate with female CEO</i>	0.139 (1.42)	
<i>Foreign ESG Mandate with older CEO</i>		0.257*** (3.63)
<i>Foreign ESG Mandate with younger CEO</i>		0.027 (0.16)
<i>Foreign ESG Mandate with long-tenured CEO</i>		0.265*** (3.34)
<i>Foreign ESG Mandate with short-tenured CEO</i>		0.205** (2.43)
Tests of diff. in coefficients (p-value)	0.129	0.204
Year&Firm FE	YES	YES
Control	YES	YES
N	21,127	21,127
Adj. R ²	0.588	0.588

This table presents the role of CEO characteristics in the effect of foreign ESG reporting mandates implemented after returnee CEOs' return to China on the ESG performance of Chinese firms. The control sample is firms managed by local CEOs. The dependent variable is firms' ESG performance (*ESG Perf*). The cross-sectional variables examined are *Foreign ESG Mandate with male CEO*, *Foreign ESG Mandate with female CEO*, *Foreign ESG Mandate with older CEO*, *Foreign ESG Mandate with younger CEO*, *Foreign ESG Mandate with long-tenured CEO*, and *Foreign ESG Mandate with short-tenured CEO*. All variables are defined in Appendix A. The control variables are included in all regressions but are not reported for simplicity. The t-statistics are presented under the coefficients in parentheses and are calculated using standard errors clustered by firm. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

foreign countries where their CEOs have studied or worked, even when these mandates are enacted *after* the CEOs return to China.

This key finding illuminates a dynamic and ongoing process of "sustained learning," challenging the conventional view that the impact of an experience abroad is static and confined to knowledge acquired before returning home. Our results are robust to a series of rigorous tests, including the exclusion of cross-listed firms and comparison with different control samples.

Furthermore, our analysis reveals that this effect is not uniform but is significantly amplified under specific conditions. The positive relationship is more pronounced for CEOs returning from countries with stronger institutional frameworks, such as higher levels of investor protection. It is also stronger for firms audited by Big 4 auditors, those with more foreign sales and those with overseas subsidiaries. These cross-sectional findings are critical because they suggest that the CEO's internal drive for global alignment is strongly reinforced by external market pressures and operational ties. Returnee CEOs thus act as a crucial linchpin, linking global normative changes to domestic corporate strategy.

Overall, our findings offer new insights into the transnational diffusion of corporate practices. We highlight how the personal and professional networks forged through international experiences can transcend geographical and temporal boundaries, creating a durable channel for policy learning and strategic adaptation. This study underscores the role of individual executives as active agents in global convergence, demonstrating that their continued involvement in international regulatory developments is a potent yet underexplored force to shape corporate sustainability outcomes globally.

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.

Acknowledgements

We thank the National Natural Science Foundation of China (Grant No. 72262030) and the University-Level Scientific Research Fund Project of Xinjiang University of Finance and Economics (Grant No. 2022XGC061) for their financial support.

Appendix A. Variable definitions

Dependent variable

ESG Perf

The nine ESG ratings, namely C to AAA, are assigned scores of 1–9, respectively.

Key variable of interest

Foreign ESG Mandate

An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and zero otherwise.

Other variables

Foreign ESG Mandate with Investor Protection_high (low)

An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO's foreign experience is obtained from a foreign country with a high (low) level of investor protection, and zero otherwise. We identify a country as having a high level of investor protection if this index is above (below) the median of the investor protection index from the "Global Competitiveness Index" created by the World Economic Forum.

Foreign ESG Mandate with Protection of Minority Shareholders_high (low)

An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO's foreign experience is obtained from a foreign country with a high (low) level of protection of minority shareholders, and zero otherwise. We identify a country as having a high level of protection of minority shareholders if this index is above (below) the median of the protection of minority shareholders index from the "Global Competitiveness Index" created by the World Economic Forum.

Foreign ESG Mandate_Big4 (NonBig4)

An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the firm is (not) audited by a Big 4 auditor, and zero otherwise.

Foreign ESG Mandate_ForeignSale_high (low)

An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the proportion of foreign sales is above (below) the median value, and zero otherwise.

(continued on next page)

<i>Foreign ESG Mandate_WithOverseasSub (Foreign ESG Mandate_WithoutOverseasSub)</i>	An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO leads a firm with overseas subsidiaries, and zero otherwise.
<i>Foreign ESG Mandate Issued by Stock Exchange</i>	An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO's foreign experience is obtained from a country where ESG reporting mandates are issued by the stock exchange.
<i>Foreign ESG Mandate Issued by Government Institution</i>	An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO's foreign experience is obtained from a country where ESG reporting mandates are issued by a government institution.
<i>Foreign ESG Mandate Comply</i>	An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO's foreign experience is obtained from a country where ESG reporting mandates are implemented on a full-compliance basis.
<i>Foreign ESG Mandate Comply or Explain</i>	An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO's foreign experience is obtained from a country where ESG reporting mandates are implemented on a comply-or-explain basis.
<i>Foreign ESG Mandate All at Once</i>	An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO's foreign experience is obtained from a country where ESG reporting mandates are implemented all at once.
<i>Foreign ESG Mandate Gradual</i>	An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO's foreign experience is obtained from a country where ESG reporting mandates are implemented one by one.
<i>Foreign ESG Mandate with male (female) CEO</i>	An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the returnee CEO is a man (woman), and zero otherwise.

<i>Foreign ESG Mandate with older (younger) CEO</i>	An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the age of the returnee CEO is above (below) the median value, and zero otherwise.
<i>Foreign ESG Mandate with long (short)-tenured CEO</i>	An indicator variable that is set to one for all years following the introduction of ESG reporting mandates in the foreign country where the returnee CEO lived or studied after their return, and the tenure of the returnee CEO is above (below) the median value, and zero otherwise.
<u>Control variables</u>	
<i>Gender</i>	An indicator variable that equals one if the CEO is a man, and zero otherwise.
<i>Age</i>	The age of the CEO.
<i>Tenure</i>	The tenure of the CEO.
<i>Duality</i>	An indicator variable that equals one if the chair of the board and the CEO are the same person, and zero otherwise.
<i>Size</i>	The natural logarithm of total assets.
<i>Leverage</i>	The ratio of total liabilities to total assets.
<i>ROA</i>	The ratio of net income to total assets.
<i>Directors</i>	The total number of directors on the board.
<i>Independence</i>	The ratio of independent directors.
<i>LnAnalysts</i>	The natural logarithm of the number of analysts following a firm.
<i>Receivables</i>	Other receivables divided by total assets.
<i>Firm age</i>	The logarithm of the year the company was established.
<i>Top1</i>	The percentage of shares held by the largest shareholder.
<i>EquityBalance</i>	The ratio of the shareholding ratio of the 2nd–5th largest shareholders to the shareholding ratio of the largest shareholder.
<i>ForeignSale</i>	The ratio of foreign sales.
<i>Fixed assets</i>	The ratio of fixed assets.
<i>Advertising</i>	Advertising expense scaled by total assets. Missing values are set to 0.
<i>CFO</i>	The ratio of net cash flows from operating activities to total assets.
<i>Growth</i>	The revenue growth rate.
<i>Big4</i>	An indicator variable that equals one if the auditor is among the Big 4 auditors, and zero otherwise.

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Institutional shareholders' geographical concentration, coordinated governance effects, and ESG rating disagreement



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ARTICLE INFO

Article history:

Received 9 December 2024

Accepted 9 December 2025

Available online 12 January 2026

Keywords:

Institutional shareholders' geographical concentration
ESG rating disagreement
Coordinated governance
ESG information disclosure

ABSTRACT

Drawing on agency theory, this study explores how the geographical distribution of institutional shareholders affects corporate ESG rating disagreements. A higher geographical concentration of institutional shareholders is found to correlate with reduced ESG rating disagreements, as concentration supports coordinated governance and enhances ESG disclosure quality. Heterogeneity analyses show that this effect of geographical concentration is more pronounced in environments with higher competition among institutional shareholders and less media attention toward ESG issues. Analysis of economic consequences indicates that reducing ESG rating disagreements enhances stock liquidity. This study offers important insights regarding how coordinated governance among institutional shareholders can improve corporate ESG performance and optimize governance structures. The findings have practical implications for promoting shareholder collaboration to enhance capital market efficiency and support sustainable development.

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1. Introduction

In recent years, global warming has intensified, exacerbating extreme weather and ecosystem degradation, as well as environmental challenges and their adverse impacts on sustainable development, thereby sparking widespread international concern (Liu et al., 2022). In response, China has actively addressed climate change by setting ambitious targets: achieving a carbon peak by 2030 and carbon neutrality by 2060. These dual

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carbon objectives outline a clear pathway for corporate green growth. Firms are increasingly incorporating environmental protection (E), social responsibility (S) and corporate governance (G) factors into their strategies (Shen et al., 2023; Xue et al., 2023), thus driving momentum for ESG investments. According to data from the International Green Finance Research Institute of the Central University of Finance and Economics, by the end of 2023, China's market included 586 ESG public fund products with total assets of 543.786 billion yuan.¹ ESG ratings play a crucial role in guiding investors' decisions, with agencies evaluating corporate ESG performance based on disclosed data. These agencies act as intermediaries, providing essential support for investment decisions. However, significant discrepancies exist among ESG ratings of the same firm by different agencies, a phenomenon known as ESG rating disagreement (Berg et al., 2022). Such disagreements weaken ESG's risk-mitigation function, increase investors' costs (Avramov et al., 2022) and potentially trigger capital market volatility (Luo et al., 2023). Research suggests that these disagreements stem from a lack of unified rating standards and suboptimal corporate ESG information disclosure quality (Berg et al., 2022; Kimbrough et al., 2022). As the development of global mandatory ESG standards would require prolonged collaboration, improving corporate ESG disclosure has become the primary strategy for mitigating rating disagreements (Kimbrough et al., 2022). Market mechanisms should further incentivize corporations to enhance their ESG disclosure quality and address the root causes of rating disagreement.

In alignment with sustainable development goals, institutional shareholders possess the motivation and capacity to govern and constrain corporate ESG performance and reporting and thus can help mitigate ESG rating disagreements. Regarding regulatory motivations, institutional investors can be classified as either active or passive. Active investors prioritize ESG performance by integrating ESG factors into asset allocation to influence corporate behavior and disclosures and thus improve returns and reduce risks (Dyck et al., 2019). The 2021 EY Survey showed that institutional investors scrutinize ESG reports and monitor ESG-related risks closely when making investment decisions.² Passive investors also face increasing regulatory pressures amid the global sustainability movement, leading them to make increasingly strict demands regarding corporate ESG performance and disclosure. For instance, the China Banking and Insurance Regulatory Commission requires financial institutions to integrate ESG principles into their management processes and risk management systems. Regarding regulatory capability, institutional investors use their shareholdings to establish a coordinated governance model that engages both internal and external stakeholders. As shareholders, these investors directly participate in corporate governance by appointing directors or engaging in audit committees. This involvement grants them access to critical information, industry expertise and analytical capabilities and thus enables them to effectively scrutinize ESG disclosure quality. Additionally, institutional investors signal their intentions by adjusting shareholdings and pressuring management to enhance ESG practices and disclosures. Due to their influence, these investors are positioned as central actors in the external supervision of corporate ESG performance and reporting (Admati et al., 1994; Fan et al., 2024).

Prior research shows that as independent entities, institutional investors positively influence corporate governance by mitigating agency problems, improving information transparency and enhancing capital allocation efficiency (Boone and White, 2015; Jiang and Kim, 2015; Yang et al., 2024). However, institutional shareholders frequently establish collaborative networks to bolster collective ownership, which amplifies their influence on corporate governance through coordinated actions (Crane et al., 2019). Empirical evidence suggests that collaborative networks of institutional shareholders in the same firm enhance information exchange efficiency, reduce transaction costs (Brooks et al., 2018), curb related-party transactions by controlling shareholders (Liu and Gao, 2021) and promote corporate innovation efficiency (Gao et al., 2019). Furthermore, for institutional shareholders, geographical proximity facilitates bidirectional information and knowledge flows, reduces transaction costs and enhances collective cooperation, thus strengthening corporate oversight (Crescenzi et al., 2016). Geographical concentration reduces the costs of interaction among institutional shareholders and creates effective channels for information transmission and feedback while expanding the collective information pool. Such concentration also enables mutual information verification, which helps institutional shareholders

¹ International Green Finance Research Institute of the Central University of Finance and Economics. 2024 Annual ESG Public Fund Progress Analysis Report [EB/OL] (2024-08-20) [2025-06-20]. <https://iigf.cufe.edu.cn/info/1013/9087.htm>.

² EY. 2021 EY Global Institutional Investor Survey [EB/OL] (2021-11-04) [2025-06-20]. <https://www.ey.com/content/dam/ey-unified-site/ey-com/pl-pl/newsroom/2021/12/documents/ey-institutional-investor-survey.pdf>.

make consistent decisions within cooperative networks and thereby enhances their inter-institutional coordination capabilities (Kim et al., 2018). In essence, geographical concentration of institutional shareholders promotes private information sharing, enhances informational advantages, enables coordinated oversight, constrains managerial opportunism (Huang and Kang, 2017) and, ultimately, positively influences corporate ESG disclosure. Moreover, institutional shareholders committed to ESG principles develop shared preferences and use a “coordinated voice” to improve supervision and drive ESG adoption in investee firms (Wu et al., 2023; Yang et al., 2024). These collective efforts enhance disclosure quality and reduce rating disagreements stemming from information asymmetry.

In the context of global integration of ESG governance frameworks, Chinese corporate ESG disclosure remains in its early stages compared with the mature systems of developed countries (Geng et al., 2024). The lack of uniform standards regarding content and format creates challenges for rating agencies seeking to obtain standardized information, leading to substantial ESG rating disagreements. Accordingly, strategies are needed to improve disclosure quality and reduce rating disagreements. China’s collectivist culture emphasizes social interaction and communication and thus encourages coordination among institutional shareholders, especially those who are geographically concentrated. Such concentration enhances supervisory effects, offering a unique context in which to study the relationship between geographic concentration and ESG rating disagreements. China’s distinctive cultural and institutional environment can provide valuable insights into how social dynamics and geographic concentration may influence ESG disclosure practices and mitigate rating disagreements, enabling the challenges posed by information inconsistency in China’s ESG landscape to be addressed.

This paper examines how institutional shareholders’ geographic concentration affects corporate ESG rating disagreements. The study focuses on Chinese A-share listed companies on the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) from 2009 to 2022. The results show that the geographic concentration of institutional shareholders reduces ESG rating disagreements. This finding remains robust through various tests, including alternative variable measures and endogeneity checks using omitted variable analysis, entropy balancing and instrumental variable methods. Mechanism analyses reveal that the geographic concentration of institutional shareholders incentivizes firms to improve their ESG disclosure quality, thereby reducing ESG rating disagreements. Heterogeneity tests reveal that this effect is stronger in environments with higher inter-institutional competition and less media attention directed toward ESG issues. Furthermore, economic consequence analyses reveal that a reduction in ESG rating disagreements, driven by geographic concentration, positively impacts capital markets by improving corporate stock liquidity.

This study contributes to the literature in three key ways. First, it broadens the understanding of shareholders’ geographic distribution by integrating insights from new economic geography and corporate governance. While prior research is focused on how geographic proximity between shareholders and firms reduces information and monitoring costs and thus facilitates local bias in shareholder decisions, less attention has been given to shareholders’ geographic concentration. Recent studies suggest that geographically concentrated institutional shareholders can form efficient coordinated networks that enhance oversight, innovation and firm value (Huang and Kang, 2017; Mathers et al., 2020). Building on this, the current paper explores how institutional shareholders’ geographic concentration affects ESG rating disagreement, providing a fresh perspective on the economic consequences of shareholder geographic distribution. This approach deepens the understanding of how geographic concentration among institutional investors influences corporate governance and ESG outcomes.

Second, this paper enriches the literature on coordinated governance among institutional shareholders. Previous studies explore institutional investor networks based on shared holdings (Crane et al., 2019), arguing that network members demonstrate consistent decision-making and enhance their influence on target firms’ governance through collective collaboration (Liu and Gao, 2021). From the perspective of new economic geography, geographic proximity reduces the costs of information communication and supervision between economic entities (Baik et al., 2010). Some studies suggest that such proximity facilitates consistent collective action among institutional shareholders, thereby enhancing corporate governance (Huang and Kang, 2017). Building on this corporate governance framework, the current study highlights how institutional shareholders’ geographic concentration enhances ESG disclosure quality and reduces ESG disagreements, while offering fresh insights into the dynamic coordinated governance of institutional shareholders.

Third, this paper offers new insights into reducing ESG rating disagreements from a micro perspective. Prior research attributes such disagreements mainly to inconsistent rating standards and the varying quality of corporate ESG disclosures (Berg et al., 2022; Kimbrough et al., 2022). Improving ESG disclosure is viewed as a more immediate and effective solution than addressing rating standards (Kimbrough et al., 2022; Ma and Yu, 2023). The current study demonstrates that institutional shareholders' geographic concentration improves oversight of ESG disclosures, mitigates rating disagreements and enhances stock liquidity. These findings expand the body of research on ESG disclosure, rating disagreements and capital market efficiency and provide a fresh perspective rooted in corporate governance.

The remainder of this paper is organized as follows. Section 2 covers the institutional background, literature review and hypotheses. Section 3 describes the study's data, samples and research design. Section 4 presents the empirical results. Section 5 discusses further analyses. Finally, Section 6 concludes the study.

2. Institutional background, literature review and hypothesis development

2.1. Institutional background

During the 1960s and 1970s, increasing human rights awareness and social movements in Western nations advanced labor rights, business ethics and environmental sustainability. This paradigm shift prompted the international community to prioritize sustainable social and environmental resources. In a 1987 report, titled "Our Common Future," the World Commission on Environment and Development (WCED) analyzed global economic, social and environmental challenges and introduced the concept of sustainable development. In the 1990s and early 2000s, sustainable development indices emerged, including the Domini 400 Social Responsibility Index (1990) by MSCI and the Sustainability Reporting Index (1999) by Doug Jones. These indices exemplify the evolution of social responsibility toward sustainable development. The 21st century has witnessed the global proliferation of the ESG framework. The United Nations Environment Program introduced the concept of ESG in December 2004. In 2006, the United Nations issued "Principles for Responsible Investment," offering guidelines for corporate ESG practices and disclosure and laying the foundation for advancing ESG initiatives.

In China, ESG practices are rapidly evolving despite being implemented later than in Western countries. Initial policies developed by regulators, exchanges and associations to guide ESG practices focus on environmental and governance disclosure. ESG development in China comprises three stages: institutional establishment, framework development and institutional deepening.

The first stage, institutional establishment, spanned the 2002–2017 period and marked the foundation of ESG disclosure in China. In January 2002, the China Securities Regulatory Commission (CSRC) issued its "Guidelines on Governance of Listed Companies," which defined corporate governance disclosure for the first time. In 2006 and 2008, the SZSE and SSE respectively introduced "Guidelines on the Social Responsibility of Listed Companies," which encourage enterprises to fulfill social responsibilities and disclose their social responsibility reports. In 2010, the Ministry of Environmental Protection (MEP) issued a draft, "Guidelines on Environmental Information Disclosure of Listed Companies," with the aim of standardizing the timing and scope of environmental disclosure. In 2012, the CSRC released "Guidelines on Disclosure of Information Contents and Format of Publicly Offered Securities by Companies" (Guideline No. 30), which urges firms to disclose social responsibility reports reviewed by their boards of directors. In 2015, the State Council issued an "Overall Plan for the Reform of the Ecological Civilization System," proposing mandatory environmental information disclosure by listed companies. In its Announcement No. 17, issued in 2017, the CSRC encouraged industry-specific ESG disclosure, urging firms to detail their efforts toward social responsibility, shareholder and creditor rights protection, employee welfare, consumer and supplier interests and environmental protection. In that announcement, this disclosure was also extended to firms' public relations, social welfare initiatives and broader commitments to corporate social responsibility. These regulations have laid a foundation for China's ESG practices by promoting transparency and accountability across industries.

The second stage, the framework-building period, spanned the 2018–2021 period and marked key advancements in China's ESG disclosure system. In September 2018, the CSRC revised the *Code of Governance for Listed Companies* to add sections on stakeholders, environmental protection and social responsibility, thus

establishing a foundational ESG disclosure framework. In November of that year, the China Securities Investment Fund Association released the *Research Report on ESG Evaluation System for Listed Companies in China*, creating an ESG evaluation framework inspired by global ESG standards but tailored to China's national conditions and market characteristics. In December 2020, the SSE updated the *Rules for Listing of Stocks on the KIC Board*, requiring KIC-listed companies to disclose social responsibility efforts in their annual reports and to publish separate reports on social responsibility, environmental responsibility and sustainability. In June 2021, the CSRC issued *Guidelines on the Content and Format of Information Disclosure for Companies Issuing Public Securities No. 2 (Revised in 2021)*, introducing a chapter on environmental and social responsibility and formally integrating ESG elements into annual reports for the first time. In September 2021, the State Council issued the *Opinions on Complete and Accurate Comprehensive Implementation of the New Development Philosophy and Doing a Good Job in Carbon Peak Achievement and Carbon Neutrality*. This policy supports green financial products such as green credits and bonds, incorporates green credits into the macro-prudential assessment framework and encourages institutional investors to focus on corporate carbon emissions and energy structure transformation. These measures have further solidified China's ESG framework and advanced its sustainable finance practices.

The third stage, institutional deepening, began in 2022 and is ongoing, with further solidification of ESG practices in China. In April 2022, the CSRC issued the *Guidelines on Investor Relations Management for Listed Companies*, requiring listed companies to incorporate ESG information into their communications and align these with sustainable development concepts. In June 2022, the China Banking and Insurance Regulatory Commission released the *Guidelines on Green Finance in the Banking and Insurance Industry*, which require banking and insurance institutions to integrate ESG requirements into their strategies, management processes and risk systems while enhancing their disclosure and stakeholder engagement practices. In January 2023, the Ministry of Finance introduced a draft of its *Guidelines on Corporate Sustainability Disclosure – Basic Guidelines*, marking the start of a unified national sustainability disclosure system. In April 2023, the SSE, SZSE and Beijing Stock Exchange issued sustainability reporting guidelines for listed companies, which took effect on 1 May 2024. These guidelines require firms listed in key indices, such as the SSE 180, Kechuan 50, Shenzhen 100 and GEM, as well as dual-listed companies, to disclose their sustainability reports. The first batch of compliance mandates that 2025 sustainability reports must be published by 30 April 2026, representing a major step forward in ESG disclosure within the A-share market. These developments highlight China's commitment to integrating ESG principles into its financial and corporate systems.

2.2. Literature review

2.2.1. ESG rating disagreement

Research on the factors influencing ESG rating disagreement remains at an early stage. Rating disagreement in capital markets is a common and extensively studied phenomenon. In capital markets, opinion disagreements are a key driver of stock price fluctuations (Miller, 1977). For investors, such disagreements often arise from inconsistent information sets or differing interpretations of the same data (Cookson and Niessner, 2020). For example, Xue and Wang (2022) find that detailed information disclosure during the inquiry period of an initial public offering review can reduce information asymmetry between issuers and investors. During pricing inquiries, comprehensive, readable and well-visualized disclosures in response letters can effectively reduce opinion disagreements among institutional investors. For analysts, forecast disagreements reflect differences in beliefs and information asymmetry (Ajinkya et al., 1991; Lang and Lundholm, 1996). Market participants facing limited public information must increase their reliance on private data, leading to increases in forecast disagreements and information risks (Ali et al., 2016). Improving the quality of corporate information disclosure attracts additional analysts, enhances forecast accuracy and reduces forecast disagreements (Bai, 2009). In bond markets, rating disagreements arise from differences in agencies' opinions on the default risk. Factors such as asset opacity, low readability of financial reports and aggressive tax avoidance can lower the quality of financial disclosure and lead to increased credit rating disagreement (Livingston et al., 2007; Bonsal et al., 2017; Bonsall and Miller, 2017). Overall, improving the quality of corporate information disclosure is essential to reducing opinion disagreement and mitigating information asymmetry in capital markets.

In response to the increasing focus on sustainable development, the capital market increasingly is valuing firms' ESG performance. In previous research, ESG rating disagreements are studied from two primary perspectives: differences in rating agency methodologies and information asymmetry. First, as ESG ratings remain at an early stage, the underlying methodologies are underdeveloped. Berg et al. (2022) identify differences in scope, measurement and weighting as the main drivers of ESG rating disagreements. Differences in scope arise from variations in the topics that agencies use to evaluate ESG performance. Differences in measurement reflect the application of diverse metrics to the same topic, while differences in weighting pertain to variations in the importance assigned to each topic by different agencies. Second, information asymmetry plays an important role in rating inconsistencies, and improving ESG disclosure transparency is key to resolving this issue. By issuing voluntary ESG disclosures, firms can reduce disagreements among rating agencies. Specifically, longer reports with fewer ambiguous terms provide more meaningful information and thus enhance rating consistency. However, Christensen et al. (2022) suggest that merely increasing ESG disclosure would not necessarily reduce disagreements in interpretation among market participants. A unified and effective ESG rating system is needed to address the root causes of rating disagreements. Such a system would improve the comparability of disclosure standards, reduce methodological discrepancies and enhance the overall reliability of ESG ratings.

2.2.2. Institutional shareholders' geographic concentration

The theory of new economic geography posits that transaction costs arising from geographic distance influence the decision-making behavior of economic entities and thereby affect the spatial distribution of economic activities (Krugman, 1994). In research, geographic distance is used frequently to measure information asymmetry and supervision costs between economic entities (Baik et al., 2010). This paper examines how geographic proximity affects microeconomic activities, particularly at the shareholder level, focusing on information asymmetry and monitoring costs.

Some prior studies explore the effects of geographic proximity between shareholders and firms, suggesting that proximity enhances information transmission efficiency and reduces information asymmetry. Effective information exchange is essential for optimizing market resource allocation (Mao et al., 2013). Despite decreased information acquisition costs due to advances in communication technologies, "soft information" from close-range interactions remains a key advantage in trading decisions (Loughran, 2008). For instance, Chen et al. (2022) find that fund managers frequently visit local companies to maintain an informational edge, which enables both individual and institutional investors to exhibit a local bias in investment decisions. Investors with geographic proximity to listed companies are better able to evaluate the expected returns and risks, guide strategies and achieve superior returns (Hong et al., 2008). Additionally, proximity reduces decision-making costs and enhances monitoring and oversight. As geographic distance between shareholders and firms increases, monitoring costs also increase, making it easier for management to pursue self-interested actions (Boubaker et al., 2015) such as accumulating excess cash holdings. To align with shareholders' expectations and mitigate agency conflicts, managers in remote firms may increase their cash dividend payments (John et al., 2011) and increase their voluntary disclosures (Derouiche et al., 2016). By contrast, proximity to institutional shareholders lowers monitoring costs and enables more effective deterrence of managers' opportunistic behavior. Institutional investors can thus increase their shareholder proposals (Chhaochharia et al., 2012), reduce CEOs' compensation, replace ineffective CEOs and improve firms' financial reporting quality (Ayers et al., 2011), thereby strengthening corporate governance and performance.

Additionally, recent studies explore how the geographic distribution of institutional shareholders has affected micro firms from an economic perspective. Huang and Kang (2017) argue that the geographic concentration of institutional shareholders enables the establishment of a shareholder coordination network that operates at a lower cost, leading to more effective management oversight and enhanced firm value. Kim et al. (2018) find that the monitoring effect of institutional shareholders' geographic concentration promotes timely information disclosure by management, thereby enhancing the informativeness of stock prices. Building on these findings, the literature suggests that the geographic concentration of institutional shareholders also encourages corporate innovation. Specifically, it incentivizes management to innovate by improving oversight and reducing the risk of dismissal associated with short-term performance fluctuations (Mathers et al., 2020). Furthermore, this concentration encourages investment in corporate innovation by increasing corporate risk-

taking through coordinated networks that enhance decision-making consistency, reduce stock turnover and diversify the investment risk (Huang et al., 2021).

2.3. Hypothesis development

Increasing emphasis is being placed on the importance of low-carbon sustainable development, with institutional investors favoring firms with strong ESG performance to achieve long-term returns³ (Fan et al., 2024). Investors with this preference seek to generate a synergistic outcome for long-term investment returns (Kotsantonis and Serafeim, 2019). ESG provides a comprehensive measure of corporate environmental, social responsibility and governance performance and is now a key benchmark for evaluating corporate sustainability and investment value (Huang, 2021). As critical intermediaries in capital markets, ESG rating agencies help investors identify risks and benefits by systematically assessing the ESG performance of listed companies to promote sustainable investment (Chatterji et al., 2016). However, substantial disagreements in ESG ratings persist. Researchers use various methodologies to assess the concordance of rating outcomes across agencies. Zhu et al. (2023) find that only 35 % of firms appeared in the top 100 lists of all seven rating agencies, reflecting substantial discrepancies. These disagreements arise from two primary factors. First, the evolving regulatory framework for ESG disclosures results in uneven disclosure quality. In 2022, only a third of listed companies in China disclosed ESG reports, which had common issues such as excessive qualitative descriptions, insufficient quantitative metrics and poor industry comparability. Second, inconsistencies in rating methodologies, such as differences in indicator selection and weight allocation, further exacerbate disagreements (Kotsantonis and Serafeim, 2019; Kimbrough et al., 2022). Such discrepancies undermine the reliability of ESG ratings by reducing their incremental market value and weakening investors' ESG investment forecasts, thus potentially increasing market volatility (Luo et al., 2023; Avramov et al., 2022; Gloßner, 2019). Consequently, some investors may avoid firms with inconsistent ESG ratings, leading to increases in these firms' financing costs (Christensen et al., 2022). While establishing a globally uniform ESG rating system will require long-term international collaboration, improving the quality of corporate ESG disclosure is a critical step toward reducing rating disagreements, especially in the context of localized policy challenges such as China's rural revitalization strategy (Kimbrough et al., 2022).

Institutional shareholders substantially enhance governance effectiveness through a dual approach that combines an information-sharing network with a collaborative monitoring mechanism; this approach drives firms to improve their ESG disclosure quality and mitigates disparities in ESG ratings (Kim et al., 2018). At the information-sharing level, institutional investors leverage their advantages in information acquisition and analysis. Geographic concentration further enhances informal knowledge spillovers among these investors, leading to reduced information acquisition costs and facilitating interaction and learning. Institutional shareholders can adopt advanced ESG practices from benchmark firms within their networks, understand the industry's ESG standards, assist firms in developing effective ESG management systems and encourage firms to address existing ESG issues. In turn, firms with improved corporate ESG performance are motivated to proactively disclose governance outcomes. By enhancing the completeness and timeliness of ESG disclosures, firms can reduce the interpretive ambiguity encountered by rating agencies, thereby minimizing rating disagreements. At the collaborative monitoring level, the geographic concentration of institutional shareholders creates coordinated effects that strengthen collective action capabilities. Publicly disclosed ESG information offers a basis for these shareholders' investment decisions, motivating them to jointly apply pressure to management. Through shareholder proposals and collective voting, these shareholders encourage firms to eliminate ambiguities in their ESG disclosures. By facilitating collaboration and improving disclosure practices, institutional shareholders' geographical concentration plays a crucial role in enhancing corporate ESG transparency and aligning ESG ratings.

³ The key premise underlying the influence of institutional shareholders' geographic concentration on corporate ESG ratings disagreement is that institutional shareholders continuously pay attention to corporate ESG performance. To verify this premise, this study conducts a textual analysis of Q&A transcripts from institutional investor surveys. The findings reveal that ESG-related topics are discussed frequently within these sessions, thereby corroborating the integration of corporate ESG performance into institutional shareholders' decision-making processes. Specific evidence is presented in the **Appendix**.

Therefore, we propose the following hypothesis:

Hypothesis 1. The geographic concentration of institutional shareholders can enhance the quality of firms' ESG information disclosure, thereby reducing ESG rating disagreement.

3. Research design

3.1. Sample and data

Compared with developed regions such as Europe and the United States, which have established ESG regulatory frameworks, ESG disclosure in China remains at an early stage. Given the global focus on ESG, it is necessary to enhance disclosure quality and reduce rating discrepancies. This study analyzes A-share firms listed on the SSE and SZSE from 2009 to 2022. To ensure a sufficient sample size, firms with ESG scores from at least two rating agencies are included according to established research practices (Avramov et al., 2022). The following are excluded to refine the initial sample: (1) firms with financial difficulties (special treatment [ST], *ST); (2) firms in the financial industry, as these have unique balance sheets and regulatory frameworks; (3) firms lacking ESG data from at least two rating agencies (Christensen et al., 2022) and institutional shareholder data from the Wind database; and (4) firm-years lacking necessary variable data for analysis. The final sample comprises 24,287 firm-year observations. Institutional shareholder data are obtained from the Wind database, and corporate registration locations are sourced from the Tiansyancha Database. Regional per capita GDP information is retrieved from the National Bureau of Statistics of China. ESG news coverage data are collected from the DataGo database, and all corporate financial and governance data are obtained from the China Stock Market and Accounting Research (CSMAR) database. The sample sizes in specific regression analyses vary due to variations in the model variables.

3.2. Variable measurement and empirical model

3.2.1. Measuring ESG rating disagreement

As the research object is A-share companies listed on the SSE and SZSE, to ensure a sufficient research sample size and objectivity of ratings, we draw on prior research (Tan and Pan, 2024; Wang et al., 2024) and adopt the natural logarithm of the standard deviation of rating scores provided by five rating agencies, namely Huazheng, Hexun, Wind, Bloomberg and FTSE Russell, for the same listed company as a measure of ESG rating disagreement.

3.2.2. Measuring geographic concentration of institutional shareholders

Building on prior research (Huang and Kang, 2017; Kim et al., 2018), we measure the geographic concentration of institutional shareholders as the inverse of their geographic distance as follows. First, institutional shareholder data for listed companies are obtained from the Wind database, and only shares holding over 5 % of a firm's shares are retained. Second, the registration locations of these institutional shareholders are identified using the Tiansyancha Database, and their addresses are converted into latitude and longitude coordinates using Baidu Map's geocoding system. Reverse geocoding is used to map these coordinates to specific administrative divisions. Third, Model (1) is used to calculate the geographically weighted distance between each pair of institutional shareholders based on the latitude, longitude and shareholding ratios of institutional shareholders. The negative value of the natural logarithm of this distance is then calculated to generate the institutional geographic concentration index ($IGC1$). In Model (1), j and k represent a firm's institutional shareholders in a given year, N represents the total number of institutional shareholders, w_j and w_k respectively represent the shareholding ratios of institutional shareholders j and k in outstanding A-shares and $Distance_{j,k}$ refers to the geographic distance between institutional shareholders j and k , measured in kilometers. A higher $IGC1$ value indicates a greater geographic concentration of institutional shareholders.

$$IGC1 = - \left[\ln \left(1 + \left(\sum_j^{N-1} w_j \sum_{k=j+1}^N w_k Distance_{j,k} \right) \right) \right] \quad (1)$$

Simultaneously, the negative value of the natural logarithm of the number of cities housing institutional shareholders with over 5 % shareholdings is calculated as a proxy for geographic concentration ($IGC2$). A higher $IGC2$ value indicates a greater geographic concentration of institutional shareholders.

3.2.3. Control variables

Drawing on previous research (Huang and Kang, 2017; Mathers et al., 2020; Wang et al., 2024), we control for the following variables: firm size ($Size$), leverage (Lev), fixed asset ratio (PPE), return on assets (ROA), book-to-market ratio (BM), cash flow (CF), capital expenditure ($CAPEX$), firm age (Age), board size ($Board$), independent director ratio ($Indrt$), top shareholders' shareholding ratio (Top), state-owned enterprise (SOE), foreign institutional investors' shareholding ratio ($FShrate$), share of export sales revenue ($Saleratio$), industry competition (HHI) and regional development level ($PCGDP$). We present detailed definitions of all the variables in Table 1.

3.2.4. Empirical model

To examine the influence of the geographic concentration of institutional shareholders on ESG rating disagreement, we construct the following basic empirical model:

$$ESGDis_{i,t} = \alpha + \beta IGC_{i,t} + \gamma Controls_{i,t} + Firm_i + Year_i + \varepsilon_{i,t} \quad (2)$$

The dependent variable in Model (2) is $ESGDis$, which represents ESG rating disagreement. The independent variable is IGC , which encompasses $IGC1$ and $IGC2$ and represents the institutional shareholders' geographic concentration. We include year fixed effects ($Year$) to rule out the influence of the macroeconomic environment.

Table 1
Definitions of variables.

Variable	Abbreviation	Definition
ESG rating disagreement	<i>ESGDis</i>	Natural logarithm of the standard disagreement of ESG scoring results from the five rating agencies (Huazheng, Bloomberg, Wind, Hexun and FTSE Russell)
Institutional shareholders' geographic concentration	<i>IGC1</i>	Institutional shareholders holding more than 5 % of the shares of a listed company are retained, and their geographic concentration is calculated according to Eq. (1)
	<i>IGC2</i>	Opposite of the natural logarithm of the number of cities in which institutional shareholders holding more than 5 % of the shares of a listed company are located
Firm size	<i>Size</i>	Natural logarithm of total assets at the end of the fiscal year
Firm leverage	<i>Lev</i>	Total long-term liabilities divided by total assets
Return on assets	<i>ROA</i>	Net operating income deflated by average total assets
Book-to-market ratio	<i>BM</i>	Book value of equity divided by book market value of equity at the end of the fiscal year
Cash flow	<i>CF</i>	Cash flows from operating activities divided by total assets
Capital expenditure	<i>CAPEX</i>	Cash paid for the acquisition and construction of fixed assets, intangible assets and other long-term assets divided by total assets
Firm age	<i>Age</i>	Years of business establishment divided by 100
Board size	<i>Board</i>	Number of directors in a listed company divided by 100
Independent director ratio	<i>Indrt</i>	Number of independent directors divided by total number of directors
Top shareholders' shareholding ratio	<i>Top</i>	Number of shares held by the largest shareholder divided by total number of share capital
State-owned enterprise	<i>SOE</i>	Takes a value of 1 for a state-owned enterprise, and otherwise 0
Foreign institutional investors shareholding ratio	<i>FShrate</i>	Number of shares held by the largest foreign institutional investors divided by total number of share capital
Share of export sales revenue	<i>Saleratio</i>	Ratio of firms' export sales revenue to total operating revenue
Industry competition	<i>HHI</i>	Accumulation of the square of the ratio of each company's main business revenue in the industry to the industry's total main business revenue
Regional development level	<i>PCGDP</i>	GDP per capita by province

Table 2
Summary statistics.

Variable	N	Mean	Std.	Min.	Med.	Max.
<i>ESGDis</i>	24,287	3.161	0.598	0.628	3.313	3.874
<i>IGC1</i>	24,287	-1.296	1.763	-5.600	0.000	0.000
<i>IGC2</i>	24,287	-0.307	0.411	-1.386	0.000	0.000
<i>Size</i>	24,287	22.541	1.335	19.941	22.359	26.406
<i>Lev</i>	24,287	0.445	0.201	0.056	0.441	0.892
<i>ROA</i>	24,287	0.042	0.064	-0.206	0.038	0.222
<i>BM</i>	24,287	0.621	0.265	0.117	0.610	1.186
<i>CF</i>	24,287	0.193	0.135	0.016	0.157	0.678
<i>CAPEX</i>	24,287	0.047	0.045	0.000	0.034	0.226
<i>Age</i>	24,287	0.193	0.058	0.050	0.190	0.330
<i>Board</i>	24,287	0.087	0.017	0.050	0.090	0.150
<i>Indrt</i>	24,287	0.376	0.054	0.333	0.364	0.571
<i>Top</i>	24,287	0.349	0.151	0.084	0.326	0.742
<i>SOE</i>	24,287	0.433	0.496	0.000	0.000	1.000
<i>FShrate</i>	24,287	0.184	1.183	0.000	0.000	52.500
<i>Saleroatio</i>	24,287	5.583	15.602	-0.863	0.000	100.000
<i>HHI</i>	24,287	0.125	0.135	0.000	0.086	0.793
<i>PCGDP</i>	24,287	0.847	0.392	0.198	0.784	1.903

Note: This table reports the main summary statistics of all variables. Std., Min., Med. and Max. represent the standard deviation, minimum, median and maximum, respectively.

ment on the dependent variable. Firm fixed effects (*Firm*) are included to mitigate the effect of unobservable firm characteristics. We winsorize all continuous variables at the 1 % and 99 % levels to eliminate the influence of extreme values.

4. Empirical results

4.1. Descriptive statistics

Table 2 reports the summary statistics of the key variables. The mean and standard deviation of *ESGDis* are 3.161 and 0.598, respectively, with a minimum value of 0.628 and a maximum of 3.874. This indicates considerable variance in the rating outcomes of listed companies across different rating agencies. The means of *IGC1* and *IGC2* are -1.296 and -0.307, with standard deviations of 1.763 and 0.411, respectively, suggesting a degree of variability in the geographic distribution of institutional shareholders across Chinese listed companies. The other control variables remain consistent with prior research and thus are not further elaborated here (Baik et al., 2010).

4.2. Baseline regression results

Table 3 reports the regression results on the impact of institutional shareholders' geographic concentration (*IGC*) on ESG rating disagreement (*ESGDis*). Columns (1) and (3) only include firm and year fixed effects, while columns (2) and (4) include control variables. The coefficients on *IGC* are negative and significant at the 1 % level, indicating that an increase in geographic concentration reduces ESG rating disagreement, supporting Hypothesis 1. This conclusion also holds economic significance. A one-standard-deviation increase in *IGC1* and *IGC2* reduces *ESGDis* by 2.95 % and 3.30 % of its standard deviation, respectively.⁴

⁴ As an example of the regression results in Column (2), for every one-standard-deviation (1.763) increase in *IGC1*, the standard deviation of *ESGDis* decreases by $0.010 \times 1.763/0.598 = 2.95\%$.

Table 3
Baseline regression results.

Variable	(1) <i>ESGDis</i>	(2) <i>ESGDis</i>	(3) <i>ESGDis</i>	(4) <i>ESGDis</i>
<i>IGC1</i>	−0.009*** (−3.83)	−0.010*** (−4.40)		
<i>IGC2</i>			−0.042*** (−4.38)	−0.048*** (−5.05)
<i>Size</i>		0.054*** (5.58)		0.055*** (5.62)
<i>Lev</i>		−0.338*** (−8.41)		−0.338*** (−8.41)
<i>ROA</i>		−0.744*** (−9.97)		−0.747*** (−10.02)
<i>BM</i>		−0.010 (−0.40)		−0.011 (−0.45)
<i>CF</i>		−0.047 (−1.20)		−0.047 (−1.21)
<i>CAPEX</i>		0.211** (2.29)		0.207** (2.26)
<i>Age</i>		0.044 (0.03)		0.059 (0.04)
<i>Board</i>		0.111 (0.27)		0.092 (0.22)
<i>Indrt</i>		0.157 (1.52)		0.157 (1.52)
<i>Top</i>		0.122** (2.06)		0.129** (2.17)
<i>SOE</i>		−0.055** (−2.28)		−0.054** (−2.27)
<i>FShrate</i>		−0.016*** (−3.00)		−0.016*** (−2.98)
<i>Saleroatio</i>		0.001* (1.68)		0.001* (1.69)
<i>HHI</i>		0.161*** (3.84)		0.160*** (3.81)
<i>PCGDP</i>		0.186*** (4.35)		0.187*** (4.37)
Constant	3.149*** (1034.65)	1.837*** (5.00)	3.148*** (1066.58)	1.824*** (4.97)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24,287	24,287	24,287	24,287
Adj R ²	0.001	0.017	0.001	0.017

4.3. Robustness test

4.3.1. Substitution of independent variables

Robustness tests are conducted by modifying the independent variables as follows. First, the baseline geographic concentration measure, calculated using a shareholding-weighted approach, is replaced with an equal-weight method (*IGC3*). Second, we limit the sample to institutional shareholders whose shareholding ratios exceed 10 % and recalculate the geographic concentration indicator (*IGC4*) using Model (1). Third, we use the same sample and construct a robust indicator (*IGC5*) by taking the negative natural logarithm of the number of cities where institutional shareholders are located. Table 4 reports the regression results after these

Table 4
Robustness: alternative measures of institutional shareholders' geographic concentration.

Variable	(1) <i>ESGDis</i>	(2) <i>ESGDis</i>	(3) <i>ESGDis</i>
<i>IGC3</i>	-0.003*** (-2.92)		
<i>IGC4</i>		-0.007** (-1.99)	
<i>IGC5</i>			-0.031* (-1.80)
<i>Size</i>	0.055*** (5.66)	0.062*** (5.69)	0.062*** (5.70)
<i>Lev</i>	-0.337*** (-8.39)	-0.352*** (-7.96)	-0.352*** (-7.95)
<i>ROA</i>	-0.742*** (-9.94)	-0.810*** (-9.89)	-0.810*** (-9.89)
<i>BM</i>	-0.015 (-0.63)	-0.022 (-0.81)	-0.022 (-0.83)
<i>CF</i>	-0.043 (-1.11)	-0.056 (-1.28)	-0.056 (-1.28)
<i>CAPEX</i>	0.210** (2.29)	0.228** (2.21)	0.229** (2.22)
<i>Age</i>	0.103 (0.07)	1.544 (0.94)	1.548 (0.94)
<i>Board</i>	0.148 (0.36)	0.271 (0.60)	0.273 (0.61)
<i>Indrt</i>	0.158 (1.53)	0.111 (1.01)	0.112 (1.02)
<i>Top</i>	0.121** (2.03)	0.071 (1.10)	0.071 (1.11)
<i>SOE</i>	-0.054** (-2.25)	-0.034 (-1.21)	-0.034 (-1.22)
<i>FShrate</i>	-0.016*** (-2.99)	-0.017*** (-2.87)	-0.017*** (-2.87)
<i>Saleratio</i>	0.001* (1.72)	0.000 (1.42)	0.000 (1.45)
<i>HHI</i>	0.164*** (3.89)	0.151*** (3.30)	0.151*** (3.30)
<i>PCGDP</i>	0.185*** (4.32)	0.220*** (4.85)	0.220*** (4.84)
Constant	1.810*** (4.94)	1.400*** (3.42)	1.398*** (3.42)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	24,287	20,591	20,591
Adj R ²	0.016	0.018	0.017

Note: The sample sizes of the regressions in columns (2) and (3) differ from that of the baseline regressions; this is attributable to the exclusion of observations lacking institutional shareholders with holdings exceeding 10 %. The t-values are shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

adjustments. Regardless of the measurement method used (*IGC3*, *IGC4* or *IGC5*), the coefficients on the effect of institutional shareholders' geographic concentration on *ESGDis* remain negative and significant at a statistical level of at least 10 %. These results confirm that the study's findings are robust and unaffected by changes in the measurement of the core explanatory variable.

4.3.2. Substitution of the dependent variable

To mitigate the impact of measurement errors in the dependent variable, we conduct a robustness test by altering the method of calculating ESG rating disagreement. Drawing on previous research (He et al., 2023), we use six different ESG rating systems: Huazheng ESG rating index, Wind ESG rating index, SynTao Green Finance ESG rating index, Bloomberg ESG rating index, China Alliance of Social Value Investment ESG rating index and FTSE Russell ESG rating index. We then construct the ESG rating disagreement indicator by assigning values to the ratings and calculating the standard deviation. As shown in Table 5, the regression

Table 5
Robustness: alternative measures of ESG rating disagreement.

Variable	(1) <i>ESGDis1</i>	(2) <i>ESGDis1</i>	(3) <i>ESGDis1</i>	(4) <i>ESGDis1</i>
<i>IGC1</i>	-0.009** (-2.14)	-0.008* (-1.89)		
<i>IGC2</i>			-0.035** (-2.12)	-0.031* (-1.90)
<i>Size</i>		0.101*** (5.30)		0.102*** (5.32)
<i>Lev</i>		-0.156** (-2.10)		-0.155** (-2.09)
<i>ROA</i>		-0.104 (-0.87)		-0.106 (-0.89)
<i>BM</i>		-0.100** (-2.28)		-0.102** (-2.34)
<i>CF</i>		0.030 (0.45)		0.030 (0.45)
<i>CAPEX</i>		0.053 (0.29)		0.050 (0.28)
<i>Age</i>		5.161** (2.24)		5.182** (2.26)
<i>Board</i>		0.301 (0.40)		0.295 (0.40)
<i>Indrt</i>		0.375** (2.03)		0.375** (2.03)
<i>Top</i>		-0.109 (-0.99)		-0.107 (-0.97)
<i>SOE</i>		0.018 (0.45)		0.019 (0.46)
<i>FShrate</i>		-0.013* (-1.90)		-0.013* (-1.89)
<i>Saleratio</i>		-0.002** (-2.16)		-0.002** (-2.15)
<i>HHI</i>		-0.016 (-0.21)		-0.018 (-0.22)
<i>PCGDP</i>		0.201*** (2.58)		0.200** (2.58)
Constant	1.405*** (248.90)	-2.067*** (-3.39)	1.406*** (270.17)	-2.078*** (-3.41)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	20,313	20,313	20,313	20,313
Adj R ²	0.000	0.006	0.000	0.006

Note: The sample sizes used to calculate changes in ESG rating disagreement differ from that of the benchmark regression due to the variations in the samples of ESG ratings assigned to listed companies by different rating agencies. The t-values are shown in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.1.

results continue to demonstrate that the geographic concentration of institutional shareholders (*IGC*) significantly reduces ESG rating disagreement (*ESGDis1*) at a statistical level of at least 10 %, indicating the robustness of our findings.

4.4. Endogeneity

4.4.1. Omitted variable analysis

Although we control for numerous confounding variables, as well as firm and year fixed effects, in the regression model, the impact of unobservable variables remains unavoidable. To assess the severity of omitted variable bias, we use methods proposed by Altonji et al. (2005) and Oster (2019). Altonji et al. (2005) suggest using the formula $|\beta^F/\beta^R - \beta^F|$ to infer the impact of omitted unobservable variables, where β^F is the coefficient obtained with all control variables (i.e., unrestricted regression) and β^R is the coefficient obtained with partial controls (i.e., restricted regression). If $|\beta^F/\beta^R - \beta^F|$ exceeds 1, this would suggest that the omission of unobservable variables does not significantly affect the coefficient estimates. Oster (2019) offers an approach to correct for omitted variable bias by estimating the true parameter using $\beta^* = \beta^*(R_{\max}, \delta)$, where δ represents the selection ratio, a measure of the correlation strength between the unobservable variables and the explanatory variable relative to the observable variables. R_{\max} represents the maximum goodness of fit achievable if unobservable variables were included. Two key tests are applied. First, by setting $|\delta| = 1$ and R_{\max} to 1.3 times the R-squared value of the current regression, a value of $\beta^* = \beta^*(R_{\max}, \delta)$ within the 95 % confidence interval of the estimated coefficient would indicate that the omitted variable bias is not severe. Second, setting R_{\max} to 1.3 times the current R-squared value and calculating $|\delta|$ when $\beta^* = 0$, if $|\delta|$ exceeds 1 would suggest that the omission of unobservable variables does not significantly affect the coefficient estimates.

Table 6 analyzes the impact of omitted unobservable variables using the method by Altonji et al. (2005). In columns (1) and (4), the regression coefficients vary within a narrow range of 0.042 and 0.048, indicating that

Table 6
Endogeneity: omitted variable analysis based on Altonji et al.'s (2005) methodology.

Variable	ESGDis					
	(1) <i>IGC1</i> coefficient	(2) t-value	(3) $ \beta^F/(\beta^R - \beta^F) $	(4) <i>IGC2</i> coefficient	(5) t-value	(6) $ \beta^F/(\beta^R - \beta^F) $
<i>Size</i>	-0.009***	-3.77	7.120	-0.042***	-4.35	7.849
<i>Lev</i>	-0.009***	-3.72	6.415	-0.041***	-4.28	6.852
<i>ROA</i>	-0.010***	-4.20	20.353	-0.046***	-4.78	20.165
<i>BM</i>	-0.010***	-4.14	19.074	-0.045***	-4.75	19.033
<i>CF</i>	-0.010***	-4.18	23.294	-0.046***	-4.78	22.358
<i>CAPEX</i>	-0.010***	-4.17	21.430	-0.045***	-4.76	19.705
<i>Age</i>	-0.010***	-4.17	21.169	-0.045***	-4.76	19.578
<i>Board</i>	-0.010***	-4.21	24.966	-0.046***	-4.80	24.194
<i>Indrt</i>	-0.010***	-4.20	26.339	-0.046***	-4.80	23.821
<i>Top</i>	-0.010***	-4.36	177.187	-0.048***	-5.02	374.351
<i>SOE</i>	-0.010***	-4.39	674.309	-0.048***	-5.04	2026.057
<i>Shrate</i>	-0.010***	-4.35	528.550	-0.048***	-5.02	404.663
<i>Saleratio</i>	-0.010***	-4.30	79.920	-0.047***	-4.98	99.968
<i>HHI</i>	-0.010***	-4.23	34.784	-0.047***	-4.89	35.210
<i>PCGDP</i>	-0.010***	-4.37	—	-0.048***	-5.04	—

Note: The coefficients in columns (1) and (4) represent the regression coefficients of ESG rating disagreement (*ESGDis*) on the geographic clustering of institutional shareholders (*IGC1* and *IGC2*), after controlling for firm and vintage year fixed effects and sequentially incorporating the relevant control variables. For instance, in column (1), the regression coefficient of *ESGDis* on *IGC1* is -0.009 after controlling for firm size (*Size*). When further controlling for gearing (*Lev*), the regression coefficient of *ESGDis* on *IGC1* remains -0.009. Columns (2) and (5) present the corresponding t-values. Columns (3) and (6) display the values of $|\beta^F/(\beta^R - \beta^F)|$, where β^F represents the regression coefficient of *IGC* after controlling for all variables (-0.010 and -0.048), and β^R denotes the sequential cumulative regression coefficients after accounting for the variables. Importantly, $|\beta^F/(\beta^R - \beta^F)|$ is calculated based on the original coefficients rather than the coefficients rounded to three decimal places, which accounts for the differences from the manually calculated values.

Table 7

Endogeneity: omitted variable analysis based on the Oster (2019) methodology.

Variable	Test method	Standard of judgement	Actual results	Whether or not to pass
IGC1	Method 1	$\beta^*(R_{max}, \delta) \in [-0.014, -0.005]$	-0.011	Yes
	Method 2	$ \delta > 1$	26.361	Yes
IGC2	Method 1	$\beta^*(R_{max}, \delta) \in [-0.067, -0.030]$	-0.050	Yes
	Method 2	$ \delta > 1$	24.350	Yes

the additional control variables have a weak impact on the relationship between *IGC* and *ESGDis*. Columns (3) and (6) reveal minimum $|\beta^F/\beta^R - \beta^F|$ values of 6.415 and 6.852, which both exceed the critical threshold of 1, indicating a limited influence of omitted unobservable factors. Table 7 conducts the same analysis using Oster's (2019) method, showing that $\beta^* = \beta^*(R_{max}, \delta)$ falls within the 95 % confidence interval of the estimated parameters and the values of δ are greater than 1. These results suggest that omitted unobservable variables have little effect on the study's conclusions, confirming the robustness and reliability of our findings.

4.4.2. Entropy balancing method

Multivariate linear regression can identify causal effects by controlling observable confounding variables, but its validity depends on the correct specification of the functional form. Misspecification can lead to residual errors, which may introduce endogeneity issues. Accordingly, entropy balancing is used to mitigate endogeneity arising from model misspecification (Hainmueller, 2012). This method adjusts the control group observations by assigning optimal weights to make them more similar to the treatment group observations. Specifically, entropy balancing minimizes the higher-order moments of variables, which are grouped based on whether the geographic concentration of institutional shareholders exceeds the annual mean (*IGC_Dum*). Two weighting schemes are used: (1) all control variables (*Weight 1*) and (2) control variables plus their interaction, quadratic and cubic terms (*Weight 2*). Table 8 presents the descriptive statistics, showing that after applying entropy balancing, the differences in first-, second- and third-order moments between the treatment group (*IGC_Dum* = 1) and the control group (*IGC_Dum* = 0) are minimal. This approach reduces reliance on

Table 8

Endogeneity: descriptive statistics of entropy balance.

Variable	<i>IGC_Dum</i> = 1			<i>IGC_Dum</i> = 0		
	Mean	Std.	Skewness	Mean	Std.	Skewness
<i>Size</i>	22.51888	1.769352	0.698805	22.51899	1.769346	0.698764
<i>Lev</i>	0.448725	0.041102	0.111641	0.448725	0.041102	0.111635
<i>ROA</i>	0.037602	0.003758	-0.59475	0.037603	0.003758	-0.59473
<i>BM</i>	0.636381	0.068319	0.085448	0.636381	0.068319	0.085447
<i>CF</i>	0.188062	0.016811	1.353456	0.188062	0.016811	1.353455
<i>CAPEX</i>	0.044966	0.001936	1.690014	0.044966	0.001936	1.690016
<i>Age</i>	0.19314	0.003256	0.094507	0.19314	0.003256	0.094503
<i>Board</i>	0.086014	0.000304	0.754715	0.086014	0.000304	0.7547
<i>Indrt</i>	0.377503	0.003053	1.337301	0.377504	0.003053	1.337275
<i>Top</i>	0.365872	0.024115	0.373142	0.365874	0.024115	0.373141
<i>SOE</i>	0.467739	0.248976	0.129315	0.467732	0.248986	0.129342
<i>Shrate</i>	0.149671	1.140657	28.121183	0.149700	1.141350	28.110200
<i>Salratio</i>	5.318485	227.2477	3.654628	5.318517	227.2481	3.65461
<i>HHI</i>	0.125827	0.017974	2.773188	0.125827	0.017973	2.773186
<i>PCGDP</i>	0.849304	0.157092	0.720603	0.849306	0.157092	0.720593

specific functional forms in subsequent analyses. The regression results obtained using entropy-balanced samples (Table 9) confirm that, regardless of the weighting scheme, *IGC* remains negative and significant at the 1 % level. These findings suggest that functional form misspecification does not cause significant endogeneity issues and support the robustness of the results.

Table 9
Endogeneity: entropy balance method.

Variable	Weight 1		Weight 2	
	(1) <i>ESGDis</i>	(2) <i>ESGDis</i>	(3) <i>ESGDis</i>	(4) <i>ESGDis</i>
<i>IGC1</i>	-0.010*** (-3.89)		-0.008*** (-3.28)	
<i>IGC2</i>		-0.043*** (-4.49)		-0.036*** (-3.58)
<i>Size</i>	0.044*** (4.22)	0.041*** (3.99)	0.048*** (4.25)	0.044*** (3.98)
<i>Lev</i>	-0.352*** (-7.81)	-0.349*** (-7.82)	-0.351*** (-7.56)	-0.341*** (-7.41)
<i>ROA</i>	-0.801*** (-10.02)	-0.816*** (-10.27)	-0.818*** (-9.68)	-0.835*** (-10.06)
<i>BM</i>	0.009 (0.32)	0.013 (0.46)	0.006 (0.17)	0.005 (0.14)
<i>CF</i>	-0.054 (-1.25)	-0.060 (-1.40)	-0.081* (-1.76)	-0.089* (-1.95)
<i>CAPEX</i>	0.206** (2.08)	0.199** (2.03)	0.207** (2.05)	0.205** (2.04)
<i>Age</i>	-0.879 (-0.57)	-0.773 (-0.53)	1.386 (0.73)	0.924 (0.54)
<i>Board</i>	0.105 (0.24)	0.112 (0.26)	0.124 (0.29)	0.044 (0.10)
<i>Indrt</i>	0.187 (1.58)	0.181 (1.57)	0.256** (2.22)	0.212* (1.84)
<i>Top</i>	0.155** (2.40)	0.161** (2.53)	0.157** (2.28)	0.180*** (2.67)
<i>SOE</i>	-0.039 (-1.49)	-0.043* (-1.67)	-0.051* (-1.94)	-0.053** (-2.09)
<i>Shrate</i>	-0.144 (-0.48)	-0.110 (-0.36)	-0.415 (-1.12)	-0.402 (-1.07)
<i>Saleratio</i>	0.001 (1.56)	0.001 (1.58)	0.001* (1.76)	0.001* (1.81)
<i>HHI</i>	0.158*** (3.44)	0.163*** (3.59)	0.169*** (3.71)	0.174*** (3.87)
<i>PCGDP</i>	0.186*** (4.06)	0.197*** (4.31)	0.181*** (3.46)	0.199*** (3.83)
Constant	2.209*** (5.75)	2.245*** (6.07)	1.656*** (3.61)	1.845*** (4.42)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24,287	24,287	24,287	24,287
Adj R ²	0.017	0.018	0.018	0.018

Note: The regression weight (*Weight 1*) in columns (1) and (2) is the entropy balance weight calculated based on all control variables. In contrast, the regression weight (*Weight 2*) in columns (3) and (4) is derived from the entropy balance weights computed using all control variables, as well as their interaction, quadratic and cubic terms. The t-values are shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

4.4.3. Instrumental variable analysis

The findings of this study may be subject to reverse causality. Specifically, firms with a lower ESG rating disagreement can communicate more valuable ESG information to external investors and thus may attract geographically concentrated institutional shareholders with similar investment preferences. This would complicate the relationship between *IGC* and *ESGDis*. To alleviate this concern, we use the urban geographic slope (*Slope*) as an instrumental variable for *IGC*. This choice is justified by the fact that this slope measures the complexity of urban topography; a steeper geographic slope typically indicates the historical formation of a relatively closed market, which would result in spatial concentrations of population, trade flows and other economic activities. Consequently, the urban geographic slope is correlated with the geographic concentration of institutional shareholders. Additionally, as this slope is a naturally occurring phenomenon and not directly related to other time-varying economic indicators, it satisfies the exogeneity requirements of an instrumental variable. Table 10 presents the results of instrumental variable analysis. Columns (1) and (3) show that *Slope* positively and significantly affects *IGC* at the 1 % level, indicating that a steeper urban slope leads to a greater concentration of institutional shareholders. Columns (2) and (4) demonstrate that *IGC* negatively and significantly impacts *ESGDis* at the 1 % level. Additionally, the weak instrument tests yield values of 17.835 and 12.048, both exceeding the critical threshold of 10, suggesting that these results are not affected by weak instruments. In summary, after accounting for endogeneity, our conclusion that the geographic concentration of institutional shareholders reduces ESG rating disagreement remains robust and valid.

5. Further analysis

5.1. Economic mechanisms

We argue that the geographic concentration of institutional shareholders promotes coordinated governance by encouraging firms to enhance their ESG disclosure quality, thereby reducing disagreement among ESG rating agencies. We use two methods to measure ESG disclosure quality. First, based on Zou (2018), we select 12 aspects from the “Basic Information Table of Listed Companies’ Social Responsibility Report” in the CSMAR database as a comprehensive framework for evaluating firms’ ESG responsibilities to stakeholders. Each listed company is assessed on whether it discloses information on these 12 aspects, and the resulting scores are summed. The natural logarithm of the summed score is adjusted by adding 1 to yield the *ESG_DQ* index, which takes the range of [0, 12]. Firms that do not disclose social responsibility reports are assigned an *ESG_DQ* value of 0, and higher *ESG_DQ* values indicate more detailed and higher-quality ESG disclosures. Second, drawing on Kimbrough et al. (2024), we evaluate the readability of ESG reports by calculating the ratio of adverbs and conjunctions to the total number of words (*Readability*), with a higher ratio representing greater readability and higher ESG disclosure quality. Tables 11 and 12 report the regression results, showing that ESG disclosure quality (*ESG_DQ* and *Readability*) mediates the main relationship. In other words, the geographic concentration of institutional shareholders effectively reduces corporate ESG rating disagreement by improving the *quality* and *readability* of ESG disclosures, thereby supporting our main argument.

5.2. Heterogeneity analysis

5.2.1. Degree of competition between institutional shareholders

Institutional investors, as informed traders, are more likely to achieve collective action and exercise positive governance when ownership is concentrated among a few institutions and competition is weak (Black and Coffee, 1994). We find that the geographic concentration of institutional shareholders reduces ESG rating disagreement by improving corporate ESG disclosures through coordinated governance. Accordingly, we argue that this effect is more pronounced when institutional competition is high. We measure institutional shareholder competition using the method of Kong and Wang (2016) and calculate the inverse of the Herfind-

Table 10

Endogeneity: instrumental variables.

Variable	(1) <i>IGC1</i>	(3) <i>IGC2</i>	(2) <i>ESGDis</i>	(4) <i>ESGDis</i>
<i>IGC1</i>			−0.320*** (−3.77)	
<i>IGC2</i>				−1.751*** (−3.26)
<i>Slope</i>	0.125*** (4.22)	0.023*** (3.47)		
<i>Size</i>	−0.183*** (−4.02)	−0.031*** (−2.88)	0.007 (0.31)	0.011 (0.44)
<i>Lev</i>	−0.028 (−0.18)	−0.005 (−0.13)	−0.358*** (−5.72)	−0.357*** (−4.88)
<i>ROA</i>	−0.500** (−2.02)	−0.171*** (−2.84)	−0.921*** (−7.78)	−1.060*** (−6.61)
<i>BM</i>	1.096*** (9.98)	0.209*** (8.33)	0.316*** (3.15)	0.331*** (2.74)
<i>CF</i>	−0.494*** (−3.27)	−0.115*** (−3.19)	−0.204*** (−2.80)	−0.246*** (−2.61)
<i>CAPEX</i>	−0.441 (−1.23)	−0.166* (−1.92)	0.084 (0.59)	−0.066 (−0.35)
<i>Age</i>	−6.047 (−1.16)	−1.011 (−0.70)	−1.976 (−0.87)	−1.811 (−0.62)
<i>Board</i>	−7.001*** (−3.74)	−1.880*** (−4.35)	−2.022** (−2.24)	−3.073** (−2.38)
<i>Indrt</i>	−0.166 (−0.40)	−0.034 (−0.34)	0.107 (0.66)	0.101 (0.52)
<i>Top</i>	1.439*** (5.19)	0.446*** (6.90)	0.562*** (3.48)	0.883*** (3.27)
<i>SOE</i>	−0.106 (−1.03)	−0.014 (−0.55)	−0.086** (−2.18)	−0.077 (−1.61)
<i>Shrate</i>	0.000 (0.02)	0.002 (0.32)	−0.016 (−1.48)	−0.012 (−1.00)
<i>Saleratio</i>	−0.004*** (−3.07)	−0.001*** (−2.58)	−0.001 (−1.23)	−0.001 (−1.14)
<i>HHI</i>	−0.380** (−2.04)	−0.117** (−2.57)	0.046 (0.57)	−0.038 (−0.35)
<i>PCGDP</i>	0.317 (1.60)	0.089** (2.02)	0.292*** (3.73)	0.346*** (3.53)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24,287	24,287	24,287	24,287
Kleibergen-Paap rk Wald F			17.835	12.048

Note: The parentheses in columns (1) and (2) contain t-values. Those in columns (3) and (4) contain Z-values.

ahl–Hirschman Index (*InsHHI*)⁵ based on the shareholding proportions of institutional shareholders in a listed company. A higher *InsHHI* value indicates a more dispersed shareholding structure and stronger competition among institutional shareholders. Table 13 presents the results of heterogeneity analysis of institutional shareholder competition. The interaction term of *IGC* × *InsHHI* is negative and significant at the

⁵ To enhance the intuitive presentation and interpretation of the heterogeneity analysis, we reverse the signs of the two variables associated with heterogeneity analysis, specifically institutional shareholder competitiveness and media ESG attention, to improve the logical flow and readability of this section.

Table 11
Mechanism analysis: quality of ESG disclosure.

Variable	(1) <i>ESG_DQ</i>	(2) <i>ESG_DQ</i>	(3) <i>ESGDis</i>	(4) <i>ESGDis</i>
<i>IGC1</i>	0.007* (1.87)		-0.010*** (-4.27)	
<i>IGC2</i>		0.039** (2.45)		-0.046*** (-4.87)
<i>ESG_DQ</i>			-0.048*** (-8.43)	-0.048*** (-8.40)
<i>Size</i>	0.223*** (11.95)	0.223*** (11.96)	0.065*** (6.61)	0.065*** (6.65)
<i>Lev</i>	-0.158** (-2.42)	-0.158** (-2.42)	-0.346*** (-8.65)	-0.345*** (-8.65)
<i>ROA</i>	-0.305*** (-2.97)	-0.302*** (-2.94)	-0.759*** (-10.17)	-0.762*** (-10.21)
<i>BM</i>	-0.270*** (-6.00)	-0.270*** (-5.99)	-0.023 (-0.92)	-0.024 (-0.98)
<i>CF</i>	0.019 (0.31)	0.020 (0.32)	-0.046 (-1.18)	-0.046 (-1.19)
<i>CAPEX</i>	0.087 (0.56)	0.090 (0.58)	0.215** (2.35)	0.211** (2.31)
<i>Age</i>	2.786 (1.48)	2.782 (1.49)	0.179 (0.12)	0.193 (0.13)
<i>Board</i>	-0.174 (-0.26)	-0.151 (-0.22)	0.102 (0.25)	0.085 (0.21)
<i>Indrt</i>	0.188 (1.12)	0.188 (1.12)	0.166 (1.61)	0.166 (1.61)
<i>Top</i>	-0.227** (-2.06)	-0.234** (-2.12)	0.111* (1.87)	0.117** (1.98)
<i>SOE</i>	0.070* (1.94)	0.070* (1.94)	-0.051** (-2.16)	-0.051** (-2.14)
<i>Shrate</i>	0.006 (0.80)	0.006 (0.79)	-0.016*** (-2.97)	-0.016*** (-2.96)
<i>Saleratio</i>	0.001 (1.56)	0.001 (1.56)	0.001* (1.82)	0.001* (1.83)
<i>HHI</i>	-0.058 (-0.70)	-0.056 (-0.68)	0.159*** (3.82)	0.157*** (3.78)
<i>PCGDP</i>	0.075 (1.15)	0.073 (1.13)	0.190*** (4.46)	0.191*** (4.48)
Constant	-4.697*** (-8.44)	-4.691*** (-8.44)	1.610*** (4.44)	1.598*** (4.42)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24,287	24,287	24,287	24,287
Adj R ²	0.019	0.020	0.022	0.022

Note: The t-values are shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 12

Mechanism analysis: ESG report readability.

Variable	(1) <i>Readability</i>	(2) <i>Readability</i>	(3) <i>ESGDis</i>	(4) <i>ESGDis</i>
<i>IGC1</i>	0.004 (1.22)		-0.010*** (-4.32)	
<i>IGC2</i>		0.021* (1.82)		-0.047*** (-4.97)
<i>Readability</i>			-0.034*** (-4.96)	-0.034*** (-4.97)
<i>Size</i>	0.109*** (7.77)	0.109*** (7.80)	0.058*** (5.89)	0.058*** (5.97)
<i>Lev</i>	-0.127** (-2.51)	-0.126** (-2.50)	-0.343*** (-8.55)	-0.342*** (-8.53)
<i>ROA</i>	-0.154** (-2.04)	-0.153** (-2.03)	-0.749*** (-10.04)	-0.752*** (-10.08)
<i>BM</i>	-0.106*** (-3.10)	-0.108*** (-3.15)	-0.011 (-0.43)	-0.015 (-0.60)
<i>CF</i>	-0.009 (-0.19)	-0.008 (-0.18)	-0.048 (-1.22)	-0.047 (-1.22)
<i>CAPEX</i>	0.051 (0.45)	0.055 (0.47)	0.211** (2.30)	0.209** (2.28)
<i>Age</i>	2.334 (1.19)	2.294 (1.17)	0.195 (0.13)	0.137 (0.09)
<i>Board</i>	-0.338 (-0.60)	-0.325 (-0.58)	0.103 (0.25)	0.081 (0.20)
<i>Indrt</i>	-0.073 (-0.54)	-0.073 (-0.55)	0.157 (1.51)	0.155 (1.49)
<i>Top</i>	-0.063 (-0.78)	-0.069 (-0.85)	0.121** (2.05)	0.126** (2.13)
<i>SOE</i>	0.006 (0.20)	0.005 (0.19)	-0.055** (-2.28)	-0.054** (-2.27)
<i>Shrate</i>	-0.156 (-0.90)	-0.009* (-1.69)	0.014 (0.08)	-0.016*** (-3.04)
<i>Saleratio</i>	0.000 (0.56)	0.000 (0.56)	0.001* (1.72)	0.001* (1.72)
<i>HHI</i>	-0.043 (-0.57)	-0.042 (-0.56)	0.159*** (3.80)	0.158*** (3.78)
<i>PCGDP</i>	0.072 (1.34)	0.071 (1.32)	0.189*** (4.42)	0.189*** (4.43)
Constant	-2.314*** (-4.64)	-2.305*** (-4.62)	1.747*** (4.81)	1.745*** (4.81)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24,287	24,287	24,287	24,287
Adj R ²	0.008	0.008	0.017	0.018

Note: The t-values are shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

1 % level or better. This finding indicates that stronger competition among institutional shareholders amplifies the effect of geographic concentration in reducing ESG rating disagreement.

5.2.2. Media ESG attention

The media plays a vital role in contemporary society by raising public awareness, shaping opinions and monitoring corporate behavior (Zhai et al., 2022). By providing detailed coverage on firms, the media reduces information asymmetry and broadens public access to critical information. Consequently, shareholders and stakeholders can address their concerns more effectively (Saxton et al., 2021). Beyond information sharing,

Table 13
Heterogeneity analysis: institutional shareholder competition.

Variable	(1) <i>ESGDis</i>	(2) <i>ESGDis</i>	(3) <i>ESGDis</i>	(4) <i>ESGDis</i>
<i>IGCI</i>	-0.020*** (-3.71)	-0.022*** (-4.24)		
<i>IGCI</i> × <i>InsHHI</i>	-0.047*** (-2.99)	-0.050*** (-3.29)		
<i>IGC2</i>			-0.069*** (-3.41)	-0.077*** (-3.89)
<i>IGC2</i> × <i>InsHHI</i>			-0.145** (-2.29)	-0.155** (-2.47)
<i>InsHHI</i>	0.056*** (2.70)	0.059*** (2.82)	0.054*** (2.63)	0.057*** (2.70)
<i>Size</i>		0.049*** (5.02)		0.050*** (5.12)
<i>Lev</i>		-0.330*** (-8.23)		-0.331*** (-8.24)
<i>ROA</i>		-0.765*** (-10.25)		-0.765*** (-10.24)
<i>BM</i>	0.002 (0.07)			-0.001 (-0.05)
<i>CF</i>	-0.054 (-1.38)			-0.053 (-1.35)
<i>CAPEX</i>	0.191** (2.08)			0.190** (2.06)
<i>Age</i>	-0.053 (-0.04)			-0.013 (-0.01)
<i>Board</i>	0.079 (0.19)			0.070 (0.17)
<i>Indrt</i>	0.157 (1.52)			0.156 (1.51)
<i>Top</i>	0.145** (2.43)			0.145** (2.44)
<i>SOE</i>	-0.049** (-2.05)			-0.049** (-2.06)
<i>Shrate</i>	-0.017*** (-3.13)			-0.017*** (-3.10)
<i>Saleratio</i>	0.001 (1.63)			0.001* (1.67)
<i>HHI</i>	0.158*** (3.78)			0.158*** (3.78)
<i>PCGDP</i>	0.183*** (4.29)			0.184*** (4.31)
Constant	3.176*** (301.96)	1.992*** (5.40)	3.176*** (300.71)	1.961*** (5.32)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24,287	24,287	24,287	24,287
Adj R ²	0.002	0.018	0.002	0.018

Note: The t-values are shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 14
Heterogeneity analysis: media attention to ESG.

Variable	(1) <i>ESGDis</i>	(2) <i>ESGDis</i>	(3) <i>ESGDis</i>	(4) <i>ESGDis</i>
<i>IGC1</i>	-0.012*** (-3.99)	-0.013*** (-4.39)		
<i>IGC1</i> × <i>ESGnews</i>	-0.005*** (-2.63)	-0.006*** (-2.70)		
<i>IGC2</i>			-0.052*** (-4.42)	-0.057*** (-4.87)
<i>IGC2</i> × <i>ESGnews</i>			-0.022** (-2.43)	-0.022** (-2.46)
<i>ESGnews</i>	0.041*** (9.29)	0.039*** (8.75)	0.041*** (9.46)	0.040*** (8.92)
<i>Size</i>		0.062*** (6.36)		0.063*** (6.39)
<i>Lev</i>		-0.334*** (-8.33)		-0.333*** (-8.33)
<i>ROA</i>		-0.736*** (-9.91)		-0.739*** (-9.95)
<i>BM</i>		-0.026 (-1.06)		-0.027 (-1.11)
<i>CF</i>		-0.040 (-1.02)		-0.040 (-1.04)
<i>CAPEX</i>		0.224** (2.44)		0.221** (2.41)
<i>Age</i>		0.112 (0.08)		0.126 (0.09)
<i>Board</i>		0.144 (0.35)		0.131 (0.32)
<i>Indrt</i>		0.151 (1.48)		0.150 (1.47)
<i>Top</i>		0.109* (1.84)		0.117** (1.97)
<i>SOE</i>		-0.055** (-2.32)		-0.055** (-2.31)
<i>Shrate</i>		-0.015*** (-2.82)		-0.015*** (-2.82)
<i>Saleratio</i>		0.000 (1.40)		0.000 (1.40)
<i>HHI</i>		0.164*** (3.96)		0.163*** (3.93)
<i>PCGDP</i>		0.173*** (4.05)		0.175*** (4.08)
Constant	3.173*** (744.41)	1.687*** (4.64)	3.172*** (764.14)	1.677*** (4.61)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	24,287	24,287	24,287	24,287
Adj R ²	0.006	0.021	0.006	0.022

Note: The t-values are shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 15
Analysis of economic consequences: stock liquidity.

Variable	(1) <i>Amihud</i> _{t+1}	(2) <i>Amihud</i> _{t+1}	(3) <i>Amihud</i> _{t+1}	(4) <i>Amihud</i> _{t+1}
<i>IGC1</i>	0.005*** (3.42)	0.003* (1.87)		
<i>IGC1</i> × <i>ESGDis</i>	-0.001*** (-3.33)	-0.001** (-2.34)		
<i>IGC2</i>			0.020*** (3.21)	0.009 (1.47)
<i>IGC2</i> × <i>ESGDis</i>			-0.006*** (-3.14)	-0.003* (-1.80)
<i>ESGDis</i>	0.004*** (4.49)	0.003*** (3.79)	0.004*** (4.31)	0.004*** (3.84)
<i>Size</i>		-0.021*** (-12.77)		-0.021*** (-12.71)
<i>Lev</i>		0.009 (1.20)		0.009 (1.19)
<i>ROA</i>		-0.054*** (-5.78)		-0.054*** (-5.78)
<i>BM</i>		0.045*** (15.35)		0.045*** (15.09)
<i>CF</i>		-0.002 (-0.32)		-0.002 (-0.29)
<i>CAPEX</i>		0.006 (0.36)		0.007 (0.36)
<i>Age</i>		0.096 (0.44)		0.096 (0.44)
<i>Board</i>		-0.037 (-0.81)		-0.037 (-0.79)
<i>Indrt</i>		0.004 (0.25)		0.004 (0.24)
<i>Top</i>		0.031*** (3.87)		0.031*** (3.86)
<i>SOE</i>		-0.001 (-0.36)		-0.001 (-0.32)
<i>Shrate</i>		-0.001 (-1.30)		-0.001 (-1.29)
<i>Saleratio</i>		0.000** (2.44)		0.000** (2.45)
<i>HHI</i>		-0.008 (-1.06)		-0.008 (-1.06)
<i>PCGDP</i>		-0.003 (-0.75)		-0.003 (-0.77)
Constant	0.028*** (10.19)	0.439*** (7.88)	0.028*** (9.52)	0.437*** (7.84)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	20,928	20,928	20,928	20,928
Adj R ²	0.002	0.044	0.002	0.044

the media wields substantial public influence (Hartmann et al., 2021). Stakeholders can use media platforms to praise, question or criticize corporate social responsibility practices and create external pressure on companies to improve their ESG practices and enhance the transparency and quality of their ESG disclosures (He et al., 2024).

We argue that the geographic concentration of institutional shareholders promotes ESG disclosure through coordinated governance, thereby reducing inconsistencies in the ESG ratings issued by agencies. However, this effect is expected to be more pronounced when less media attention is given to a firm's ESG issues. To explore this possibility, we follow Zhou et al. (2023) and measure media attention to ESG issues (*ESGnews*) by dividing the number of ESG-related news reports in the Datago news sentiment database by 100 and taking the inverse. A higher *ESGnews* value indicates lower media coverage of a firm's ESG issues. Table 14 presents the heterogeneity analysis of media ESG attention. The interaction term of $IGC \times ESGnews$ is negative and significant at the 5 % level. This result suggests that the reducing effect of the geographic concentration of institutional shareholders on ESG rating disagreement becomes more pronounced when the media pays less attention to a firm's ESG issues.

5.3. Economic consequences

Stock liquidity facilitates information flow (Chen and Gu, 2017), resource allocation and price discovery in capital markets. When a company's ESG performance exhibits significant disparities, ESG ratings cannot objectively and accurately reflect the company's ESG performance, nor can they provide incremental information to support investors' decision-making. This scenario leads to higher perceived market risks, higher market premiums and lower investment demand (Healy and Palepu, 2001). Our study finds that by enhancing synergistic governance capabilities, the geographic concentration of institutional shareholders improves the quality of corporate ESG information disclosure and reduces ESG rating disagreement. Moreover, the extent of a company's information disclosure is a crucial factor influencing stock liquidity. Higher information disclosure quality encourages investors to have greater confidence in the fairness of stock trading prices, thereby enhancing the liquidity of the company's stocks. In this section, we explore the economic consequences of reduced ESG rating disagreement resulting from the geographic concentration of institutional shareholders from the perspective of stock liquidity. Specifically, we use Amihud's (2002) methodology to calculate the stock illiquidity index (*Amihud*) and further construct Model (3) to test the economic consequences of stock liquidity.

$$Amihud_{i,t+1} = \beta_0 + \beta_1 IGC_{i,t} + \beta_2 ESGDis_{i,t} \times IGA_{i,t} + \beta_3 ESGDis_{i,t} + \gamma Controls_{i,t} + Firm_i + Year_t + \varepsilon_{i,t+1} \quad (3)$$

Here, *Amihud* represents the illiquidity index, and a higher *Amihud* value indicates lower stock liquidity. As evident from the regression results in Table 15, columns (1) to (3) reveal that regression coefficient on the interaction term of $ESGDis \times IGC$ is negative and significant at a statistical level of at least 10 %. This result suggests that the geographic concentration of institutional shareholders not only mitigates corporate ESG rating disagreement but also enhances stock liquidity and improves the operational efficiency of capital markets.

6. Conclusion and discussion

ESG factors are a crucial aspect of economic activity, with stakeholders often relying on weighted scores from rating agencies to assess firms' performance. However, the correlation between these scores and actual ESG performance remains inconsistent. Building on principal–agent theory, research suggests that institutional shareholders' geographic concentration facilitates the formation of coordinated networks, which in turn improve governance efficiency. Using data from Chinese firms listed on the SSE and SZSE between 2009 and 2022, empirical analysis reveals that institutional shareholders' geographic concentration reduces ESG rating disagreement. This is achieved by promoting coordinated governance, which encourages firms to enhance the transparency and quality of their ESG disclosures and ultimately reduces disagreement among rating agencies. Heterogeneity analysis shows that this governance effect is stronger when institutional shareholder

competition is higher and less media attention is directed toward ESG issues. Additionally, analysis of the economic consequences finds that reducing ESG rating disagreement through institutional shareholders' geographic concentration improves corporate stock liquidity.

This study offers valuable theoretical and practical insights. Theoretically, it provides three key contributions. First, this study explores the impact of the geographic concentration of institutional shareholders on corporate ESG rating disagreement and offers new perspectives. The results demonstrate that these key external stakeholders strongly encourage firms to engage in high-quality ESG disclosures. This finding enriches agency theory by highlighting the governance role of geographical concentration. Unlike the prevalent view in the literature, which treats institutional investors as independent entities, this study emphasizes their collective influence. The results show that when geographically concentrated shareholders coordinate their actions, their impact is amplified. This finding extends prior research by showing how external stakeholders can enhance corporate governance through collaboration. Specifically, geographically concentrated institutional shareholders can motivate firms to adopt proactive ESG disclosure practices, thus effectively reducing rating disagreements.

Second, this study examines how firms respond to institutional shareholders' calls for sustainability and how this affects ESG rating disagreement. The results highlight the crucial role of the geographic concentration of shareholders in elevating ESG disclosure standards and reducing discrepancies among rating agencies. These findings are aligned with those of prior studies on the value of voluntary ESG disclosures, while the current study refines the discussion on this topic by focusing on the governance effects of shareholder concentration. Coordinated action among geographically concentrated shareholders effectively promotes improvements in ESG disclosure quality and consistency, thus addressing the issue of rating disagreements.

Third, this study emphasizes the economic significance of reducing ESG rating disagreements. It empirically demonstrates that a greater geographic concentration of institutional shareholders is associated with fewer rating inconsistencies and enhanced pricing efficiency in capital markets. More accurate ratings provide a clearer reflection of a firm's true value and risk profile. Thus, this study offers a novel theoretical framework for understanding the economic implications of ESG rating disagreements while providing empirical support for the relationship between ESG factors and corporate value in capital markets.

Practically, the findings offer two key insights. First, institutional shareholders should leverage collective action to strengthen their influence and encourage firms to improve ESG disclosures. As firms often prioritize their immediate economic interests, some managers, particularly those focused on short-term gains, may undervalue the importance of addressing ESG rating disagreements. To counter this, firms must recognize institutional shareholders as crucial stakeholders and respond to their expectations. For institutional shareholders, collective action is essential for amplifying their impact. Geographic concentration facilitates information sharing and coordination and thus enables a unified approach to pressuring firms to enhance their ESG disclosure quality and transparency.

Second, the effectiveness of collective actions taken by geographically concentrated institutional shareholders is influenced by factors such as shareholder behavior and media involvement. Consistency in decision-making among institutional shareholders further strengthens the impact of their collective action. Even when consensus is not achieved, geographic concentration significantly enhances the influence of these stakeholders on firms. Moreover, the media plays a vital role by increasing public awareness of ESG issues and can apply external pressure on companies to improve ESG practices. Media attention can partially substitute for shareholder influence and can drive improvements in ESG disclosures even when shareholder influence is limited. By highlighting these dynamics, the current study highlights how shareholder coordination and media interact to promote better ESG practices and resolve rating disagreements.

This study has several limitations. The measurement of institutional investors' concerns about ESG issues is limited by data constraints and could be improved. While shareholder proposals theoretically reflect these concerns, our searches of the CSMAR, Wind or CNRDS databases do not reveal systematic proposal data. Consequently, we manually review announcements from the shareholder meetings of listed companies. However, these announcements mainly include routine motions, such as approving annual reports and profit distributions, and do not disclose the sources of proposals, making it difficult to identify institutional shareholders. To address this limitation, we adopt a second-best approach, constructing an ESG keyword dictionary using a "seed words + Word2Vec expansion" method. We use the frequency ratio of ESG keywords in institutional

investors' Q&A minutes as a proxy variable. While this approach is feasible, some keywords may lose their original ESG meanings due to contextual differences, which could lead to measurement errors. Future research could address this limitation by applying contextual semantic models, such as BERT, to improve recognition accuracy and measurement reliability.

Declaration of competing interest

We declare that we have no known competing financial interests or personal relationships that can inappropriately influence the work reported in this paper, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled, "*Institutional shareholders' geographical concentration, coordinated governance effects, and ESG rating disagreement*".

Appendix A. Institutional shareholders' concerns regarding corporate ESG performance

This study investigates institutional shareholders' practical concerns regarding corporate ESG performance by extending Zhao et al.'s (2025) work and developing a comprehensive ESG lexicon using the "seed words + Word2Vec expansion" method. This lexicon is then used to construct an indicator of institutional shareholders' ESG concerns through a textual analysis of institutional investors' research Q&A transcripts. The process involves three key steps.

First, relevant ESG-related keywords are identified. In the absence of an established ESG lexicon, a proprietary dictionary is developed using seed words covering the three ESG dimensions. To ensure the validity and comprehensiveness of this dictionary, the seed words are extracted from the semantic structure of national policy documents and institutional investors' research Q&A summaries with a focus on environmental, governance and social aspects, including employee and management issues.

Second, the ESG keyword dictionary is constructed. After preprocessing the Q&A transcripts by removing extraneous symbols, performing word segmentation and eliminating stop words, the Word2Vec model is trained. Using this model, seed words are expanded by calculating the semantic similarities, and words with a similarity above 50 % are filtered; ultimately, this process yields 1200 candidate words. After manual review and screening, 93 keywords are selected to form the final ESG keyword dictionary (see Table A1).

Third, an index is developed to measure institutional investors' ESG focus. Using Python, the frequency of ESG keywords in the Q&A transcripts is quantified. To account for differences in text length, the ratio of the ESG keyword frequency to the total word count of each document is calculated. This method is used to assess whether firms' institutional shareholders hold ESG preferences. Fig. A1 shows a year-over-year increase in the proportion of listed companies with institutional shareholders who demonstrate ESG preferences.

Table A1

ESG keyword dictionary.

Climate	Atmospheric conditions	Weather	Natural environment	Natural disaster	Geographical environment
Air Pollution	Temperature Difference	Diseases	Ecological Environment	Environmental Pollution	Haze
Pest and Disease	Energy Conservation	Environmental Protection	Emission Reduction	Low Carbon	Green
Water Conservation	Environmental Management	Clean	Carbon Reduction	Air Pollution	Carbon Decrease
Waste Gas	Industrial Pollution	Wastewater	Three Wastes	Zero Emission	High Energy Consumption
Resource-Saving	Polluted Environment	Energy Consumption	Pollution Control	Sulfur Dioxide	Sewage Treatment
Water Pollution	Electricity Saving	Pollution Control	Nitrogen Oxides	Air Quality	Volatility
Pollution Treatment	Energy Consumption	Solid Waste	Zero Carbon	Environmental Protection	Industrial Pollution
Resource Conservation	Wasteful Spending	Management Structure	Talent Development	Risk Management	Management Model
Management System	Assessment System	Risk Control	Cost Reduction and Efficiency Improvement	Reward System	Management Mechanism
Management Level	Management Framework	Management Strategy	Management Means	Employees	Welfare Benefits
Performance Evaluation	Impoverished Families	Care	Talent Cultivation	Medical Security	Public Opinion Guidance
Disturbing the Public	Food Safety	Drought Resistance	Flood Control	Livelihood	Welfare
Charity	Public Interest	Dedication	Caring	Sense of Happiness	Pursue Welfare
Social Stability	Responsibility	ESG	Common Prosperity	Public Welfare	Beneficial to the Country and the People

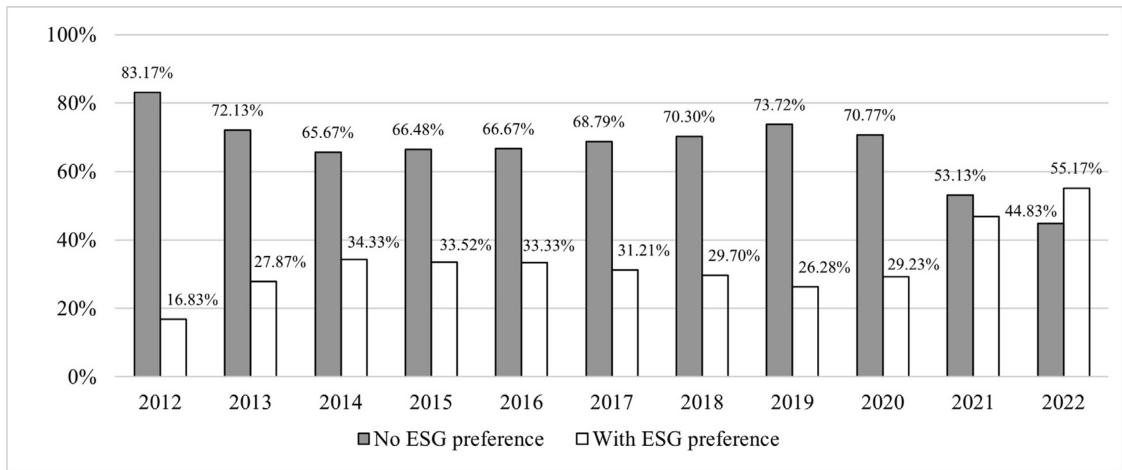


Fig. A1. The percentage of firms with and without institutional shareholders with ESG preferences.

Additionally, group regressions are performed based on the presence of ESG-preferring institutional shareholders within firms, and the results are presented in Table A2. The regression results indicate that the geographic concentration of institutional shareholders decreases ESG rating disagreement, regardless of whether firms are supported or not by ESG-preferring institutional shareholders. This finding rules out the alternative explanation that only the geographic concentration of ESG-preferring institutional shareholders can reduce ESG rating disagreement.

Table A2

Subgroup analysis: presence of ESG-preferring institutional shareholders in firms.

Variable	(1)	(2)	(3)	(4)
	Without ESG preference	With ESG preference	Without ESG preference	With ESG preference
	<i>ESGDis</i>	<i>ESGDis</i>	<i>ESGDis</i>	<i>ESGDis</i>
<i>IGC1</i>	-0.011*** (-3.60)	-0.015*** (-2.96)		
<i>IGC2</i>			-0.047*** (-3.71)	-0.065*** (-3.37)
<i>Size</i>	0.047*** (3.49)	0.112*** (5.00)	0.048*** (3.55)	0.112*** (5.00)
<i>Lev</i>	-0.349*** (-7.00)	-0.442*** (-4.50)	-0.349*** (-7.01)	-0.440*** (-4.48)
<i>ROA</i>	-0.892*** (-9.93)	-0.761*** (-4.39)	-0.894*** (-9.95)	-0.767*** (-4.42)
<i>BM</i>	-0.020 (-0.60)	-0.015 (-0.25)	-0.022 (-0.67)	-0.015 (-0.27)
<i>CF</i>	-0.130*** (-2.62)	0.047 (0.52)	-0.128*** (-2.59)	0.043 (0.48)
<i>CAPEX</i>	0.238** (2.07)	0.180 (0.84)	0.239** (2.07)	0.169 (0.78)
<i>Age</i>	0.758 (0.35)	-5.351* (-1.82)	0.764 (0.36)	-5.182* (-1.78)
<i>Board</i>	0.297 (0.59)	-0.087 (-0.08)	0.292 (0.58)	-0.092 (-0.08)

Table A2 (continued)

Variable	(1)	(2)	(3)	(4)
	Without ESG preference	With ESG preference	Without ESG preference	With ESG preference
	<i>ESGDis</i>	<i>ESGDis</i>	<i>ESGDis</i>	<i>ESGDis</i>
<i>Indrt</i>	0.114 (0.89)	0.394 (1.57)	0.114 (0.90)	0.391 (1.55)
<i>Top</i>	0.082 (1.09)	0.282* (1.88)	0.085 (1.13)	0.289* (1.93)
<i>SOE</i>	-0.064** (-2.06)	0.011 (0.20)	-0.063** (-2.03)	0.008 (0.16)
<i>HHI</i>	0.208*** (3.55)	0.225* (1.83)	0.207*** (3.53)	0.222* (1.80)
<i>PCGDP</i>	0.266*** (5.22)	-0.022 (-0.16)	0.268*** (5.24)	-0.019 (-0.14)
<i>Shrate</i>	-0.011 (-1.55)	-0.020** (-2.19)	-0.011 (-1.56)	-0.020** (-2.15)
<i>Saleratio</i>	0.001 (1.52)	0.000 (0.60)	0.001 (1.54)	0.000 (0.59)
Constant	1.837*** (3.47)	1.502** (2.00)	1.819*** (3.44)	1.467* (1.96)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	14,763	6899	14,763	6899
Adj R ²	0.023	0.018	0.023	0.019

Note: The t-values are shown in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

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Contents lists available at ScienceDirect

China Journal of Accounting Research

journal homepage: www.elsevier.com/locate/cjar



Voluntary ESG information disclosure on social media and ESG rating divergence: evidence from Sina Weibo



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ARTICLE INFO

Article history:

Received 3 February 2025

Accepted 10 December 2025

Available online 9 January 2026

Keywords:

ESG information disclosure

ESG rating divergence

Social media

Sina Weibo

ABSTRACT

This paper examines the impact of firms' voluntary ESG disclosures on social media on ESG rating divergence using data from China's Sina Weibo. The results show that social media disclosure of ESG information alleviates ESG rating divergence, supporting the information effect hypothesis rather than the noise effect hypothesis of voluntary disclosure. ESG-related posts on Weibo contain significant informational value, as evidenced by their association with lower stock price synchronicity. Moreover, the mitigating effect is more pronounced for social media posts disclosing ESG information with more likes, reposts and comments. Heterogeneity analysis reveals that the effect of voluntary ESG information disclosure in reducing ESG rating divergence is more significant for firms rated by domestic agencies, non-polluting firms and firms in areas with higher Internet penetration. Additional tests rule out the possibility that firms disclose ESG information on social media primarily for greenwashing purposes. Overall, the findings highlight that social media is an effective channel for enhancing ESG information transparency, improving the ESG disclosure system and strengthening the reliability of ESG ratings.

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1. Introduction

ESG rating divergence has become a critical challenge for investors and policymakers, as it undermines the reliability of ESG assessments and the efficiency of capital allocation, thereby leading to a range of adverse economic consequences (Serafeim and Yoon, 2023; He et al., 2025; Sun et al., 2025). Consequently, uncovering the causes of ESG rating divergence and exploring ways to mitigate such divergence are important issues in academic research. Prior studies attribute ESG rating divergence to differences in rating agencies' legal origins,

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conceptual interpretations and methodological approaches (Chatterji et al., 2016; Liang and Renneboog, 2017; Berg et al., 2022; Kurbus and Rant, 2025) and to inconsistencies in information acquisition capabilities (Easley and O'Hara, 2004; Garfinkel, 2009; Chatterji et al., 2016). Notably, firms' disclosure practices shape ESG rating divergence. Some studies find that voluntary ESG reporting reduces ESG rating divergence (Kimbrough et al., 2022), whereas others find that increased disclosure may, paradoxically, exacerbate divergence (Christensen et al., 2022; Kimbrough et al., 2022). However, these studies predominantly focus on formal reporting channels, overlooking the heterogeneity of information dissemination media and the impact of informal channels such as social media. To address this gap in the literature, this study investigates the effect of social media disclosures on ESG rating divergence.

Compared with standardized reports, social media disclosure is characterized by timeliness, interactivity and wide dissemination (Blankespoor, 2018). Such disclosure may provide incremental information with positive implications (Blankespoor, 2018), but it may also introduce information noise because of selective disclosure and semantic embellishment (Dye, 2001). In international research, scholars examine Twitter as a representative platform and find that it has become an important channel for firms to release news, broaden dissemination and provide information to investors (Blankespoor et al., 2014). In China, Sina Weibo serves a similar role. As one of the most representative social media platforms in China, Weibo not only shares Twitter's short-text mechanism but also integrates diverse functions such as images and videos while enhancing interactivity through comments, likes and reposts (Zheng and Guo, 2024). Its massive user base and wide dissemination enable rating agencies to access firm-related ESG information at a low cost. Studies reveal that a large proportion of the information disclosed by listed companies on Weibo is not contained in official announcements, with as much as 69 % related to daily operations and strategies (He et al., 2018). For example, in 2023, GAC Group used Weibo to share its ESG goals and practices, embedding ESG concepts into the entire product life cycle: exploring multi-energy structures at the R&D stage; accelerating the transition to new energy at the product stage; building a green, zero-carbon supply chain in production; constructing a carbon-inclusive platform for consumers; supporting rural revitalization through developing an aromatic industry chain in Bijie, Guizhou; and actively participating in pandemic control, earthquake relief and flood disaster donations. This demonstrates that social media disclosure of ESG information has become an important form of voluntary ESG disclosure.

Given the growing prevalence of such voluntary ESG disclosures on social media, the natural question arises of whether and how these disclosures affect the ESG assessments made by different rating agencies. Because ESG ratings often rely on publicly available information, the voluntary and immediate nature of social media disclosures may play a crucial role in reducing information asymmetry among rating agencies. The literature shows that voluntary disclosure on Weibo attracts the attention of analysts and regulators (Chen et al., 2023). Analysts interpret the information disclosed on Weibo and incorporate it into earnings forecasts (Hu and Wang, 2015). Accordingly, social media disclosure serves not only as an informational basis for investors' decisions but also as a critical input for analysts' forecasts. ESG ratings by rating agencies are also influenced by media, with numerous instances of downward adjustments to ESG scores because of media exposure of negative corporate ESG behaviors. For instance, in 2023, a supplier scandal exposed by China's CCTV caused Tingyi's ESG rating to plummet.¹ In 2024, SAIC Motor's ratings were downgraded following negative media coverage of product quality issues and employee overtime disputes. Such negative media exposure often prompts rating agencies to reassess firms' ESG performance, leading to downgrades or even exclusion from ESG indices.² This indicates that media information is an important reference source for rating agencies when evaluating corporate ESG performance.

We therefore posit that voluntary ESG disclosure on social media can provide incremental information to rating agencies, reducing inter-agency information gaps and promoting ESG rating convergence. However,

¹ FTSE Russell noted the absence of supply chain monitoring policies, assigning a score of 0 in supply chain management and lowering the overall ESG score to 1.5 (out of 5). Refinitiv similarly downgraded the firm to 35.5 (out of 100), citing deficiencies in product safety and disclosure transparency.

² MSCI downgraded SAIC to a CCC rating, assigning a score of 0 in governance and 2 (out of 5) in the social dimension. Huazheng also assigned CCC, ranking SAIC last within its industry. Refinitiv issued a B-rating, while FTSE Russell assigned a score of 1.5 (out of 5), both below the industry average.

voluntary disclosure may also generate information noise that disrupts judgment, intensifying ESG rating divergence. Therefore, the effect of voluntary ESG disclosure on ESG rating divergence remains an empirical question.

This study uses a sample of Chinese A-share listed companies from 2018 to 2022 to empirically examine the impact and mechanisms of firms' voluntary ESG information disclosures on Weibo on ESG rating divergence. The findings show that voluntary ESG disclosures on Weibo significantly reduce ESG rating divergence. Further analysis indicates that these disclosures also decrease stock price synchronicity, supporting the information effect hypothesis. Moreover, the mitigating effect is more pronounced when Weibo disclosures receive more likes, comments and reposts. We also show that the impact of voluntary ESG disclosure via social media is stronger for domestic rating agencies and non-polluting enterprises than for foreign agencies and other enterprises. The effect is also stronger in regions with higher Internet penetration. Finally, we rule out the possibility that firms' ESG disclosures on social media are driven by greenwashing motives. Overall, our findings suggest that voluntary ESG disclosure via social media platforms such as Weibo can effectively reduce ESG rating divergence, supporting the information effect hypothesis rather than the noise effect hypothesis.

This study makes three important contributions. First, it enriches the literature on the determinants of ESG rating divergence by examining voluntary ESG disclosures on social media. Prior research explores technical factors, social factors and information asymmetry as influences on ESG rating divergence. This study is closely related to the study by Feng et al. (2024), who use Bloomberg ESG disclosures as a proxy for corporate disclosure and find that greater disclosure exacerbates ESG rating divergence. In contrast, this paper finds that ESG information disclosed on Weibo mitigates ESG rating divergence, highlighting the economic effects of voluntary ESG disclosures on social media and complementing previous studies.

Second, we extend the literature on the economic consequences of corporate social media disclosure by examining ESG rating divergence. Prior studies document effects on stock price synchronicity (Hu and Wang, 2015; Shen et al., 2017; He et al., 2018), firm value (Toombs and Harlow, 2014; Sun et al., 2021), stock returns (Xu and Chen, 2016), analyst forecast bias (Hu et al., 2016), information acquisition costs (Blankespoor et al., 2014) and consumer trust (Toombs and Harlow, 2014). However, no prior studies explore the impact of social media disclosures on ESG rating divergence. Based on Weibo data, we provide novel evidence on this issue and expand the literature on the economic consequences of corporate social media disclosure.

Third, our findings highlight that firms can use social media disclosure to enhance their interactions with stakeholders and improve corporate reputation. At the same time, firms should prioritize disclosure quality to ensure credibility. Regulators should pay close attention to the authenticity of social media disclosures and prevent the misuse of platforms for generating information noise that misleads stakeholders.

2. Literature review

2.1. Economic consequences of social media disclosure

Research on social media primarily focuses on platforms such as Twitter and Sina Weibo. Regarding the economic consequences of social media disclosure, studies find that social media provides incremental information that reduces information asymmetry between investors and firms (Hu et al., 2016; Blankespoor, 2018; He et al., 2018; Feng and Johansson, 2019; Gomez et al., 2024).

The effects of social media disclosure can be categorized into five areas: analyst forecasts and ratings, asset pricing and market efficiency, corporate investment and financing, corporate governance and customer management. First, regarding analyst forecasts and ratings, investor interactions on Sina Weibo attract the attention of analysts, regulators and other market participants (Zheng and Guo, 2024), thereby reducing analysts' forecast dispersion (Hu et al., 2016). Similarly, consumer comments on firms' Twitter accounts serve as important references for analysts' ratings (Kim and Youm, 2017). Second, regarding asset pricing and market efficiency, Weibo disclosures reduce stock price synchronicity by increasing the information content of stock prices (He et al., 2018), and the use of positive language increases abnormal trading volume (Xu and Chen, 2016). Incremental information disclosed via Twitter is rapidly incorporated into stock prices, thereby improving market efficiency (Blankespoor et al., 2014) and demonstrating predictive power for stock returns (Bartov

et al., 2018; Gu and Kurov, 2020; Cookson et al., 2024) and short-term cryptocurrency price trends (Li and Ma, 2024). Positive words embedded in such disclosures enhance market returns, abnormal cryptocurrency trading volume (Zhang and Zhang, 2022) and abnormal stock trading volume (Ammari et al., 2023). Third, regarding corporate investment and financing, Twitter disclosures significantly reduce the cost of equity capital (Al Guindy, 2021) and financing costs (Blankespoor et al., 2014; Xing and Niu, 2025), thereby promoting corporate innovation (Xing and Niu, 2025). Fourth, regarding corporate governance, Twitter acts as a “public monitor,” enhancing governance quality (Xing and Niu, 2025), which constrains earnings management (Zhu and Yu, 2025) and greenwashing practices (Lyon and Montgomery, 2013). Fifth, in terms of customer management, Twitter interactions narrow the distance between firms and investors, improving corporate reputation (Toombs and Harlow, 2014; Elliott et al., 2018; Saxton et al., 2021). Such interactions enhance brand reputation and customer loyalty, provide real-time market insights, allow firms to adjust product strategies in response to consumer demand (Hamilton and Kaltcheva, 2016) and increase repurchase and word-of-mouth intentions (Nisar and Whitehead, 2016), thereby reducing customer churn risks (Maecker et al., 2016).

Although numerous studies highlight the positive effects of social media disclosure, other studies identify negative consequences. Social media provides firms with opportunities for impression management, such as reducing the release of unfavorable news and selectively disclosing or embellishing positive news (Dye, 2001; Yang and Liu, 2017; Jung et al., 2018) or strategically adjusting the timing of disclosure (Hu et al., 2022), which may lead to information asymmetry. Moreover, social media facilitates the dissemination of false information. Investors lacking information discernment are more easily misled (Zheng and Guo, 2024). In addition, repeated exposure to similar information within social networks leads users to overestimate its credibility (Jia et al., 2020; Campbell et al., 2023). The spread of such false information, coupled with irrational sentiment, may cause asset prices to be driven more by rumors than by facts, leading to short-term deviations of stock prices from fundamentals and thus reducing market efficiency (Jia et al., 2020).

In summary, social media has emerged as a significant force shaping capital markets and corporate behavior. It is a double-edged sword that can reduce information asymmetry, improve corporate governance, lower financing costs, promote innovation and enhance firm value but may also distort prices and increase market risks by accelerating the spread of rumors and amplifying emotional noise.

2.2. Determinants of ESG rating divergence

ESG rating divergence generates a range of adverse consequences. For instance, it increases stock price synchronicity (Liu et al., 2023), heightens stock price crash risk (Sun et al., 2025), raises firms’ financing costs and constraints (He et al., 2025; Zhao et al., 2025) and reduces the effectiveness of ESG investment (Serafeim and Yoon, 2023). Given these negative economic implications, scholars have paid close attention to the driving factors of ESG rating divergence. First, rating agencies differ in their legal origins (Liang and Renneboog, 2017; Kurbus and Rant, 2025), which are associated with variations in cultural heritage, geographic distance and institutional context (Ma and Yu, 2023). Divergent institutional understandings of environmental and social responsibilities (Chatterji et al., 2016) contribute to ESG rating divergence. Second, differences in technical factors such as ESG indicator scope, data selection and weighting schemes (Kotsantonis and Serafeim, 2019; Berg et al., 2022) can lead to inconsistencies across agencies. Third, even excluding technical factors, the variation in agencies’ information acquisition capacity and channels induces information gaps that exacerbate ESG rating divergence (Easley and O’Hara, 2004; Garfinkel, 2009; Chatterji et al., 2016; Zhang et al., 2023). Firm-specific characteristics and behaviors may also influence ESG rating divergence. For example, firms with executives with overseas experience (Wang et al., 2023) or those voluntarily issuing ESG reports (Kimbrough et al., 2022) tend to experience reduced divergence. In contrast, some studies find that greater disclosure (Christensen et al., 2022) or the use of positive tones and sticky words in ESG reports (Kimbrough et al., 2022) may amplify divergence.

In summary, although prior research has provided extensive insights into voluntary disclosure on social media, few studies examine its role in ESG rating divergence. In particular, the impact of Sina Weibo on ESG rating divergence remains underexplored. To address this gap, we use Weibo disclosure as a setting of voluntary ESG information disclosure to investigate its impact on ESG rating divergence, thereby extending the literature on the economic consequences of voluntary ESG disclosure via social media.

3. Hypothesis development

3.1. The information effect hypothesis of voluntary social media disclosure

ESG rating divergence reflects the information asymmetry or uncertainty in rating agencies' evaluation of firms' ESG performance. Information gaps are a key driver of divergence (Kimbrough et al., 2022). Agencies' differences in their capacity and channels for collecting information lead to substantial informational discrepancies, which exacerbate ESG rating divergence (Easley and O'Hara, 2004; Garfinkel, 2009; Chatterji et al., 2016; Zhang et al., 2023). Therefore, broadening the sources of ESG information and increasing the amount of common information shared between rating agencies can facilitate consensus formation (Kimbrough et al., 2022) and serve as a crucial mechanism for mitigating ESG rating divergence.

With the rapid development of Internet technologies, numerous social media platforms have emerged. Platforms such as Sina Weibo have become important channels for corporate disclosure because of their low information transmission costs, rapid dissemination speed and broad reach (He et al., 2018). An increasing number of firms have established official Weibo accounts and voluntarily and timely disclosed ESG-related information. Such disclosure enables external stakeholders to access firms' ESG performance at a low cost, thereby increasing the information available to rating agencies (Hope, 2003). This process helps to break down information barriers arising from resource disparities between agencies, reducing informational discrepancies. Prior studies provide evidence that Weibo disclosure can transmit firm-specific information (Hu and Wang, 2015; Shen et al., 2017; He et al., 2018). By analyzing voluntarily disclosed incremental information, rating agencies can better identify firms with strong ESG performance and ESG-related risks, thereby reducing misassessment of corporate ESG practices (Yang et al., 2011). Ultimately, such voluntary disclosure can mitigate ESG rating divergence. Based on the above reasoning, we propose the following hypothesis.

H1a: Firms' voluntary ESG disclosure on social media mitigates ESG rating divergence.

3.2. The noise effect hypothesis of voluntary social media disclosure

Voluntary ESG disclosure may also generate noise that interferes with rating agencies' analysis and judgment. When a firm discloses limited ESG information, agencies may regard the absence of certain disclosures as nonessential (Kotsantonis and Serafeim, 2019) or interpret missing core information as a signal of weak ESG performance. Thus, when disclosure is minimal, agencies may more easily reach consensus on core indicators (Feng et al., 2024). Because of a lack of standardization and effective regulation in social media disclosure, firms release more ESG information through Weibo, fostering information noise and overload, which allows for interpretive divergence and thereby intensifies ESG rating divergence (Christensen et al., 2022).

More critically, firms may use Weibo to greenwash. Firms may strategically highlight positive aspects of ESG performance while concealing negative information (Liu and Hu, 2024), such as overstating investments in environmental protection while hiding instances of environmental harm (Wang et al., 2024). Firms may also adopt more subtle forms of greenwashing, such as favoring vague qualitative descriptions over concrete quantitative data (Xu et al., 2025). Given that rating agencies differ in their capacity to detect greenwashing, strategic disclosure is likely to mislead evaluations (Christensen et al., 2022; Wang et al., 2024) and widen interagency divergence. Accordingly, as the volume of ESG information on Weibo increases, ESG rating divergence becomes more pronounced. Based on the above analysis, we propose a competing hypothesis.

H1b: Firms' voluntary ESG disclosure on social media exacerbates ESG rating divergence.

4. Research design

4.1. Sample selection and data sources

Because ESG data in the Wind Financial Terminal are available from 2018, we select Chinese A-share listed firms from 2018 to 2022 as the initial research sample. Data on firms' Weibo activities are collected from Sina Weibo. Data on firms' characteristics and financial information are obtained from the CSMAR database. We collect Weibo data through web crawling using Python, which identifies 852 verified corporate Weibo accounts. The sample is processed as follows. First, firms designated as ST or *ST are excluded. Second, financial firms are excluded. Third, firms with missing data are removed. The final sample consists of 2843 firm-year observations. To mitigate the influence of outliers, all of the continuous variables are winsorized at the 1% and 99% levels.

4.2. Model specification and variable definitions

Following Zhang et al. (2025) and Chen et al. (2025), we construct Model (1) to examine whether voluntary ESG disclosure on social media mitigates ESG rating divergence:

$$ESGdif_{i,t} = \alpha_0 + \alpha_1 Wb_num_{i,t} + \beta Controls_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (1)$$

Following Avramov et al. (2022), we use *ESGdif* to measure ESG rating divergence, defined as ESG ratings from six agencies—Wind, Huazheng, SynTao Green Finance, Menglang, FTSE Russell and Bloomberg. For each firm-year, we calculate the percentile ranking of ESG scores across agencies and then compute the standard deviation of these percentile rankings. A larger standard deviation indicates greater divergence.

Following He et al. (2018), we use *Wb_num* to measure voluntary ESG disclosure on social media, defined as $\ln(1 + \text{the total number of ESG-related Weibo posts in a given year})$. A Weibo post is classified as ESG-related if its text contains keywords such as "ESG," "sustainability," "social responsibility," "environmental protection" or "corporate governance."

Following Zhang et al. (2025) and Chen et al. (2025), we control for a series of firm-level characteristics: leverage (*Lev*), return on assets (*Roa*), ownership concentration (*TOP*), CEO duality (*Dual*), firm size (*Size*), firm growth (*Growth*), internal control quality (*IC*), Tobin's *Q*, price-to-earnings ratio (*PE*), board size (*Board*), cash-to-assets ratio (*Cash*) and industry concentration (*HHI*). Year fixed effects (*Year*) and industry fixed effects (*Industry*) are also included to account for macroeconomic cycles and industry-specific environments. Detailed definitions of all of the variables are provided in Table 1.

5. Empirical results

5.1. Descriptive statistics

Table 2 presents the descriptive statistics. ESG rating divergence has a minimum value of 0 and a maximum value of 0.4714, indicating significant disparities in firms' ESG scores. The logarithmic values of the number of ESG-related Weibo posts (*Wb_num*) range from 0 (corresponding to 0 posts) to 2.4849 (corresponding to 11 posts), suggesting considerable variation in the extent of voluntary ESG disclosure by firms on social media.

Fig. 1 displays the temporal trend of ESG-related information disclosure by the sample firms on Weibo. As shown, the volume of ESG-related Weibo posts demonstrates a general upward trend, laying the groundwork for examining the impact of social media ESG disclosure on ESG rating divergence.

5.2. Correlation analysis

This study conducts a Pearson correlation test to examine the correlations between the main variables. As shown in Table 3, ESG rating divergence is significantly and negatively correlated with the number of ESG-related Weibo posts, providing preliminary evidence in support of H1a that voluntary ESG disclosure on

Table 1

Variable symbols, names and definitions.

Variable	Symbol	Definition
ESG rating divergence	<i>ESGdif</i>	The standard deviation of the percentile rankings of ESG scores from six raters: Wind, Huazheng, SynTao Green Finance, Menglang, FTSE Russell and Bloomberg
The number of Weibo posts	<i>Wb_num</i>	$\ln(1 + \text{firm's annual total number of Weibo posts related to ESG})$
The number of comments	<i>Comment</i>	$\ln(1 + \text{annual total number of comments on the firm's ESG-related Weibo posts})$
The number of reposts	<i>Repost</i>	$\ln(1 + \text{annual total number of reposts of the firm's ESG-related Weibo posts})$
The number of likes	<i>Likenum</i>	$\ln(1 + \text{annual total number of likes on the firm's ESG-related Weibo posts})$
Tobin Q	Tobin's <i>Q</i>	Market value/total assets
Firm size	<i>Size</i>	Natural logarithm of total assets
Ownership concentration	<i>Top</i>	The shareholding ratio of the company's largest shareholder
Return on assets	<i>Roa</i>	Net profit/total asset balance
Price-to-earnings ratio	<i>PE</i>	Closing price/(annual net profit/year-end paid-in capital)/100
Leverage	<i>Lev</i>	Total liabilities/total assets
Firm growth	<i>Growth</i>	(Current quarter revenue – previous quarter revenue)/previous quarter revenue
CEO duality	<i>Dual</i>	Whether the chair and CEO are the same person: 1 if so and 0 otherwise
Internal control quality	<i>IC</i>	The Dibo Internal Control Index/100
Board size	<i>Board</i>	$\ln(\text{number of directors on the board} + 1)$
Cash-to-assets ratio	<i>Cash</i>	Closing balance of cash and cash equivalents/current liabilities
Industry concentration	<i>HHI</i>	Herfindahl-Hirschman Index
Year fixed effects	<i>Year</i>	Year fixed effects
Industry fixed effects	<i>Industry</i>	Industry fixed effects

Note: This table provides detailed definitions of all of the variables in the study.

Table 2

Descriptive statistics.

Variable	<i>N</i>	<i>Mean</i>	<i>Std</i>	<i>Median</i>	<i>Min</i>	<i>Max</i>
<i>ESGdif</i>	2843	0.1230	0.0775	0.1179	0	0.4714
<i>Wb_num</i>	2843	0.0440	0.2130	0	0	2.4849
Tobin's <i>Q</i>	2843	2.0829	1.4570	1.6505	0.7131	20.8933
<i>Size</i>	2843	22.2967	1.3538	22.0285	19.5852	28.6067
<i>Top</i>	2843	3.3762	0.4833	3.4009	2.0906	4.3129
<i>Roa</i>	2843	0.0359	0.0641	0.0364	-0.2289	0.2006
<i>PE</i>	2843	0.5918	1.8724	0.3610	-7.4677	11.0285
<i>Lev</i>	2843	0.3843	0.1889	0.3698	0.0558	0.8259
<i>Growth</i>	2843	0.1467	0.4319	0.0904	-0.7186	2.7240
<i>Dual</i>	2843	0.3908	0.4880	0	0	1
<i>IC</i>	2843	6.4616	0.9185	6.5877	0	9.4131
<i>Board</i>	2843	2.0871	0.1997	2.1972	1.6094	2.7081
<i>Cash</i>	2843	0.0094	0.0135	0.0049	0.0014	0.2121
<i>HHI</i>	2843	0.1512	0.1147	0.1188	0.0014	0.8099

Note: Table 2 reports the summary statistics of the key variables. The definitions of the variables are presented in Table 1.

social media mitigates ESG rating divergence. Moreover, the correlation coefficients of other variables indicate no severe multicollinearity. In addition, we compute the variance inflation factor (VIF) values for the main variables. The mean value is 1.69, which is far below the critical threshold of 10, further suggesting that multicollinearity is not a concern in our model.

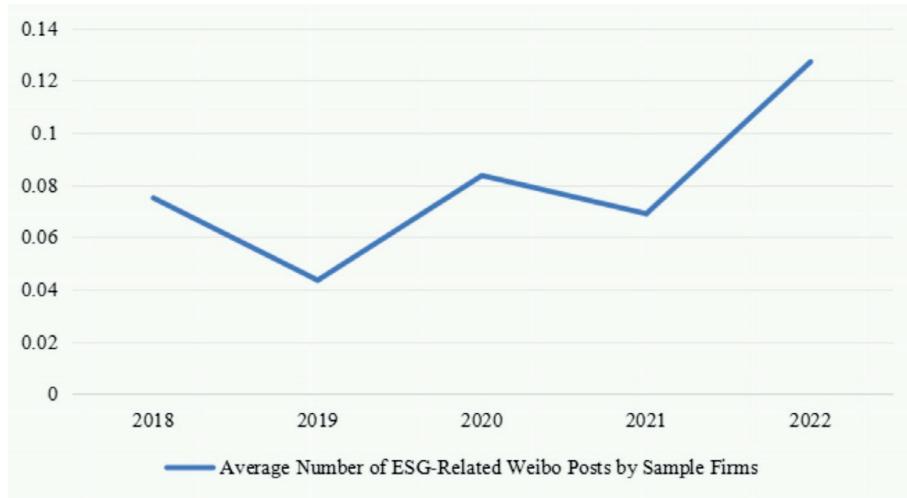


Fig. 1. Temporal trend of ESG information disclosure by firms on the Weibo platform.

5.3. Baseline results and analysis

Table 4 reports the regression results for ESG-related Weibo disclosures on ESG rating divergence. In Column (1), we control for industry and year fixed effects and include only the explanatory variable of the number of ESG-related Weibo posts. The coefficient of *Wb_num* is negative and significant at the 1 % level. Column (2) adds control variables while retaining industry and year fixed effects, and the coefficient of *Wb_num* remains negative and significant at the 1 % level. These results suggest that firms' voluntary ESG disclosures on social media significantly reduce ESG rating divergence, supporting H1a.

Columns (3)–(5) report the regression results for the sub-dimensions of ESG rating divergence. The findings reveal that voluntary ESG disclosures on social media significantly reduce ESG rating divergence in the dimensions of environmental protection and social responsibility, with coefficients significant at the 5 % and 1 % levels, respectively; however, the coefficient for the governance dimension is nonsignificant.

5.4. Endogeneity tests

5.4.1. Instrumental variable approach

To address potential endogeneity issues arising from reverse causality, we draw on the literature and use the average volume of ESG-related Weibo posts published by other firms in the same industry and region (*Mean_wb_num*) as an instrumental variable (IV). Theoretically, firms within the same industry face similar operating environments and risks; thus, whether an individual firm discloses ESG information on Weibo is correlated with the average disclosure level of other firms in the same industry and year. As shown in Column (1) of Table 5, the total volume of ESG-related Weibo posts by other firms in the same year is not significantly correlated with the focal firm's ESG rating divergence, indicating that ESG rating divergence is not directly related to the average disclosure of other same-industry same-year firms. Thus, the IV satisfies both relevance and exogeneity conditions.

The regression results are presented in Column (2) of Table 5. In the first-stage regression, the coefficient of the IV is 0.3097 ($t = 3.98$), which is significant at the 1 % level. Moreover, both the Cragg–Donald Wald F statistic and the Kleibergen–Paap rk Wald F statistic exceed the critical values of the Stock–Yogo weak instrument test, indicating no weak instrument problem. The Kleibergen–Paap rk LM test significantly rejects the null hypothesis of under identification, suggesting that the model is well identified. These results demonstrate

Table 3
Results of the Pearson correlation analysis.

	ESGdif	Wb_Num	Tobin's Q	Size	Top	Roa	PE	Lev	Growth	Dual	IC	Board	Cash	HHI
ESGdif	1													
Wb_num	-0.056***	1												
Tobin's Q	0.023	0.032*	1											
Size	0.264***	0.056***	-0.172***	1										
Top	0.094***	-0.003	-0.041**	0.158***	1									
Roa	0.019	0.034*	0.309***	-0.013	0.181***	1								
PE	0.022	0.019	0.029	0.047**	-0.019	-0.001	1							
Lev	0.079***	0.020	-0.250***	0.554***	0.054***	-0.284***	0.059***	1						
Growth	-0.009	0.018	0.095***	0.026	-0.038***	0.202***	0.029	0.031*	1					
Dual	-0.011	-0.050***	0.090***	-0.231***	0.006	0.033*	0.011	-0.130***	0.024	1				
IC	0.096***	0.009	0.080***	0.182***	0.110***	0.303***	0.015	0.131***	0.002	1				
Board	0.010	-0.011	-0.052***	0.290***	0.019	0.022	0.007	0.161***	0.011	-0.208***	0.048***	1		
Cash	-0.033*	0.022	0.187***	-0.262***	-0.016	0.173***	-0.001	-0.545***	-0.011	0.068***	0.005	-0.112***	1	
HHI	0.137***	0.001	-0.049***	0.186***	0.855***	0.180***	-0.0180	0.0260	-0.037***	0.012	0.124***	0.0290	-0.0100	1

Note: Table 3 reports the correlation coefficients between the major variables. Levels of significance are reported as * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$.

Table 4
Baseline regressions.

	(1) <i>ESGdif</i>	(2) <i>ESGdif</i>	(3) <i>E dif</i>	(4) <i>S dif</i>	(5) <i>G dif</i>
<i>Wb_num</i>	-0.0201*** (-4.82)	-0.0240*** (-6.32)	-0.0312** (-2.26)	-0.0411*** (-3.66)	0.0113 (0.81)
Tobin's <i>Q</i>		0.0048*** (4.25)	-0.0071** (-2.79)	-0.0015 (-0.74)	0.0063** (2.95)
<i>Size</i>		0.0183*** (13.45)	-0.0110** (-3.11)	-0.0036 (-1.18)	-0.0007 (-0.22)
<i>Top</i>		-0.0117** (-2.07)	0.0189 (1.28)	-0.0304** (-2.59)	0.0010 (0.09)
<i>Roa</i>		-0.0447 (-1.63)	-0.1024 (-1.44)	-0.0128 (-0.24)	-0.0362 (-0.63)
<i>PE</i>		0.0006 (0.77)	-0.0039** (-2.28)	0.0017 (1.12)	-0.0012 (-0.93)
<i>Lev</i>		-0.0458*** (-4.21)	0.0231 (0.78)	0.0288 (1.28)	-0.0234 (-1.01)
<i>Growth</i>		-0.0022 (-0.61)	-0.0016 (-0.19)	0.0054 (0.82)	0.0020 (0.27)
<i>Dual</i>		0.0064** (2.11)	-0.0038 (-0.50)	-0.0039 (-0.66)	-0.0023 (-0.37)
<i>IC</i>		0.0023 (1.61)	-0.0010 (-0.25)	-0.0050 (-1.64)	-0.0108** (-3.04)
<i>Board</i>		-0.0216** (-2.88)	-0.0071 (-0.35)	-0.0346** (-2.20)	-0.0141 (-0.87)
<i>Cash</i>		-0.0869 (-0.72)	-0.3607 (-0.94)	-0.1566 (-0.79)	0.4066 (1.48)
<i>HHI</i>		0.0720** (3.13)	-0.1638** (-2.71)	0.1370** (2.57)	-0.0199 (-0.40)
<i>Constant</i>	0.1249** (2.75)	-0.2040*** (-3.57)	0.4680*** (3.64)	0.3245*** (4.03)	0.2017** (2.36)
<i>Year</i>	Yes	Yes	Yes	Yes	Yes
<i>Industry</i>	Yes	Yes	Yes	Yes	Yes
<i>N</i>	2843	2843	2843	2843	2843
<i>R</i> ²	0.0774	0.1391	0.0576	0.0525	0.0352

Note: This table shows the correlations between voluntary ESG information disclosure on social media and the divergence in ESG ratings. Column (3) shows the regression results for ESG rating divergence in the environmental dimension (*E dif*), Column (4) shows the regression results for ESG rating divergence in the social dimension (*S dif*) and Column (5) shows the regression results for ESG rating divergence in the governance dimension (*G dif*). All of the regressions control for industry and year fixed effects. The *t*-statistics are reported in parentheses. *, ** and *** represent $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively. The definitions of the variables are presented in Table 1.

that the IV strongly explains the endogenous variable. As shown in Column (3), in the second-stage regression, the coefficient of the volume of ESG-related Weibo posts is negative and significant at the 5 % level, consistent with the main regression results. This confirms that voluntary disclosure of ESG information on social media significantly reduces ESG rating divergence.

5.4.2. Firm fixed effects

The aforementioned time-industry fixed effects model may suffer from the effects of unobservable factors or omitted variable bias, leading to endogeneity concerns. To control for firm-specific and time-varying factors that could affect the regression results, we use a time-individual fixed effects model for robustness testing. The results, presented in Column (1) of Table 6, hold.

Table 5
IV approach.

	(1) ESGdif	(2) Wb_num	(3) ESGdif
<i>Mean_wb_num</i>	-0.0177 (-1.38)	0.3208*** (4.48)	-0.0832** (-2.43)
Tobin's <i>Q</i>	0.0046*** (4.04)	0.0057* (1.72)	0.0041*** (3.77)
<i>Size</i>	0.0183*** (13.23)	0.0049 (1.03)	0.0194*** (14.90)
<i>Top</i>	-0.0120** (-2.11)	-0.0063 (-0.47)	-0.0122** (-2.13)
<i>Roa</i>	-0.0456* (-1.66)	0.1224** (2.01)	-0.0411 (-1.49)
<i>PE</i>	0.0006 (0.71)	0.0002 (0.10)	0.0005 (0.63)
<i>Lev</i>	-0.0467*** (-4.26)	0.0343 (1.01)	-0.0332*** (-3.02)
<i>Growth</i>	-0.0035 (-0.96)	0.0054 (0.45)	-0.0033 (-0.94)
<i>Dual</i>	0.0071** (2.33)	-0.0184** (-2.39)	0.0040 (1.26)
<i>IC</i>	0.0023 (1.61)	-0.0030 (-0.58)	0.0032** (2.29)
<i>Board</i>	-0.0195** (-2.58)	-0.0384* (-1.70)	-0.0267*** (-3.60)
<i>Cash</i>	-0.1029 (-0.84)	0.6203 (1.32)	-0.0067 (-0.05)
<i>HHI</i>	0.0781*** (3.33)	-0.0311 (-0.52)	0.1012*** (4.35)
<i>Constant</i>	-0.1983** (-2.93)	0.0119 (0.13)	-0.2396*** (-7.50)
Cragg-Donald Wald <i>F</i> statistic			84.964
Kleibergen-Paap rk Wald <i>F</i> statistic			20.074
Kleibergen-Paap rk <i>LM</i> statistic			14.199 ***
Hansen <i>J</i> statistic			0.000
<i>Year</i>	Yes	Yes	Yes
<i>Industry</i>	Yes	Yes	Yes
<i>N</i>	2811	2811	2811
<i>R</i> ²	0.1342	0.0349	0.0747

Note: This table reports the results of our IV estimation. In Column (1), ESG rating divergence is not directly related to *Mean_wb_num*. In Column (2), the relationship between *Mean_wb_num* and *Wb_num* is examined. In Column (3), the predicted value of *Mean_wb_num* is included in the regression as the independent variable. Year and industry fixed effects are included as indicated. The *t*-statistics are reported in parentheses. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

5.4.3. Dependent variables in period $t + 1$

Weibo is characterized by its rapid information diffusion, with posts frequently achieving broad platform-wide circulation within days or even hours. To examine the persistence of the impact of voluntary corporate ESG disclosure via social media on ESG rating divergence, we conduct a test measuring the effect of Weibo posts in period t on ESG rating divergence in period $t + 1$. As shown in Column (2) of Table 6, the mitigating effect of voluntary ESG disclosure on ESG rating divergence remains significant in period $t + 1$, confirming the robustness of the results.

Table 6
Individual fixed effects and dependent variables in period $t + 1$.

	(1) <i>ESGdif</i>	(2) <i>ESGdif</i>
<i>Wb_num</i>	-0.0220** (-3.07)	-0.0285*** (-3.74)
Tobin's Q	0.0012 (0.70)	0.0067*** (5.73)
<i>Size</i>	0.0229*** (3.48)	0.0159*** (8.98)
<i>Top</i>	-0.0125 (-0.66)	-0.0112 (-1.59)
<i>Roa</i>	-0.0824** (-2.44)	-0.0053 (-0.16)
<i>PE</i>	0.0006 (0.77)	0.0004 (0.43)
<i>Lev</i>	-0.0177 (-0.74)	-0.0293** (-2.14)
<i>Growth</i>	-0.0035 (-0.93)	-0.0008 (-0.16)
<i>Dual</i>	0.0031 (0.52)	0.0019 (0.49)
<i>IC</i>	0.0016 (0.82)	0.0005 (0.26)
<i>Board</i>	0.0023 (0.12)	-0.0170* (-1.82)
<i>Cash</i>	-0.1745 (-0.58)	0.0144 (0.10)
<i>HHI</i>	0.0134 (0.16)	0.0596** (2.02)
Constant	-0.3544** (-2.31)	-0.1196** (-2.67)
Industry	No	Yes
Year	Yes	Yes
Firm	Yes	No
<i>N</i>	2693	1868
<i>R</i> ²	0.3134	0.1269

Note: This table presents the results for the alternative fixed effects model and temporal processing of the independent variables. In Column (1), year and firm fixed effects are included as indicated. In Column (2), all of the dependent variables are led by one year. All of the regressions control for industry and year fixed effects. The *t*-statistics are reported in parentheses. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

5.5. Robustness tests

5.5.1. Alternative explanatory variables

Because ESG information disclosed on Weibo may have already been released through official channels, such disclosures may not necessarily contain incremental information. To more accurately capture the information effect of Weibo ESG disclosures, we restrict effective disclosures to the first-time release of ESG information. We manually compare ESG-related Weibo posts with information disclosed on firms' official websites and construct a variable *Wb_F* to represent the number of first-time ESG disclosures on Weibo. We classify Weibo posts as first-time disclosures if the information was not disclosed on the official website or the information released on the official website was subsequent to its disclosure on Weibo. As Column (1) of Table 7

Table 7
Robustness tests.

	(1) <i>ESGdif</i>	(2) <i>ESGdif</i>	(3) <i>ESGdif</i>	(4) <i>ESGdif_var</i>
<i>Wb_F</i>	-0.0082*** (-4.02)			
<i>Wb</i>		-0.0239*** (-6.02)		
<i>Wb_R</i>			-0.4035*** (-5.30)	
<i>Wb_num</i>				-0.0052*** (-5.67)
Tobin's <i>Q</i>	0.0047*** (4.16)	0.0048*** (4.26)	0.0047*** (4.17)	0.0002 (0.96)
<i>Size</i>	0.0182*** (13.34)	0.0184*** (13.50)	0.0183*** (13.38)	-0.0018*** (-5.82)
<i>Top</i>	-0.0115** (-2.03)	-0.0118** (-2.09)	-0.0117** (-2.06)	-0.0040** (-2.92)
<i>Roa</i>	-0.0472* (-1.72)	-0.0445 (-1.63)	-0.0481* (-1.75)	-0.0113* (-1.76)
<i>PE</i>	0.0006 (0.72)	0.0006 (0.71)	0.0005 (0.63)	0.0002 (1.00)
<i>Lev</i>	-0.0464*** (-4.28)	-0.0455*** (-4.19)	-0.0462*** (-4.25)	-0.0048* (-1.95)
<i>Growth</i>	-0.0023 (-0.64)	-0.0023 (-0.63)	-0.0023 (-0.65)	0.0013 (1.52)
<i>Dual</i>	0.0066** (2.16)	0.0064** (2.13)	0.0066** (2.18)	0.0011 (1.63)
<i>IC</i>	0.0023 (1.64)	0.0023 (1.61)	0.0023* (1.66)	0.0000 (0.01)
<i>Board</i>	-0.0209** (-2.78)	-0.0216** (-2.88)	-0.0210** (-2.80)	-0.0063*** (-3.50)
<i>Cash</i>	-0.0984 (-0.81)	-0.0868 (-0.72)	-0.0931 (-0.77)	-0.0231 (-0.87)
<i>HHI</i>	0.0712** (3.10)	0.0728** (3.17)	0.0714** (3.09)	0.0235*** (4.26)
<i>Constant</i>	-0.2107*** (-3.69)	-0.2131*** (-3.73)	-0.2119*** (-3.70)	0.0920*** (7.35)
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>N</i>	2843	2843	2843	2843
<i>R</i> ²	0.1370	0.1391	0.1372	0.1053

Note: This table presents the results of several robustness tests of the baseline findings. In Column (1), we replace the independent variable with the number of posts containing the company's first-time released information on Weibo. In Column (2), we include *Wb* as a dummy variable. In Column (3), we replace the independent variable with the ratio of ESG-related Weibo posts to the total number of posts in a given year. In Column (4), we use the coefficient of variation across six rating agencies as the dependent variable. All of the regressions control for industry and year fixed effects. The *t*-statistics are reported in parentheses. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

reports, the coefficient of *Wb_F* is negative and significant at the 1 % level, indicating that first-time ESG disclosures on Weibo mitigate ESG rating divergence.

We adopt additional alternative measures to ensure robustness. First, we define *Wb* as a dummy variable equal to 1 if a firm makes any ESG-related Weibo post during the year and 0 otherwise. Second, we construct *Wb_R* as the ratio of ESG-related Weibo posts to the total number of posts in a given year. As Column (2) of Table 7 shows, *Wb* is significantly and negatively associated with ESG rating divergence at the 1 % level. As

shown in Column (3), *Wb_R* is also significantly and negatively correlated with ESG rating divergence at the 1 % level. These findings are consistent with our baseline results.

5.5.2. Alternative dependent variables

Following Zhang et al. (2023), we use the coefficient of variation (i.e., ESG rating divergence divided by the mean of ESG ratings) for six rating agencies—Wind, Huazheng, SynTao Green Finance, Menglang, FTSE Russell and Bloomberg—as an alternative dependent variable (*ESGdif_var*). Column (4) of Table 7 presents the regression results, showing that *Wb_num* is associated with *ESGdif_var* at the 1 % level. These results confirm our baseline findings.

Table 8
ESG disclosure on Weibo and greenwashing.

	Gws				
	(1) Full Sample	(2) Low Financing Constraints	(3) High Financing Constraints	(4) Low Managerial Ownership	(5) High Managerial Ownership
<i>Wb_num</i>	-0.0569 (-0.36)	0.1336 (0.55)	0.0547 (0.22)	0.4260 (1.26)	0.0848 (0.39)
Tobin's <i>Q</i>	0.0588** (2.02)	0.0881* (1.92)	0.0814** (2.29)	0.1262* (1.84)	0.0628** (2.06)
<i>Size</i>	0.1066* (1.71)	0.0791 (0.97)	0.2808* (1.66)	-0.0145 (-0.08)	0.3376*** (4.67)
<i>Top</i>	0.2139 (0.80)	0.4224 (1.20)	-0.0340 (-0.10)	0.6465 (0.88)	-0.3468 (-1.33)
<i>Roa</i>	-1.7721* (-1.82)	-2.1432 (-1.37)	0.4304 (0.28)	-0.9760 (-0.45)	-1.1681 (-0.92)
<i>PE</i>	0.0751 (1.36)	0.0608 (1.42)	-0.0468 (-0.82)	0.0312 (0.57)	0.0210 (0.46)
<i>Lev</i>	-0.0725 (-0.17)	0.3413 (0.53)	-2.0942** (-2.63)	0.7825 (0.76)	-1.1021** (-2.01)
<i>Growth</i>	0.3111** (2.73)	0.5287*** (3.97)	0.0183 (0.08)	0.6847*** (3.71)	0.2284* (1.70)
<i>Dual</i>	0.2402 (1.60)	0.3849** (2.15)	0.2998 (1.20)	0.1961 (0.65)	0.3305* (1.91)
<i>IC</i>	0.0516 (1.02)	0.0732 (1.06)	-0.0775 (-0.98)	0.1005 (0.87)	-0.0750 (-1.36)
<i>Board</i>	0.1043 (0.36)	0.2322 (0.66)	0.4572 (0.68)	-0.3828 (-0.59)	0.4499 (1.13)
<i>Cash</i>	21.4149*** (4.64)	23.1955*** (4.30)	11.1728 (0.87)	17.5574** (2.67)	28.0207** (2.80)
<i>HHI</i>	-0.4287 (-0.49)	-0.9389 (-0.80)	0.1359 (0.11)	-1.1532 (-0.28)	1.0677 (1.24)
<i>Constant</i>	-4.3212** (-2.82)	-2.7509 (-1.38)	-3.1788 (-0.85)	-0.7022 (-0.15)	-4.1918** (-2.43)
<i>Year</i>	Yes	Yes	Yes	Yes	Yes
<i>Industry</i>	Yes	Yes	Yes	Yes	Yes
<i>N</i>	877	641	236	345	532
<i>R</i> ²	0.0294	0.2360	0.5110	0.3023	0.3012

Note: This table presents the results of correlation tests between ESG information disclosure on Weibo and corporate greenwashing. The sample is further partitioned based on financing constraints and management governance levels for separate regression analyses. All of the regressions control for industry and year fixed effects. The *t*-statistics are reported in parentheses. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

5.6. Ruling out alternative explanations

Although the above analyses indicate that Weibo ESG disclosures reduce ESG rating divergence, a possible alternative explanation is that such disclosures may reflect firms' greenwashing motives rather than the provision of credible incremental information. To exclude this possibility, we test whether Weibo ESG disclosures are associated with firms' greenwashing behavior.

Table 8 reports the regression results of Weibo ESG disclosures on greenwashing behavior measured by a greenwashing score (Gws), following Hu et al. (2023). A higher positive value of Gws indicates more severe greenwashing, while a negative value suggests concealment of actual environmental performance. The specific calculation formula is as follows:

$$\text{Greenwash Score}_i, t = \left(\frac{ESGdis_i, t - \overline{ESGdis}}{\sigma_{dis}} \right) - \left(\frac{ESGperi_i, t - \overline{ESGper}}{\sigma_{per}} \right) \quad (2)$$

Gws is calculated as the standardized difference between firms' environmental disclosure scores (Bloomberg ESG) and environmental performance scores (Wind ESG). Column (1) shows no significant relationship between Weibo ESG disclosures and Gws , which suggests that Weibo disclosures are not driven by greenwashing motives. Furthermore, prior studies suggest that firms with higher financing constraints (Wedari et al., 2021) and those with more myopic management (Li and Xin, 2024) are more likely to engage in greenwashing. Accordingly, we divide firms into subsamples based on the degree of financing constraints (measured by the SA index) and managerial myopia (proxied by the management shareholding ratio) (Gao and Zhou, 2013; Zhong et al., 2017). Columns (2)–(5) show that across all subsamples, the number of ESG-related Weibo disclosures is not significantly related to greenwashing scores. Taken together, these results indicate that voluntary ESG disclosures on Weibo are not associated with greenwashing behavior, but rather reflect genuine ESG performance. This finding further strengthens the credibility of our conclusion that voluntary ESG disclosures on social media mitigate ESG rating divergence.

6. Mechanism tests

The preceding analysis confirms that firms' ESG-related disclosures on Weibo alleviate ESG rating divergence. We conduct two additional tests to further verify the information effect mechanism underlying voluntary ESG disclosure on social media.

First, if ESG disclosure on Weibo provides incremental information, such voluntary disclosure should transmit firm-specific information to the capital market, thereby reducing stock price synchronicity. Following Liu et al. (2023), we measure stock price synchronicity (SYN) and regress it on the number of ESG-related Weibo posts (Wb_num). As reported in Column (1) of Table 9, the coefficient of Wb_num on SYN is negative and significant at the 5 % level, indicating that ESG-related Weibo disclosure reduces stock price synchronicity, consistent with the presence of incremental information.

Second, we examine the role of user interactions with ESG-related Weibo posts, measured by the numbers of likes ($Likenum$), comments ($Comment$) and reposts ($Repost$). In modern information dissemination, reposts reflect the breadth of information dissemination, comments represent the depth of public participation and likes indicate the popularity and approval of the disclosed information. When ESG information posted on Weibo receives greater public interaction through likes, comments and reposts, the information is amplified and disseminated more broadly, thereby strengthening its incremental effect. These interactive behaviors provide additional signals about a firm's ESG performance for rating agencies, which may value these signals, reducing divergence in their assessments. Therefore, we expect that if voluntary ESG disclosure on social media provides valuable incremental information, the mitigating effect on ESG rating divergence will be more pronounced when likes, comments and reposts are higher.

To mitigate the impact of multicollinearity, we mean-center the variables Wb_num , $Likenum$, $Comment$ and $Repost$. The regression results are presented in Table 9. Column (2) shows that the coefficient of Wb_num and the interaction term $Wb_num \times Likenum$ are negative and significant at the 1 % level, indicating that the divergence-mitigating effect of ESG-related Weibo disclosure is stronger when posts receive more likes. Col-

Table 9

The transmission mechanism: Information effect.

	(1) SYN	(2) ESGdif	(3) ESGdif	(4) ESGdif
<i>Wb_num</i> × <i>Likenum</i>		-0.0118*** (-3.80)		
<i>Wb_num</i> × <i>Comment</i>			-0.0114** (-3.17)	
<i>Wb_num</i> × <i>Repost</i>				-0.0091** (-3.04)
<i>Likenum</i>		0.0173*** (3.79)		
<i>Comment</i>			0.0160** (2.99)	
<i>Repost</i>				0.0117** (2.50)
<i>Wb_num</i>	-0.1235** (-2.14)	-0.0265*** (-6.19)	-0.0252*** (-6.09)	-0.0241*** (-6.03)
Tobin's <i>Q</i>	0.0208** (2.01)	0.0048*** (4.25)	0.0048*** (4.25)	0.0048*** (4.24)
<i>Size</i>	0.1751*** (11.61)	0.0182*** (13.30)	0.0183*** (13.37)	0.0183*** (13.38)
<i>Top</i>	-0.1064* (-1.92)	-0.0116** (-2.06)	-0.0118** (-2.08)	-0.0117** (-2.07)
<i>Roa</i>	0.1430 (0.55)	-0.0451 (-1.64)	-0.0446 (-1.63)	-0.0443 (-1.62)
<i>PE</i>	-0.0018 (-0.26)	0.0005 (0.67)	0.0006 (0.78)	0.0006 (0.76)
<i>Lev</i>	-0.2024* (-1.86)	-0.0461*** (-4.24)	-0.0457*** (-4.20)	-0.0457*** (-4.20)
<i>Growth</i>	-0.0245 (-0.71)	-0.0021 (-0.57)	-0.0021 (-0.58)	-0.0022 (-0.60)
<i>Dual</i>	-0.0029 (-0.10)	0.0064** (2.10)	0.0064** (2.11)	0.0064** (2.11)
<i>IC</i>	-0.0026 (-0.18)	0.0024* (1.72)	0.0023 (1.60)	0.0023 (1.61)
<i>Board</i>	-0.1307* (-1.69)	-0.0216** (-2.88)	-0.0215** (-2.87)	-0.0215** (-2.86)
<i>Cash</i>	0.7093 (0.64)	-0.0846 (-0.70)	-0.0843 (-0.70)	-0.0846 (-0.70)
<i>HHI</i>	-0.0808 (-0.34)	0.0719** (3.13)	0.0727** (3.16)	0.0723** (3.15)
<i>Constant</i>	-3.5592*** (-8.00)	-0.2097*** (-3.67)	-0.2100*** (-3.68)	-0.2108*** (-3.69)
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>N</i>	2843	2843	2843	2843
<i>R</i> ²	0.2999	0.1392	0.1389	0.1387

Note: This table reports the information effect mechanism of corporate voluntary ESG disclosure on social media. In Column (1), we regress stock price synchronicity on the number of ESG-related Weibo posts. In Columns (2)–(4), we examine the role of user interactions with ESG-related Weibo posts, measured by the number of likes, comments and reposts. All of the regressions control for industry and year fixed effects. The *t*-statistics are reported in parentheses. ***, ** and * denote significance at the 1 %, 5 % and 10 % significance levels, respectively.

umn (3) shows that *Wb_num* remains negative and significant at the 1 % level, while the interaction term *Wb_num* × *Comment* is negative and significant at the 5 % level, suggesting that more comments reinforce the mitigating effect. Column (4) demonstrates that *Wb_num* is again negative and significant at the 1 % level

and $Wb_num \times Repost$ is negative and significant at the 5 % level, confirming that higher repost activity strengthens the mitigating effect. Taken together, these results indicate that firms' voluntary ESG disclosure on Weibo generates incremental information that alleviates ESG rating divergence.

7. Heterogeneity analysis

7.1. Characteristics of ESG rating agencies: Domestic versus foreign agencies

The regional attributes of ESG rating agencies may influence their interpretation of "soft culture" and thereby affect their assessments (Feng et al., 2024). First, compared with foreign agencies, domestic ESG rating agencies possess the advantage of geographic proximity. Because foreign agencies rely primarily on firms' official reports, their information channels are relatively limited. In contrast, domestic agencies can access incremental information beyond official reports through multiple channels, which reduces differences in subjective interpretations (Feng et al., 2024). Second, domestic agencies are more policy-oriented, being closely aligned with national regulations and policy developments. As a result, the criteria used by domestic agencies are relatively more consistent, thereby alleviating more of their ESG rating divergence compared with their foreign counterparts.

To account for the influence of regional attributes, we follow Feng et al. (2024) and categorize ESG rating agencies into domestic and foreign types. Specifically, we use the coefficient of variation of ESG scores from Bloomberg and FTSE Russell to measure foreign ESG rating divergence ($ESGdif_for$). This measure is defined as the standard deviation of the percentile rankings of ESG scores divided by the average of the two agencies after the exclusion of cases where one or more agencies report missing values. Similarly, we use the coefficient of variation of ESG scores from Wind, Huazheng, SynTao Green Finance and Menglang to measure domestic ESG rating divergence ($ESGdif_dom$). This is defined as the standard deviation of the percentile rankings divided by the average of the four agencies after the exclusion of cases with two or more missing values.

Table 10 presents the results on the impact of firms' voluntary ESG disclosure on Weibo across domestic and foreign agencies. Column (1) reports the association between the number of ESG-related Weibo posts (Wb_num) and domestic ESG rating divergence, and Column (2) reports the results for foreign ESG rating divergence. The findings show that voluntary ESG disclosure on Weibo significantly reduces divergence among domestic ESG agencies, whereas the effect is nonsignificant among foreign agencies. One possible explanation is that foreign agencies pay relatively less attention to Weibo as an information channel. This result suggests that voluntary ESG disclosure on social media is more effective in alleviating ESG rating divergence among domestic agencies than among foreign agencies.

7.2. Industry characteristics: polluting versus non-polluting firms

Industry characteristics may condition the effect of voluntary ESG disclosure via social media on ESG rating divergence. Firms in heavily polluting industries such as metallurgy and chemicals are more environmentally sensitive and receive greater external scrutiny. To mitigate negative perceptions among investors and regulators, such firms are strongly motivated to fully disclose ESG information through formal ESG reports or other official channels. Rating agencies are therefore more likely to reach consensus on these firms' performance. Because heavily polluting firms already engage in relatively comprehensive disclosure, the incremental information contained in their Weibo posts may be limited. Accordingly, we argue that ESG-related Weibo disclosure should have a stronger mitigating effect on ESG rating divergence among non-polluting firms.

Table 11 reports the regression results after we divide the sample into non-polluting and heavily polluting firms. In Column (1), the coefficient of ESG-related Weibo disclosure is negative and significant at the 1 % level for non-polluting firms, but the coefficient is nonsignificant for heavily polluting firms. Moreover, the difference in coefficients between the two groups is significant at the 1 % level. These results suggest that voluntary ESG disclosure on Weibo more effectively alleviates ESG rating divergence for non-polluting firms than for heavily polluting firms.

Table 10
Heterogeneity analysis: characteristics of ESG rating agencies.

	(1) <i>ESGdif_dom</i>	(2) <i>ESGdif_for</i>
<i>Wb_num</i>	-0.0374** (-2.47)	0.1636 (1.11)
Tobin's <i>Q</i>	0.0047 (1.07)	0.0008 (0.03)
<i>Size</i>	0.0001 (0.02)	-0.1360** (-3.10)
<i>Top</i>	-0.0049 (-0.18)	-0.5707*** (-3.76)
<i>Roa</i>	0.1390 (1.28)	-0.9289 (-1.07)
<i>PE</i>	-0.0027* (-1.71)	-0.0184 (-0.87)
<i>Lev</i>	-0.1310** (-2.86)	0.4199 (0.91)
<i>Growth</i>	0.0189 (1.11)	0.1078 (0.69)
<i>Dual</i>	0.0063 (0.46)	-0.0075 (-0.06)
<i>IC</i>	0.0023 (0.53)	-0.0314 (-0.97)
<i>Board</i>	-0.0212 (-0.73)	-0.4531* (-1.78)
<i>Cash</i>	0.3795 (0.50)	-4.3250 (-0.80)
<i>HHI</i>	0.2496** (2.43)	2.5212*** (4.65)
<i>Constant</i>	0.2031 (1.07)	9.7651*** (7.47)
<i>Year</i>	Yes	Yes
<i>Industry</i>	Yes	Yes
<i>N</i>	833	369
<i>R</i> ²	0.1794	0.1930

Note: This table reports the results regarding the effect of characteristics of ESG rating agencies on the association between voluntary ESG disclosure on social media and ESG rating divergence. The foreign ESG rating agencies are Bloomberg and FTSE Russell. The domestic ESG rating agencies are Wind, Huazheng, SynTao Green Finance and Menglang. All of the regressions control for industry and year fixed effects. The *t*-statistics are reported in parentheses. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

7.3. Regional Internet penetration: High versus low

Regional differences in Internet penetration may also affect the impact of voluntary ESG disclosure on social media. In regions with higher Internet penetration, online events are more likely to enter public discussion, as information users and providers share a common network community that fosters sustained public attention and opinion (Zhang, 2014), which increases the incremental information effect of ESG disclosures. Therefore, we expect that ESG-related Weibo disclosure will more effectively mitigate ESG rating divergence for firms located in regions with higher Internet penetration.

Table 12 presents the regression results for the sample divided into high- and low-penetration regions. In both groups, the coefficients of ESG-related Weibo disclosure are negative and significant at the 5 % level. However, the absolute magnitude of the coefficient is larger for firms in high-penetration regions, and the dif-

Table 11
Heterogeneity analysis: Industry characteristics.

	(1) Non-polluting Firms	(2) Polluting Firms
<i>Wb_num</i>	-0.0268*** (-3.72)	-0.0110 (-0.72)
Tobin's <i>Q</i>	0.0058*** (4.80)	0.0019 (0.84)
<i>Size</i>	0.0180*** (11.33)	0.0204*** (4.81)
<i>Top</i>	-0.0118* (-1.96)	-0.0139 (-0.83)
<i>Roa</i>	-0.0478* (-1.65)	-0.0475 (-0.73)
<i>PE</i>	0.0004 (0.54)	0.0009 (0.51)
<i>Lev</i>	-0.0430*** (-3.52)	-0.0610** (-2.16)
<i>Growth</i>	-0.0052 (-1.41)	0.0137 (1.49)
<i>Dual</i>	0.0056* (1.72)	0.0115 (1.56)
<i>IC</i>	0.0031* (1.74)	-0.0038 (-0.96)
<i>Board</i>	-0.0206** (-2.42)	-0.0272 (-1.37)
<i>Cash</i>	0.0230 (0.17)	-0.4277 (-1.60)
<i>HHI</i>	0.0682** (2.64)	0.0925 (1.20)
<i>Constant</i>	-0.2130*** (-3.94)	-0.2010* (-1.68)
<i>Year</i>	Yes	Yes
<i>Industry</i>	Yes	Yes
<i>P</i> -value	0.0000***	
<i>N</i>	2332	511
<i>R</i> ²	0.1539	0.0616

Note: This table reports the results regarding the effect of industry characteristics on the association between voluntary ESG disclosure on social media and ESG rating divergence. Column (1) reports the results for the subsample of non-polluting firms, while Column (2) presents the results for the subsample of heavily polluting firms. All of the regressions control for industry and year fixed effects. The *t*-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

ference between the two groups is significant at the 10% level. These findings indicate that the mitigating effect of Weibo disclosure on ESG rating divergence is more pronounced in regions with higher Internet penetration.

8. Conclusion and implications

Using a sample of Chinese A-share listed firms from 2018 to 2022, this study uses ESG disclosure data from Sina Weibo to empirically examine the impact of voluntary ESG disclosure on ESG rating divergence. The results are as follows. First, ESG information disclosed through Weibo significantly reduces ESG rating divergence, and this result remains robust when we address endogeneity concerns and conduct a series of robustness checks. Second, Weibo disclosures contain highly incremental information, and the mitigating effect on rating divergence becomes more pronounced when such disclosures receive greater market attention in the form of

Table 12
Heterogeneity analysis: Regional Internet penetration.

	(1) High Internet penetration	(2) Low Internet penetration
<i>Wb_num</i>	-0.0290** (-2.78)	-0.0204** (-2.42)
Tobin's <i>Q</i>	0.0059*** (4.11)	0.0036** (2.20)
<i>Size</i>	0.0180*** (7.52)	0.0189*** (9.23)
<i>Top</i>	-0.0132 (-1.48)	-0.0098 (-1.28)
<i>Roa</i>	-0.0995** (-2.45)	-0.0066 (-0.19)
<i>PE</i>	0.0006 (0.53)	0.0008 (0.83)
<i>Lev</i>	-0.0405** (-2.36)	-0.0478** (-3.12)
<i>Growth</i>	-0.0071 (-1.44)	0.0042 (0.89)
<i>Dual</i>	0.0095** (2.20)	0.0037 (0.85)
<i>IC</i>	0.0046** (1.98)	0.0005 (0.20)
<i>Board</i>	-0.0124 (-1.07)	-0.0212* (-1.91)
<i>Cash</i>	0.1459 (0.75)	-0.2068 (-1.32)
<i>HHI</i>	0.0577 (1.41)	0.0814** (2.61)
<i>Constant</i>	-0.2710** (-2.83)	-0.2046** (-3.12)
<i>Year</i>	Yes	Yes
<i>Industry</i>	Yes	Yes
<i>P</i> -value	0.0912*	
<i>N</i>	1376	1476
<i>R</i> ²	0.1142	0.1760

This table reports the results regarding the effect of regional Internet penetration on the association between voluntary ESG disclosure on social media and ESG rating divergence. Column (1) reports the results for firms located in regions with higher Internet penetration and Column (2) presents the results for firms located in regions with lower Internet penetration. All of the regressions control for industry and year fixed effects. The *t*-statistics are reported in parentheses. ***, ** and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

likes, reposts and comments. Third, the effect of Weibo disclosures on alleviating rating divergence is more salient for domestic rating agencies, firms in non-polluting industries and firms located in regions with higher Internet penetration, compared with their respective counterparts. Finally, there is no evidence that voluntary ESG disclosure via Weibo constitutes greenwashing. Instead, the results lend support to the information effect hypothesis, highlighting the role of voluntary ESG disclosure on social media as a credible channel for reducing rating divergence.

This study has several important implications. First, at the firm level, companies can leverage the disclosure advantages of social media platforms to strengthen engagement with stakeholders. Firms should also enhance the quality of ESG disclosures on Weibo by more effectively fulfilling their ESG responsibilities and contin-

uously communicating their positive ESG performance to the public, thereby improving their reputation in the capital market. Second, at the social media level, Internet platforms should foster a secure and constructive online environment, providing retail investors with accessible channels for ESG information exchange, which can reduce information asymmetry and promote the sustainable development of capital markets. Third, at the regulatory level, government agencies should raise policy requirements for standardized ESG disclosure, improve the transparency of ESG rating methodologies and encourage firms to adopt third-party audits and assurance mechanisms, thereby reducing noise in ESG rating outcomes and enhancing the credibility of ESG information.

Funding

Wenfei Li would like to thank the National Natural Science Foundation of China (Grant No. 72472036) and the Guangdong Province Philosophy and Social Sciences Co-construction Project (Grant No. GD23XGL069).

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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Contents lists available at ScienceDirect

China Journal of Accounting Research

journal homepage: www.elsevier.com/locate/cjar



Tax avoidance and CEO turnover: evidence from China



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ARTICLE INFO

Article history:

Received 20 January 2025

Accepted 28 October 2025

Available online 15 December 2025

Keywords:

Tax avoidance

CEO turnover

Ownership structure

Political connections

Regional tax enforcement

China

ABSTRACT

As the literature documents inconclusive evidence on whether tax avoidance affects CEO turnover, we examine the impact of tax avoidance on forced CEO turnover and the moderating effect of ownership structure, political connections and regional tax enforcement on this relationship. Using data on Chinese listed firms involving 10,653 observations for the 2011–2018 period, we test our hypotheses using logistic regressions. We find that tax avoidance is positively associated with forced CEO turnover, suggesting that tax-avoiding firms are more likely to face leadership crises. Furthermore, the positive association is pronounced for firms that are state-owned, lack political connections or are located in developed regions with active tax enforcement. Our results, which are robust to alternative proxies and endogeneity tests, should interest policymakers and investors as they demonstrate the impact of tax avoidance on corporate governance and leadership.

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1. Introduction

Tax avoidance (hereafter, TAV) is defined as the legal practice of minimizing tax expenses or deferring tax payments (Dyreng et al., 2008). It is a major concern for researchers and regulators due to its potential economic implications, particularly as taxes constitute the government's primary source of revenue. Taxes

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represent one of the largest costs for firms (Wang et al., 2021a, 2021b; Jiang et al., 2023); by reducing the tax burden, TAV can increase after-tax income and thereby enhance shareholder returns (Crocker and Slemrod, 2005; Dyring et al., 2008). However, TAV may entail risks, as firms and managers face potential reputational costs (Hanlon and Slemrod, 2009; Graham et al., 2012). Often, it is perceived as unethical because tax avoiders evade their social responsibilities (Lenz, 2020), which may harm their reputation and erode public trust. Empirical studies indicate that reputational concerns are a critical deterrent to TAV (Desai and Dharmapala, 2006; Cheng et al., 2012). Blouin (2014) emphasizes that such behavior depends on the CEO's tolerance for reputational risks. Given the importance of taxation for firms and shareholders, tax-related issues can influence corporate leadership. This study investigates whether TAV leads to forced CEO turnover.

In practice, tax avoidance strategies are generally initiated and managed by top executives, primarily the CEO and the board, who oversee financial reporting and tax planning activities. Although shareholders may benefit from lower tax liabilities, they typically lack the information or direct involvement needed to assess whether such strategies are prudent, aggressive or misaligned with long-term interests. Examining the association between tax avoidance and CEO turnover is important for two key reasons. First, it enhances our understanding of how tax avoidance influences corporate governance and second, the empirical evidence on the relationship between tax avoidance and forced CEO turnover remains inconclusive. Although the literature explores the consequences of tax avoidance—including its effects on firm and executive reputation—the findings are mixed. For instance, Gallemore et al. (2014) find no evidence of reputational costs for firms or executives engaging in tax avoidance. In contrast, Chyz and Gaertner (2018) demonstrate that lower tax payments are associated with higher CEO turnover. Conversely, Lanis et al. (2019) show that CEOs and directors often experience reputational gains following tax avoidance activities, as reflected in increased appointments to outside boards. Given these conflicting results, the link between tax avoidance and forced CEO turnover remains unresolved, and is a puzzle that motivates our study.

From a reputational perspective, CEOs may benefit from a positive reputation when firms maintain a low tax burden (Lanis et al., 2019). However, other evidence suggests that CEOs face a higher likelihood of forced turnover when firms exhibit low effective tax rates (ETR) (Chyz and Gaertner, 2018). TAV depends on executives' willingness to engage in such practices. In the Chinese context, research identifies several factors influencing TAV, including state ownership, tax enforcement and CEO political connections (Hoopes et al., 2012; Bradshaw et al., 2016; Kim and Zhang, 2016; Richardson et al., 2016; Chen et al., 2022). For example, Cao et al. (2017) find that politically connected CEOs are less likely to be dismissed than those lacking such connections, whereas Conyon and He (2020) document a significant relationship between state ownership and CEO turnover. Although studies largely overlook these moderating factors, we argue that investigating their role is critical for advancing academic understanding and providing actionable insights for regulators.

China provides an ideal setting for investigating our research question for three key reasons. First, the Chinese capital market is uniquely characterized by the dominance of state ownership, a feature that distinguishes it from developed markets. By the end of 2014, state-owned enterprises (SOEs) accounted for approximately 64.36 % of the total market (Wong, 2016). This ownership structure contributes to weaker corporate governance, lower investor protection and less efficient tax enforcement compared with private firms (Lin et al., 2018; Xiao and Shao, 2020), making TAV more prevalent among SOEs because their CEOs face lower detection and punishment risks. Despite government efforts to curb tax avoidance, challenges persist owing to complex tax laws, a lack of transparency and varying tax rates across industries and firm types (Tsai et al., 2021; Jiang et al., 2023). In addition, China's diverse tax treaties with other nations complicate compliance (Wang et al., 2021a, 2021b). Given that tax avoidance can harm China's reputation as an investment destination, studying this issue offers critical insights for policymakers. Second, CEOs in SOEs often have strong political connections and therefore turnover decisions are influenced by political and social factors rather than purely economic factors (Cao et al., 2017). This creates a contrast between SOEs and non-SOEs, which enables us to examine how state ownership moderates the relationship between TAV and forced CEO turnover.

Furthermore, provincial tax authorities face varying targets, and failure to meet them can strain local economies. As a result, tax collectors may negotiate tax payments with non-SOE management, leading to regional disparities in TAV practices (Chen, 2021). The coexistence of more and less developed regions in China facilitates an analysis of how regional development influences this relationship. Third, as the world's

largest emerging economy and the second-largest economy overall, China's dynamics have broad implications. Our findings are likely to hold significance for global stakeholders, particularly those in emerging markets facing similar governance and tax challenges.

Using a sample of Chinese firms for the period from 2011 to 2018, we find a significant positive association between tax avoidance and forced CEO turnover. Our results indicate that a one-unit increase in book–tax differences (BTD) raises the probability of forced CEO turnover by 1.509,¹ suggesting that firms engaging in TAV activities face substantially higher leadership instability than other firms. We examine how this relationship varies across different institutional contexts by analyzing the moderating effects of state ownership, CEO political connections and regional tax enforcement (proxied by regional development). The positive association between TAV and forced CEO turnover is particularly pronounced in SOEs, firms without politically connected CEOs and firms located in more developed regions where tax enforcement tends to be stricter. To strengthen our findings, we conduct a falsification test following Chyz and Gaertner (2018), which reveals no significant relationship between TAV and unforced CEO turnover (e.g., due to retirement, health issues or death), thereby supporting our main results. In addition, our conclusions remain robust across multiple sensitivity tests, including alternative measures of TAV, firm fixed effects regressions, two-stage least squares (2SLS) estimation with instrumental variables and system generalized method of moments (GMM) estimation. These rigorous approaches help address potential endogeneity concerns and reinforce the validity of our findings.

This study makes several key contributions to the literature on corporate governance and tax strategy, particularly in the context of emerging markets. We examine how boards respond to corporate TAV, a legal practice aimed at minimizing or deferring tax liabilities, and find that despite its potential to enhance firm value, TAV is associated with an increased likelihood of forced CEO turnover. This finding provides empirical support for the governance perspective that views TAV not only as a financial decision but also as a signal of potential ethical concerns or agency problems. Our work addresses ongoing theoretical tension in the literature regarding the consequences of TAV. On the one hand, TAV can be interpreted as a legitimate, value-enhancing activity that benefits shareholders by improving after-tax earnings (Desai and Dharmapala, 2006; Scholes et al., 2014). On the other hand, it may be regarded as a vehicle for managerial opportunism, particularly when tax strategies are opaque, complex or perceived as overly aggressive (Desai and Dharmapala, 2009; Kim et al., 2011). By showing that even legal tax strategies can lead to CEO dismissal, our study highlights how corporate boards actively weigh ethical and reputational dimensions of executive decisions, even in the absence of public or regulatory pressure. We consider that China's unique institutional context enables us to provide a more definitive conclusion than studies based in Western economies with diffuse ownership, well-established investor protection and depoliticized board processes. China's corporate environment features stronger political oversight, regional variation in enforcement and significant state ownership. These characteristics make CEOs more vulnerable to reputational scrutiny and internal governance actions, even in the case of legal but ethically ambiguous decisions such as whether to adopt TAV. Thus, the Chinese context provides a sharp lens through which to observe disciplinary responses to TAV.

We differentiate our study from research that focuses on tax-related controversies involving publicly disclosed use of tax shelters—that is, “tax violations” (e.g., Wang et al., 2021a, 2021b). Our study focusses on broader, non-disclosed TAV activities captured via BTD. Tax violations, although not illegal, are publicly exposed and often trigger strong external reactions, leading to relatively predictable governance responses. In contrast, our focus on routine TAV, which is legal and less visible than tax violations, provides new insight into internal governance mechanisms that operate without the stimulus of public enforcement or reputational crises. This distinction allows us to explore how boards interpret the risks and benefits of tax strategies in ambiguous settings. Empirically, we contribute to the literature by examining a considerably larger and more representative dataset than those of other studies. Our sample includes 1043 forced CEO turnover events and 10,653 firm-year observations from listed SOEs and non-SOEs in China between 2011 and 2018. In contrast, Wang et al. (2021a, 2021b) analyze a much smaller sample of 64 treated firms. Our sample allows us to better capture variation across ownership types, firm characteristics and institutional contexts. In addition, by using

¹ $e^{0.92} - 1 = 1.509$.

BTD, a continuous measure of TAV, our analysis captures a wide range of tax behaviors beyond the extreme cases such as tax sheltering, thereby improving the generalizability of our findings.

Furthermore, we extend the literature by examining moderating factors that influence the TAV–turnover relationship. Specifically, we analyze how CEO political connections and regional development levels—factors that receive limited attention in the literature—shape board responses to TAV. These contextual variables help explain when and why boards may tolerate or penalize TAV behavior, providing a nuanced understanding of governance dynamics in China. Our contribution in this regard is twofold. First, the Western literature predominantly examines the governance consequences of tax avoidance in settings with strong investor protection and uniform legal enforcement, whereas we provide evidence from China, where political influence, heterogeneous tax enforcement and the dual socioeconomic objectives of SOEs create distinct governance pressures. Second, compared with Wang et al. (2021a, 2021b), who focus on the direct TAV–turnover link in the Chinese context, we broaden the framework by identifying and empirically testing moderating factors such as political ties and regional institutional quality. These findings not only refine theory by explaining when and why boards may tolerate or penalize TAV behavior but also hold practical value for investors, regulators and policymakers seeking to design effective oversight mechanisms in environments where political and regional heterogeneity strongly influence corporate governance outcomes.

The remainder of this paper is organized as follows. Section 2 presents our literature review and develops the hypotheses. Section 3 describes the sample selection criteria and research methodology. Section 4 reports the descriptive statistics and our empirical findings. Section 5 provides robustness checks and addresses endogeneity concerns. Finally, Section 6 concludes with a discussion of our key findings and their implications.

2. Literature review and hypothesis development

2.1. CEO turnover

The literature extensively examines the determinants of CEO turnover, identifying several key factors that influence turnover decisions. Performance metrics emerge as a consistent predictor, with studies demonstrating that both individual CEO performance and firm-level performance significantly affect turnover likelihood. Barro and Barro (1990) establish that underperforming CEOs face higher departure rates than other CEOs, a finding corroborated by Neumann and Voetmann (2005) in the Spanish context and Murphy and Zimmerman (1993) at the firm performance level. Furthermore, these performance–turnover relationships are validated in transitional economies, as evidenced by Muravyev's (2003) analysis of Russian privatized firms.

Another critical determinant of turnover is governance quality. Multiple studies (Fan et al., 2007; Chen et al., 2013; Dikolli et al., 2014) demonstrate that weaker corporate governance structures are associated with reduced CEO turnover, suggesting that governance mechanisms play a crucial monitoring role. The literature also highlights important institutional moderators, particularly political connections and ownership structures. Buchholtz et al. (1998) emphasize the relevance of political connections, with subsequent research (You and Du, 2012; Cao et al., 2017) showing that these connections provide job security even during declines in performance. Ownership characteristics also influence turnover dynamics, with Nguyen (2011) presenting evidence in the French context, and Shen and Cannella (2003) presenting findings regarding managerial ownership concentration. These studies collectively underscore the multifaceted nature of the determinants of CEO turnover, which incorporate performance, governance and institutional factors.

2.2. Corporate tax avoidance (TAV)

In recent decades, the issue of TAV has received considerable attention in agency research. TAV refers to strategies employed by firms to legally reduce their tax liabilities (Hanlon and Heitzman, 2010). These strategies involve various transactions or arrangements aimed at minimizing the tax burden a firm is obligated to pay.

A considerable body of literature explores the factors influencing corporate TAV behavior. From a governance perspective, strong internal controls and board oversight are found to deter opportunistic tax strategies, whereas weak governance facilitates them (Kim and Li, 2014). Ownership structure is another influential

factor, with studies showing that different ownership arrangements can significantly affect the extent of TAV (Khurana and Moser, 2013; Farooq and Zaher, 2020). Politically connected firms tend to engage in less aggressive tax planning than politically connected firms to maintain legitimacy and reduce scrutiny (Chen et al., 2018). Managerial characteristics are crucial in understanding TAV. Studies demonstrate that CEO traits significantly influence tax avoidance decisions (Dyreng et al., 2010; Chyz, 2013; Olsen and Stekelberg, 2016; Chyz and Gaertner, 2018). Research also examines the effects of vertical interlock and government social media on TAV practices (Jiang et al., 2023; Wen et al., 2025). Moreover, CEO compensation schemes that are closely tied to financial performance may incentivize aggressive tax strategies (Gaertner, 2014; Armstrong et al., 2015; Duan et al., 2018). Chen et al. (2021) report that Chinese listed firms are less likely to engage in TAV following the appointment of a new CEO, suggesting that leadership transitions may prompt changes in tax behavior.

Tax enforcement is another important determinant of corporate TAV behavior. Higher levels of tax enforcement by authorities are associated with reduced TAV activities (Dyreng et al., 2016; Slemrod, 2016; Bozanic et al., 2017). Institutional environments characterized by weak enforcement and legal loopholes create opportunities for aggressive tax planning. Firms also face reputational and economic incentives that shape their tax behavior. Executives may pursue TAV to improve cash flow, maximize after-tax profits and alleviate financial constraints (Edwards et al., 2016). However, reputational concerns can function as significant deterrents, as executives seek to preserve their professional reputation for future career opportunities (Desai and Dharmapala, 2009; Austin and Wilson, 2015).

The consequences of TAV are explored in the literature. Desai and Dharmapala (2009) find no significant effect of TAV on firm value, whereas Kim et al. (2011) report a positive relationship between TAV and stock price crashes. Hanlon and Slemrod (2009) document a negative association between tax sheltering and stock prices, reflecting reputational costs, whereas Wilson (2009) finds a positive link between tax sheltering and stock returns. Kovermann (2018) shows that tax avoidance is negatively associated with the cost of debt, indicating potential financial benefits. However, Bayar et al. (2018) find no significant association between TAV and financial constraints. TAV practices often vary across firms (Dyreng et al., 2008), driven by a complex mix of governance quality, managerial incentives, institutional environments and political considerations. These multidimensional motivations explain the heterogeneity in TAV behavior and suggest that aggressive practices may provoke governance responses—such as CEO turnover—when they are misaligned with shareholder expectations or regulatory standards.

2.3. Hypothesis development

2.3.1. TAV and forced CEO turnover

According to economic theory, firms decide whether to engage in TAV by weighing its potential benefits against its costs (Crocker and Slemrod, 2005; McCarty, 2012). TAV can enhance firm value by reducing tax liabilities and freeing up financial resources, which can then be reinvested or distributed to shareholders (Crocker and Slemrod, 2005). Because taxes represent a significant drain on operational cash flows, minimizing them may be viewed as a shareholder-aligned strategy. However, TAV can entail reputational costs, especially for those involved in designing and approving aggressive tax strategies, such as CEOs (Austin and Wilson, 2017). As the central decision-maker, the CEO plays a pivotal role in determining a firm's approach to tax planning (Fama and Jensen, 1983). Although agency theory acknowledges that TAV may align with shareholder interests, it also recognizes that CEOs have personal incentives—such as performance-based compensation or career advancement (Lanis et al., 2019)—which may lead them to pursue aggressive tax strategies. Conversely, reputational consequences, such as dismissal or damage to future career prospects, may function as constraints, aligning CEO actions more closely with long-term shareholder and stakeholder expectations.

The literature on the relationship between TAV and forced CEO turnover remains inconclusive. On the one hand, TAV may be interpreted as a value-enhancing activity that benefits shareholders, especially if the financial gains outweigh the associated risks (Scholes et al., 2014). From this perspective, TAV could enhance the CEO's standing, provided that reputational damage is limited or nonexistent (Ordower, 2010). On the other hand, there is a growing ethical critique of aggressive tax behavior. Hansen et al. (1992) argue that executives

are responsible not only to shareholders but also to broader society. Rose (2007) suggests that CEOs must account for the expectations of all stakeholders when making strategic decisions. In response to such concerns, several jurisdictions, including the UK and Australia, have expanded corporate governance frameworks to include a wider range of stakeholder interests (Ibrahim et al., 2003). In this context, TAV can be seen as a violation of public trust by diminishing communal tax revenues (Lanis and Richardson, 2015).

From both a societal and an agency perspective, reputational risks represent a critical cost of TAV. Desai and Dharmapala (2006) highlight that managers may face reputational or civil sanctions for aggressive tax practices. Austin and Wilson (2015) contend that both executive and firm-level reputations are closely tied to TAV behavior. Consistent with this, Chyz and Gaertner (2018) find a positive relationship between TAV and forced CEO turnover. Wang et al. (2021a, 2021b) show that such consequences are more pronounced for SOEs, where reputational standards and public accountability are more stringent than among non-SOEs. Firms engaging in TAV may attract heightened scrutiny from tax authorities, leading to regulatory investigations, public criticism and financial penalties. These outcomes can damage a firm's reputation and reduce investor confidence, particularly if the firm is exposed for unethical conduct. Under the principal–agent framework, such events may cause shareholders to reevaluate the CEO's leadership and strategic judgment.

Empirical evidence suggests that aggressive TAV is linked to reduced firm value and declining stock prices (Hanlon and Slemrod, 2009; Tang, 2020), which may be due to investment inefficiencies and increased risk (Asiri et al., 2020). As a result, shareholders may view a CEO engaging in aggressive TAV as failing to act in their best interests. CEOs perceived as responsible for these negative outcomes are more likely to face dismissal, particularly during performance evaluations and shareholder meetings. Although studies in Western contexts, such as Lanis et al. (2019) and Gallemore et al. (2014), report negative or no relationships between TAV and CEO turnover, we argue that the inconsistencies in the literature may partly reflect differences in institutional context. In Western economies with strong legal protections and well-established governance mechanisms, the reputational consequences of TAV tend to be less severe or more difficult to attribute directly to individual executives. In contrast, China's institutional setting, characterized by concentrated state ownership, political influence in board decisions and varying degrees of regional enforcement, makes disciplinary consequences more observable. This context allows us to examine more clearly whether boards perceive even legal tax avoidance as a governance concern warranting executive dismissal. Based on the above theoretical and empirical foundation, we propose the following hypothesis:

H1: TAV activities are positively associated with forced CEO turnover.

2.3.2. The moderating effect of ownership structure, political connection and regional tax enforcement

The agency literature posits that a firm's TAV behavior is strongly influenced by the types of shareholders (Chen et al., 2010). Ownership structure, particularly in an institutional context such as China's, plays a critical role in shaping managerial decisions related to TAV (Wong et al., 2015). Empirical evidence shows that SOEs in China are generally less inclined to engage in aggressive tax avoidance than non-SOEs. This difference stems from SOEs pursuing the dual objectives of economic performance and social responsibility, including contributing to national tax revenues (Tang et al., 2017; Bradshaw et al., 2019).

SOEs operate under closer public and political scrutiny than their private counterparts and are expected to fulfill broader societal obligations. Failing to align with these expectations—such as concealing subsidiary operations or minimizing tax contributions—can result in substantial reputational and political costs (Dyreng et al., 2016). In this context, aggressive tax sheltering by SOEs may be viewed as directly conflicting with government interests and societal norms, thereby damaging the enterprise's public image and legitimacy. In addition, the appointment and dismissal of CEOs in SOEs is influenced often by political and social considerations rather than purely by economic performance (Fan et al., 2007). As such, a CEO's engagement in controversial tax strategies can trigger reputational backlash, increasing their vulnerability to forced turnover. In SOEs, where public accountability is more prominent, the reputational consequences of TAV are magnified, making CEOs susceptible to dismissal when such strategies are exposed. This institutional difference suggests that the relationship between TAV and CEO turnover is likely to be stronger in SOEs than in non-SOEs. The reputational risks and political sensitivities associated with TAV in SOEs imply that such activities are more likely to lead to forced CEO replacement in these entities. Therefore, we propose the following hypothesis:

H2: The positive relationship between TAV and forced CEO turnover is stronger in SOEs than in non-SOEs.

Political connections are a prevalent feature of Chinese corporate governance and play a considerable role in shaping firm behavior and outcomes (You and Du, 2012). China's transitional economy, characterized by a relatively weak legal framework and limited protection for private investors, amplifies the importance of such connections (Allen et al., 2005). With the government retaining controlling stakes in more than half of China's publicly listed firms (Chen et al., 2006; Chen et al., 2016), CEO appointments and dismissals in China often hinge more on political and social criteria than on economic performance (Fan et al., 2007). As such, many CEOs are selected to fulfill political or social objectives rather than to maximize shareholder wealth. Political connections are examined both as a mechanism of resource acquisition and as an indicator of managerial risk aversion (Christensen et al., 2016). Empirical studies find that politically connected CEOs are more inclined to engage in aggressive tax planning strategies (Kim and Zhang, 2016; Chen et al., 2018; Lin et al., 2018). For instance, Wu et al. (2012) report that appointing former politicians as CEOs in private firms significantly reduces their ETRs. Similarly, Shen et al. (2019) find that a CEO's political connection to their hometown increases firm-level TAV by approximately 7.4 %.

From the perspective of resource dependence theory, political connections are valuable firm resources that enhance access to regulatory support and economic benefits, ultimately contributing to firm value (Pfeffer and Salancik, 2003). Hillman (2005) provides evidence that politically connected board members are associated with improved accounting performance. Lin et al. (2018) argue that non-SOEs in China strategically appoint politically connected executives to tap into these advantageous networks.

However, agency theory offers the contrasting view that political connections may create manager-specific entrenchment, allowing executives to prioritize their personal interests over those of shareholders (Jensen and Meckling, 1976). This perspective suggests that political ties can insulate CEOs from accountability, reducing the likelihood of performance-based dismissal. Shleifer and Vishny (1989) note that such connections function as investments that help executives retain their positions despite underperformance. Empirical studies support this notion; Cao et al. (2017) find that politically connected CEOs in non-SOEs are less likely to be dismissed for poor performance, and You and Du (2012) demonstrate that the performance sensitivity of CEO turnover is lower for politically connected executives than for other executives. Therefore, although politically connected CEOs may engage in TAV practices, they are less likely to face forced turnover as a result than are CEOs lacking political connections. Political capital appears to offer a buffer against the governance consequences typically associated with aggressive tax strategies. Based on this reasoning, we propose the following hypothesis:

H3: The positive relationship between TAV and forced CEO turnover is weaker for politically connected firms than for firms lacking these connections.

A distinctive feature of the Chinese institutional landscape is its regional diversity. China comprises multiple regions, each exhibiting substantial variation in economic development and institutional quality. To foster localized growth, the central government delegates considerable autonomy to regional governments, including the authority to collect taxes and enforce tax policies (Lin et al., 2018; Xiao, 2020). Furthermore, China's tax laws grant preferential treatment to firms based on factors such as industry type, firm age and ownership structure, resulting in notable disparities in regional tax policies and enforcement mechanisms. This decentralization leads to heterogeneous tax enforcement practices across regions. More developed regions, with stronger institutional infrastructures, are better equipped to implement rigorous tax enforcement strategies, often incorporating technologies such as electronic tax filing and data analytics (He and Fang, 2016). These regions can absorb the high costs associated with detecting and penalizing tax avoidance behavior. In contrast, less developed regions often lack the financial and institutional capacity to enforce tax regulations effectively, which may encourage firms in these areas to engage in TAV (Xu, 2011).

Strong tax enforcement serves as both a corporate governance mechanism and a deterrent to managerial opportunism. Strong enforcement raises the perceived litigation and reputational risks associated with aggressive tax behavior, thereby discouraging managers from engaging in such activities (Hoopes et al., 2012; Kubick et al., 2015). Empirical evidence supports this notion; for instance, Xu (2011) finds that robust tax enforcement reduces agency conflicts by aligning managers' interests with those of shareholders. Furthermore, developed regions have greater incentives to curtail tax avoidance to fund public services and support eco-

nomic expansion (Tanzi and Zee, 2000). These regions are also more likely to penalize firms and executives involved in tax sheltering, thereby increasing the personal and professional costs of such behavior.

From a governance perspective, regional disparities in institutional quality affect how CEO performance is evaluated and sanctioned. In more developed regions, corporate boards tend to function more effectively compared with less developed regions, with higher performance sensitivity in executive turnover decisions (He and Fang, 2016). The CEO labor market is also more competitive in these areas, making it easier and less costly to replace underperforming executives (Cordeiro et al., 2013). Therefore, CEOs in developed regions face greater accountability for firm performance, including the reputational and financial consequences of TAV.

In contrast, boards in less developed regions may lack the capacity or incentives to monitor and discipline executives effectively. As a result, the performance sensitivity of CEO turnover is weaker and executives may be less likely to face consequences for engaging in tax avoidance than in more developed regions. Given that strong regional tax enforcement increases reputational and litigation risks and that CEO dismissal is more closely tied to performance in more developed regions, we expect that the relationship between TAV and forced CEO turnover will be stronger in these areas. Accordingly, we propose the following hypothesis:

H4: The positive relationship between TAV and forced CEO turnover is stronger in more developed regions with stronger tax enforcement than in less developed regions with weaker tax enforcement.

3. Methodology

3.1. Measurement of variables

3.1.1. Forced CEO turnover

CEO turnover refers to the voluntary or involuntary departure of a CEO. Typically, voluntary departures occur for reasons such as term expiration, retirement, health issues or changes in the firm's ownership structure, and are not indicative of dissatisfaction with the CEO. In contrast, involuntary or forced turnover reflects a breakdown in the relationship between shareholders and the CEO, often due to performance issues or agency conflicts.

Given that TAV is primarily considered an agency-related behavior, this study focuses on forced CEO turnover as the relevant outcome variable. We manually collect data on CEO turnover events to ensure accuracy and reliability. The data are sourced from the "*Changes of Chairperson of the Board and General Managers*" section within the corporate governance sub-database of the China Stock Market and Accounting Research (CSMAR) database. This dataset provides detailed information on CEO transitions, including the nature of the change, departure reasons and specific departure dates.

To identify forced turnover events, we employ a manual classification approach based on specific criteria consistent with other studies (Chyz and Gaertner, 2018; Wang et al., 2021a, 2021b). A turnover event is classified as forced if the CEO departs for any of the following reasons: personal reasons, dismissal, litigation involvement or resignation. Next, we create a binary variable, *FORCED*, which equals 1 if a CEO is involuntarily dismissed in year $t + 1$, and 0 otherwise. Our focus on the turnover of CEOs rather than of other executives (e.g., the CFO or tax director), is based on two considerations. First, the CEO is primarily responsible for strategic decisions, including tax planning. Thus, a CEO's forced departure is a clear signal of the board's or shareholders' intentions to alter the firm's leadership due to dissatisfaction with agency-related behaviors such as TAV. In contrast, the turnover of subordinate executives is typically a decision made by the CEO. Second, reliable identification of CEOs is feasible through the available data, allowing for manual verification. However, collecting comparable forced turnover data for CFOs or tax directors is significantly more difficult due to data limitations.

To further validate our empirical strategy, we construct a falsification variable for voluntary CEO turnover, labeled *UNFORCED_(t+1)*. This indicator equals 1 if the CEO's departure in year $t + 1$ is attributed to retirement, health issues, term expiration or ownership changes, and 0 otherwise. This variable allows us to evaluate whether the association between TAV and CEO turnover is specific to forced performance-related exits.

3.1.2. TAV measures

We use *BTD* as our primary proxy for TAV, which is a choice that aligns with the literature (e.g., Manzon Jr. and Plesko, 2001) and is motivated by both conceptual and empirical considerations, particularly within the institutional context of China. First, *BTD* is a more accurate measure of tax avoidance than alternative proxies such as the *ETR* in tax systems such as China's that are characterized by nonuniform tax rates. In contrast with countries such as the United States, China applies heterogeneous income tax rates depending on ownership structure, industry classification and geographical location (Shevlin et al., 2012; Tang et al., 2017; Tang, 2020). As a result, measures based on the *ETR* can be distorted by legitimate differences in statutory tax rates, thereby confounding intentional tax avoidance with structural tax variations.

Second, *BTD* offers a conceptually precise proxy for TAV, particularly for Chinese firms facing diverse tax treatments. Studies confirm the superiority of *BTD* over *ETR* in capturing the discretionary component of tax behavior under such institutional settings (Tang and Firth, 2011; Shevlin et al., 2012). Thus, *BTD* enables us to isolate the intentional component of TAV accurately, making it suitable for investigating the consequences of TAV, such as forced CEO turnover. Nevertheless, to ensure the robustness of our findings, we use additional tax avoidance proxies in our sensitivity analyses, including the *ETR*, as well as 3-year and 5-year long-run *ETRs* (*3LETR* and *5LETR*, respectively). Detailed descriptions of the variables and their construction are provided in the Appendix.

3.2. Empirical model

We use the following logistic regression model to investigate the relationship between TAV and forced CEO turnover and to examine the moderating impact of ownership structure, political connections and regional tax enforcement on this relationship:

$$\begin{aligned}
 \text{FORCED}_{i,t} = & \beta_0 + \beta_1 \text{BTD}_{i,t} + \beta_2 \text{SOE}_{i,t} + \beta_3 \text{CEOPOL}_{i,t} + \beta_4 \text{REGD}_{i,t} + \beta_5 \text{CEOAGE}_{i,t} \\
 & + \beta_6 \text{CEOTENU}_{i,t} + \beta_7 \text{CEOSHAR}_{i,t} + \beta_8 \text{DUALITY}_{i,t} + \beta_9 \text{BINDP}_{i,t} + \beta_{10} \text{BSIZE}_{i,t} \\
 & + \beta_{11} \text{BMEET}_{i,t} + \beta_{12} \text{DEBT}_{i,t} + \beta_{13} \text{FSIZE}_{i,t} + \beta_{14} \text{ROA}_{i,t} + \beta_{15} \text{CASHFR}_{i,t} + \beta_{16} \text{VOTR}_{i,t} \\
 & + \beta_{17} \text{ICW}_{i,t} + \beta_{18} \text{TOP10}_{i,t} + \text{INDUSTRY} + \text{YEAR} + \varepsilon_{i,t}
 \end{aligned} \tag{1}$$

FORCED is the forced CEO turnover dummy, which is coded 1 if there is a forced CEO turnover in year $t + 1$, and 0 otherwise. *BTD* is defined as the difference between pre-tax income from financial reports and taxable income from tax returns, as proposed by Manzon and Plesko (2001). To examine H1, we focus on the coefficient β_1 , which must be positive and significant if tax avoidance enhances the likelihood of forced CEO turnover. To examine H2–H4, we rerun Eq. (1) using subsamples divided into SOEs vs. non-SOEs, firms with political connections vs. firms without political connections and firms operating in more vs. less developed regions.

Following the literature, we include a set of control variables linked to CEO turnover (Gallemore et al., 2014; Chyz and Gaertner, 2018; Lanis et al., 2019). State ownership (*SOE*) is a dummy variable coded 1 if the firm is affiliated with the central or local government, and 0 otherwise. CEO political connection (*CEO-POL*) is a dummy variable coded 1 if the CEO is politically connected (i.e., if the CEO is or was an officer of the central or local government), and 0 otherwise. For the regional development (*REGD*) control variable, we classify China's provinces into more and less developed categories based on their GDP, with firms operating in more (less) developed regions coded 1 (0). In addition, we control for CEO characteristics including age (*CEO-AGE*), defined as the average age of the CEO; tenure (*CEOTENU*), defined as the number of years the CEO retained their position; and ownership (*CEOSHAR*), the percentage of shares held by the CEO.

In addition, we control for governance quality. We use indicator variables for the duality of leadership structure (*DUALITY*), which equals 1 if the CEO is also the chairperson of the board, and 0 otherwise; board independence (*BINDP*), measured as the ratio of independent directors on the board; board size (*BSIZE*), measured as the number of directors on the board; and board meetings (*BMEET*), measured as the number of annual board meetings. To control for firm-level characteristics, we include firm leverage (*DEBT*), measured as total liabilities scaled by total assets; firm size (*FSIZE*), defined as the logarithm of total assets;

and return on assets (*ROA*), defined as the firm's net profit scaled by total assets. To control for the effect of controlling shareholders on CEO turnover, we include controlling shareholders' cash flow rights (*CASHFR*), measured as the percentage of controlling shareholders' cash flow rights in a firm, and controlling shareholders' voting rights in a firm (*VOTR*), measured as the percentage of controlling shareholders' voting rights in a firm. We also include internal control status (*ICW*) and, to control for the firm's auditor (*TOP10*), we use a dummy variable coded 1 (0) if a firm is audited (not audited) by a top 10 audit firm. Finally, we include industry (*INDUSTRY*) and time (*YEAR*) fixed effects and cluster standard errors at the firm level.

3.3. Data and sample

We begin with all A-share listed firms with available data on TAV spanning the period from 2011 to 2018, which yields an initial sample of approximately 23,697 firm-year observations. We exclude financial firms (721 firm-year observations), firms with missing CEO turnover data (7290 firm-year observations) and observations with missing data on control variables (5033 firm-year observations). After applying these filters, our final sample consists of 10,653 firm-year observations. Table 1, Panel A summarizes this sample selection process. We assign 2011 as the starting year to avoid any confounding effects of the Chinese tax law reform in 2008, and select 2018 as the end date because of data availability. Following the tax accounting literature (Gupta and Newberry, 1997; Wu et al., 2012; Feng et al., 2019), we exclude firms with negative profits, financial firms and special treatment firms as their inclusion would distort ETRs (see Gupta and Newberry (1997) for an explanation). As explained previously, data on forced CEO turnover are hand collected, and the TAV data are sourced from the financial reports sub-database of CSMAR. Data for the moderating and control variables are also sourced from CSMAR, and data on tax returns come from the WIND database. To avoid the impact of outliers, we winsorize all continuous variables at the top and bottom 1 % of their respective distributions. Panel A of Table 1 shows the time distribution of our sample firms. The number of observations ranges from 993 (9.3 % of all firm-year observations) in 2011 to a peak of 1805 (16.9 %) in 2017. Panel B of Table 1 presents the sample distribution by industry. The majority of our sample firms belong to the manufacturing sector (63.9 % of all firm-year observations), followed by the IT industry (6.9 %) and the wholesale and retail business industry (4.15 %).

4. Empirical results

4.1. Descriptive statistics and correlation matrix

Panel A of Table 2 reports descriptive statistics for firms experiencing forced CEO turnover (*FORCED* = 1) and those not experiencing forced CEO turnover (*FORCED* = 0). The average *BT* is 0.014 for firms with forced CEO turnover, with approximately 19 % of these firms classified as SOEs. Among the CEOs, 9.3 % have political connections, and nearly 64.7 % of the firms are operating in more developed regions. For firms with no forced CEO turnover, the average *BT* is 0.002, with around 34.9 % of these firms categorized as SOEs. Among the CEOs, 16.2 % have political connections, and nearly 63.4 % of the firms are located in more developed regions. The mean differences for most of the variables in Panel A are significant, suggesting that the two subsamples of firms differ considerably.

The descriptive statistics for the entire sample are reported in Panel B of Table 2. Around 7.4 % of our sample firms dismissed their CEOs. This is slightly higher than the 5.1 % and 5.7 % reported by Chyz and Gaertner (2018) and Martinez and Brito (2019), respectively. In contrast, Gallemore et al. (2014) and Wang et al. (2021a, 2021b) report forced CEO turnover rates of 11 % and 12 %, respectively. The mean (median) *BT* is 0.003 (-0.002) with a standard deviation of 0.044. Around 34.5 % of our sample firms are controlled by the government, and the average number of firms with politically connected CEOs is 0.158. Within our sample, 65 % of the sample firms are located in more developed regions, suggesting that most are located in regions with strong tax enforcement actions. On average, CEOs are 49.33 years old, own 6.8 % of firm shares and have tenure of 3.67 years. Around 28.2 % of our sample companies have a CEO who simultaneously serves as chairperson of the board. The mean (median) ratio of independent directors on the board is 32.5 % (33.3 %). The average board size is 8.61, and the board of directors of our sample firms meet an average

Table 1
Sample distribution.

Panel A: Sample selection process		
TAV observations available for A-share listed firms		23,697
(–) observation for financial firms		(721)
(–) observations for firms with missing CEO turnover data		(7290)
(–) observations with missing data on control variables		(5033)
Final Sample		10,653

Panel B: The time distribution		
Year	N	Percentage
2011	993	9.3%
2012	1201	11.3%
2013	1195	11.2%
2014	1237	11.6%
2015	1371	12.9%
2016	1545	14.5%
2017	1805	16.9%
2018	1306	12.3%
Total Observations	10,653	100%

Panel C: The industry distribution			
Code	Industry	N	Percentage
A	Agriculture, forestry, animal husbandry and fishery	137	1.29%
B	Mining industry	279	2.62%
C	Manufacturing industry	6805	63.8%
D	Electricity, Thermal, Gas and Water Production and Supply Industry	399	3.74%
E	Construction business	308	2.89%
F	Wholesale and retail business	442	4.14%
G	Transportation, Warehousing and Postal Service	327	3.06%
H	Accommodation and catering	36	0.34%
I	Information transmission, software and information technology services	738	6.90%
K	Real Estate	304	2.85%
L	Leasing and Business Services	156	1.46%
M	Scientific Research and Technology Services	141	1.31%
N	Water Conservancy, Environment and Public Facilities Management Industry	201	1.88%
Q	Health and social work	45	0.42%
R	Culture, Sports and Entertainment	203	1.91%
S	Comprehensive	72	0.68%
Total observations		10,653	100%

Note: This table shows sample distribution by time and industry.

of 10 times a year. The average debt ratio is 0.397, with a firm size of 21.53. The average firm performance (*ROA*) is 4.3 %. The percentage of cash flow rights is 36.86 %, whereas the percentage of voting rights is 41.59 %. The mean *ICW* is 636.90, with a median of 668.24. On average, 41.6 % of our sample firms are audited by *TOP10* audit firms. Finally, the means of *ETR*, *3LETR* and *5LETR* are 0.185, 0.186 and 0.188, respectively. Studies using *ETR* as a proxy for TAV report values of 0.157 (Chyz and Gaertner, 2018) and 0.310 (Lanis et al., 2019).

Table 3 shows the results of Pearson correlation analysis. The coefficient correlation between CEO turnover (*FORCED*) and tax avoidance (*BTD*) is positive and significant. Furthermore, politically connected CEOs (*CEOPOL*) and state ownership of firms (*SOE*) are negatively and significantly correlated with *FORCED*. However, the correlation between *FORCED* and *REGD* is positive and significant. These results lend some initial support to our hypotheses. None of the correlation coefficients between the independent variables exceeds 0.65. Finally, the highest variance inflation factor value is 5.108 for *CASHFR*, indicating that the results are unlikely to be biased because of multicollinearity.

Table 2
Descriptive statistics.

Panel A: descriptive statistics for firm with CEO forced turnover (N = 788)

Variables	<i>FORCED = 1</i> (N = 788)		<i>FORCED = 0</i> (N = 9865)		Mean differences	
	Mean		Mean			
<i>BTD</i>	0.014		0.002		0.012***	
<i>SOE</i>	0.194		0.349		0.155***	
<i>CEOPOL</i>	0.093		0.162		0.069***	
<i>REGD</i>	0.647		0.634		0.013*	
<i>CEOAGE</i>	48.45		49.40		0.95***	
<i>CEOTENU</i>	1.005		3.759		2.75***	
<i>CEOSHAR</i>	0.037		0.069		0.032	
<i>DUALITY</i>	0.259		0.283		0.024	
<i>BINDP</i>	0.335		0.324		0.010***	
<i>BSIZE</i>	8.203		8.627		0.424***	
<i>BMEET</i>	7.719		8.610		0.891	
<i>DEBT</i>	0.409		0.397		0.012	
<i>FSIZE</i>	9.451		9.528		0.077**	
<i>ROA</i>	0.029		0.043		0.014***	
<i>CASHFR</i>	30.65		37.26		6.61***	
<i>VOTR</i>	35.816		41.954		6.14***	
<i>ICW</i>	538.058		643.97		105.9***	
<i>TOP10</i>	0.341		0.421		0.079***	

Panel B: Descriptive statistics for full sample

Variables	Mean	Standard deviation	Minimum	First quartile	Median	Third quartile	Maximum
<i>FORCED</i>	0.074	0.262	0.000	0.000	0.000	0.000	1.000
<i>BTD</i>	0.003	0.044	-0.197	-0.013	-0.002	0.013	0.152
<i>SOE</i>	0.345	0.475	0.000	0.000	0.000	1.000	1.000
<i>CEOPOL</i>	0.158	0.365	0.000	0.000	0.000	0.000	1.000
<i>REGD</i>	0.650	0.477	0.000	0.000	1.000	1.000	1.000
<i>CEOAGE</i>	49.333	6.433	27.000	45.000	50.000	53.000	65.000
<i>CEOTENU</i>	3.675	3.040	0.080	1.330	2.830	5.330	12.920
<i>CEOSHAR</i>	0.068	0.411	0.000	0.000	0.000	0.050	0.550
<i>DUALITY</i>	0.282	0.450	0.000	0.000	0.000	1.000	1.000
<i>BINDP</i>	0.325	0.054	0.000	0.333	0.333	0.333	0.500
<i>BSIZE</i>	8.614	1.692	4.000	7.000	9.000	9.000	15.000
<i>BMEET</i>	9.789	3.294	2.000	6.000	9.000	11.000	14.000
<i>DEBT</i>	0.397	0.220	0.010	0.220	0.380	0.550	0.840
<i>FSIZE</i>	9.525	0.534	7.170	9.140	9.450	9.820	11.160
<i>ROA</i>	0.043	0.050	0.000	0.020	0.040	0.070	0.190
<i>CASHFR</i>	36.860	16.520	0.000	24.130	35.820	49.060	75.310
<i>VOTR</i>	41.590	15.400	0.000	29.860	40.690	52.570	77.130
<i>ICW</i>	636.900	142.670	0.000	620.520	668.140	702.710	821.660
<i>TOP10</i>	0.416	0.493	0.000	0.000	0.000	1.000	
<i>ETR</i>	0.185	0.123	0.004	0.106	0.157	0.219	0.703
<i>3LETR</i>	0.186	0.089	0.046	0.121	0.164	0.233	0.475
<i>5LETR</i>	0.188	0.079	0.055	0.132	0.171	0.231	0.435

Note: This table shows summary statistics. Panel A reports the results of the mean difference test for the subsample of firms experiencing forced CEO turnover and those not experiencing forced CEO turnover. Panel B reports summary statistics for all variables using the whole sample. *, **, *** denotes significance at less than 0.10, 0.05, and 0.01, respectively. All variables are as defined in the Appendix.

Table 3
Pearson correlation matrix (N = 10,653).

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19.	
<i>I. FORCED</i>	1.000																			
<i>2. BTD</i>	1.145	0.063	1.000																	
<i>3. SOE</i>	1.543	-0.064	-0.056	1.000																
<i>4. CEOPOL</i>	1.062	-0.050	0.016	-0.110	1.000															
<i>5. REGD</i>	1.075	0.010	0.038	-0.218	0.017	1.000														
<i>6. CEOAGE</i>	1.107	-0.014	0.008	0.105	0.057	-0.041	1.000													
<i>7. CEOTENU</i>	1.096	-0.061	0.031	-0.065	0.055	0.044	0.163	1.000												
<i>8. CEOSHAR</i>	1.602	-0.018	0.002	-0.117	0.068	0.129	0.017	0.004	1.000											
<i>9. DUALITY</i>	1.551	-0.037	0.034	-0.307	0.205	0.110	0.141	0.111	0.185	1.000										
<i>10. BINDP</i>	2.362	0.047	0.010	-0.256	0.008	0.081	-0.067	-0.036	0.031	0.121	1.000									
<i>II. BSIZE</i>	2.486	-0.055	-0.015	0.308	-0.030	-0.096	0.051	0.019	-0.058	-0.200	-0.337	1.000								
<i>12. BMEET</i>	1.062	-0.061	0.006	0.027	0.005	0.011	0.030	0.043	0.013	-0.007	-0.011	0.032	1.000							
<i>13. DEBT</i>	1.761	0.023	-0.203	0.345	-0.051	-0.137	0.026	-0.007	-0.088	-0.176	-0.152	0.178	-0.149	1.000						
<i>14.FSIZE</i>	1.729	-0.010	-0.013	0.393	-0.055	-0.065	0.100	0.069	-0.099	-0.226	-0.282	0.309	-0.160	0.417	1.000					
<i>15. ROA</i>	1.521	-0.035	0.351	-0.106	0.023	0.066	0.003	0.013	0.034	0.068	0.021	-0.025	0.031	-0.368	-0.053	1.000				
<i>16. CASHFR</i>	5.108	-0.078	0.052	0.089	0.011	0.065	-0.004	-0.117	0.063	0.038	-0.003	-0.065	0.016	-0.078	0.072	0.087	1.000			
<i>17. VOTR</i>	4.846	-0.075	0.051	0.065	0.002	0.050	0.003	-0.112	0.037	0.006	-0.012	-0.039	0.031	-0.043	0.117	0.090	0.089	1.000		
<i>18. ICW</i>	1.164	-0.121	0.227	-0.056	0.037	0.061	0.002	0.065	0.058	0.031	-0.032	0.017	0.012	-0.138	0.099	0.277	0.104	0.113	1.000	
<i>19. TOP10</i>	1.016	-0.037	0.018	0.025	0.056	0.036	-0.033	0.050	-0.029	-0.011	-0.047	0.042	-0.012	0.036	0.077	-0.008	-0.007	0.011	0.062	1.000

Note: This table shows correlation results among variables. Bold values show significance at the 0.01 level. All variables are defined in the Appendix.

4.2. Regression findings

4.2.1. Baseline results

The results for the relationship between tax avoidance (*BTD*) and forced CEO turnover (*FORCED*) are reported in Column (1) of Table 4. The coefficient of *BTD* is positive and significant (0.920, $p < 0.01$). Regarding economic significance, a one-unit increase in *BTD* increases the odds of forced CEO turnover in the following year by 1.509. This implies that TAV activities increase the likelihood of forced CEO turnover, supporting H1. Our findings support societal and principal–agent arguments that TAV is an unethical behavior, and that executives incur reputational costs if they behave unethically. Our results are consistent with the results of Chyz and Gaertner (2018), who use US data and find a positive relationship between *ETR* and forced CEO turnover. Conversely, our findings contradict the results of Lanis et al. (2019), who report a negative association between TAV and CEO turnover.

Regarding the control variables, we find that the odds of forced CEO turnover are higher for firms in well-developed regions and for firms with a CEO who is also the chairperson. The probability of forced CEO turnover is lower for firms with CEOs who own a high percentage of shares, have affiliations with government, political connections, long tenure and high numbers of annual board meetings. Large firms, firms with a high percentage of controlling shareholders' voting rights and those with a robust internal control environment also have a lower probability of forced CEO turnover.

To test H2, we divide our sample into two groups based on state ownership status, SOEs (*SOE* = 1) and non-SOEs (*SOE* = 0). Columns (2) and (3) of Table 4 report the results of the moderating effect of state ownership on the relationship between TAV and CEO turnover. For the SOE sample, as shown in Column (2), the coefficient on *BTD* is positive and significant (1.038, $p < 0.05$), whereas for non-SOEs, Column (3) indicates that the coefficient is positive but not significant. In other words, state ownership significantly moderates the association between TAV and forced CEO turnover,² such that a positive association exists between TAV and forced CEO turnover for SOEs but not for non-SOEs. The Chow test reveals that the estimated coefficient of *BTD* differs significantly across both samples ($X^2 = 2.23$, $p = 0.084$). Together, these findings support H2 and align with the results of Wang et al. (2021a, 2021b), who find that CEOs in SOEs incur reputational costs when engaging in tax shelter activities.

To test H3, we divide our sample firms into two subsamples consisting of firms with CEO political connections (*CEOPOL* = 1) and firms without CEO political connections (*CEOPOL* = 0). Table 4 reports the findings of the moderating effect of political connections on the relationship between TAV and CEO turnover. Column (4) (*CEOPOL* = 1) indicates that the coefficient on *BTD* is negative and nonsignificant, whereas in Column (5) (*CEOPOL* = 0), it is positive and significant (1.111, $p < 0.01$). These findings suggest that CEOs with political connections are less likely to be dismissed than CEOs lacking political connections even if the firm engages in TAV. Our findings support the argument that political connections compromise the performance evaluation mechanism in leadership replacement. The Chow test demonstrates that the estimated coefficient of *BTD* differs significantly for the two subsamples ($X^2 = 3.24$, $p = 0.71$), thereby supporting H3. Contrary to the conventional assumption that SOE leadership is more politically connected than non-SOE leadership, our dataset indicates that only 9.5 % of CEOs in SOEs possess political ties compared with 19 % in non-SOEs. This divergence suggests that political connections are not a defining characteristic of SOE leadership within our sample. One plausible explanation lies in the recent institutional reforms, particularly China's "decoupling of party and enterprise" initiative launched in 2016, which seeks to reduce direct political interference in SOEs (Lin et al., 2020).

² We also examine the association of TAV with CEO turnover contingent on internal control weakness (*ICW*), another important internal governance mechanism. To perform this analysis, we create two subsamples based on the sample median of the *ICW* index. A higher (lower) value on the *ICW* index indicates stronger (weaker) internal control quality. The results show that TAV is more likely to result in CEO turnover when internal control quality is high, thereby reinforcing our documented findings for ownership structure. We do not report these findings for brevity but they are available from the corresponding author upon request. We are grateful to an anonymous reviewer for this valuable suggestion.

Table 4
Results of the relationship between TAV and forced CEO turnover and the moderating effects of SOE, political connections, and regional tax enforcement.

Variables	Whole sample	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
		FORCED	SOE = 1	FORCED	SOE = 0	FORCED	SOE = 1	FORCED	SOE = 0	FORCED	SOE = 1	FORCED	SOE = 0	FORCED	SOE = 1
BTD	0.920***(2.73)	1.038**(2.07)	0.803(1.33)	—	—	-0.547*(-0.61)	1.111***(2.67)	1.069**(2.13)	1.111***(2.67)	-0.049***(-2.61)	-0.061***(-7.57)	-0.056***(-5.55)	-0.067***(-5.87)	0.797(1.37)	0.797(1.37)
SOE	-0.060***(-8.05)	—	—	-0.006*(-0.49)	-0.028**(-2.53)	—	—	—	—	-0.021**(-2.00)	—	-0.021**(-2.00)	-0.020(-1.44)	—	—
CEOPOL	-0.021**(-2.50)	-0.006(-0.49)	0.002(0.30)	0.010(1.07)	0.001**(2.37)	0.001(1.09)	0.010(0.72)	0.005(0.68)	0.005(1.44)	0.001(1.16)	0.001(1.16)	0.001(1.16)	0.001(1.02)	0.001(1.02)	0.001(1.02)
REGD	0.005**(1.88)	0.001(1.63)	-0.001(-1.26)	-0.001*(-0.52)	-0.011***(-8.65)	-0.008***(-3.87)	-0.032*(-0.61)	-0.150***(-4.12)	-0.008***(-7.45)	-0.008***(-7.45)	-0.008***(-7.45)	-0.008***(-7.45)	-0.008***(-7.45)	-0.008***(-7.45)	-0.008***(-7.45)
CEOAGE	0.001(1.63)	-0.001(-1.26)	0.002(0.30)	0.010(1.07)	0.001**(2.37)	0.001(1.09)	0.001(1.09)	0.005(0.56)	0.005(0.56)	0.012(1.25)	0.012(1.25)	0.012(1.25)	0.012(1.25)	0.012(1.25)	0.012(1.25)
CEO TENU	-0.008***(-8.08)	-0.008***(-8.08)	-0.376(-1.04)	-0.111***(-3.07)	-0.026*(-1.79)	-0.026*(-1.79)	-0.026*(-1.79)	-0.026*(-1.79)	-0.026*(-1.79)	-0.026*(-1.79)	-0.026*(-1.79)	-0.026*(-1.79)	-0.026*(-1.79)	-0.026*(-1.79)	-0.026*(-1.79)
CEO SHAR	-0.119***(-3.90)	-0.119***(-3.90)	0.001(0.07)	0.003(-0.33)	0.003(-0.33)	0.003(-0.33)	0.003(-0.33)	0.003(-0.33)	0.003(-0.33)	0.003(-0.33)	0.003(-0.33)	0.003(-0.33)	0.003(-0.33)	0.003(-0.33)	0.003(-0.33)
DUALITY	-0.003(-0.33)	0.001(0.07)	0.023(-0.29)	-0.107(-1.02)	-0.003(-0.03)	0.274(1.63)	0.274(1.63)	0.274(1.63)	0.274(1.63)	-0.080(-0.90)	-0.009(-0.09)	-0.009(-0.09)	-0.009(-0.09)	-0.009(-0.09)	-0.009(-0.09)
BINDP	-0.023(-0.29)	-0.017**(-2.37)	-0.006**(-2.28)	-0.006**(-1.98)	-0.007*(-1.84)	-0.003(-0.47)	-0.007*(-2.40)	-0.007*(-2.40)	-0.007*(-2.40)	-0.007*(-2.40)	-0.006*(-1.87)	-0.006*(-1.87)	-0.006*(-1.87)	-0.006*(-1.87)	-0.006*(-1.87)
BSIZE	-0.006**(-2.28)	0.001***(-2.68)	-0.000(-0.83)	0.000**(-2.49)	0.001*(-2.49)	-0.001(-1.33)	-0.001(-1.33)	-0.001(-1.33)	-0.001(-1.33)	-0.001(-1.33)	-0.001(-1.44)	-0.001(-1.44)	-0.001(-1.44)	-0.001(-1.44)	-0.001(-1.44)
BMEET	0.001***(-2.68)	0.022(1.22)	-0.001(-0.04)	0.034(1.38)	0.039(0.85)	0.017(0.90)	0.028(1.14)	0.028(1.14)	0.028(1.14)	0.028(1.14)	0.009(0.34)	0.009(0.34)	0.009(0.34)	0.009(0.34)	0.009(0.34)
DEBT	0.022(1.22)	-0.017**(-2.37)	-0.013(-1.55)	-0.015(-1.22)	-0.025(1.41)	-0.021***(-2.65)	-0.021***(-2.65)	-0.021***(-2.65)	-0.021***(-2.65)	-0.019*(-1.95)	-0.019*(-1.95)	-0.019*(-1.95)	-0.019*(-1.95)	-0.019*(-1.95)	-0.019*(-1.95)
FSIZE	-0.017**(-2.37)	-0.114**(-2.21)	-0.115(-1.46)	-0.102(-1.50)	-0.278*(-1.89)	-0.107*(-1.93)	-0.107*(-1.93)	-0.107*(-1.93)	-0.107*(-1.93)	-0.107*(-1.93)	-0.093(-1.40)	-0.093(-1.40)	-0.093(-1.40)	-0.093(-1.40)	-0.093(-1.40)
ROA	-0.114**(-2.21)	0.001(1.09)	-0.001**(-2.33)	0.001**(-2.20)	0.002***(-2.63)	0.000(0.41)	0.000(0.63)	0.000(0.63)	0.000(0.63)	0.000(0.63)	0.001(1.08)	0.001(1.08)	0.001(1.08)	0.001(1.08)	0.001(1.08)
CASHFR	0.001(1.09)	-0.001***(-1.98)	0.001***(-2.06)	-0.002***(-2.88)	-0.003***(-3.34)	-0.001(-1.06)	-0.001(-1.35)	-0.001(-1.35)	-0.001(-1.35)	-0.001(-1.35)	-0.001(-1.62)	-0.001(-1.62)	-0.001(-1.62)	-0.001(-1.62)	-0.001(-1.62)
VOTR	-0.001***(-4.94)	-0.001***(-4.94)	-0.001(-0.45)	-0.001***(-6.64)	-0.001***(-6.64)	-0.001***(-6.64)	-0.001***(-6.64)	-0.001***(-6.64)	-0.001***(-6.64)	-0.001***(-6.64)	-0.001***(-4.39)	-0.001***(-4.39)	-0.001***(-4.39)	-0.001***(-4.39)	-0.001***(-4.39)
ICW	0.001(0.09)	-0.001(-0.89)	0.002(0.18)	0.004(0.67)	0.004(0.67)	0.004(0.67)	0.004(0.67)	0.004(0.67)	0.004(0.67)	0.004(0.67)	0.006(0.70)	0.006(0.70)	0.006(0.70)	0.006(0.70)	0.006(0.70)
TOP10	0.339***(-4.03)	0.306***(-3.04)	0.359***(-2.68)	0.359***(-2.68)	-0.237(-1.28)	0.409***(-4.34)	0.409***(-4.34)	0.409***(-4.34)	0.409***(-4.34)	0.409***(-4.34)	0.344***(-3.05)	0.344***(-3.05)	0.344***(-3.05)	0.344***(-3.05)	0.344***(-3.05)
Constant	—	—	—	—	—	—	—	—	—	—	6924	3728	3728	3728	3728

Note: This table reports the logistic regression results of the relationship between TAV and forced CEO turnover, and results of the moderating effect of SOE, political connections, and tax regional enforcement. Robust *t*-statistics are reported in parentheses. *, **, *** denote a two-tailed *p*-value of less than 0.10, 0.05, and 0.01, respectively. *FORCED* refers to an indicator variable coded 1 if there is a forced turnover of the CEO in the year *t* + 1 and zero otherwise. *BTD* refer to book-tax differences, defined as the difference between pre-tax income from financial reports and taxable income from tax returns. *SOE* refers to a dummy variable coded 1 if the firm is affiliated with central or local government and zero otherwise. *CEOAGE* is the CEO political connection, *REGD* is the regional development coded one if a firm is located in more developed regions and zero otherwise, *CEOAGE* refers to the average age of the CEO, *CEOENU* refers to number of years being in the CEO position, *CASHAR* refers to the percentage of a firm's shares held by the CEO, *DUALITY* refers to an indicator coded 1 if the CEO is also the chairman of the firm, *BINDP* is the proportion of independent directors on the board, *BSIZE* is the number of directors on the board, *FSIZE* is the number of meetings held by the board in a year, *DEBT* refers to a firm's leverage, defined as total liabilities scaled by total assets, *FSIZE* refers to firm size defined as logarithm the total assets, *ROA* is the return on assets, *CASHFR* is the percentage of the controlling shareholders' cash flow rights in a firm, *VOTR* is the percentage of the controlling shareholders' voting rights in a firm, *ICW* stands for internal control weakness, *TOP10* is a dummy variable coded 1 if the firm is audited by top 10 tier auditors and zero otherwise.

It is likely that the stronger effects that we observe in SOEs are driven by their distinct institutional environment rather than by political affiliations. For example, SOEs often operate under strict regulatory oversight and benefit from stable access to financing, thus reducing their reliance on TAV as a means of liquidity management (Chen et al., 2021). In contrast, politically connected non-SOEs may avoid aggressive tax strategies to minimize reputational risks and maintain their favorable relationships with government stakeholders. This differentiation underscores the importance of distinguishing between ownership structure and political connections when analyzing firm behavior, particularly in the context of corporate TAV and executive accountability.

Finally, we test whether the level of regional development moderates the relationship between forced CEO turnover and TAV. Following Alkebsee et al. (2021), we measure regional development status using a dummy variable *REGD*, which equals 1 if the firm is headquartered in a province with GDP above the annual median GDP of all provinces, and 0 otherwise. Firms in provinces with GDP above (equal to or below) the annual median GDP are categorized as more (less) developed. We split our sample firms into two subsample groups of firms located in more (less) developed regions, denoted by *REGD* = 1 (*REGD* = 0). Columns (6) and (7) of Table 4 report the regression results for these two subsamples. Column (6) indicates that the coefficient on *BTD* is positive and significant ($1.069, p < 0.05$) for firms located in more developed regions, whereas Column (7) shows that it is positive but nonsignificant for firms in less developed regions. This suggests that firms in developed regions have better monitoring mechanisms to mitigate agency issues and thus CEOs are more likely to be dismissed when they engage in TAV activities compared with CEOs of firms in less developed regions. The Chow test results show that the estimated coefficient of *BTD* differs significantly between the two samples for different regional development levels ($X^2 = 8.13, p = 0.011$), thereby validating H4.

5. Robustness analysis

5.1. Alternative measurement of key variables

It may be argued that the positive association between forced CEO turnover and TAV is affected by the TAV measure selected. To ensure that our results are robust and consistent using different measures, we reexamine H1 by replacing *BTD* with *ETR*, *3LETR* and *5LETR* in separate regressions. Columns (1), (2) and (3) of Table 5 show the results for the relationship between *FORCED* and *ETR*, *FORCED* and *3LETR* and *FORCED* and *5LETR*, respectively. These results confirm that TAV has a positive impact on forced CEO turnover irrespective of the measure selected.

Next, to ensure that our main results are not influenced by omitted variables, we follow Chyz and Gaertner (2018) and perform a falsification analysis using normal CEO turnover rather than forced CEO turnover. To do so, we separate the observations on forced CEO turnover (788 year-firm observations) from those of unforced CEO turnover ($UNFORCED_{t+1}$). As the unforced departures of CEOs are not driven by poor performance or involvement in questionable practices such as TAV (Fee et al., 2013), it is less likely that we will find a positive association between voluntary CEO turnover and TAV for this sample. Column (4) of Table 5 presents the results of the falsification analysis. The coefficient on *BTD* is negative and nonsignificant, suggesting that unforced CEO turnover is not associated with TAV activities. Accordingly, the findings of the falsification test confirm that our main results are reliable and robust.

The literature (e.g., Agrawal et al., 1999) shows that forced CEO turnover is influenced by several other factors, including earnings management activities, which can be harmful to shareholders (Desai et al., 2006; Agrawal and Cooper, 2017). Thus, boards may take proactive actions, including forcing CEO turnover, to protect shareholder interests and mitigate litigation risk. Accordingly, one may argue that our baseline results are driven by the magnitude of earnings management. To address this concern, we control for firms' earning

Table 5
Robustness tests.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FORCED	FORCED	FORCED	UNFORCED	CONTROLLING EARNINGS MANAGEMENT	CONTROLLING RETURN VOLATILITY	CONTROLLING POOR PERFORMANCE	FORCED,
ETR	0.022**(1.87)	—	—	—	—	—	—	—
ETR3	—	0.803*(1.67)	—	—	—	—	—	—
ETRS	—	—	1.174*(1.75)	—	—	—	—	—
BTD	—	—	—	—	4.072*(1.78)	1.307*(1.68)	—	10.515(1.71)*
DACC	—	—	—	—	-0.046(-0.04)	—	—	—
SOE	-0.060***(-8.14)	-1.050***(-7.78)	-1.053***(-7.80)	0.346***(-3.73)	-1.425***(-5.82)	-1.476***(-6.06)	-0.355(-3.80)***	-1.123(-7.21)***
CEO _{OL}	-0.021**(-2.34)	-0.407*(-2.46)	-0.408**(-2.46)	-0.070(-0.69)	-0.385(-1.36)	-0.450*(-1.66)	-0.233(-1.90)*	-0.326(-1.70)*
REGD	0.006(0.90)	0.097(0.93)	0.096(0.92)	0.011(0.75)	0.133(0.75)	0.189(1.10)	-0.070(-0.86)	0.018(0.15)
CEO _{AGE}	0.001(1.56)	0.010(1.42)	0.011(1.42)	0.030***(-4.89)	0.016(1.32)	0.019*(1.88)	0.011(0.12)*	0.011(0.129)
CEO _{TOENU}	-0.008***(-8.11)	-0.138***(-7.55)	-0.138***(-7.54)	-0.256***(-3.14)	-1.046***(-11.41)	-1.055***(-7.71)	-1.522(-13.97)***	-0.962(-16.37)***
CEO _{SHAR}	-0.117***(-3.83)	-1.952***(-3.30)	-1.946***(-3.30)	-0.608*(-1.42)	-1.970***(-2.07)	-1.834*(-1.77)	-0.497(-0.95)	-1.618(-2.44)*
DUALITY	-0.003(-0.34)	-0.065(-0.51)	-0.066(-0.51)	0.025(0.24)	0.518*(-2.56)	0.463*(-2.26)	0.299(2.09)**	0.299(-0.26)
BINDP	0.025(-0.31)	-0.601(-0.48)	-0.618(-0.49)	0.200(0.20)	-1.692(-0.79)	-0.932(-0.50)	-0.842(-0.84)	-2.442(-1.67)*
BSIZE	-0.006**(-2.31)	-0.125***(-2.71)	-0.125***(-2.71)	-0.032(-0.98)	-0.094(-1.22)	-0.080(-1.05)	-0.131(-2.51)***	-0.131(-2.51)***
BMEET	-0.001***(-2.87)	-0.006***(-2.73)	-0.006***(-2.73)	0.001(0.09)	-0.006(-1.54)	-0.006(-1.59)	-0.003(-1.46)	-0.007(-2.72)***
DEBT	0.021(1.20)	0.213(0.84)	0.203(0.80)	0.413*(1.71)	0.222(0.56)	0.123(0.32)	0.263(1.23)	0.211(0.82)
FSIZE	-0.019**(-2.48)	-0.321***(-2.57)	-0.321***(-2.61)	-0.021(-0.22)	-0.552*(-1.68)	0.252(-1.55)	-0.253(-1.88)*	-0.253(-1.88)*
ROA	-0.076(-1.54)	-0.357(-0.64)	-0.380(-0.61)	-2.534***(-2.97)	0.358(0.30)	0.682(0.64)	-0.138(-0.30)	-0.138(-0.30)
VOLTROA	—	—	—	—	—	—	-0.248(-0.71)	—
CASHFR	0.000(0.113)	0.007(0.98)	0.007(0.98)	0.001(0.01)	0.012(1.03)	1.654*(-2.15)	-0.006(-1.13)	-0.006(-1.13)
POTR	-0.001**(-2.02)	-0.012*(-1.71)	-0.012*(-1.70)	0.002(0.30)	-0.007(-0.58)	0.011(0.95)	-0.006(-0.54)	0.006(1.16)
ICW	-0.001***(-4.87)	-0.001***(-4.64)	-0.001***(-4.64)	0.022(0.20)	-0.001*(-1.92)	-0.002***(-3.20)	-0.002***(-3.04)	0.059(0.73)
TOP10	0.001(0.10)	0.020(0.18)	0.020(0.18)	-0.087(-1.18)	0.206(1.14)	0.154(0.92)	0.029(0.16)	0.142(1.16)
LOSS	—	—	—	—	—	—	-0.231(-0.21)	—
Constant	0.344***(-4.08)	1.533(1.07)	1.525(1.07)	-0.337*(-2.88)	2.202(0.91)	1.329(0.59)	-0.359(-3.80)***	2.875(1.84)*
Pseudo R ²	0.302	0.310	0.310	0.309	0.295	0.303	0.367	0.249
F-FISHER	512.10(0.000)	415.6(0.000)	413.2(0.000)	218.3(0.000)	494.817	208.26(0.000)	390.05(0.000)	41(0.000)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,653	10,653	10,653	10,653	7389	10,653	10,653	10,653

Note: This table reports the results of the relationship between tax avoidance (*TAV*) and forced CEO turnover using alternative measures of *TAV* activities, and falsification test results. Robust *t*-statistics are reported in parentheses. *, **, *** denote a two-tailed *p*-values of less than 0.10, 0.05, and 0.01, respectively. *FORCED* refers to an indicator coded 1 if there is a forced turnover of a CEO in the year *t* + 1, zero otherwise. *BTD* is book-tax differences, defined as the difference between pre-tax income from financial reports and taxable income from tax returns. *DACC* is discretionary accruals based on the modified Jones model. *SOE* refers to a dummy variable coded 1 if the firm is affiliated with central or local government and zero otherwise. *CEO_{OL}* is the CEO political connection. *REGD* is the regional development coded one if a firm is located in more developed regions and zero otherwise. *CEO_{AGE}* refers to the average age of the CEO in the year *t*. *CEOTENU* refers to number of years being in the CEO position. *CEOTENU* refers to the percentage of firm's shares held by the CEO. *DUALITY* refers to an indicator coded 1 if the CEO is also the chairman of the firm. *BINDP* is the proportion of independent directors on the board. *BSIZE* is the number of directors on the board. *BMEET* is the number of meetings held by the board in a year. *DEBT* refers to a firm's leverage, defined as total liabilities scaled by total assets. *FSIZE* refers to firm size defined as logarithm the total assets. *ROA* is the return on assets. *CASHFR* is the percentage of the controlling shareholders' cash flow rights in a firm. *VOTR* is the percentage of the controlling shareholders' voting rights in a firm. *ICW* stands for internal control weakness. *TOP10* is a dummy variable coded 1 if the firm is audited by top 10 tier auditors and zero otherwise. *LOSS* is a dummy variable coded 1 if the firm reported negative earnings during the year and zero otherwise.

management as it tends to affect CEO turnover (Hazarika et al., 2012). To do so, we follow the literature in using firms' discretionary accruals (*DACC*),³ calculated based on the modified Jones model (e.g., Dechow et al., 1995; Teshima and Shuto, 2008; Alkebsee et al., 2022) and augment our baseline model with the addition of *DACC*. The results in Column (5) of Table 5 show that irrespective of the inclusion of *DACC*, we continue to find that TAV has a positive and significant impact on forced CEO turnover. Furthermore, the coefficient on *DACC* is negative and nonsignificant, suggesting that earnings management has no impact on forced CEO turnover.

As the literature documents that the volatility of returns is significantly associated with forced CEO turnover (Chakraborty et al., 2007; Chen et al., 2023), we control for return volatility using the standard deviation of return on assets (*VOLTROA*) as our control variable. Column (6) of Table 5 presents the results, indicating that despite the positive impact of *VOLTROA* on forced CEO turnover (1.65, $p < 0.05$), the coefficient on *BTD* remains positive and significant (1.307, $p < 0.10$), implying that our baseline results are robust. Overall, our results remain robust to these alternative definitions and specifications.

Although we control for financial performance using *ROA* throughout the analysis, it is important to consider the impact of poor firm performance in our analysis because it is likely that CEO turnover is influenced significantly by poor performance. Therefore, we create a new variable (*LOSS*), which is coded 1 if the firm reports negative earnings during the year, and 0 otherwise, and replicate the main analysis after including *LOSS* in the model. The results in Column (7) of Table 5 reveals that TAV is positively and significantly associated with CEO turnover, implying that omitted variable bias is not a major concern for our main findings.

Finally, as Wang et al. (2021a, 2021b) report that CEO turnover is more likely to occur in the same year in which TAV behavior is exposed, we assess the sensitivity of our main finding to this timing assumption. To do so, we run our main Equation (1) using forced CEO turnover in year t (*FORCED* _{t}) rather than in year $t + 1$. The sensitivity analysis using *FORCED* _{t} instead of *FORCED* as a dependent variable also confirms our main findings. In Column (8) of Table 5, the coefficient on *BTD* remains positive and significant (10.515, $p < 0.10$), implying that the positive association between TAV and forced CEO turnover persists even when the timing assumption is altered.

5.2. Addressing endogeneity

The baseline model and subsequent analysis indicate a link between TAV and forced CEO turnover. However, our findings may be subject to endogeneity bias due to omitted variables and reverse causality (Gull et al., 2018; Nekhili et al., 2020). For instance, a CEO might be terminated for reasons other than TAV, or a new CEO might engage in TAV after taking over. To address these issues and validate our findings, we use the system GMM and 2SLS regressions.

The system GMM model assesses the association between TAV and forced CEO turnover using both level and first-difference equations. In the first level equation, TAV is expressed as a function of its past (lagged) value, firm-level characteristics and the error term. The difference equation (i.e., the second level) provides time differences as an instrument for the first level. The Sargan test for over-identification and the Hansen test for the exogeneity of the instruments are used to demonstrate the strength of the system GMM model. The estimates, shown in Column (2) of Table 6, show that the coefficient on *BTD* is positive and significant (1.88, $p < 0.01$), suggesting that our main results are consistent and robust to simultaneity and dynamic endogeneity. In addition, the Arellano–Bond (AR) test statistic AR(1) is significant ($-3.28, p < 0.002$), indicating

³ $TAC_{i,t}/AST_{i,t-1} = \beta_0 * (1/AST_{i,t-1}) + \beta_1 * (\Delta REV_{i,t}/AST_{i,t-1}) + \beta_2 * (PPE_{i,t}/AST_{i,t-1})$ (2) $NONDA_{i,t}/AST_{i,t-1} = \beta_0 * (1/AST_{i,t-1}) + \beta_1 * [(\Delta REV_{i,t} - \Delta REC_{i,t})/AST_{i,t-1}] + \beta_2 * (PPE_{i,t}/AST_{i,t-1}) + \varepsilon_{i,t}$ (3) $DACC_{i,t} = TAC_{i,t}/AST_{i,t-1} - NONDA_{i,t}/AST_{i,t-1}$ (4) where $TAC_{i,t}$ refers to total accruals (net income before extraordinary items less free operating cash flows) for firm i in fiscal year t ; $AST_{i,t-1}$ is total assets lagged 1 year; $\Delta REV_{i,t}$ is revenue in fiscal year t minus revenue in fiscal year $t-1$, scaled by total assets in fiscal year $t-1$; $PPE_{i,t}$ is gross property, plant and equipment in fiscal year t scaled by total assets in fiscal year $t-1$; $\Delta REC_{i,t}$ denotes receivables in fiscal year t less net receivables in fiscal year $t-1$, scaled by total assets in fiscal year $t-1$; and $NONDA_{i,t}$ is nondiscretionary accruals for firm i in fiscal year t . We estimate Equation (2) cross-sectionally for industry years with at least 20 observations. Then, we insert the residuals from Equation (2) into Equation (3) to obtain abnormal accruals. As earnings management includes both positive and negative values of expected *DACC*, we use the absolute value of *DACC* as the proxy for earnings management.

that the null hypothesis of no autocorrelation in the first difference is rejected, whereas the coefficient of AR(2) is nonsignificant ($-1.45, p < 0.350$), indicating that the error terms in the level regressions are not correlated. Moreover, the Sargan test p value is statistically significant ($52.11, p < 0.005$), whereas the Hansen test is non-significant ($44.07, p < 0.258$).

To alleviate concerns that the results of our logistic regression suffer from reverse causality and simultaneity issues, we use a 2SLS estimator. The main challenge in applying 2SLS is identifying an instrumental variable that is correlated with the endogenous explanatory variable but uncorrelated with the dependent variable. As China's tax laws provide preferential tax rates to firms based on the industry, firm age and other characteristics (Lin et al., 2018; Xiao, 2020), they may create differences in TAV intensity across regions. Therefore, we use the average local tax avoidance (*LOCAL_BTD*) as an instrument, assuming that it is related to our independent variable (*BTD*) but not related to our dependent variable (*FORCED*).

We perform a series of tests to assess the validity of our instrumental variable in the first stage of the 2SLS analysis. First, to determine the association between the instrumental variable and the endogenous variable, we use Shea's partial R-squared, which quantifies the increased explanatory power of the excluded instrument while accounting for potential intercorrelations. Second, to address the issue of weak identification, we use several statistical tests, including the Cragg–Donald Wald F statistic, the Kleibergen–Paap Wald F statistic and the 10 % critical value for the maximum instrumental variable size proposed by Stock and Yogo. Our findings collectively indicate that the instrumental variable is significantly correlated with the endogenous variable and prove the validity of instrumental variable estimation. Furthermore, to test the validity of our instrument, we apply the Montiel–Pflueger robust weak instrument test to examine the null hypothesis that our instrument is weak with one endogenous regressor. The results reveal that *LOCAL_BTD* is very strong. The effective F statistic is 96.17, while the highest critical value for worst-case bias derived using the limited information maximum likelihood framework is 37.42. As the F statistic exceeds this threshold, this indicates that *LOCAL_BTD* serves as a very good instrument, supporting our prediction that our instrument is valid. In addition, the results presented in Column (3) of Table 6 support our prediction as the coefficient on *LOCAL_BTD* is positive and significant ($p < 0.01$). Column (4), which presents the estimates of the second stage of the 2SLS, reveals that the coefficients on *BTD* remain positive significant at the 1 % level, thereby supporting our baseline results.

5.3. Placebo test

To address potential endogeneity concerns and assess the robustness of our main findings, we conduct a placebo test by constructing two fake variables, *FORCEDPLACEBO* and *PLACEBO_BTD*. *FORCEDPLACEBO* is created by randomly reassigning the original values of forced CEO turnover across firm-year observations. This procedure retains the distributional properties of the actual variable but removes any systematic relationship with TAV (*BTD*). Similarly, *PLACEBO_BTD* is constructed by randomly reallocating the actual *BTD* values across observations while preserving their distribution. This randomization breaks any genuine or spurious associations between TAV and CEO turnover, helping to rule out correlations that may arise from omitted variables or unobserved firm characteristics. The results of this placebo test are presented in Columns (4) and (5) of Table 6. In Column (4), we find that the coefficient on *BTD* using *FORCEDPLACEBO* is positive but statistically nonsignificant ($1.214, p = 0.396$), whereas the coefficient on the actual *FORCED* variable in Column (1) of Table 4 is positive and significant ($0.920, p < 0.01$). In Column (5), the coefficient on *PLACEBO_BTD* is also statistically nonsignificant ($-13.989, p = 0.157$), contrasting with the significant and positive coefficient of actual *BTD* reported in Table 4 ($0.920, p < 0.01$). These placebo test results strengthen the credibility of our main analysis by suggesting that the documented relationship between TAV and forced CEO turnover is unlikely to be driven by random chance or unobserved firm-level factors.

5.4. Value implications of tax avoidance and forced CEO turnover

In this section, we examine the value implications of the association between TAV and forced CEO turnover. We use a 2SLS regression to examine the consequences of forced CEO turnover caused by TAV for firm shareholders. Specifically, we use tax avoidance (*BTD*) as an instrumental variable to explain forced CEO

Table 6
Endogeneity tests.

Variables	(1)		(2)		(3)		(4)		(5)	
	GMM	FORCED	2SLS (1st stage)	BTD	FORCED	2SLS (2nd stage)	Placebo	FORCED	PLACEBO	FORCED
<i>L_FORCED</i>	0.118***(2.88)	—	—	—	—	—	—	—	—	—
<i>LOCAL_BTD</i>	—	1.881**(2.36)	—	—	—	—	—	—	—	—
<i>PLACEBO_BTD</i>	—	—	—	—	—	—	—	—	—	—
<i>SOE</i>	—	-1.686***(-2.40)	—	-0.001***(-3.02)	—	-0.057***(-7.21)	0.117(0.84)	—	-1.455**(-6.06)	—
<i>CEOOL</i>	—	-0.073(-0.06)	0.0001-1.15	—	—	-0.019***(-2.62)	0.247(1.62)	—	-0.482*(-1.77)	0.174(1.02)
<i>REGD</i>	0.113(0.24)	0.000***(-2.14)	0.0000***(-2.48)	0.0000***(-2.84)	0.0001(1.64)	0.0005(0.81)	0.0056(0.49)	—	—	—
<i>CEOAGE</i>	0.013(0.64)	0.038(1.09)	0.0000(-0.96)	0.0002**(-2.49)	0.0001(-1.87)	0.001(1.87)	0.0008*(-0.88)	0.018*(1.79)	—	—
<i>CEOTENU</i>	—	3.169***(-2.46)	0.014(0.04)	0.0000(0.00)	0.0001(0.41)	0.0001(-0.31)	0.003(-0.31)	—	-1.039***(-7.81)	—
<i>CEOShar</i>	—	8.331(-1.45)	0.090(0.37)	-0.001(0.34)	-0.006*(-2.29)	-0.006*(-2.29)	0.003(0.14)	—	-1.848*(-1.79)	—
<i>DUALITY</i>	—	-0.002(-0.42)	0.697(0.40)	0.001*(1.82)	-0.001***(-6.46)	-0.001***(-6.46)	0.202(0.35)	—	0.497**(-2.43)	—
<i>BNDP</i>	—	0.578(-0.61)	-4.230***(-2.30)	-0.001***(-2.13)	0.038***(-2.28)	0.027(-0.32)	0.356(0.23)	—	-1.192(-0.64)	—
<i>BSIZE</i>	—	-4.230***(-2.30)	0.198***(-3.34)	0.0000(0.92)	0.0001(0.89)	0.0001(0.89)	0.058(1.16)	—	-0.093(-1.22)	—
<i>BMEET</i>	—	-0.578(-0.61)	0.198***(-3.34)	0.0000(0.92)	-0.006*(-2.29)	-0.006*(-2.29)	0.001(1.53)	—	-0.007*(-1.85)	—
<i>DEFT</i>	—	-4.230***(-2.30)	-0.185***(-3.61)	-0.001(-1.55)	-0.001*(-1.66)	-0.001*(-1.66)	0.001(0.35)	—	0.211(0.51)	—
<i>FSIZE</i>	—	0.001(1.33)	0.000***(-3.80)	0.0001(-0.29)	0.0001(-4.03)	0.0001(-4.03)	0.377(1.16)	—	-0.358*(-1.71)	—
<i>ROA</i>	—	0.062(0.24)	0.016(0.54)	0.005**(1.96)	0.001(0.14)	0.001(0.14)	0.518(1.19)	—	1.006(0.92)	—
<i>CASHFR</i>	—	—	—	—	0.325***(-3.71)	0.325***(-3.71)	0.009(0.83)	—	—	—
<i>YOTR</i>	—	—	—	—	—	—	0.014*(-1.98)	—	—	—
<i>ICW</i>	—	—	—	—	—	—	0.013*(-1.80)	—	—	—
<i>TOP10</i>	—	—	—	—	—	—	0.0000(0.77)	—	-0.005(-0.45)	—
Constant	—	—	—	—	—	—	-0.046(-0.39)	—	0.127(0.76)	—
					—	—	—	—	1.962(0.88)	—
Pseudo R ²	0.089	0.195	0.123	0.011	—	—	—	—	—	—
Year	Yes	Yes	Yes	Yes	—	—	—	—	—	—
Industry	Yes	Yes	Yes	Yes	—	—	—	—	—	—
Observations	4205	10,653	10,653	10,653	—	—	—	—	—	—
AR(1)	Chi ² = -3.28 P = 0.002	—	—	—	—	—	—	—	—	—
AR(2)	Chi ² = -1.45 P = 0.350	—	—	—	—	—	—	—	—	—
Sargan	Chi ² = 52.11P < 0.005	—	—	—	—	—	—	—	—	—
Hansen	Chi ² = 44.07P < 0.258	—	—	—	—	—	—	—	—	—
Wald chi ² /F ratio	Chi ² = 68.33, P = 0.014	—	—	—	—	—	—	—	—	—
F-Statistic	—	32.80***	—	—	—	—	—	—	—	—
Shea's partial R ² -BTD	—	0.117	—	—	—	—	—	—	—	—
Cragg-Donald Wald F statistic	—	120.191***	—	—	—	—	—	—	—	—
Kleibergen-Paap rk Wald F-statistic	—	121.679***	—	—	—	—	—	—	—	—
Stock-Yogo (2005) (critical value)	—	28.34***	—	—	—	—	—	—	—	—

Note: This table reports the endogeneity tests with respect to the relationship between tax avoidance and forced CEO turnover. Robust t-statistics are reported in parentheses. *, **, *** denote a two-tailed p-value of less than 0.10, 0.05 and 0.01, respectively. *FORCED* refers to a dummy variable coded 1 if there is a forced turnover of the CEO in the year t + 1 and zero otherwise. *FORCEDPLACEBO* refers to the fake FORCED events created by randomly assigning the FORCED dummy across our sample based on the kernel density plots. *BTD* refer to book-tax differences, defined as the difference between pre-tax income from financial reports and taxable income from tax returns. *PLACEBO_BTD* refers to the fake BTD variable created by shuffling the main variable of BTD across our sample firms. *SOE* refers to a dummy variable coded 1 if the firm is affiliated with central or local government and zero otherwise. *CEOOL* is the CEO political connection, *REGD* is the regional development coded one if a firm is located in more developed regions and zero otherwise. *CEOAGE* refers to the average age of the CEO, *CEOTENU* refers to the percentage of a firm's shares held by the CEO position, *DUALITY* refers to the proportion of independent directors on the board, *BMEET* is the number of meetings held by the board in a year, *DEFT* refers to a firm's leverage, defined as total liabilities scaled by total assets, *FSIZE* refers to firm size defined as logarithm the total assets, *ROA* is the return on assets, *CASHFR* is the percentage of the controlling shareholders' cash flow rights in a firm, *YOTR* is the percentage of the controlling shareholders' voting rights in a firm, *ICW* stands for internal control weakness, *TOP10* is a dummy variable coded 1 if the firm is audited by top 10 tier auditors and zero otherwise.

turnover (*FORCED*) in the first-stage regression, whereas in the second stage, *FORCED* (instrumented) is used to test how it affects shareholder value measured by *ROA* and Tobin's Q (*TOBINQ*). We expect *BTD* to be associated with *FORCED* but not with the variables capturing shareholder value (*ROA* and *TOBINQ*). Table 7 reports the results of these estimations. Columns (1) and (3) present the first-stage results of the 2SLS regression, demonstrating that the coefficient on the instrument (*BTD*) is positive and significant (0.459 and 0.435, $p < 0.10$), demonstrating the validity of our instrument and explaining forced CEO turnover (*FORCED*). Columns (2) and (4) report the second-stage results and show that the coefficient on *FORCED* (instrumented) is positive and significant (4.206 and 7.956, $p < 0.10$). This suggests that forced CEO turnover

Table 7
Value implications of tax avoidance and forced CEO turnover.

Variables	(1)	(2)	(3)	(4)
	<i>FORCED</i>	<i>ROA</i>	<i>FORCED</i>	<i>TOBINQ</i>
<i>BTD</i>	0.459*(1.74)	—	0.435*(1.89)	—
<i>FORCED</i> (<i>instrumented</i>)	—	4.206*(1.74)	—	7.956*(1.76)
<i>SOE</i>	-0.035***(-6.60)	0.145(1.65)	-0.033***(-3.89)	0.263(0.93)
<i>CEOPOL</i>	-0.014**(-2.44)	0.060(1.41)	-0.001(-0.04)	0.005(0.04)
<i>REGD</i>	0.005(1.12)	-0.021(-0.96)	0.000(-0.04)	0.003(0.04)
<i>CEOAGE</i>	0.001***(2.73)	-0.004(-1.45)	0.000(0.09)	-0.001(-0.08)
<i>CEOTENU</i>	-0.010***(-15.02)	0.043*(1.75)	-0.013***(-4.55)	0.101(1.27)
<i>CEOSHAR</i>	-0.087***(-4.02)	0.372*(1.65)	0.064(0.42)	-0.507(-0.70)
<i>DUALITY</i>	0.017***(3.04)	-0.076(-1.55)	-0.001(-0.05)	0.008(0.05)
<i>BINDP</i>	-0.038(-0.66)	0.163(0.64)	0.161(0.75)	-1.284(-1.68)
<i>BSIZE</i>	-0.002(-1.12)	0.010(1.03)	0.004(0.62)	-0.034(-1.21)
<i>BMEET</i>	0.000**(-2.46)	0.001(1.37)	0.001*(-1.92)	0.003(1.30)
<i>DEBT</i>	0.007(0.65)	-0.163***(-3.26)	-0.220(-0.97)	1.748***(10.04)
<i>FSIZE</i>	-0.006(-1.20)	0.050*(1.89)	0.209(0.98)	-1.664***(-19.63)
<i>ROA</i>	—	—	-0.019(-0.25)	0.151(0.29)
<i>CASHFR</i>	0.000(0.78)	-0.001(-0.91)	0.001(1.12)	-0.006(-1.64)
<i>VOTR</i>	0.000(-1.19)	0.002(1.24)	-0.001(-1.29)	0.008*(1.79)
<i>ICW</i>	0.000***(-4.21)	0.001**(2.32)	0.001(-1.31)	0.000(0.63)
<i>TOP10</i>	0.003(0.78)	-0.012(-0.59)	-0.015(-0.78)	0.123**(2.05)
Constant	-0.224***(-11.89)	-0.838*(-1.96)	0.149**(2.46)	16.552***(11.86)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Observations	10,653	10,653	10,653	10,653
F-Statistic	39.01***		40.65***	
Shea's partial R ² -FORCED	0.142		0.1223	
Cragg-Donald Wald F statistic	3.045***		2.536***	
Kleibergen-Paap rk Wald F-statistic	3.010***		2.521***	
Stock-Yogo (2005) (critical value)	3.028***		2.521***	

Note: This table shows the results of the 2SLS estimator for the relationship between tax avoidance, the CEO forced turnover and shareholders value captured through *ROA* and *TOBINQ*. Robust t-statistics are shown in brackets. *, **, *** denote a two-tailed p value of less than 0.10, 0.05 and 0.01, respectively. *TOBINQ* is the ratio of firms market value to book or replacement value, *FORCED* refers to an indicator variable coded 1 if there is a forced turnover of the CEO in the year $t + 1$ and zero otherwise, *BTD* refer to book-tax differences, defined as the difference between pre-tax income from financial reports and taxable income from tax returns, *SOE* refers to a dummy variable coded 1 if the firm is affiliated with central or local government and zero otherwise, *CEOPOL* is the CEO political connection, *REGD* is the regional development coded one if a firm is located in more developed regions and zero otherwise, *CEOAGE* refers to the average age of the CEO, *CEOTENU* refers to number of years being in the CEO position, *CEOSHAR* refers to the percentage of a firm's shares held by the CEO, *DUALITY* refers to an indicator coded 1 if the CEO is also the chairman of the firm, *BINDP* is the proportion of independent directors on the board, *BSIZE* is the number of directors on the board, *BMEET* is the number of meetings held by the board in a year, *DEBT* refers to a firm's leverage, defined as total liabilities scaled by total assets, *FSIZE* refers to firm size defined as logarithm the total assets, *ROA* is the return on assets, *CASHFR* is the percentage of the controlling shareholders' cash flow rights in a firm, *VOTR* is the percentage of the controlling shareholders' voting rights in a firm, *ICW* stands for internal control weakness, *TOP10* is a dummy variable coded 1 if the firm is audited by top 10 tier auditors and zero otherwise.

caused by TAV is associated with improved shareholder value.⁴ The results provide a useful insight into the value implications of forced CEO turnover for shareholders.

6. Conclusion

This paper investigates the effect of TAV activities on forced CEO turnover. Using a sample of 1043 forced CEO turnover events in Chinese listed firms spanning the period from 2011 to 2018, the results reveal that TAV activities are positively associated with forced CEO turnover. Our results are consistent with the theoretical perspective that engagement in TAV activities results in a change in firm leadership. Furthermore, we demonstrate that the positive association between TAV and forced CEO turnover is more pronounced for SOEs, firms with CEOs lacking political connections and firms located in more developed regions with intensive tax enforcement compared with their respective counterparts.

This study makes important contributions to various strands of literature. First, it contributes to the TAV literature by providing robust evidence that TAV activities increase the likelihood of CEO dismissal using a different setting to that of other studies. It also enriches the limited body of literature on forced CEO turnover in emerging economies. Second, this study contributes to the literature on the governance role of corporate ownership by documenting a major implication of state ownership for the association between TAV activities and forced CEO turnover. Third, from a policy perspective, our study is the first attempt to consider the regional tax enforcement implications of CEO reputational costs arising from TAV activities; thus by verifying the common belief that tax enforcement is a good tool for corporate governance, our study has important implications for tax authorities. Finally, we reveal that forced CEO turnover following tax avoidance may result in improved firm performance and value.

The findings of this study have significant implications and limitations. First, the research highlights the impact of TAV on forced CEO turnover, emphasizing the need for vigilant corporate governance practices. The setting of our study in China makes it applicable to other emerging economies, and by elucidating the unique dynamics and challenges of CEO turnover in such contexts, we provide valuable insights for both scholars and practitioners. Furthermore, the study highlights the role of state ownership, particularly of SOEs, in moderating the relationship between TAV and CEO turnover, suggesting that governments and regulatory bodies should pay particular attention to the TAV activities of non-SOEs. Our study underscores the potential effectiveness of regional development in deterring TAV activities, which may have policy implications for regional tax authorities in China's less developed regions. Moreover, our findings suggest that regulatory authorities and investors should be vigilant when monitoring tax activities within firms led by politically affiliated CEOs.

Despite its contributions, our study has some limitations, foremost among them being that its generalizability is constrained beyond the specific context of China. Furthermore, we do not address the impact of disclosure transparency on the tax avoidance–CEO turnover nexus. Future studies may investigate this impact to deepen the insights into this intricate relationship. Although we make rigorous efforts to mitigate endogeneity issues, the intrinsic complexity of this matter remains a challenge, and concerns persist regarding omitted factors beyond our purview. Acknowledging these implications and limitations is crucial when interpreting and applying the study's findings and designing future research or corporate governance strategies.

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.

⁴ The reported Cragg–Donald Wald F statistic (3.045) and Stock–Yogo value (3.028) are below the 10% maximal instrumental variable size threshold of 16.38, indicating that the instrument is weak by Stock–Yogo (2005) standards. Therefore, the results in Table 7 should be interpreted as suggestive, highlighting the potential value implications of the interaction between forced CEO turnover and tax avoidance, rather than providing definitive causal evidence.

Appendix. Variables definition

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Merger and acquisition prediction based on deep learning with attention mechanism[☆]



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ARTICLE INFO

Article history:

Received 20 November 2024

Accepted 16 November 2025

Available online 5 January 2026

Keywords:

Mergers and acquisitions
Prediction model
Deep learning
Attention mechanism

ABSTRACT

This study proposes a novel attention-based deep neural network (AttDNN) model specifically designed for predicting mergers and acquisitions (M&A). The model extends existing deep learning frameworks by incorporating M&A-specific features, regularization layers, and an attention mechanism that emulates human cognitive processes to structure M&A drivers and improve predictive performance. Empirical results demonstrate that the AttDNN model significantly outperforms traditional algorithms in forecasting M&A outcomes, achieving a 29.2 % improvement in predictive accuracy over conventional deep learning methods. This study provides valuable insights at the intersection of artificial intelligence and financial economics, offering practical implications for financial strategy and corporate M&A decision-making.

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1. Introduction

Mergers and acquisitions (M&A) are key strategic initiatives that corporations undertake to achieve specific objectives and often lead to changes in both short-term stock prices and long-term corporate value. Predicting M&A activity has long been a key topic in corporate finance research and practice and is comparable to forecasting financial crises, profitability, and stock prices in terms of its importance (Arikan and McGahan, 2010). Traditionally, studies on M&A prediction have primarily used logit regression models to empirically analyze and forecast such activities. Although these models provide some explanatory power for

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☆ This work was supported by the National Natural Science Foundation of China [grant numbers 71972076, 72071083] and the Natural Science Foundation of Guangdong Province [grant number 2025A1515011425].

the occurrence of M&A events (Adelaja et al., 1999; Beccalli and Frantz, 2013), their predictive accuracy remains suboptimal, largely because of their inability to effectively address complex nonlinear relationships and high-dimensional interactive features (De Prado, 2018).

Machine learning (ML), particularly deep learning (DL), has become the mainstream approach for predictive tasks because of its robust feature extraction capabilities, ability to process high-dimensional data, and strong fault tolerance (Dong et al., 2021; Fan et al., 2024). In financial accounting research, DL has been successfully applied in various areas, including financial fraud detection (Bao et al., 2020; Achakzai and Peng, 2023), audit quality monitoring (Hunt et al., 2021), financial market prediction (Zhao et al., 2022; Wang et al., 2024; Zhang and Wang, 2024), and financial risk warning (Ristolainen, 2018; Töölö, 2020; Bluwstein et al., 2020; De et al., 2024). However, despite these advancements, the application of DL to M&A prediction remains relatively underexplored. A major challenge is the reliance on manual procedures for selecting input features, which are time-consuming and often introduce subjective bias, thereby reducing the adaptability and stability of the model.

Recently, attentive DL has emerged as a promising approach to address these challenges (Chaudhari et al., 2021). Attention mechanisms enable automatic feature extraction and helps identify the most critical information for M&A prediction from a broader set of features, thereby overcoming the limitations of traditional methods. The design of attention mechanisms is partly inspired by human cognitive processes. When processing information, humans tend to selectively focus on crucial details and disregard less relevant ones. Attention mechanisms partially mimic this human cognitive process, making the model's functioning more intuitive. The attention mechanism used in the present study enables the model to dynamically evaluate the importance of different input features and assign them weights accordingly, ensuring that the most task-relevant information receives greater focus and thus improving predictive accuracy. For instance, the attention mechanism can adaptively determine that a company's operating profit margin has a greater impact on the model's predictive accuracy than its accounts receivable turnover and therefore assign it a higher weight.

To address the limitations of previous studies, the present study proposes a novel M&A prediction model based on the attentive deep neural network (AttDNN). This model uses a deep neural network (DNN) as its core framework and incorporates key components, including a regularization layer, an attention mechanism, and a loss function. To improve the predictive performance of the AttDNN model, 30 M&A driving factors identified from previous studies are incorporated to construct an M&A feature pool. The model simulates the human attention mechanism to adaptively extract key features from data samples. Furthermore, a series of experiments are conducted to objectively evaluate the model's predictive accuracy. In addition, the necessity of each module as well as the robustness and universality of the proposed model are verified.

In summary, this study makes two contributions. First, it proposes a novel M&A prediction framework based on an attention-enhanced DL architecture. Unlike traditional econometric models that rely on pre-specified relationships, our proposed approach automatically captures complex, nonlinear interactions among variables, thereby improving predictive accuracy. Second, it provides new empirical insights into the determinants of M&A by interpreting the model's predictions. Our analysis contributes to the finance literature by confirming established drivers and highlighting the significant but previously underemphasized predictive power of internal control quality.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature, including studies on corporate M&A prediction and DL applications in financial accounting. Section 3 presents the proposed model, and Section 4 reports the experimental analyses. Section 5 concludes the paper and discusses directions for future research.

2. Related works

2.1. Corporate M&A prediction

Early studies on M&A prediction have mainly used statistical methods, such as logit regression models, to explain factors influencing M&A activities, but their predictive performance was often limited. For instance, Adelaja et al. (1999) used two logit models to predict whether a firm would become an M&A target and the likelihood of that target being acquired, focusing on M&A activities in the US food manufacturing industry.

However, the limited scope of variables in these models constrained their predictive accuracy. Building on this, Baker et al. (2012) incorporated additional factors, including technological innovation and patent activity, and developed a more advanced model using segmented regression and interaction terms. Despite these improvements, the predictive accuracy of these models remained low.

Other empirical studies have examined the effects of specific factors on the initiation of M&A activities, such as monetary policy (Adra et al., 2020), exchange rate uncertainty (Si et al., 2024), and M&A risk levels (Ott, 2020). Through rigorous research design and data analysis, these studies have significantly contributed to the theoretical understanding of M&A. However, their primary focus has not been on predicting M&A activities.

Several scholars have focused on improving the predictive capability of M&A models, recognizing that the rarity of failed M&A cases creates data imbalance issues that affect predictive performance. To address this problem, Branch et al. (2008) used resampling techniques to reduce bias and achieved an average predictive accuracy of 72.52 % for both successful and failed cases. However, this approach assumes equal costs for all classification errors, which is a limitation in acquisition prediction. In response, Rodrigues and Stevenson (2013) combined multiple nonlinear models to construct a prediction ensemble, reduce misclassification rates, and demonstrate robustness over time. Nevertheless, this approach merely aggregates models without addressing the root cause of misclassification. To overcome this limitation, Lee et al. (2020) proposed an optimization method that accounts for asymmetric misclassification costs by prioritizing samples with higher costs. This method shifts the algorithm's focus from minimizing squared errors to minimizing misclassification costs, thereby improving predictive performance.

The aforementioned studies have primarily used structured data. However, with advances in text mining technology, unstructured data, such as free text, have been increasingly incorporated into research. For instance, Moriarty et al. (2019) applied Latent Dirichlet Allocation to analyze the annual reports of US listed companies, and Jiang (2021) used the L2-regularized Least Absolute Shrinkage and Selection Operator for a similar purpose. Both studies extracted key variables through text analysis to construct logit regression models, which improved the accuracy of M&A prediction.

Because complex factors affect corporate M&A, simple regression models often fail to capture implicit relationships in the data. Thus, researchers have used various ML algorithms, such as Decision Tree, Bayesian Network, and Support Vector Machines (SVM), to improve M&A prediction. For instance, Xiang et al. (2021) used topic models to extract features from company profiles and social media news, which were then incorporated into a Bayesian network, and achieved a true positive rate of 80%. Similarly, Futagami et al. (2021) developed a light gradient boosting machine to improve M&A predictive performance and used SHapley Additive explanation (SHAP) values to enhance model interpretability. In addition, Yang et al. (2014) proposed an ensemble learning model based on the C4.5 decision tree algorithm to address data imbalance in M&A prediction. Arsimi et al. (2023) introduced a continuous projection space to quantify technical correlations between firms, providing a novel perspective for M&A prediction.

Overall, previous research on corporate M&A forecasting has made significant progress by incorporating new data sources and optimizing model algorithms, which improved both predictive accuracy and explanatory power. Despite these advances, important limitations remain in feature selection and model construction. Most studies have mainly relied on the expertise and judgment of domain experts and have not used systematic, automated methods for feature engineering. This reliance restricts the generalizability of prediction models. As market conditions evolve and M&A activities become increasingly complex, traditional ML models may not capture all key factors and their intricate interrelationships, resulting in significant variability in predictive performance.

2.2. Application of DL in financial accounting

Traditional ML methods have performed well with structured data but are less effective at handling high-dimensional, dynamically changing unstructured data and spatiotemporal sequences. In contrast, DL, a key technology in artificial intelligence (AI), offers distinct advantages. The core breakthrough of DL is its end-to-end feature learning capability. By stacking multiple layers of nonlinear transformations, DL can extract hierarchical representations of data (Fig. 1). These hierarchical representations enable DL to effectively capture

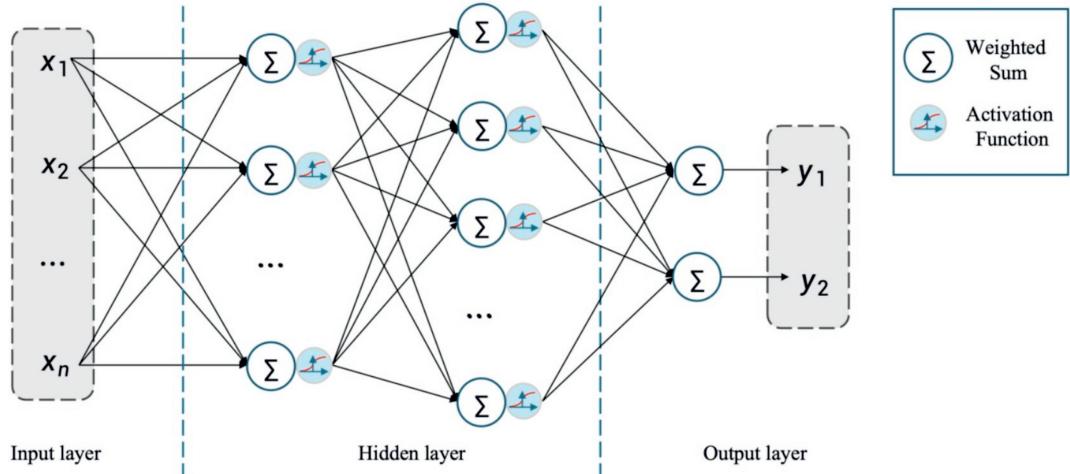


Fig. 1. Structure of the deep learning network.

global dependencies within input data, allowing it to process complex data types such as images, text, audio, and time series, and achieve superior performance.

In recent years, DL has been increasingly applied in financial accounting, providing more effective tools for accurate financial forecasting and risk monitoring. For financial fraud detection, Bao et al. (2020) developed a fraud prediction model that combines DL with accounting theory to select input variables. This model outperformed traditional ML models in detecting accounting fraud among publicly listed companies. Furthermore, Achakzai and Peng (2023) demonstrated the effectiveness of DL in detecting financial statement fraud by dynamically combining multiple DL algorithms to improve predictive accuracy.

In market prediction, Zhou et al. (2020) used DL to extract and integrate features from multi-source heterogeneous data, demonstrating strong prediction capability in the Chinese stock market. Furthermore, Zhao et al. (2022) used ML to analyze linguistic specificity in annual reports and examine its role in reducing stock price synchronicity and improving market pricing efficiency. In addition, Chen et al. (2024) used deep neural networks (DNNs) to develop an asset pricing model for individual stock returns. Using this model, the authors successfully identified key factors influencing asset prices and constructed more efficient investment portfolios. Zhang and Wang (2024) applied DL to analyze rumors from investor platforms and investigated their impact on stock price efficiency. They determined that both positive and negative rumors contribute to stock mispricing. Beyond stock price prediction, Wang et al. (2024) developed a hybrid DL model for Bitcoin price prediction that combines feature selection across different frequency domains with Long Short-Term Memory (LSTM) models. The model demonstrated better predictive performance and higher returns on investment than benchmark models in simulated trading scenarios.

For financial risk early warning, Ristolainen (2018) used DNNs to develop a crisis early warning model for the banking industry and demonstrated that the nonlinear representation capability of DL significantly outperformed traditional models. In addition, Bluwstein et al. (2020) and Töölö (2020) compared various ML techniques for systemic financial risk prediction and found that DL provided clear advantages in financial crisis early warning. Recently, De et al. (2024) applied DL based on LSTM models to analyze tail risk connections among Japanese public banks. The results showed that larger banks were more affected by economic crises, whereas medium-sized banks were more vulnerable to international risks.

DL has considerable potential for applications in financial accounting; however, its use in corporate M&A prediction remains limited. Studies have not yet fully examined the potential of attention mechanisms for adaptive feature selection in this area (Niu et al., 2021). The transformer model, a major breakthrough in self-attention mechanisms, has achieved remarkable success in natural language processing tasks, such as machine translation, demonstrating a strong ability to model long sequences (Vaswani et al., 2017). Subsequent large language models, including Bidirectional Encoder Representations from Transformers (Devlin

et al., 2019) and Generative Pretrained Transformer (Brown et al., 2020), have also adopted attention mechanisms to effectively capture dependencies among variables.

Attention mechanisms have proven highly effective in identifying complex relationships among variables by learning their dynamic importance for a given predictive task. Instead of assigning static importance to all input features, attention-based models can perform instance-wise feature selection. For example, the TabNet architecture proposed by Arik and Pfister (2021) employs an attention process to select a sparse subset of the most relevant features at each inference stage, mimicking cognitive focus by concentrating on the most critical information for each specific case.

Beyond selecting individual features, attention mechanisms are also highly effective at modeling the complex interactions among them. The AutoInt model, developed by Song et al. (2019), uses a multi-head self-attention network to automatically capture high-order feature interactions, which are critical for accuracy in complex prediction scenarios. This line of research has given rise to powerful, general-purpose architectures. Models such as the FT-Transformer (Gorishniy et al., 2021) and feature-weighting methods such as tabular feature weighting transformer (Zhang et al., 2024) further demonstrate that designing deep learning architectures around attention mechanisms leads to robust performance by enabling a more refined understanding of each feature's contribution.

This body of work indicates that the core strength of attention mechanisms is their ability to dynamically evaluate and adapt to the context provided by the data. In the field of M&A, where outcomes are influenced by a complex and often subtle interplay of financial, strategic, and market factors, this capability is particularly valuable.

Accordingly, this study integrates a deep learning framework with an attention mechanism to combine the representational power of DL for capturing complex nonlinear relationships with the distinct advantages of the attention mechanism in dynamically weighting predictive factors and modeling their interactions, thereby enhancing the effectiveness of corporate M&A prediction.

3. Model design

3.1. Overview of the AttDNN model

The complexity and diversity of factors driving M&A activities make it challenging to predict M&A behavior because their relationships are often difficult to discern. The proposed AttDNN prediction model addresses this challenge by leveraging DNNs that incorporate regularization layers and attention modules inspired by the human attention mechanism. This model effectively extracts essential data features, thereby enhancing predictive performance.

Initially, we identify 30 driving factors for M&A from the theoretical literature and incorporate them into the network with input layer regularization. These factors are then processed through three hidden layers containing both regularization layers and attention modules to extract intermediate features within the network. The extracted features are fully connected to the output layer, where the model determines the probability of each sample being classified as “M&A” or “non-M&A”, producing the final prediction results. The flowchart of the AttDNN model is illustrated in Fig. 2.

3.2. Modules of the AttDNN model

3.2.1. Regularization layer

As shown in Fig. 3(a), a traditional DNN hidden layer consists of two main components. First, neurons in the previous layer are fully connected to neurons in the next layer, where linear operations are used to weight and sum the input data x_i . Second, an activation function applies a nonlinear activation to the summed features, producing the output x_{i+1} . To overcome the limitations of this traditional structure, we implement a regularization layer composed of four components, as shown in Fig. 3(b): fully connected weighted summation, batch normalization, activation function, and dropout operation. The rationale for this design choice is explained below:

First, the fully connected weighted summation aggregates features from the previous layer by performing a weighted summation of the input data. However, the output from this layer can often exhibit an uneven distribution, which reduces the activation range available for the subsequent nonlinear activation function. To address this issue, batch normalization is applied after forward propagation through the fully connected layer. Because the data remain linear after batch normalization, nonlinearity is reintroduced into the training process using the *LeakyReLU* activation function. This approach helps the DNN approximate nonlinear functions more effectively. In addition, to prevent overfitting, the regularization layer incorporates dropout, which randomly removes parameters with a certain probability. This technique enhances the diversity of training networks in each batch and improves the stability of model training. In summary, the output formula of the regularization layer is defined in Eq. 1:

$$L(x) = DP \left\{ LLU \left\{ \gamma \left[\frac{(w_i^1 x_i^1 + w_i^2 x_i^2 + \dots + w_i^\ell x_i^\ell + b) - \mu}{\sqrt{\delta^2 + \epsilon}} \right] + \beta \right\} \right\} \quad (1)$$

where *DP* denotes the *Dropout* operation and *LLU* refers to the *LeakyReLU* activation function. The parameter γ represents the scaling factor in batch normalization, and β represents the shift parameter in batch normalization. In the numerator, w_i^j denotes the weight of the j^{th} neuron in the i^{th} layer, and x_i^j corresponds to the j^{th} feature of the i^{th} input data. The bias terms b and μ represent the mean of the batch data. In the denominator, δ^2 denotes the variance of the batch data, and ϵ is a small constant introduced for numerical stability to prevent division by zero.

3.2.2. Attention mechanism

Fig. 4 illustrates the operational process of the attention mechanism module. In this module, the input data are represented as $U(P, Len)$, where P denotes the batch size and *Len* indicates the length of the data features. The input data first pass through a regularization layer to obtain nonlinear activation features, expressed as $L(x) = L(U(P, Len))$. Subsequently, deep attention learning is applied using the softmax function and adaptive factors.

Softmax transforms regularized features into a probability representation, yielding the attention feature vector, as shown in Eq. (2):

$$\sigma(x) = \frac{\exp(L(x)_i)}{\sum_{c=1}^C \exp(L(x)_c)} \quad (2)$$

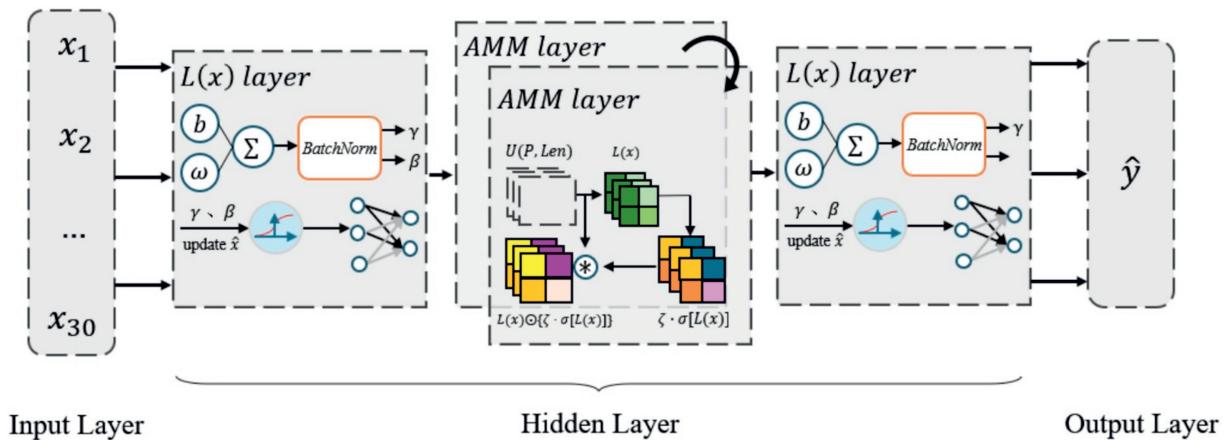


Fig. 2. Flowchart of the AttDNN model.

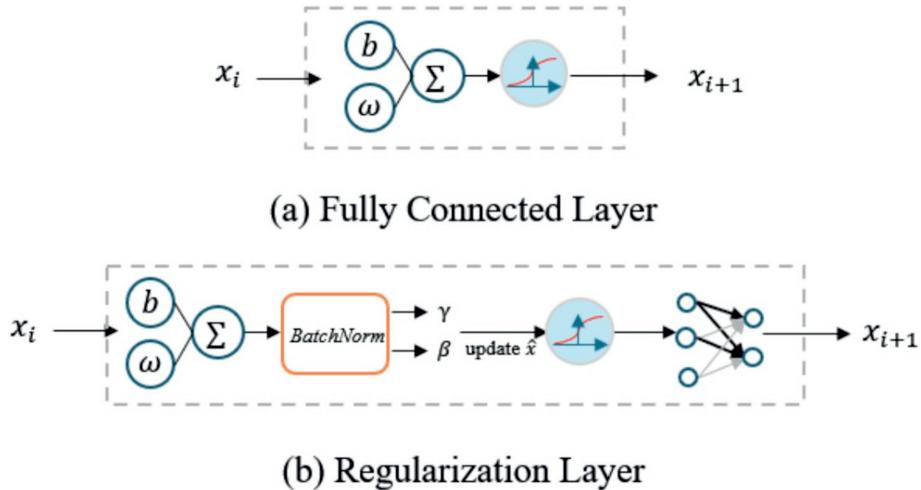


Fig. 3. Structure of the regularization layer.

where i represents the index of the output neuron and C denotes the total dimension of the feature output. Through the softmax operation $L(x)$, the output of the regularization layer is converted into an attention feature vector within the range $[0, 1]$, with all elements summing to 1. Finally, the value at each position represents the importance of the output of $L(x)$.

The adaptive factor restricts the influence of the attention feature weights on the output features of the regularization layer. Moreover, the attention feature vector $\sigma(x)$ is multiplied element-wise with the output of $L(x)$ to generate the feature output of the attention module $AMM(x)$, as described in Eq. (3):

$$AMM(x) = L(x) \odot \{\zeta \cdot \sigma[L(x)]\} \quad (3)$$

where \odot represents element-wise multiplication, ζ denotes the network adaptive factor, and $\sigma(x)$ refers to the softmax operation. Compared with a single regularization layer, the attention feature vector can capture more attention features, enabling the extraction of more critical information. During the training phase, this process allows the model to identify complex data distributions more effectively, thereby improving the accuracy and robustness of the AttDNN model.

3.2.3. Loss function

In the network's forward propagation, it is crucial to evaluate the error between the predicted outcomes and the actual labels by defining an appropriate loss function. Let $f(\cdot; \Omega)$ represent the mapping relationship determined by the learnable parameter Ω in the AttDNN model, where y denotes the actual labels, x represents the network inputs, and $\{(X, Y)\}$ indicates the input set. The following loss function is defined to train the AttDNN model:

$$\min_{\Omega} \|CE(f(X; \Omega), Y)\|_2 + \lambda \|\nabla f(X; \Omega)\|_1 \quad (4)$$

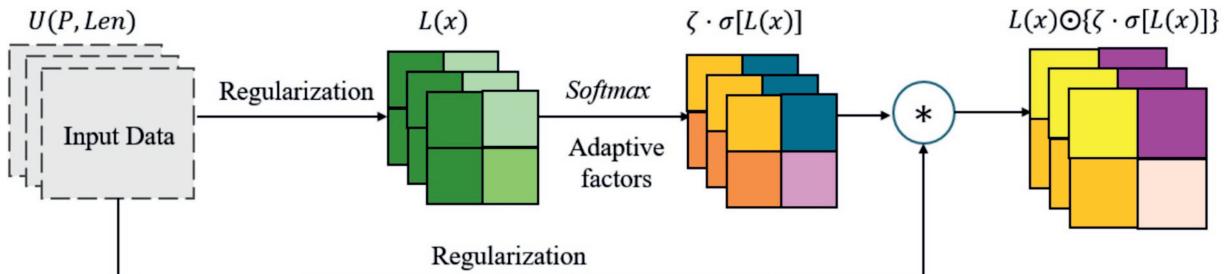


Fig. 4. Structure of the attention mechanism.

where $f(X; \Omega)$ represents the predicted output of the network. The first term of the expression corresponds to the cross-entropy loss function, which is formulated in Eq. (5):

$$CE(\cdot) = \frac{1}{BS} \sum_{i=0}^{BS} -[y_i \log f(x_i; \Omega) + (1 - y_i) \log (1 - f(x_i; \Omega))] \quad (5)$$

where BS denotes the batch size, y_i represents the actual label (0 or 1) of sample i , and $f(X; \Omega)$ indicates the probability that sample i is predicted as belonging to the positive class (i.e., merger). The second term in the expression accounts for the normalization of the gradient penalty for the input data in the network.

Network parameters are updated by minimizing the cross-entropy loss function using the Adam optimization algorithm. During backpropagation, the weights and biases between network layers are adjusted to move the model's predictions closer to the actual labels for each class. This process completes one training iteration of the DNN. In addition, a gradient penalty is applied to the network parameters to reduce overfitting and improve model regularization during training.

3.2.4. The overall network structure

The AttDNN model consists of an input layer $O_{input}(\cdot)$, a hidden layer $O_{hidden}(\cdot)$, and an output layer $O_{output}(\cdot)$. The 30 M&A driving factors are fed into the prediction model through the input layer. These factors are then processed and fitted to the data features in the hidden layer. The output layer uses a Sigmoid function to calculate the probability of each sample being classified as “M&A” or “non-M&A”, thereby enabling M&A prediction. The forward propagation process of the network can be summarized using the following equations:

$$O_{input}(x_i) = L(x_i), i = 0 \quad (6)$$

$$O_{hidden}(x_i) = L(x_i) \odot \{\zeta \cdot \sigma[L(X_i)]\}, i = 1, 2 \quad (7)$$

$$O_{hidden}(x_i) = L(x_i), i = 3 \quad (8)$$

$$O_{hidden}(x_i) = 1/[1 + \exp(-MLP(X_i))], i = 4 \quad (9)$$

4. Experiments and analysis of results

4.1. Data sample and preprocessing

Since January 1st, 2007, Chinese enterprises have adopted new accounting standards. To control the impact of these changes on financial data, this study uses A-share listed companies from 2007 to 2020 as the sample. The M&A data are obtained from the “M&A Database” of the China Stock Market and Accounting Research (CSMAR) database. Following the methodology proposed by Eaton et al. (2022), the sample selection criteria are as follows:

1. Transactions in which the acquiring party are not a listed company are excluded (removing 24,729 observations).
2. Samples involving firms in the financial and real estate industries are excluded (removing 6,412 observations).
3. M&A Transactions identified as asset divestitures, debt restructurings, or asset swaps are excluded (removing 25,610 observations).
4. Transactions with a total value of less than CNY 1 million are excluded (removing 1,279 observations).
5. Related-party M&A transactions are excluded (removing 6,515 observations).
6. Samples with missing critical information are excluded (removing 3,042 observations).

After the application of these exclusion criteria, the final sample used in this study consists of 10,101 M&A observations. A listed company is classified as an M&A sample if it completed at least one M&A transaction in a given year; otherwise, it is classified as a non-M&A sample.

The model's initial input variables comprise 30 M&A factors obtained from the CSMAR and Wind databases. The output variable predicts "whether M&A occurred". To enhance the model's learning efficacy, samples with missing values are removed. In addition, continuous variables are truncated at the 1% level to mitigate the influence of extreme values.

4.2. Input variables

This study systematically analyzes and organizes the driving factors of M&A based on the literature. Thirty key publicly available factors are selected as input variables for the AttDNN prediction model, as shown in Table 1.

The first category is *Executive Characteristics*. It includes variables such as age, gender, education level (Huang and Kisgen, 2013), experience (Zhou et al., 2020), compensation (Datta et al., 2009), and granted stock options (Gormley et al., 2013) of executives.

The second category is *Corporate Governance Characteristics*. It includes variables related to governance structure, such as board size (Cheng, 2008), presence of female directors (Chen et al., 2016), proportion of independent directors (Datta et al., 2009), shareholding ratio of the largest shareholder (Liu and Tian, 2012), ownership structure (Margaritis and Psillaki, 2010), and internal control (Harp and Barnes, 2018).

The third category is *Financial Condition of the Company*. It covers various financial indicators related to profitability, operational capability, debt-paying capability, and equity expansion capacity (Popa and Ciobanu, 2014).

Finally, the fourth category is *Other Important Driving Factors*. It includes variables such as a firm's prior M&A experience (Arikan and Stulz, 2016), industry competition pressure (Uhlenbruck et al., 2017), market valuation level (Andriopoulos et al., 2016), and the year of the M&A event (Rossi and Volpin, 2004).

Collectively, these factors facilitate a comprehensive analysis and prediction of M&A activities.

4.3. Experimental setup and evaluation metrics

The AttDNN model is implemented using PyTorch on a system equipped with an Intel Core-i7 CPU and an NVIDIA Titan RTX GPU. For model evaluation, we use a single holdout test set. Specifically, 90% of the dataset is allocated for training and 10% is reserved as the final test set. From the training data, a validation set comprising 10% of the total data is separated for hyperparameter tuning. Before conducting the main experiments, we employ a systematic approach to analyze the effect of individual hyperparameters on the model's predictive performance while holding others constant and identify an optimal hyperparameter configuration. The network weight parameters in the AttDNN model are set using Kaiming initialization (He et al., 2016). The adaptive factor ζ is initialized to 0.1, the learning rate η is set to 0.0002, and the network random seed is set to 918. The results indicate that the random seed setting does not materially affect the experimental results. The number of neurons in each layer of the AttDNN model, from the input layer to the output one, is set as follows: 30, 80, 60, 40, and 2, respectively. The training process runs for 1,000 epochs. For all models evaluated in this study, we employ a fixed classification threshold of 0.5, which is the default setting and a common practice for classification tasks.

Given the data imbalance problem in the acquisition samples, accuracy (ACC) is not used as the performance evaluation metric. Instead, balanced accuracy (bACC), F1 score, and area under the curve (AUC) are used to evaluate the effectiveness of the prediction model. The use of these metrics provides a more accurate and reliable evaluation of the model's performance.

The bACC represents the average accuracy in predicting both positive and negative samples. We define it as follows:

$$bACC = \frac{TPR + TNR}{2} \quad (10)$$

where the true positive rate (TPR) is defined as $TPR = TP / (TP + FN)$, representing the proportion of positive samples correctly identified among all positive samples. Similarly, the true negative rate (TNR) is defined as

Table 1
Input variables of the AttDNN model.

Category		Variable	Mean	Std. dev.	Min	Max
Executive characteristics	Demographics	CEO Age	49.982	6.432	33	65
		CEO Gender	0.93	0.254	0	1
		CEO Education Level	3.467	0.858	1	5
	Leadership Experience	CEO Tenure	4.045	3.514	0	13
		Is the Executive Team Collectively Granted Stock Options?	0.025	0.156	0	1
	Incentive Level	Are Board Members Granted Stock Options?	0.022	0.148	0	1
Corporate Governance Characteristics	Board Structure	Board Size	8.596	1.685	5	15
		Are There Female Members on the Board?	0.735	0.441	0	1
		Do External Directors Constitute the Majority?	0.02	0.139	0	1
	Shareholding	Is the Chairman also Serving as the CEO?	0.25	0.433	0	1
		Shareholding Ratio of the Largest Shareholder	0.341	0.146	0.085	0.743
	Internal Control	Nature of Equity	0.37	0.483	0	1
		Strength of Internal Control	1.718	0.45	1	2
Financial Condition of the Company	Profitability	Operating Profit Margin	0.048	0.217	-1.779	0.48
		Return on Total Assets	0.032	0.063	-0.343	0.202
		Return on Equity	0.051	0.156	-1.132	0.501
		Earnings Per Share	0.328	0.533	-1.510	2.582
		Sales Expense Ratio	0.074	0.088	0.001	0.478
	Operational Capability	Total Asset Turnover	0.605	0.41	0.04	2.564
		Accounts Receivable Turnover	45.781	183.976	0.834	1491.715
		Inventory Turnover	11.336	43.355	0.121	437.363
		Debt-to-Equity Ratio	0.43	0.202	0.051	1.016
		Current Ratio	2.292	2.233	0.235	17.395
Others	Solvency	Quick Ratio	1.781	2.026	0.148	15.525
		Net Asset Value Per Share	4.573	2.731	-0.066	16.22
	Equity Expansion Capability	Retained Earnings Per Share	1.5	1.637	-3.124	8.196
	Company Experience	Previous Acquisition Experience	0.906	1.414	0	7
	Level of Industry Competition	Herfindahl Index	0.125	0.129	0.02	0.88
	Market Valuation Level	Market Valuation Level	119.537	96.102	55.397	413.775
	Year	M&A Year	/	/	/	/

$TNR = TN / (FP + TN)$, indicating the proportion of negative samples correctly identified among all negative samples.

Another commonly used metric for evaluating predictive accuracy in imbalanced datasets is the F1 score. We define it as follows:

$$F1 - Score = \frac{2 \times precision \times recall}{precision + recall} \quad (11)$$

where $precision$ is defined as $precision = TP / (TP + FP)$, representing the proportion of correctly identified positive samples among all samples predicted as positive. Moreover, the $recall$ variable is defined as

$recall = TP / (TP + FN)$, representing the proportion of correctly identified positive samples among all actual positive samples.

Finally, the AUC is defined as the area under the receiver operating characteristic (ROC) curve. The horizontal axis of the ROC curve represents the false positive rate (FPR), calculated as $FPR = FP / (FP + TN)$, which represents the proportion of negative samples incorrectly classified as positive. The vertical axis represents TPR . When the model predicts probabilities, these values are compared against a classification threshold: values above the threshold are classified as positive, whereas those below the threshold are classified as negative. Different thresholds yield different TPR and FPR values, which together form key points on the ROC curve. These points are then connected to form the ROC curve.

4.4. Model comparison

To validate the predictive performance of the AttDNN model, seven models are selected for comparison: linear regression, logistic regression, decision tree regression, XGBoost, AdaBoost, SVM, baseline DNN, Gated Recurrent Unit (GRU), and LSTM. The first six are classical ML models, whereas the last three are mainstream DL models. The baseline DNN model adopts the same network structure as the AttDNN model but excludes the regularization layers and attention mechanism module.

In the experiments, all models use the same dataset and partitioning method to ensure fairness in comparison. The results presented in Table 2 demonstrate that the proposed AttDNN model outperforms all other methods across all evaluation metrics. Specifically, the AUC values for all models are above 0.5, indicating that their predictive performance is better than random guessing. In other words, these models demonstrate a certain level of capability in fitting the M&A prediction task.

A comparison reveals significant performance differences. The classical ML benchmarks evaluated—Linear Regression, Logistic Regression, Decision Tree Regression, AdaBoost, SVM, and XGBoost—demonstrate notable limitations for this task. Although XGBoost achieves the highest AUC (0.712), its practical performance is hindered by a very low F1 score (0.011) and balanced accuracy (bACC = 0.503), a pattern similar to that of SVMs (F1 = 0.011, bACC = 0.502). Other classical methods generally yield lower AUC values (ranging from 0.551 to 0.650) and also exhibit poor F1 scores, indicating difficulty in producing balanced predictions.

Among the mainstream DL models, the baseline DNN (which uses the same structure as AttDNN but without regularization or attention) serves as a benchmark. It performs poorly, with an AUC of 0.504 and a bACC of 0.501, both near random chance levels, although its F1 score is 0.301. This indicates that the base network structure alone is insufficient. The more advanced DL benchmarks, GRU and LSTM, show higher potential, particularly in AUC (0.703 and 0.690, respectively). However, GRU follows the same pattern as XGBoost, combining a high AUC with very low bACC (0.504) and F1 score (0.021). LSTM achieves a substantially better balance, with an AUC of 0.690, a bACC of 0.579, and an F1 score of 0.353, significantly outperforming the classical models and the baseline DNN.

Table 2
Prediction results of different models.

Method	AUC	bACC	F1 score
Linear Regression	0.634	0.523	0.050
Logistic Regression	0.650	0.515	0.063
Decision Tree Regression	0.551	0.551	0.140
XGBoost	0.712	0.503	0.011
AdaBoost	0.581	0.521	0.098
SVM	0.595	0.502	0.011
Baseline	0.504	0.501	0.301
GRU	0.703	0.504	0.021
LSTM	0.690	0.579	0.353
AttDNN	0.711	0.659	0.456

Surpassing the benchmark models in practical effectiveness, the proposed AttDNN model demonstrates superior overall performance. Although its AUC (0.711) is slightly lower than that of XGBoost (0.712), its bACC of 0.659 and F1 score of 0.456 are clearly the highest, highlighting its superior ability to make balanced predictions. Notably, compared with the most effective DL benchmark (LSTM), the AttDNN model achieves a substantial 29.2% improvement in the F1 score.

To provide a more comprehensive, threshold-independent evaluation on this imbalanced dataset, we present the precision–recall (PR) curves for all models in Fig. 5. The plot highlights the inherent difficulty of the task because all models exhibit a pronounced trade-off between precision and recall. Overall, the curve of our proposed AttDNN model remains competitive across a wide range of recall values, suggesting a more stable PR balance compared with the benchmark models.

This analysis also helps explain the performance discrepancy observed in Table 2, where certain classical ML models (e.g., XGBoost and SVM) achieve relatively high AUC scores but very low F1 scores. The lower placement of their PR curves indicates that these models struggle to identify the minority class (M&A events) without a substantial decline in precision. This suggests that while such models may demonstrate certain ranking capability, their predictions are biased toward the majority (non-M&A) class. In contrast, although not consistently superior at every recall level, the AttDNN model exhibits a more robust and balanced performance profile, supporting its practical relevance for this classification task.

4.5. Ablation study

To validate the design rationale and determine the contribution of each key component in the proposed AttDNN model, we conduct a systematic ablation study. We evaluate the performance of three model configurations:

1. **Baseline DNN (Baseline):** A standard DNN that uses the core architecture but excludes both the regularization layer and the attention mechanism. This serves as our initial performance benchmark.
2. **DNN + Regularization (Regu):** The baseline DNN augmented only with the regularization layer. This configuration allows us to measure the impact of regularization on model performance independently.
3. **AttDNN:** The complete proposed model, which incorporates both the regularization layer and the attention mechanism (i.e., the Regu model further enhanced with attention).

By comparing the performance across these configurations step-by-step (Baseline vs. Regu, then Regu vs. AttDNN), we can discern the specific benefits conferred by each added module.

The results are presented in Table 3. The baseline DNN exhibits limited predictive capability. Although its performance is better than random guessing, its F1 score is notably low. Adding the regularization layer (Regu model) results in a substantial improvement: the AUC significantly increases to 0.703, accompanied by marked increases in both bACC and F1 scores. These results confirm that the regularization layer effectively enhances the model's ability to generalize and fit the underlying data patterns.

The subsequent integration of the attention mechanism (transitioning from the Regu model to the full AttDNN model) results in an additional and distinct performance improvement. The AUC increases from 0.703 for the Regu model to 0.711 for the AttDNN model, and we observe consistent improvements across all other reported metrics. This incremental improvement achieved by adding the attention mechanism on top of the already regularized model specifically underscores the effectiveness of the attention component. While the regularization layer improves the overall model fit, the attention mechanism further refines performance by enabling the model to dynamically assign higher importance to the most critical features or data instances in the M&A prediction task. These findings validate the inclusion of the attention mechanism, demonstrating its capacity to sharpen the model's focus on key predictive signals and achieve higher predictive accuracy than regularization alone.

Considering that network depth may affect predictive performance, this study further examines the effect of varying the number of regularization layers and attention modules, as shown in Table 4. The results indicate that adding regularization layers generally enhances performance compared with the baseline. When the four-layer structure is considered, introducing attention modules significantly affects the outcome. Specifically, with

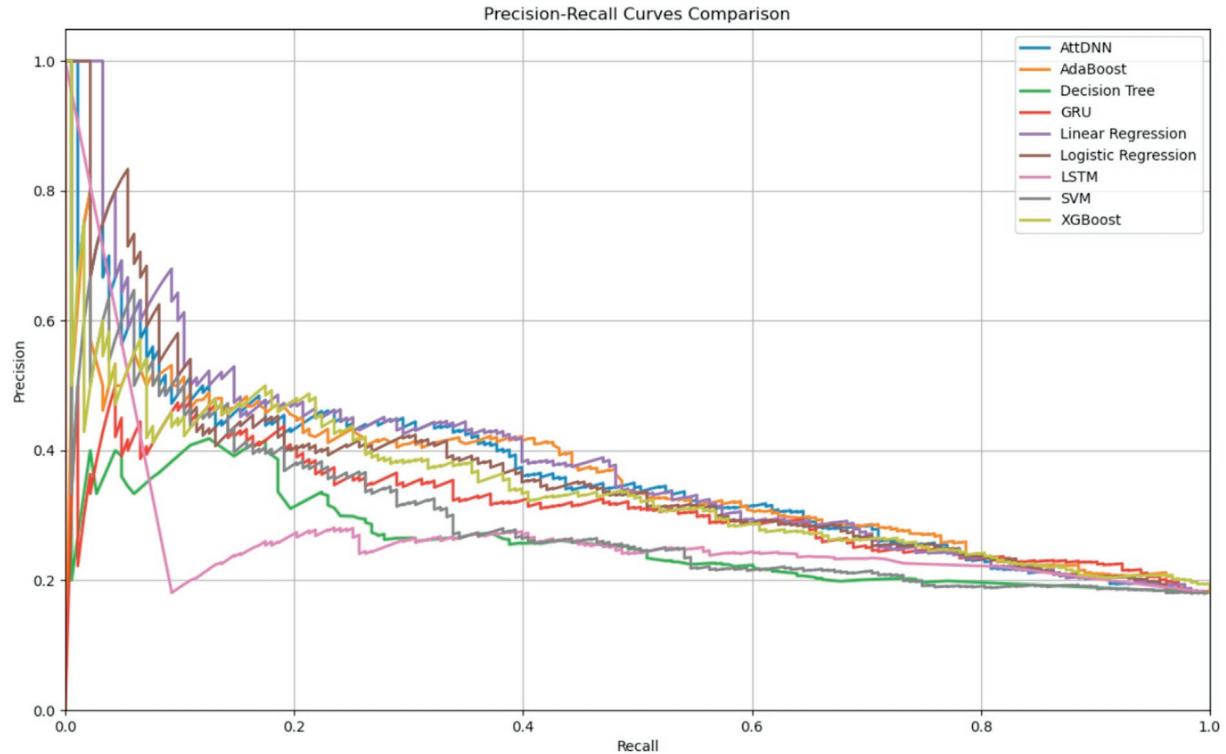


Fig. 5. Precision–Recall (PR) curves.

four regularization layers, incorporating two attention modules yields the best overall performance across all metrics, achieving an AUC of 0.711, a bACC of 0.659, and an F1 score of 0.456. However, adding a third attention module causes a sharp decline in performance, suggesting a limit to their effectiveness. Therefore, this study confirms that the optimal AttDNN structure comprises four regularization layers and two attention modules.

4.6. Impacts of different input variables

In this section, we further examine the impact of different input variables on the fitting capability and predictive performance of the AttDNN model. The 30 merger-driving factors are divided into four major groups: “Executive Features”, “Corporate Governance”, “Financial Condition”, and “Others”. Subsequently, 15 sets of input variables were constructed by various combinations of these four groups. These input variables were then used to retrain the AttDNN model, with the model architecture and experimental settings kept consistent with the previous sections. Table 5 presents the prediction results of the AttDNN model trained with different input variables, evaluated in terms of AUC, bACC, and F1 score.

Table 5 shows that the AUC values for all categories exceed 0.5, indicating that the AttDNN model outperforms random guessing. When individual input categories are evaluated, the model demonstrates moderate

Table 3
Results of the ablation experiments.

Method	AUC	bACC	F1 score
Baseline	0.625	0.522	0.301
Regu	0.703	0.656	0.452
AttDNN	0.711	0.659	0.456

Table 4

Experimental results with different numbers of hidden layers.

Different model structures	AUC	bACC	F1 score
no regularization layer, no attention module (Baseline)	0.625	0.522	0.301
1 regularization layer, non-attention module	0.705	0.644	0.443
2 regularization layers, non-attention module	0.705	0.603	0.420
3 regularization layers, non-attention module	0.703	0.633	0.433
4 regularization layers, non-attention module (Regu)	0.703	0.656	0.452
5 regularization layers, non-attention module	0.706	0.639	0.440
4 regularization layers, 1 attention module	0.701	0.626	0.431
4 regularization layers, 2 attention modules (AttDNN)	0.711	0.659	0.456
4 regularization layers, 3 attention modules	0.438	0.500	0.000

predictive performance, with AUC values around 0.6. Among these, the “Financial Condition” category achieves a higher AUC value. Although financial condition is often considered less significant in causal studies of M&A, the DL model developed in this study effectively captures key predictive features within financial data. This capability enhances predictive accuracy and further validates the effectiveness of the attention mechanism.

Further analysis reveals that increasing the number of input variable categories generally leads to higher AUC values compared with using a single category. In some cases, combining two or three categories results in even higher AUC values. However, the relationship between AUC values and the number of input variables is not linear. Moreover, certain combinations of input variables exhibit poorer performance than those with fewer categories. For instance, the AUC value for the combination of “Executive Features + Corporate Governance + Financial Condition” is lower than that for the combination “Executive Features + Others”. Overall, the results demonstrate that using all 30 input variables results in optimal predictive performance, validating the rationality of the selected input variables.

To interpret the predictive mechanism of the AttDNN model, we use two complementary analytical approaches: SHAP for assessing global feature importance (Lundberg and Lee, 2017) and an analysis of the model’s internal attention weights. The SHAP analysis (Fig. 6) reveals that market valuation level, strength of internal control, and nature of equity are the most influential variables driving the model’s final predictions. Concurrently, visualization of the internal attention layers (Fig. 7) indicates a dynamic information-processing strategy. The model initially places the highest attention on the debt-to-equity ratio and the presence of executive stock options, but in deeper layers, its focus shifts to features such as total asset

Table 5

Experimental results obtained using different input variables.

Input variables	AUC	bACC	F1 score
Executive Features	0.583	0.524	0.363
Corporate Governance	0.586	0.548	0.364
Financial Condition	0.639	0.587	0.407
Others	0.681	0.599	0.411
Executive + Governance	0.618	0.579	0.393
Executive + Financial	0.639	0.594	0.408
Executive + Others	0.686	0.646	0.443
Governance + Financial	0.647	0.611	0.421
Governance + Others	0.665	0.611	0.485
Financial + Others	0.694	0.604	0.415
Executive + Governance + Financial	0.661	0.599	0.409
Executive + Governance + Others	0.705	0.663	0.457
Executive + Financial + Others	0.694	0.617	0.427
Governance + Financial + Others	0.703	0.637	0.439
Executive + Governance + Financial + Others	0.711	0.659	0.456

turnover and market valuation level. This demonstrates that the model dynamically reweights feature importance as it develops a more abstract and nuanced understanding of a firm's M&A propensity.

The observed divergence in feature rankings between the SHAP values and attention weights provides deeper insight into the model's nonlinear decision-making process. Attention weights capture the model's focus during computation, indicating which features are most salient at specific intermediate stages. In contrast, SHAP values quantify the marginal contribution of each feature to the final prediction outcome, indicating its overall global impact. Therefore, a feature such as strength of internal control may not receive the highest initial attention but can still exhibit a high SHAP value due to its consistent and significant interaction effects with other variables throughout the network. This distinction suggests that the model extends beyond simple linear relationships and captures complex interdependencies in which a feature's ultimate contribution to prediction depends on its contextual interactions with other factors instead of its standalone initial importance.

When viewed in the context of existing research, the findings of the present study reveals both consistencies with established theories and new insights. The strong influence of market valuation level and debt-to-equity

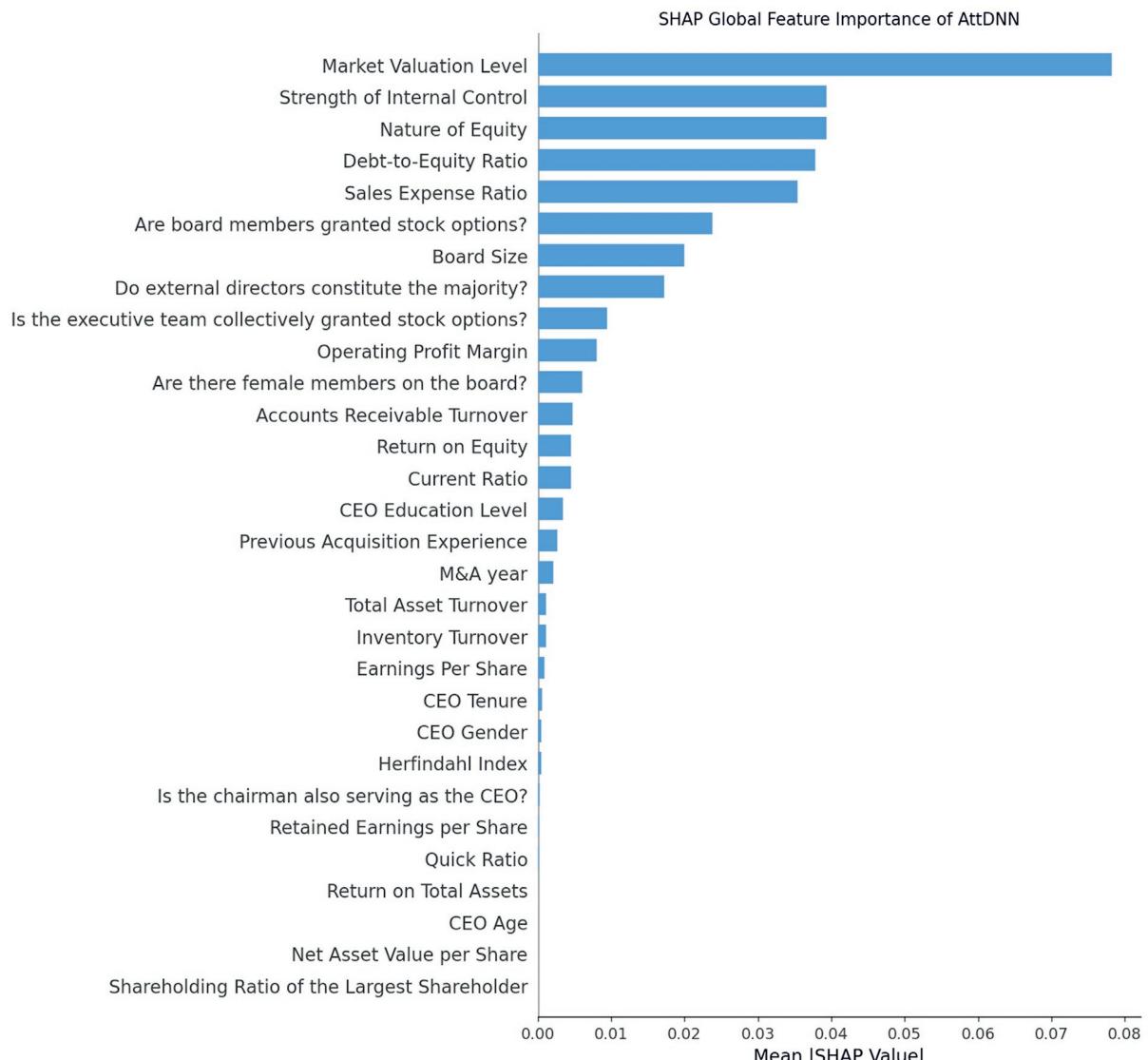


Fig. 6. SHAP global feature importance.

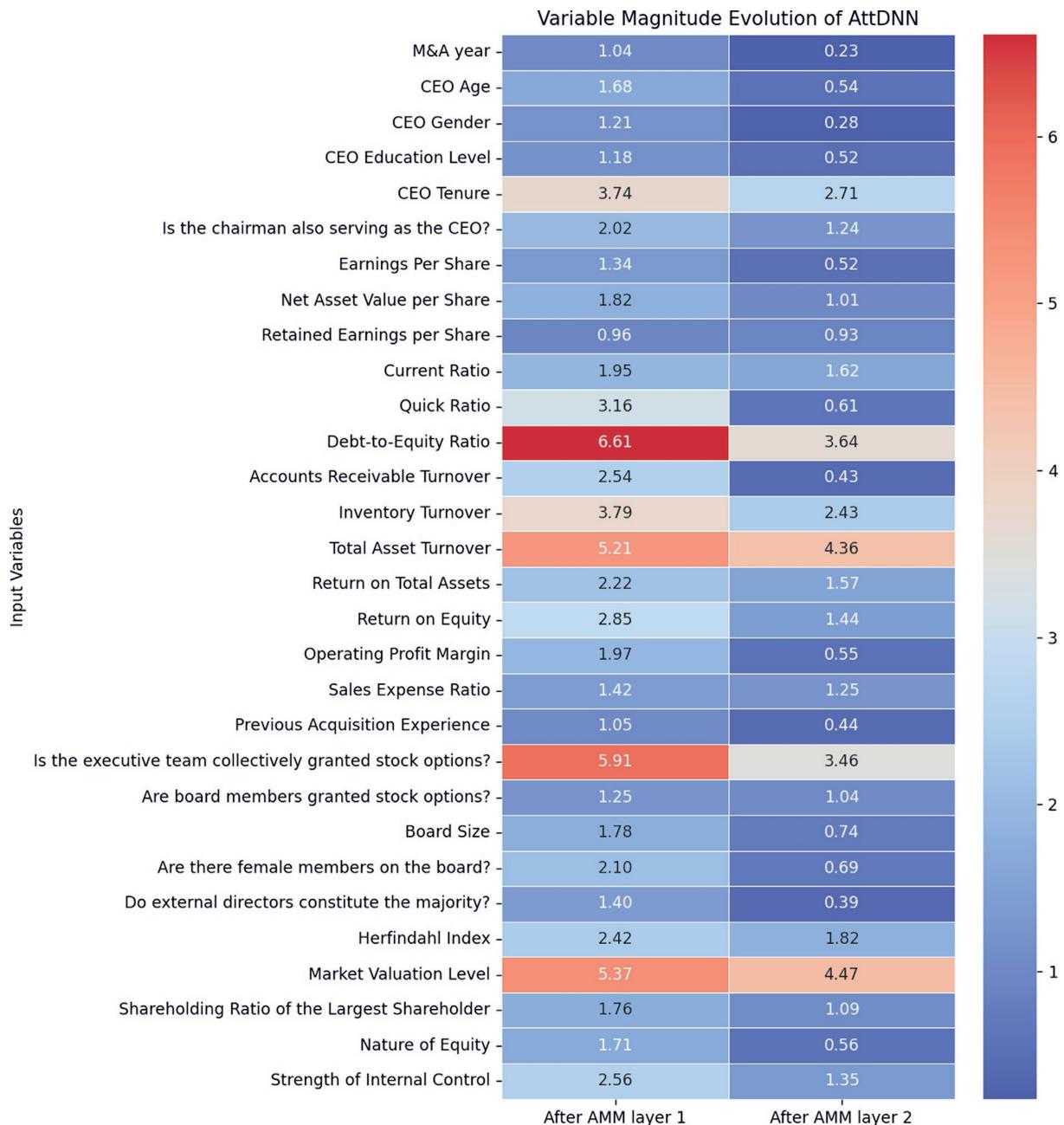


Fig. 7. Evolution of attention weights across layers.

ratio is consistent with established M&A theories, such as the market timing hypothesis and the role of financial constraints in corporate investment. Similarly, the high relevance of governance metrics supports classic agency theory perspectives. However, our model identifies strength of internal control as a top-tier predictor. Although previous studies have reported a link between internal control quality and acquisition decisions, this finding suggests that its function as a robust proxy for managerial quality and integration capability may be more significant than traditionally recognized. In contrast, the lower global importance of CEO-specific char-

acteristics does not contradict existing theories but indicates that their predictive effect may be absorbed by the stronger financial and corporate governance variables within our model's complex, data-driven framework.

4.7. Robustness check

The robustness of the AttDNN model is evaluated using datasets from various time periods: 2007–2013, 2007–2016, and 2007–2019. In these tests, the proposed model consistently exhibits superior or more balanced performance, particularly in terms of the F1 score, when compared with alternative models, as illustrated in Tables 6–8. The consistent results, also observed in Table 2 based on the original dataset ranging from 2007 to 2021, demonstrates the stability and reliability of the AttDNN model across varying time periods.

However, the improvement in the predictive performance of the AttDNN model compared with traditional ML methods is not substantial when using data from 2007 to 2013, as illustrated in Table 6. This may be attributed to the limited size of the training dataset during that period, which includes only 387 samples. Thus, the model could be trained only with a small batch size. Because DL models are highly data-dependent, the scarcity of data points restricts effective model fitting. These findings suggest that the proposed model performs more effectively when larger training datasets are available. Despite these drawbacks, the proposed AttDNN model still outperforms the seven alternative models, demonstrating its robustness and superior predictive capability.

5. Conclusions and future works

This study integrates M&A theories with DL algorithms to develop the AttDNN model for M&A prediction, advancing research methodology and paving the way for interdisciplinary exploration between AI and corporate finance. The AttDNN model is optimized through careful structural design, input variable selection, and data processing techniques. By incorporating regularization layers and an attention mechanism, the model effectively identifies key data features, thereby enhancing its predictive performance. Experimental results demonstrate that the AttDNN model outperforms traditional prediction methods in both predictive accuracy and interpretability, and robustness analyses further validate its prediction stability.

Furthermore, this study provides important implications for investment and financial analysis. The AttDNN model improves the accuracy and efficiency of M&A prediction, enabling investors to allocate resources effectively, reduce risks, and improve returns. It also addresses the common issue of data imbalance in financial analysis, demonstrating that models capable of adaptively learning data features can effectively reduce misclassification errors. In addition, financial institutions may prioritize the development of advanced DL and next-generation AI models, such as residual networks and generative AI, to maintain a competitive edge and improve predictive performance.

This study has several limitations that also present opportunities for future research. The model is developed using data from Chinese listed companies, which may limit the generalizability of the findings to other

Table 6
Experimental results obtained using data samples from 2007 to 2013.

Method	AUC	bACC	F1 score
Linear Regression	0.628	0.497	0.036
Logistic Regression	0.635	0.497	0.036
Decision Tree Regression	0.503	0.503	0.229
XGBoost	0.642	0.500	0.000
AdaBoost	0.544	0.544	0.196
SVM	0.595	0.510	0.039
Baseline	0.572	0.550	0.320
GRU	0.626	0.531	0.154
LSTM	0.625	0.568	0.382
AttDNN	0.592	0.500	0.465

Table 7

Experimental results obtained using data samples from 2007 to 2016.

Method	AUC	bACC	F1 score
Linear Regression	0.681	0.520	0.095
Logistic Regression	0.679	0.521	0.108
Decision Tree Regression	0.558	0.558	0.321
XGBoost	0.672	0.500	0.000
AdaBoost	0.583	0.583	0.309
SVM	0.619	0.500	0.000
Baseline	0.550	0.521	0.242
GRU	0.659	0.552	0.235
LSTM	0.670	0.586	0.399
AttDNN	0.696	0.628	0.471

Table 8

Experimental results obtained using data samples from 2007 to 2019.

Method	AUC	bACC	F1 score
Linear Regression	0.677	0.515	0.072
Logistic Regression	0.677	0.519	0.092
Decision Tree Regression	0.547	0.547	0.284
XGBoost	0.710	0.503	0.011
AdaBoost	0.524	0.524	0.110
SVM	0.612	0.510	0.043
Baseline	0.622	0.555	0.282
GRU	0.678	0.523	0.123
LSTM	0.664	0.521	0.340
AttDNN	0.675	0.584	0.481

regions. Future research could expand the analysis by using international M&A samples to compare the driving factors and their relative importance across different countries. Additionally, our data preprocessing excluded observations with missing critical information, which may have underestimated the performance of some benchmark models, such as tree-based methods that have built-in mechanisms to handle missing data. The impact of this exclusion on comparative results and model generalizability warrants further investigation. Although the AttDNN model shows strong predictive performance, there remains room for improvement. Future work could explore more powerful DL models and innovative network structures, such as residual networks, long-short skip connections, and encoder-decoder architectures, as well as the application of transformer models from natural language processing to M&A prediction. Finally, owing to the inherent nature of DL models, the predictive performance of the proposed method may be suboptimal when the training sample size is insufficient. Future work could therefore explore potential solutions for scenarios involving limited training data.

Data availability statement

The data supporting the findings of this study are obtained from the CSMAR and Wind databases. To access these databases, interested parties should contact their academic institution or the database providers for subscription information.

Declaration of Generative AI and AI-assisted Technologies in The Writing Process

During the preparation of this work, the authors used ChatGPT 4.0 and Gemini 2.5 Pro to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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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Can government procurement increase the labor share? Evidence from China



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ARTICLE INFO

Article history:

Received 20 May 2025

Accepted 3 December 2025

Available online 5 January 2026

Keywords:

Government procurement
contract

Labor share

Business risk

Public governance

Income equality

ABSTRACT

This paper examines the effect of government procurement on the firm-level labor share in China. Using manually collected local government contract data matched with A-share non-financial listed firms from 2015 to 2023, we find that firms receiving government procurement contracts experience increased labor shares. Government procurement enhances business stability and encourages regulatory and non-regulatory compliance, facilitating the allocation of economic gains to labor. This positive effect is primarily driven by non-SOEs and is pronounced among labor-intensive manufacturing firms. We also show that government procurement effectively promotes income equality and improves overall employee welfare. Our findings highlight the redistributive role of government procurement and the importance of contract design that aligns firm incentives with social objectives in emerging markets.

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1. Introduction

The labor share, defined as the proportion of national income allocated to labor compensation, reflects the balance between capital and labor in the distribution of economic gains and plays an important role in sustaining long-term growth, social stability and overall welfare (Kaldor, 1957, 1961). However, a growing body of research documents a persistent and widespread decline in labor share across global economies since the 1980s (e.g., Karabarbounis and Neiman, 2014; Autor et al., 2017, 2020; Bergholt et al., 2022). This trend has raised concerns among researchers and regulators, as it may cause income inequality and imbalances in economic development in the long term (e.g., Jacobson and Occhino, 2012; Hémous and Olsen, 2022). Studies

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primarily attribute the decline in the labor share to the weakening position of labor in the value creation process because of, for example, efficiency-driven capital accumulation and technological progress, which often prioritize productivity gains over equitable income distribution (e.g., Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2019, 2022). Overemphasizing efficiency can undermine the equilibrium between capital and labor. Without mechanisms to ensure that productivity gains translate into compensation growth, the virtuous cycle of demand-led expansion that underpins long-term economic development is disrupted. This highlights the importance of government intervention in preserving stable labor income shares (Stiglitz, 2012).

Government procurement is an important form of government intervention through which the state actively participates in the allocation of market resources. By directing substantial public funds to the purchase of goods, services and infrastructure, government procurement not only stimulates aggregate demand but also influences contractors' behaviors. Government procurement influences contractor firm behavior through two main channels: alleviating business risks and financial constraints (Dhaliwal et al., 2016; Cohen and Li, 2020; Di Giovanni et al., 2022; Burger et al., 2024; Gabriel, 2024) and imposing monitoring and compliance requirements such as social responsibility commitments (Flammer, 2018; Huang et al., 2023), disclosure transparency (Hope et al., 2021; Samuels, 2021) and labor protection (Chircop et al., 2022). Although the influence of government procurement on firm behavior is widely studied, its implications for income distribution at the firm level remain unexplored. Prior studies find that business risks and financial pressures often reduce firms' capability and willingness to share profits with employees (e.g., Li et al., 2023; Song et al., 2024; Liu and Si, 2025; Wang et al., 2025) and may even encourage employee mistreatment in firms' pursuit of profit maximization (e.g., Caskey and Ozel, 2017; Raghunandan, 2021). These problems are exacerbated in a weak monitoring environment (Ciminelli et al., 2022; Fard and Chung, 2024). We therefore expect government procurement to influence firms' income distribution decisions by providing business stability and enhancing employee treatment through both proactive engagement and regulatory oversight.

China provides a natural context for examining this issue. Since the reform and opening-up policy was implemented in 1978, China has experienced a significant decline in aggregate labor share driven by capital-intensive growth, structural transformation and institutional reforms (Bentolila and Saint-Paul, 2003; Bowls and Sicular, 2003; Meng, 2012; Li et al., 2021a). Recent studies document that China's labor share has gradually increased since 2007. Li et al. (2023) attribute this to industrial restructuring and technological advancement, which have expanded employment opportunities and increased wage levels. Zhang et al. (2023a) show significant regional divergence in the trends of labor share increases. China's growth model is heavily state-led, as the government plays a central role in shaping macro-level resource allocation and micro-level firm behavior (e.g., Meng, 2012; Gu et al., 2020). Government procurement has become an important driver of China's economic development and greatly influenced micro firm characteristics (e.g., Huang et al., 2023; Yu et al., 2024; Liu et al., 2024b). Even more importantly, China's pursuit of common prosperity has brought attention to the labor share as a key indicator of equitable common prosperity and economic development. As the government seeks to narrow income gaps and enhance workers' well-being, increasing the proportion of national income allocated to labor has become a policy priority (Kakwani et al., 2022).¹ Therefore, it is valuable to investigate how the Chinese government's intervention supports labor share recovery and promotes equitable growth.

To empirically investigate the effect of government procurement on the firm-level labor share in China, we manually collect local government contract data for non-financial listed companies on the Shanghai and Shenzhen A-share markets from 2015 to 2023. We find that government procurement increases the labor share of contractor firms. Our results hold when we conduct an event study around a firm's initial participation in a government procurement contract. Our main findings remain robust when we use alternative measures of government procurement. Separate regressions of the numerator and denominator of the labor share on government procurement suggest that the observed increase in the labor share is primarily driven by higher employee

¹ The Chinese government and the Chinese Communist Party repeatedly emphasize in their policy plans and goals the need to increase the proportion of labor remuneration in the primary distribution, strengthen macro guidance on wage income distribution in enterprises and improve the mechanisms for determining reasonable growth and payment guarantees for workers' wages. See the employment priority strategy of the Chinese government (https://www.gov.cn/zhengce/202409/content_6976470.htm) and the national goal of common prosperity (https://www.ndrc.gov.cn/fggz/jyysr/jyrsbxf/202305/t20230515_1355783.html).

compensation. Our findings are also robust to propensity score matching (PSM), entropy balance matching (EBM) and the inclusion of additional fixed effects.

Cross-sectional analysis reveals that the positive effect of government procurement on the labor share is more pronounced among firms facing greater uncertainty and financial constraints, poorer corporate social responsibility performance, weaker internal governance and lower financial reporting quality. The effect is also stronger for firms receiving a larger share of procurement from local governments, firms located in regions with higher minimum wages and firms located in regions where local governments place greater emphasis on labor protection. These findings suggest that government procurement increases the labor share by enhancing business stability, imposing social compliance pressures and strengthening regulatory monitoring.

Additional analyses show that the positive effect of government procurement on the labor share is driven by non-state-owned enterprises (non-SOEs). This not only alleviates concerns that the results may be driven by SOEs, which typically place a higher priority on employee welfare and bear greater social responsibilities, but also provides evidence that government procurement can encourage firms with stronger profit motives to allocate more economic gains to employees. We further find that the main effects are concentrated in the manufacturing sector, where labor intensity is higher and capital-labor substitution is more common. Moreover, government procurement is associated with higher average wages for employees and a narrower pay gap between executives and rank-and-file employees. This offers additional support for the role of government procurement in promoting income distribution equality. Our findings further suggest that government procurement improves employee welfare in broader dimensions.

Our paper makes the following contributions. First, we contribute to the growing body of research exploring the determinants of labor income share. The literature documents a significant global decline in the labor share, and China is no exception, experiencing a marked decline since the reform and opening-up policy was implemented in 1978 but showing stability and a gradual rebound in recent years (Chong-En and Zhenjie, 2010; Karabarbounis and Neiman, 2014; Li et al., 2023; Zhang et al., 2023a). A stable labor share is essential for sustaining economic growth, as it helps to ensure that household consumption keeps pace with the development of productive capacity (Kaldor, 1957, 1961). By showing that the expansion of government procurement practices can contribute to the stabilization and growth of the labor share by shaping firms' labor decisions and promoting a more equitable distribution of value added, we deepen the understanding of government intervention that can reverse labor share erosion and promote inclusive development.

Second, our research expands understanding of the economic consequences of government procurement. The literature emphasizes the role of government customers in alleviating business uncertainty and financial pressures (Cohen and Li, 2020; Dhaliwal et al., 2016; Liu et al., 2024b; Yang and Li, 2024; Yu et al., 2024) and in enhancing both regulatory and non-regulatory compliance (Flammer, 2018; Hope et al., 2021; Samuels, 2021; Huang et al., 2023). Monteiro and Suleymanov (2025) contribute to this by demonstrating that government procurement improves labor investment efficiency, which focuses on maximizing output through optimal labor allocation but does not necessarily account for how the value created is distributed between capital and labor. In contrast, our study highlights the redistributive implications of government procurement, which reflect how value is shared between labor and capital rather than how labor is optimally deployed for profit maximization.

Third, our findings support the view that the government plays a crucial role in shaping individuals' incentives and decision-making. As such, they offer policy-relevant implications for emerging economies: strategically designed procurement policies, such as increasing transparency and fairness in contract awards, accounting for firms' profitability and business risks when setting contract terms and incorporating labor-related clauses, can be effective market-oriented tools to promote economic stability, improve income distribution and enhance corporate responsibility and social welfare.

2. Institutional background and hypothesis development

2.1. Institutional background

China's government procurement system has undergone multiple stages of development. The Government Procurement Law of the People's Republic of China, effective from 1 January 2003, laid the foundational legal

framework by defining government procurement as the use of fiscal funds by state organs, public institutions and social organizations to acquire goods, construction works and services listed in centralized procurement catalogs or exceeding designated thresholds. The law introduced key principles such as openness, fairness, impartiality and good faith and emphasized budget compliance, a combination of centralized and decentralized procurement and preference for domestic products and services. It also clarified the roles and responsibilities of procurement entities, suppliers and agents while mandating monitoring by finance departments and other regulatory agencies. Building on this legal foundation, the Regulations for the Implementation of the Government Procurement Law, promulgated by the State Council of the People's Republic of China and effective from 1 March 2015, marked a significant advancement in enforcement and regulatory detail. The regulations standardized operational procedures across the procurement lifecycle, including budget planning, tendering, contract execution and post-procurement monitoring. They strengthened accountability mechanisms by requiring conflict-of-interest disclosures, mandating procurement information disclosure through public platforms and establishing clear complaint and review procedures. Furthermore, the Chinese government emphasized performance-oriented governance, shifting the focus from procedural compliance to procurement outcomes, and reinforced policy goals such as social responsibility practices, small and medium-sized enterprises (SME) participation and regional equity. To strengthen labor protection, the regulations jointly issued by the National Development and Reform Commission and the Ministry of Human Resources and Social Security in 2025 stipulate that firms defaulting on the payment of employees' compensation and included in the provincial disciplinary list will be subject to nationwide restrictions on government funding support and procurement.²

In 2002, the total value of government procurement in China was approximately 100 billion RMB. Since the implementation of the Government Procurement Law two decades ago, the scale of procurement has expanded significantly. By 2023, the total value of government procurement had reached 3.39 trillion RMB, accounting for 12.4 % of total fiscal expenditure and 2.6 % of GDP. Fig. 1 shows the distribution of government procurement dynamics from 2011 to 2023. The upward trend in government procurement and its relatively high share in national fiscal expenditure and GDP indicate that it has become an important driver of China's economic development, with growing potential to influence market participants.

The literature documents that firms in China are affected by government procurement in many ways. For example, Huang et al. (2023) find that firms with major government customers exhibit higher ESG performance. Yu et al. (2024) show that government procurement can improve firms' productivity by enhancing their innovation, improving their sales performance and increasing market supervision. Yang and Li (2024) find that government procurement improves investment efficiency by alleviating financing constraints and reducing business uncertainties. Liu et al. (2024b) show that government procurement alleviates financing constraints and facilitates green technological innovation.

2.2. Labor share

The labor share is the proportion of gross value added that is paid to labor. It can be measured at both the economy-wide and firm levels. Kaldor (1957, 1961) emphasizes that the dynamic interplay between capital accumulation, technological progress and income distribution is essential for sustaining balanced economic growth. While investment- and technology-led growth improves economic efficiency, overemphasizing efficiency risks eroding labor income (Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2019, 2022). In this context, maintaining and improving the labor income share is important, as it not only reflects social priorities such as fairness, equity and worker well-being but also ensures sufficient consumer demand and supports the cycle between production and consumption that underpins sustainable growth. However, prior studies document significant downward trends in the labor shares of many countries since the 1980s. The falling relative price of investment goods (Karabarbounis and Neiman, 2014), technological advance-

² See details at https://www.mohrss.gov.cn/ldcj/LDJCJzhengcewenjian/202501/t20250127_535554.html. A real case in a list of government procurement violations released by Tianjin in 2023 is that of a company that was disqualified from participating in government procurement because of a lack of social insurance payment records (https://www.ccgp.gov.cn/zcdt/202311/t20231114_21065387.htm).

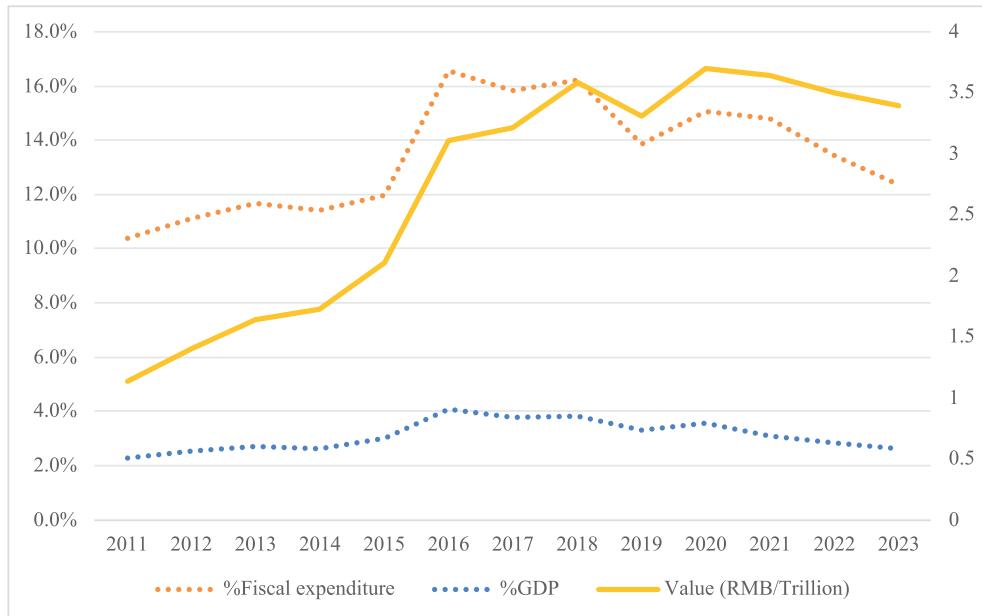


Fig. 1. The distribution of government procurement from 2011 to 2023. Fig. 1 presents the distribution of government procurement from 2011 to 2023. *%Fiscal expenditure* is defined as the percentage of total fiscal expenditure allocated to government procurement by calendar year. *%GDP* is defined as the percentage of government procurement value relative to gross domestic product (GDP) in a given calendar year. *Value* is the total value of government procurement in RMB per trillion. Our statistics start from 2011 because government procurement data were not fully available prior to that year. We obtain the national government procurement data from the information disclosed by the Ministry of Finance of the People's Republic of China. The fiscal expenditure and GDP data are obtained from the National Bureau of Statistics.

ments (Acemoglu and Restrepo, 2019, 2022), globalization (Guscina, 2007; Autor et al., 2013; Karabarbounis, 2024), the rise of firm markups (Autor et al., 2017, 2020; Bergholt et al., 2022) and employment protection deregulation in advanced economies (Ciminelli et al., 2022) weaken labor's economic position and facilitate the substitution of capital for labor. These forces have collectively driven the decline in labor share, which highlights the importance of understanding how to strengthen labor's role in economic development and promote labor share stability.

In developing countries such as China, labor shares exhibit greater volatility and larger imbalances than in developed countries. China is no exception to the global trend of declining labor shares, as its labor share has been falling since the reform and opening-up policy was implemented in 1978, driven by factors such as capital-intensive growth, structural transformation and labor misallocation resulting from institutional deficiencies (Bowles and Sicular, 2003; Chong-En and Zhenjie, 2010; Li et al., 2021a). However, recent studies document a stable and gradual increase in China's labor share in recent years. Li et al. (2023) attribute this to the expanded employment opportunities and wage payments associated with industrial restructuring and technological advancement in China. Zhang et al. (2023a) verify this phenomenon and identify regional divergence in labor share dynamics: while most eastern provinces (except for Beijing, Tianjin and Shanghai, which have experienced upward trends in their labor share) exhibit a U-shaped pattern, persistently declining from 1978 to 2007 and then gradually rising, similar trends are observed across many central and western provinces. These macro-level patterns have attracted growing attention to the determinants and implications of labor share dynamics at the firm level.

The labor share falls within the scope of firms' labor investment decisions. Prior studies show that heightened uncertainty increases the risk of labor misallocation by prompting firms to shorten employment contracts, reduce hiring and even lay off skilled workers (Rich and Tracy, 2004; Baker et al., 2016; Schaal, 2017; Bamieh et al., 2023; Caggese et al., 2024). Financial constraints and performance pressures heighten firms' sensitivity to demand shocks, thereby exacerbating their tendency to reduce labor costs (Hall, 2016;

Caggese et al., 2019; Michaels et al., 2019; Ma and Hao, 2022) and raising the risks of employee mistreatment through wage theft (Raghunandan, 2021) or decreased workplace safety (Caskey and Ozel, 2017). Precautionary saving motives against risk play a crucial role, as uncertainty is shown to decrease the labor income share, especially among financially constrained firms (Song et al., 2024; Liu and Si, 2025). Labor unions enhance workers' bargaining power in firms' risk-related decision-making processes and secure better wages and benefits for employees, thereby contributing to a higher labor share (Knepper, 2020). Similarly, digital transformation alleviates firms' financing constraints and increases demand for labor, particularly for high-skilled workers with greater bargaining power and higher wages, thereby raising the labor share (Li et al., 2023).

Government also plays a critical role in shaping firms' labor investment decisions, such as by providing subsidies to incentivize job creation (Dong et al., 2024). In addition, state ownership and the appointment of government officials impose greater employment-related social responsibilities on firms (Gu et al., 2020). By improving financial conditions and enforcing regulatory monitoring, government procurement alleviates both over-hiring and under-hiring, thereby promoting more efficient labor investment (Goldman, 2020; Monteiro and Suleymanov, 2025). Government policies are shown to have a significant influence on the labor share: entry deregulation increases the labor share by weakening monopolistic power and promoting labor input (Chen et al., 2023), whereas employment protection deregulation decreases the labor share by reducing workers' bargaining power and real wages (Ciminelli et al., 2022).

Overall, labor investment misallocation stems not only from business risk and financial frictions but also from firms' potential incentives to suppress labor input to maximize profit. Government intervention can alleviate such distortions. Although a growing body of research shows that government procurement improves labor investment efficiency, the labor share is not necessarily equivalent to this efficiency, as the labor share reflects the distributional outcome between capital and labor rather than the optimality of labor input. Therefore, the implications of government procurement for labor share remain unexplored.

2.3. Government procurement and the labor share

We argue that government procurement can shape firms' labor share in two ways. First, business risk and financial constraints reduce firms' ability to maintain or improve employee treatment, especially in terms of compensation, which reflects the extent to which value creation is attributed to labor—that is, the labor share (Li et al., 2023). The long-term nature of procurement contracts and the low risk of default make government customers a stable and reliable source of demand and profitability for contractor firms, thereby shielding them from demand volatility and financial constraints (Dhaliwal et al., 2016; Cohen and Li, 2020; Goldman, 2020; Monteiro and Suleymanov, 2025). In addition, the presence of government customers may send a positive signal to capital markets regarding the stability and credibility of a supplier firm, which can lower the firm's financing costs and risk premiums (Di Giovanni et al., 2022; Burger et al., 2024; Gabriel, 2024). Studies also document similar effects in the context of China's government procurement (e.g., Liu et al., 2024b; Yang and Li, 2024; Yu et al., 2024), enabling firms to refine employee treatment (Wang et al., 2025). Therefore, we expect government procurement to increase the labor share by reducing contractor firms' business risks and financial constraints.

Second, a higher labor share indicates that firms distribute a larger portion of their value creation to employees, potentially increasing labor-related costs. To offset these costs and achieve earnings goals, firms may be incentivized to engage in labor exploitation. Government can significantly affect corporate behavior (e.g., Huang, 2022), especially in the context of China's political economy (e.g., Marquis and Qian, 2014). Firms that receive or seek government support are associated with higher political cost considerations and are likely to bear greater burdens in fulfilling social responsibilities, such as complying with government mandates on employment stability, job creation, labor protection and participation in public welfare initiatives (e.g., Lee et al., 2017; Gu et al., 2020; Chang et al., 2021; Dong et al., 2024; Na et al., 2024). Given that major customers play a significant role in monitoring their suppliers' compliance behaviors and curbing violations (Chen et al., 2025), government procurement represents a distinct type of customer that exerts even stronger monitoring. Government customers possess the motivation and authority to reinforce compliance across multiple dimensions, such as financial transparency (Hope et al., 2021; Samuels, 2021), corporate social responsibility (Flammer, 2018; Huang et al., 2023) and employment decisions (Monteiro and Suleymanov, 2025).

Government monitoring of contractors can reduce wage theft by improving financial reporting quality and enforcing stricter contract terms (Chircop et al., 2022). Therefore, we expect government procurement to increase the labor share by enhancing compliance requirements and monitoring, which encourages firms to better fulfill their social responsibilities, curbs exploitative labor practices and ensures that a greater portion of the value created by employees is returned to them in the form of wages and benefits.

We therefore expect government procurement to increase the labor share by refining firms' labor treatment decisions through mitigating business risks and financial pressures, and by reinforcing the allocation of a greater share of value creation to labor through strengthened government monitoring and compliance requirements. We formulate our hypothesis as follows:

H1: Ceteris paribus, government procurement increases the labor share of contractor firms.

3. Research design

3.1. Data source and sample

To ensure the transparency of the procurement process, key information, including the identities of procuring entities and suppliers, product and service details, transaction amounts and contract terms, has been disclosed on the China Government Procurement website (<https://www.ccgp.gov.cn>) since 2015 in accordance with the Government Procurement Law. This public disclosure facilitates monitoring by both regulatory authorities and the public, thereby strengthening traceability and accountability. It also enables researchers to manually collect government procurement data for empirical analysis.

To explore the impact of government procurement on the labor income shares of listed companies in China, we manually collect local government contract data from 2015 to 2023 and match them to the data of non-financial listed companies on the Shanghai and Shenzhen A-share markets. After we drop observations with missing values for the regression variables, our final sample for the main analysis consists of 28,323 firm-year observations.

3.2. Methodology

We estimate the following ordinary least squares regression model to empirically investigate the effect of government procurement and the firm-level labor income share:

$$Lsr_{i,t} = \beta_0 + \beta_1 Contract_{i,t} + Controls_{i,t} + Firm + Year + \varepsilon \quad (1)$$

where the dependent variable $Lsr_{i,t}$ is the labor share for firm i in year t . Following the literature (Donangelo et al., 2019; Li et al., 2021a; Cui et al., 2023), we measure Lsr as the proportion of a firm's value creation paid to its employees, which is defined as cash payments to employees in the cash flow statement divided by the sum of cash paid to employees, operating income and the depreciation of fixed assets. $Contract_{i,t}$ is the proxy for government procurement contracting, equal to the total value of government procurement divided by the sales of the firm for the current year (Samuels, 2021). The coefficient of β_1 is of interest: a positive β_1 is consistent with our hypothesis and indicates that government procurement increases firm-level labor share. $Controls$ is a set of time-varying and firm-specific control variables related to the corporate labor share. Following prior studies (Li et al., 2023; Liu et al., 2024a), we include firm size ($Size$), leverage level (Lev), return on assets (Roa), market-to-book ratio (Mb), capital output (Ppe), cash flow from operations (Cfo), inventory turnover ratio ($Turnover$), SOE (Soe), firm age (Age), accounting loss ($Loss$), size of director board ($Boardsize$), proportion of independent directors ($Independ$), dual positions of CEO and board chairman ($Dual$), institutional ownership ($Inst$) and share proportion of the largest shareholder ($Top1$). All of the continuous variables are winsorized at the 1% and 99% levels. We include firm fixed effects ($Firm$) and year fixed effects ($Year$) in the baseline analysis to rule out unobserved time trends and time-invariant heterogeneity across firms, and we cluster standard errors by firm. All of the variables above are defined in the Appendix.

3.3. Summary statistics

Table 1 presents the descriptive statistics for the variables included in our main regression. In our sample, *Lsr* has a mean value of 0.308, which aligns with the reported value of the labor share in the literature (e.g., Cui et al., 2023). The mean value of *Contract* is 0.011, indicating that the government procurement amount obtained by the sample companies accounts for approximately 1 % of their total revenue. Untabulated statistics show that on average, 21.4 % of the observations within the sample have ever received government procurement contracts, and the average government procurement amount for these firms is approximately 5 % of their sales, with the maximum value exceeding 67 %. This substantial variation in government procurement exposure suggests that not all firms have equal access to government procurement opportunities, and it allows meaningful comparisons between firms with different levels of procurement. This wide distribution reinforces the feasibility and importance of studying how varying degrees of government procurement influence firms' labor decisions. The distributions of the other control variables are consistent with the literature.

4. Empirical results

4.1. Government procurement and labor share

Table 2 reports our main estimation results regarding the influence of government procurement on the corporate labor share. Columns (1) and (2) present the regression estimates without the control variables. In columns (3) to (6), we include all of the control variables in the regression. We control for industry and year fixed effects in columns (1) and (3), firm and year fixed effects in columns (2) and (4) and firm and industry-by-year fixed effects in columns (5) and (6). In column (6), we restrict the regression to subsamples where the government procurement value is greater than 0. The coefficients of *Contract* are positive and significant in all columns, indicating that government procurement increases the labor share, which is consistent with our hypothesis. The results further indicate that our findings are driven not solely by whether firms receive government contracts but also by the intensity of government procurement. Other control variables show effects on the labor share that are consistent with the literature (e.g., Li et al., 2023): for example, larger firms have a lower labor share.

Table 1
Descriptive statistics.

Variable	Observation	Mean	S.D.	Median	Q1	Q3
<i>Lsr</i>	28,323	0.308	0.125	0.218	0.297	0.381
<i>Contract</i>	28,323	0.011	0.071	0.000	0.000	0.000
<i>Size</i>	28,323	22.329	1.282	21.411	22.142	23.047
<i>Lev</i>	28,323	0.417	0.199	0.258	0.409	0.562
<i>Roa</i>	28,323	0.033	0.064	0.012	0.035	0.065
<i>Mb</i>	28,323	2.864	2.505	1.450	2.100	3.293
<i>Ppe</i>	28,323	0.482	0.561	0.154	0.317	0.580
<i>Cf</i>	28,323	0.049	0.066	0.011	0.048	0.088
<i>Turnover</i>	28,323	12.263	41.040	2.050	3.765	7.127
<i>Soe</i>	28,323	0.307	0.461	0.000	0.000	1.000
<i>Age</i>	28,323	2.172	0.839	1.609	2.303	2.944
<i>Loss</i>	28,323	0.138	0.345	0.000	0.000	0.000
<i>Boardsize</i>	28,323	2.102	0.194	1.946	2.197	2.197
<i>Independ</i>	28,323	0.378	0.053	0.333	0.364	0.429
<i>Dual</i>	28,323	0.314	0.464	0.000	0.000	1.000
<i>Inst</i>	28,323	0.421	0.247	0.207	0.431	0.621
<i>Top1</i>	28,323	0.333	0.144	0.222	0.310	0.426

Notes: This table presents the summary statistics for the main variables used in this paper.

Table 2
Government procurement and labor share.

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Lsr</i>					
<i>Contract</i>	0.050*** (3.814)	0.019*** (2.877)	0.054*** (4.609)	0.014*** (2.620)	0.012** (2.187)	0.009* (1.814)
<i>Size</i>			-0.025*** (-15.926)	-0.032*** (-11.418)	-0.032*** (-12.024)	-0.033*** (-5.938)
<i>Lev</i>		0.017** (1.997)	0.005 (0.598)	0.006 (0.712)	-0.002 (-0.097)	
<i>Roa</i>		-0.573*** (-23.108)	-0.472*** (-24.677)	-0.462*** (-24.767)	-0.416*** (-10.907)	
<i>Mb</i>		-0.001** (-2.271)	-0.001 (-1.634)	-0.001 (-1.597)	-0.002** (-2.105)	
<i>Ppe</i>		-0.015*** (-5.218)	0.027*** (7.297)	0.027*** (7.466)	0.035*** (4.178)	
<i>Cf</i>		-0.135*** (-8.860)	-0.167*** (-15.756)	-0.157*** (-15.272)	-0.117*** (-5.589)	
<i>Turnover</i>		0.000 (1.499)	-0.000* (-1.742)	-0.000* (-1.813)	-0.000 (-1.462)	
<i>Soe</i>		0.033*** (9.202)	0.020*** (4.210)	0.019*** (4.197)	0.016* (1.956)	
<i>Age</i>		0.006*** (3.368)	0.012*** (4.433)	0.011*** (4.254)	0.011 (1.531)	
<i>Loss</i>		0.036*** (10.663)	0.034*** (14.270)	0.033*** (14.658)	0.032*** (6.689)	
<i>Boardsize</i>		0.027*** (3.364)	0.004 (0.617)	0.005 (0.708)	0.008 (0.646)	
<i>Independ</i>		0.049* (1.855)	-0.017 (-0.911)	-0.011 (-0.632)	0.018 (0.526)	
<i>Dual</i>		0.002 (0.835)	0.000 (0.164)	-0.000 (-0.264)	-0.006 (-1.625)	
<i>Inst</i>		0.029*** (4.642)	-0.003 (-0.335)	-0.003 (-0.358)	-0.004 (-0.273)	
<i>Top1</i>		0.030*** (3.030)	0.026* (1.840)	0.023* (1.702)	-0.025 (-0.948)	
<i>Constant</i>	0.307*** (204.733)	0.307*** (4463.276)	0.762*** (20.360)	0.987*** (15.846)	0.997*** (16.732)	1.037*** (7.966)
Industry FE	Yes	No	Yes	No	No	No
Firm FE	No	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No	No
Industry-Year FE	No	No	No	No	Yes	Yes
<i>N</i>	28,323	28,323	28,323	28,323	28,323	6072
Adj. <i>R</i> ²	0.167	0.727	0.379	0.824	0.831	0.866

Notes: This table presents the regression estimates for the effect of government procurement on firm labor share based on Eq. (1). Variable definitions are presented in the Appendix. The t-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.2. Robustness tests

4.2.1. Event study evidence

To address endogeneity concerns (for example, firms with a relatively high share of labor income may have an advantage in obtaining government contracts, which could invalidate our empirical estimation), we construct quasi-exogenous shocks to government procurement and re-estimate the effects on labor share, using the difference-in-differences regression model to help establish causality. Specifically, we first select firms that

changed from having no government procurement to initially receiving government procurement during the sample period. Second, we match this sample with firms that never received government procurement during our sample period by year, using PSM. Finally, we define firms that changed from having no government procurement to obtaining contracts from the government as the treatment group and firms that were never government suppliers during our sample period as the control group.³

We then use the following regression model for this change analysis:

$$Lsr_{i,t} = \beta_0 + \beta_1 Gain_contract_{i,t} + Controls_{i,t} + Firm + Year + \varepsilon \quad (2)$$

where *Gain_contract* is set to 1 for the years after the inception year of treated firms receive government procurement contracts, and 0 otherwise. The regression results are shown in column (1) of Table 3. The coefficients of *Gain_contract* are positive and significant at the 1% level, indicating that firms' labor share increases after they gain government procurement contracts. In addition, we examine the dynamic changes in firms' labor share before and after receiving government procurement contracts. Column (2) of Table 3 presents the results, where *Gain_contract*^X ($X = 3-, -2, 0, +1, +2, 3+$) is set to 1 for the years more than 3 years before, 2 years before, equal to, 1 year after, 2 years after and more than 3 years after the first year the treatment firms received government procurement contracts, and 0 otherwise. We use the year before the firm received a government procurement contract as a benchmark in this test. The results show that there is no significant difference between the treatment and control groups before the event year, but there is a significant increase in the labor share after the firm receives government procurement. In addition, the increase in the labor share is long-lasting as the magnitude grows larger, and the coefficient of *Gain_contract*³⁺ is still positive and significant. Overall, the results in Table 3 are consistent with our main finding that a government procurement award results in an increased labor share.

4.2.2. Other robustness tests

We conduct several additional tests to enhance the robustness of our main results. First, we use two alternative variables to measure government procurement: *Contract_number*, defined as the natural logarithm of the number of government procurement contracts obtained by the company plus 1, and *Contract_size*, defined as the natural logarithm of the total value of government procurement obtained by the company plus 1. The results are shown in Panel A of Table 4. In columns (1) and (2) (columns (3) and (4)), we use *Contract_number* (*Contract_size*) as the dependent variable to replace the original dependent variable in Eq. (1). The coefficients in all columns with either industry fixed effects or firm fixed effects are positive and significant at the 1% level, consistent with our main results.

Second, we regress the numerator and the denominator of the labor share on government procurement to further examine whether the observed increase in the labor share is driven by higher employee compensation or lower value creation. We use the natural logarithm of cash paid to employees (*LnPayments*) and the raw value of cash paid to employees scaled by 1 billion (*RawPayments*) to replace the dependent variable in Eq. (1). The results are reported in Panel B of Table 4. All of the coefficients of the three government procurement measures are significantly and positively associated with labor compensation. Similarly, we define *LnValueCreation* as the natural logarithm of operating income plus the depreciation of fixed assets and *RawValueCreation* as the corresponding untransformed value scaled by 1 billion. These two measures are used to replace the dependent variable in Eq. (1) to examine the effect of government procurement on value creation. The results are reported in Panel C of Table 4. All of the coefficients of the three government procurement measures are statistically nonsignificant or positive. These results indicate that the increase in labor share is primarily driven by greater value being distributed to labor.⁴

³ The main results in Table 2 hold in this subsample with small observations.

⁴ When the labor income share is adjusted on a per-capita basis, dividing both the numerator and the denominator by the number of employees gives the ratio of average compensation to average value added per worker. Our analysis in Section 6.3 shows that government procurement significantly increases average wages. Moreover, untabulated results show that government procurement does not significantly affect value added per employee, reinforcing that the increase in the labor share is not simply a byproduct of productivity changes.

Table 3
Event study evidence.

	(1)	(2)
	<i>Lsr</i>	
<i>Gain_contract</i>	0.011*** (2.865)	
<i>Gain_contract</i> ³⁻		-0.001 (-0.192)
<i>Gain_contract</i> ⁻²		0.000 (0.091)
<i>Gain_contract</i> ⁰		0.008** (2.106)
<i>Gain_contract</i> ⁺¹		0.014*** (2.755)
<i>Gain_contract</i> ⁺²		0.020*** (2.946)
<i>Gain_contract</i> ³⁺		0.022*** (2.965)
Controls	Yes	Yes
Firm Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
<i>N</i>	4886	4886
Adj. <i>R</i> ²	0.810	0.810

Notes: This table presents the regression estimates for the effect of government procurement on firm labor share based on the events of receiving government contracts. *Gain_contract* is an indicator variable set to 1 for the years after the inception year of treated firms receive government procurement contracts, and 0 otherwise. *Gain_contract*^{*X*} (*X* = 3-, -2, 0, +1, +2, 3+) is set to 1 for the years more than 3 years before, 2 years before, equal to, 1 year after, 2 years after and more than 3 years after the first year the treatment firms received government procurement contracts, and 0 otherwise. Definitions of other variables are presented in the Appendix. The t-values are presented in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Third, to eliminate the significant differences in the fundamental characteristics of the two types of samples and to reduce sample selection bias, we use PSM (1:1 matching by year with replacement) and EBM to pair the observations with and without government procurement. The control variables used in the matching model are the same as those in our baseline regression. We then re-estimate Eq. (1) and report the results in Table 5, Panel A. Columns (1) and (2) show the results of the PSM sample, and columns (3) and (4) show the results using EBM. The coefficients of *Contract* are still significant and positive in all columns regardless of whether firm or industry fixed effects are controlled, further validating the robustness of the results in Table 2 after we control for sample selection bias.

Fourth, to address the problem of missing industry and region-level time-invariant variables, we further include industry-by-year fixed effects, region-by-year fixed effects or both in the regressions. The results, shown in Table 5, Panel B, are consistent with our main findings.

5. Cross-sectional analysis

As discussed in Section 2, we expect government procurement to increase the firm-level labor share by reducing risks and financial constraints and enhancing monitoring and compliance requirements. Therefore, we focus on the effect of economic uncertainties associated with business risks and financial constraints, firms' compliance with social responsibilities and regulatory obligations and external government monitoring. These factors may moderate the positive impact of government procurement on the labor share, providing empirical support for our theoretical expectations.

Table 4

Alternative measures and labor share decomposition.

Panel A: Alternative measure

	(1)	(2)	(3)	(4)
	<i>Lsr</i>			
<i>Contract_number</i>	0.008*** (4.969)	0.003*** (3.179)		
<i>Contract_size</i>			0.002*** (5.178)	0.001*** (2.792)
Controls	Yes	Yes		
Industry Fixed Effect	Yes	No	Yes	No
Firm Fixed Effect	No	Yes	No	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
<i>N</i>	28,323	28,323	28,323	28,323
Adj. <i>R</i> ²	0.380	0.824	0.380	0.824

Panel B: Employee payment

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>LnPayments</i>			<i>RawPayments</i>		
<i>Contract</i>	0.043* (1.685)			0.169** (2.148)		
<i>Contract_number</i>		0.023*** (4.466)			0.109*** (5.842)	
<i>Contract_size</i>			0.004*** (3.694)			0.017*** (5.335)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	28,323	28,323	28,323	28,323	28,323	28,323
Adj. <i>R</i> ²	0.969	0.969	0.969	0.899	0.900	0.900

Panel C: Value creation

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>LnValueCreation</i>			<i>RawValueCreation</i>		
<i>Contract</i>	-0.013 (-0.564)			0.242 (1.233)		
<i>Contract_number</i>		0.008* (1.701)			0.196*** (4.135)	
<i>Contract_size</i>			0.001 (0.663)			0.027*** (3.039)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	28,323	28,323	28,323	28,323	28,323	28,323
Adj. <i>R</i> ²	0.960	0.960	0.960	0.903	0.904	0.903

Notes: This table presents the regression estimates using alternative measures for government procurement and decomposition of labor share components. *Contract_number* is the natural logarithm of one plus the number of government procurement contracts obtained by the firm. *Contract_size* is the natural logarithm of one plus the total value of government procurement obtained by the firm. *LnPayments* is the natural logarithm of “cash paid to employees”. *RawPayments* is the raw value of “cash paid to employees” scaled by 1 billion. *LnValueCreation* is the natural logarithm of operating income plus depreciation of fixed assets. *RawValueCreation* is the raw value of operating income plus depreciation of fixed assets scaled by 1 billion. Definitions of other variables are presented in the Appendix. The t-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Matching results and additional fixed effects.

Panel A: PSM and EBM

	(1)	(2)	(3)	(4)
	<i>PSM</i>		<i>EBM</i>	
	<i>Lsr</i>			
<i>Contract</i>	0.055*** (4.402)	0.011* (1.718)	0.049*** (4.372)	0.011** (2.157)
Controls	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	No	Yes	No
Firm Fixed Effect	No	Yes	No	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
<i>N</i>	8602	8602	28,323	28,323
Adj. <i>R</i> ²	0.390	0.840	0.387	0.837

Panel B: Additional fixed effects

	(1)	(2)
	<i>Lsr</i>	
<i>Contract</i>	0.013** (2.522)	0.012** (2.205)
Controls	Yes	Yes
Firm Fixed Effect	Yes	Yes
Region-Year Fixed Effect	Yes	Yes
Industry-Year Fixed Effect	No	Yes
<i>N</i>	28,323	28,323
Adj. <i>R</i> ²	0.825	0.831

Notes: Panel A of this table presents the regression estimates for the effect of government procurement on firm labor share using PSM and EBM. Panel B of this table presents the regression estimates for the effect of government procurement on firm labor share, controlling for additional fixed effects. Definitions of other variables are presented in the Appendix. The t-values are presented in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

5.1. Business risks and financial constraints

We examine whether the effect of government procurement on the labor share varies with firms' exposure to business risk and financial constraints. Because government procurement may alleviate these pressures, thereby increasing firms' willingness to improve labor treatment, we expect the positive impact of procurement on the labor share to be more pronounced among firms facing higher levels of risk and financial constraints.

We use the following proxies to measure business risk and financial constraints: (1) Product market risk is measured by the Herfindahl index multiplied by -1 (*Competition*). Prior research suggests that product market competition can erode markups, increase default risk and heighten firms' vulnerability to systemic shocks (e.g., Huang and Lee, 2013; Bustamante and Donangelo, 2017). (2) The news-based Economic Policy Uncertainty (*Epu*) index developed by Baker et al. (2016) is constructed from the frequency of articles related to policy-induced economic uncertainty in the South China Morning Post. Prior studies show that *Epu* negatively affects corporate financing and investment decisions (Pástor and Veronesi, 2012; Gulen and Ion, 2016; Wan et al., 2024). Moreover, higher uncertainty increases financial constraints (Ma and Hao, 2022) and decreases firms' willingness to invest in labor (Li et al., 2024). (3) Firm-level performance uncertainties (*Volatility*) are measured by *Roa* volatility in the past three years. A higher value of *Volatility* indicates higher fluctuations of demand and revenue. (4) Financial constraints are measured by the SA Index (*SA*) developed by Hadlock and Pierce (2010). Financial constraints are associated with higher risk and uncertainty (Li, 2019; Beladi et al., 2021; Ma and Hao, 2022).

We include each of the four risk proxies and their interaction with *Contract* in Eq. (1). The results are shown in Table 6. The coefficients on the interaction terms are positive and significant in all columns, which suggests that the positive relationship between government procurement and the firm labor share is more pronounced for firms with higher product market competition (column (1)), higher economic policy uncertainty (columns (2)), higher performance uncertainties (columns (3)) and higher financial constraints (column (4)). Collectively, these findings support our argument that government procurement can contribute to the firm-level labor share by reducing risks and financial pressures.

5.2. Social responsibility performance, internal control and financial quality

We next examine how the effect of government procurement on the labor share varies with firms' compliance with social responsibilities and regulatory obligations. We argue that government procurement can increase the labor share by encouraging social responsibility commitments and curbing firms' tendency to prioritize profit maximization at the cost of employee interests. Therefore, we expect the positive relationship between government procurement and labor share to be more pronounced among firms with weaker social responsibility commitment and with governance deficiencies.

To test this conjecture, we use the following proxies. (1) Firm-level ESG performance score and Social (S) performance score data are obtained from the Wind database. We then define two indicator variables that capture low ESG compliance (*Low_esg*) and low social performance (*Low_social*), equal to 1 when the ESG or Social performance score is below the annual median, and 0 otherwise. Lower social responsibility performance reflects a greater propensity for opportunistic behavior (Zhang et al., 2023b) and is associated with a lower labor share (Zhao and Chen, 2024). Moreover, firms with poor ESG performance often face

Table 6
Business risks and financial constraints.

	(1)	(2)	(3)	(4)
<i>Lsr</i>				
<i>Contract</i> × <i>Competition</i>	0.329** (2.444)			
<i>Contract</i> × <i>Epu</i>		0.016*** (3.157)		
<i>Contract</i> × <i>Volatility</i>			0.032*** (2.639)	
<i>Contract</i> × <i>SA</i>				0.024*** (3.869)
<i>Competition</i>	0.161*** (2.731)			
<i>Volatility</i>			0.001 (0.769)	
<i>SA</i>				-0.022*** (-4.461)
<i>Contract</i>	0.024*** (3.375)	0.015*** (2.813)	-0.010 (-1.142)	0.012** (2.407)
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
<i>N</i>	28,323	28,323	25,999	28,323
Adj. <i>R</i> ²	0.824	0.824	0.820	0.825

Notes: This table presents the effect of risk and financial constraints on the relationship between government procurement and firm labor share. *Competition* is the Herfindahl index multiplied by -1. *Epu* is the news-based Economic Policy Uncertainty developed by Baker et al. (2013). *Volatility* is the *Roa* volatility in the past three years. *SA* is the financial constraint SA Index developed by Hadlock and Pierce (2010). Definitions of other control variables are presented in the Appendix. The t-values are presented in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

stricter government monitoring and a higher likelihood of regulatory penalties (He et al., 2025). (2) Internal control quality (*IC*), following the literature (Li et al., 2021b; Liu et al., 2022; Luo and Tian, 2023), is measured as the negative natural logarithm of the internal control index, with data obtained from the DIB database. Guo et al. (2016) find that employee-friendly treatment policies are associated with a lower likelihood of material internal control weaknesses and financial misstatements. In addition, inadequate internal controls indicate a lower compliance level (Heese and Pacelli, 2025). (3) Financial reporting quality (*Absda*) is measured by the absolute value of abnormal discretionary accruals following Dechow et al. (1995). Higher reporting quality is associated with a lower likelihood of misconduct (Christensen, 2016) and improved labor investment efficiency (Jung et al., 2014). Government procurement enhances firm transparency by imposing rigorous information requirements that improve firms' internal reporting systems and lead to higher-quality external disclosures (Samuels, 2021).

We separately include *Low_esg*, *Low_social*, *IC* and *Absda* and their interactions with *Contract* in Eq. (1). The results, presented in Table 7, show that the coefficients of all of the interaction terms are positive and significant. This suggests that the effect of government procurement on the labor share is more pronounced among firms with weaker commitments to social responsibility and corporate governance, as proxied by ESG performance (especially the social dimension), internal control quality and financial reporting quality. These findings support our second argument that government procurement increases the labor share by strengthening firms' fulfillment of social responsibilities and compliance with governance requirements that deter misbehaviors in labor decisions.

Table 7
Social responsibilities and corporate governance.

	(1)	(2)	(3)	(4)
<i>Lsr</i>				
<i>Contract</i> × <i>Low_esg</i>	0.040** (2.081)			
<i>Contract</i> × <i>Low_social</i>		0.043** (2.141)		
<i>Contract</i> × <i>IC</i>			0.014* (1.731)	
<i>Contract</i> × <i>Absda</i>				0.233** (1.975)
<i>Low_esg</i>	−0.002* (−1.691)			
<i>Low_social</i>		0.001 (0.654)		
<i>IC</i>			−0.001** (−2.321)	
<i>Absda</i>				−0.129*** (−12.576)
<i>Contract</i>	0.006 (0.655)	0.002 (0.219)	0.101* (1.943)	0.001 (0.070)
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
<i>N</i>	21,121	21,121	28,323	28,187
Adj. <i>R</i> ²	0.852	0.852	0.824	0.819

Notes: This table presents the effect of social responsibility commitment and corporate governance on the relationship between government procurement and firm labor share. *Low_esg* (*Low_social*) is equal to 1 when the ESG (Social performance) score is lower than the annual median, 0 otherwise. *IC* is the natural logarithm of the internal control index multiplied by −1. *Absda* is the absolute value of abnormal discretionary accruals (Dechow et al. 1995). Definitions of other variables are presented in the Appendix. The t-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.3. Government monitoring and labor protection priority

In this section, we examine external government actions that may moderate the effect of government procurement on the labor share. Specifically, we consider the intensity of government monitoring and the extent to which the government prioritizes labor protection. As discussed, we expect the positive impact of government procurement on the labor share to be stronger when the government exercises stricter oversight and places greater emphasis on labor-friendly policies.

First, to capture the variation of government monitoring intensity, we divide government procurement into two parts: procurement value from local government where the firms are located (*Contract_local*) and procurement from other governments (*Contract_nonlocal*). The literature suggests that local governments implement stronger monitoring of local firms because of incentives such as tax sharing and employment stability maintenance (Qian and Weingast, 1997), and local governments benefit from geographical proximity, which reduces the cost of regulation (Feiok, 2013). Sigman (2014) finds similar evidence that regulatory effectiveness can be lower as the distance between the government and the pollution source increases. Therefore, we expect firms receiving a greater share of contracts from local governments to face stronger monitoring and compliance pressure. We replace the main independent variable in Eq. (1) with *Contract_local* and *Contract_nonlocal*. As shown in column (1), Table 8, the coefficient on *Contract_local* is positive and significant at the 5% level, while that on *Contract_nonlocal* is nonsignificant. This indicates that the positive effect of government procurement on the labor share is mainly driven by receiving local government contracts.

Second, we use the province-level minimum wage standard (*Min_wage*) to measure the local government's practice of promoting the distribution of labor income. As a form of government enforcement, minimum wage

Table 8
Government monitoring and labor protection priority.

	(1)	(2)	(3)
<i>Lsr</i>			
<i>Contract_local</i>	0.204** (1.990)		
<i>Contract_nonlocal</i>	0.009 (1.584)		
<i>Contract</i> × <i>Min_wage</i>		0.037* (1.727)	
<i>Contract</i> × <i>High_laborfreq</i>			0.010** (2.195)
<i>Min_wage</i>		0.002* (1.772)	
<i>High_laborfreq</i>			-0.001 (-1.499)
<i>Contract</i>		-0.180 (-1.622)	0.003*** (2.600)
P value: <i>Contract_local</i> = <i>Contract_nonlocal</i>	0.06		
Controls	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
<i>N</i>	28,323	28,323	28,323
Adj. <i>R</i> ²	0.824	0.816	0.824

Notes: This table presents the effect of government monitoring and labor protection preference on the relationship between government procurement and firm labor share. *Contract_local* is the procurement value from local government where the firms are located, divided by the sales of the firm for the current year. *Contract_nonlocal* is the procurement value from other governments divided by the sales of the firm for the current year. *Min_wage* is the local province-level minimum wage standard. *High_laborfreq* is equal to 1 if the labor-related word frequency in the local government work report is above the annual median, and 0 otherwise. Definitions of other variables are presented in the Appendix. The t-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

aims to raise wage floors and improve welfare through redistribution (e.g., Autor et al., 2016; Berger et al., 2025). A higher minimum wage standard not only directly improves employee compensation but also reflects the local government's stronger preference for safeguarding labor rights. Therefore, we expect the positive effect of government procurement on the labor share to be more pronounced in regions with higher minimum wage standards. We include the interaction term between *Min_wage* and *Contract* in Eq. (1). As shown in column (2) of Table 8, the coefficient on the interaction term is positive and significant, indicating that the positive effect of government procurement on labor share is stronger in regions with higher minimum wage standards.

Third, we introduce the proportion of labor protection-related words in province-level government work reports to proxy for the local government's preference for labor protection. A higher frequency of such terms suggests that the government's future policy agenda places greater emphasis on labor protection and refining labor treatment. To construct this variable, we first apply a "seed word set + Word2Vec similarity expansion" method to generate a comprehensive list of labor protection-related terms, using "labor protection" and "labor income" as the initial seed words in the WinGo database. We then calculate the frequency of these words in each province's annual government work report. We thus create *High_laborfreq*, an indicator variable equal to 1 if a government work report's labor-related word frequency is above the annual median, and 0 otherwise. We include the interaction term between *High_laborfreq* and *Contract* in Eq. (1). The coefficient on the interaction term in Table 8, column (3) is positive and significant, indicating that the positive effect of government procurement on the labor share is more pronounced when local government places greater emphasis on labor protection.

Taken together, the results suggest that the positive impact of government procurement on the firm-level labor share is amplified in institutional environments with stronger government oversight and a greater emphasis on protecting and enhancing labor welfare.

6. Additional tests

6.1. SOEs vs. non-SOEs

We investigate whether SOEs, which are more likely than non-SOEs to obtain government contracts and already have a higher labor share, drive our findings. We split the sample into SOEs and non-SOEs, re-estimate Eq. (1) for each subsample and present the results in Panel A of Table 9. The results show that the influence of government procurement is concentrated in non-SOEs, which rules out the above concern. The reasons for this finding are as follows. First, non-SOEs typically face higher business uncertainty and tighter financial constraints (e.g., Ma and Hao, 2022; Xie et al., 2023), so the stable demand and funding associated with government contracts can more effectively support their labor investment. Second, SOEs often already operate under stronger regulatory scrutiny and social responsibility mandates (e.g., Gu et al., 2020), so the compliance and monitoring mechanisms embedded in government procurement exert less additional influence. In contrast, government procurement can significantly improve labor treatment in non-SOEs by imposing compliance requirements that they might otherwise overlook. The findings also indicate that government procurement incentivizes profit-oriented firms to pay more attention to employee welfare.

6.2. The manufacturing sector

We focus on the manufacturing sector rather than other sectors because it is typically more labor-intensive and represents a primary source of declining labor share because of its greater exposure to labor-saving capital and technological substitution (e.g., Acemoglu and Restrepo, 2019, 2022; Karabarbounis, 2024). This focus is particularly relevant in the context of China, where manufacturing plays a central role in the economy, accounting for a significant share of employment and value added; thus, any shifts in labor share within this sector have broad macroeconomic implications. We split our sample into firms in the manufacturing sector and firms in other sectors/industries, and we present the results in Table 9, Panel B. The results show that the role of government procurement in increasing the labor share is concentrated in the manufacturing sector, which suggests that government procurement may act as a stabilizing force in labor-intensive sectors by

Table 9
Heterogeneity analysis by firm characteristics.

Panel A: SOEs vs non-SOEs

	(1) Non-SOEs	(2) SOEs
	<i>Lsr</i>	
<i>Contract</i>	0.015** (2.329)	0.014 (1.553)
Controls	Yes	Yes
Firm Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
<i>N</i>	19,625	8698
Adj. <i>R</i> ²	0.828	0.835

Panel B: Manufacturing vs non-manufacturing

	(1) Manufacturing	(2) Non-manufacturing
	<i>Lsr</i>	
<i>Contract</i>	0.020** (2.429)	0.007 (1.041)
Controls	Yes	Yes
Firm Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
<i>N</i>	19,625	8698
Adj. <i>R</i> ²	0.828	0.835

Notes: This table presents the heterogeneity in the relationship between government procurement and firm labor share between SOEs and non-SOEs and between manufacturing and non-manufacturing sectors/industries. Definitions of other variables are presented in the Appendix. The t-values are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

offsetting the pressure of capital substitution and helping to preserve the labor income share. In addition, our findings suggest that government procurement plays a crucial role in maintaining balanced labor-capital dynamics and promoting economic circulation in the major manufacturing economy.

6.3. Equitable income distribution

While the labor share captures the overall share of income going to labor, income equality indicates how that income is distributed across different workers. Given that a declining labor share is often associated with rising income inequality (Hémous and Olsen, 2022) and our findings show that government procurement increases the labor share, it is valuable to further examine whether government procurement also contributes to improving income equality. We empirically test the effect of government procurement on average employee compensation and the compensation gap. Following the literature (Jiang et al., 2019), we estimate the average employee compensation (*PerWage1*) as total compensation divided by the total number of employees. The average rank-and-file employee compensation (*PerWage2*) is defined as total compensation minus executive compensation divided by the number of rank-and-file employees. The compensation gap (*WageGap*) is defined as the ratio of average executive compensation to average rank-and-file employee compensation. We use these three variables to replace the dependent variable in Eq. (1), and we present the results in Table 10. In columns (1) and (2), the coefficients of government procurement on the overall average employee compensation and average rank-and-file employee compensation are positive and significant. In column (3), the coefficient of government procurement on the compensation gap is negative and significant. These results indicate that government procurement not only contributes to raising employee wages but also narrows the pay gap between executives and rank-and-file employees, thereby promoting income equality within firms.

Table 10
Income equality.

	(1) <i>PerWage1</i>	(2) <i>PerWage2</i>	(3) <i>WageGap</i>
<i>Contract</i>	0.007*** (3.159)	0.008*** (3.234)	-0.264*** (-2.599)
Controls	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
<i>N</i>	27,567	27,567	27,567
Adj. <i>R</i> ²	0.826	0.822	0.640

Notes: This table presents the effect of government procurement on income equality. *PerWage1* is the average employee compensation, defined as total compensation divided by the total number of employees. *PerWage2* is the average rank-and-file employee compensation, defined as total compensation minus executive compensation divided by the number of rank-and-file employees. *WageGap* is the compensation gap, defined as the ratio of average executive compensation to average rank-and-file employee compensation. Definitions of other variables are presented in the Appendix. The t-values are presented in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 11
Employee welfare.

	(1) <i>EmpInvest</i>	(2) <i>EmpTreatment</i>	(2) <i>EmpAdv</i>	(2) <i>EmpConcern</i>
<i>Contract</i>	0.003*** (3.247)	0.033*** (2.651)	0.031** (2.437)	-0.010* (-1.864)
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
<i>N</i>	28,323	7942	7942	7942
Adj. <i>R</i> ²	0.839	0.483	0.489	0.119

Notes: This table presents the effect of government procurement on employee welfare. *EmpInvest* is firms' actual expenditures in union operation, staff education and social insurance and housing fund, divided by their total income. *EmpTreatment* is the employee welfare index obtained from the CNRDS database, defined as the difference between advantage and disadvantage scores. *EmpAdv* (*EmpConcern*) is the advantage (disadvantage) score. Definitions of other variables are presented in the Appendix. The t-values are presented in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

6.4. Employee welfare

Measurement of the labor share primarily focuses on compensation. We extend our analysis to employee welfare to provide a more comprehensive perspective, using the following variables as proxies for employee treatment. (1) Firms' actual expenditures in union operation, staff education and social insurance and housing fund is divided by their total income (*EmpInvest*). (2) The CNRDS database uses eight advantageous indicators and three disadvantageous indicators for firms in terms of employee treatment.⁵ Building on this, we use the advantage score (*EmpAdv*), the disadvantage score (*EmpConcern*) and the employee welfare index

⁵ Examples of the advantageous indicators include the following. Does the firm encourage its employees to participate in the enterprise's ownership through stock options? Does the enterprise have any retirement or other welfare programs? Has the firm adopted an environmental, health and safety management system? Examples of the disadvantageous indicators include the following. Does the firm have any employee safety disputes (such as paying many fines or civil compensation because of violations of employee health and safety guidelines in the current year)? Has the firm carried out many layoffs? Has the firm been exposed for corrupt practices such as extortion or bribery?

(*EmpTreatment*), defined as the difference between the advantage and disadvantage scores. We use these to replace the dependent variable in Eq. (1) and present the results in Table 11. We find that government procurement encourages firms to invest in employee welfare. This broader perspective allows us to more comprehensively capture the role of government procurement in refining labor treatment beyond compensation levels.

7. Conclusion

Motivated by the global decline in the labor share and its recent rebound in China, this paper investigates the underlying mechanisms driving labor share dynamics from a firm-level perspective. Using manually collected data on local government procurement contracts matched to Chinese listed firms from 2015 to 2023, we examine the role of government procurement in shaping labor share outcomes. We find that government procurement significantly increases the firm-level labor share, with the positive effect being more pronounced among firms facing higher business risks and financial constraints, those with weaker regulatory and non-regulatory compliance and those receiving more contracts from local governments and operating in regions with a stronger labor priority. The effect is particularly salient in non-SOEs and firms in labor-intensive manufacturing sectors. Furthermore, government procurement is associated with higher average employee compensation and reduced wage inequality, ultimately enhancing overall employee welfare.

This study contributes to the literature by identifying a new mechanism through which government procurement influences corporate labor treatment. Our study extends the economic implications of government procurement from corporate efficiency to income distribution, highlighting its potential role in promoting inclusive growth. In practice, the results suggest that well-designed procurement policies can serve as effective market-based instruments for advancing labor welfare, particularly in emerging economies.

Data availability

Data are available from the sources cited in the article.

Funding

Gaoliang Tian gratefully acknowledges the financial support from the National Natural Science Foundation of China (Grant No. 71672141), the National Social Science Foundation of China (Grant No. 21FGLB006) and the Humanities and Social Science Foundation of the Ministry of Education of China (Grant No. 21YJA630082).

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.

Appendix. Variable definitions

Dependent variables

Lsr Labor share, equals to cash paid to employees in the cash flow statement divided by the sum of cash paid to employees, operating income, and the depreciation of fixed assets.

Independent variables

Contract Government procurement contracting, equals to the total value of government procurement divided by the sales of the firm for the current year.

Control variables

Size The natural logarithm of total assets.

Lev The ratio of total liabilities to total assets.

Roa The ratio of the company's net profit to its total assets at the end of the year

Mb The sum of the book value of debt and the market value of equity divided by total assets.

Ppe The ratio of net PPE to total revenue.

Cf The ratio of cash flow from operations divided by assets.

Turnover The ratio of operating costs to the average net inventory.

Soe Dummy variable, takes 1 if the company is a state-owned enterprise, otherwise 0.

Age The natural logarithm of the years from the company's listing to the current year.

Loss An indicator variable that equals 1 if net profit is negative, and 0 otherwise.

Boardsize The natural logarithm of the number of board members.

Independ The ratio of independent directors to the total number of directors.

Dual Dummy variable, takes 1 if the chairman and CEO of a company are concurrently held by the same person, otherwise 0.

Inst The percentage of the firm's shares held by institutional investors.

Top1 The percentage of the firm's shares held by the largest shareholder.

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Contents lists available at ScienceDirect

China Journal of Accounting Research

journal homepage: www.elsevier.com/locate/cjar



Executives' poverty experience and internal and external pay disparities: Evidence from China



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ARTICLE INFO

Article history:

Received 24 December 2024

Accepted 16 November 2025

Available online 5 January 2026

Keywords:

Executives' poverty experience

Internal pay disparity

External pay disparity

Pay equality

ABSTRACT

We show that executives' early-life poverty experiences reduce both internal (executive–employee) and external (executive–peer) corporate pay disparities. Three mechanisms drive this effect: increased risk aversion in poverty-exposed executives, strategic avoidance of negative media coverage to protect reputation and curtailment of excessive executive perks. The results hold under multiple robustness tests. The poverty–equity link intensifies in state-owned enterprises, eastern-region firms, labor-intensive industries, firms with elevated donations, and firms led by executives with advanced degrees. This pay gap reduction primarily stems from restrained executive compensation, particularly when it exceeds industry benchmarks, rather than increased employee wages. These findings advance behavioral agency theory by revealing how leaders' socioeconomic origins interact with institutional contexts to reshape compensation systems, offering new insights into inequality management.

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1. Introduction

Persistent pay disparities between executives and employees, as well as among peer executives, have sparked global public debate. According to the Economic Policy Institute, the average compensation of CEOs at the top 350 U.S. firms reached 351 times the typical worker's earnings in 2020. California's Pay Transparency Law (SB 1162), effective since 1 January 2023, requires firms with over 15 employees to disclose salary ranges for all

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positions, from entry-level staff to top executives. This law has prompted similar legislative measures across ten U.S. states.

In China, the executive–employee pay gap, measured as the ratio of executives’ average compensation to average employee wages, mirrors that across U.S. public companies. Analysis of the China Stock Market & Accounting Research (CSMAR) database reveals that in 2022, 712 Chinese A-share listed companies reported pay gap ratios exceeding 5:1, with 173 firms surpassing the 10:1 ratio. To address these disparities, Chinese regulators have implemented progressive reforms: the 2009 “Guiding Opinions on Further Regulating the Salary Management of Central SOE Principals” (commonly known as the “salary cap policy”) and the 2014 “Reform Plan for the Payment Packages of Executives of SOEs” (commonly known as the “salary reform policy”) preceded the 2022 “Regulations on Compensation Governance in State-Owned Financial Institutions,” which prioritizes frontline employee welfare through structured compensation frameworks (Ye et al., 2022).

Whereas research has examined various determinants of pay disparity, including executive demographics (Kumar and Sivaramakrishnan, 2008; Brockman et al., 2016), economic conditions (Bhagat and Bolton, 2014), industry norms (Sabanci and Elvira, 2024), governance structures (Hong et al., 2016; Huang et al., 2017) and corporate performance (Liu and Mauer, 2011), limited research focuses on executives’ formative life experiences. Notably, Humphrey-Jenner et al. (2016) and Long et al. (2020) link executives’ adverse childhood experiences to decision-making patterns regarding compensation, finding that a company’s compensation structure and incentive-based contracts are influenced by executives’ early experiences.

As corporate financial decisions reflect top executives’ strategic priorities (Bhaskar et al., 2023), these executives significantly influence compensation structures (Hambrick and Mason, 1984). Using agenda-setting power and selective disclosure practices, they shape compensation agreements that typically favor executive interests (Shin, 2016). Here, top executives include board chairs, CEOs and actual controllers (Tian and Yin, 2014). These three key roles create a power dynamic due to their strategic positioning within governance systems that fundamentally shapes compensation outcomes (Choe et al., 2014). The board chair holds formal authority to convene meetings and prioritizes agenda items by appointing compensation committee members aligned with their objectives. CEOs leverage their operational control and authority over financial disclosure decisions to shape favorable compensation terms (Abernethy et al., 2015). Actual controllers influence the system through shareholder resolutions and policy interventions. Top executives strategically navigate these governance frameworks, leveraging informational control and personal influence to adjust compensation packages not only to align with internal norms regarding equity and industry benchmarks but also to reinforce their strategic position within this power structure (Göx and Hemmer, 2020). Executives with a background of poverty significantly influence team decisions through mechanisms such as agenda control (e.g., prioritizing resource allocation) or persuasion (e.g., advocating for risk-averse strategies). As Akerlof and Kranton (2005) show, these individuals shape group decisions without formal authority.

Building on upper echelons theory (Hambrick and Mason, 1984), this study investigates how executives’ formative experiences shape organizational compensation practices. The literature extensively examines demographic traits (e.g., gender, education and abilities) (Dittmar and Duchin, 2016; Conyon et al., 2019), cognitive biases (e.g., risk preferences) (Biddle and Zarkin, 1988; Bernile et al., 2017; Zhang et al., 2022) and disaster, work and overseas experiences (Malmendier et al., 2011; Benmelech and Frydman, 2015; O’Sullivan et al., 2021; Li et al., 2023; Tawiah et al., 2025) as determinants of executives’ behavior. We contribute to this discourse by focusing on the enduring impact of childhood poverty experiences. Material scarcity and psychological shocks experienced during childhood significantly shape executives’ thinking and behavior and thus influence their decision-making frameworks, particularly in the context of resource allocation (Feng and Johansson, 2018).

Whereas prior research primarily examines intra-firm (executive–employee) pay disparities (Ye et al., 2022; Song et al., 2024) and their implications for performance (Dai et al., 2017), limited attention is given to inter-firm differences in executives’ compensation. For example, Denis et al. (2020) demonstrate that executives tend to reduce their compensation when receiving excessive pay and competing with weak-vote peers; however, they provide no direct evidence regarding how executives’ early-life experiences shape executive–peer pay gaps. Guided by equity theory, which posits that a fair income distribution reduces pay inequality and narrows income gaps among different groups (Lazear, 1989; D’Mello et al., 2024; Song et al., 2024), our study attempts

to bridge the above gap by analyzing how executives' formative poverty experiences influence both internal equity and external pay gaps among peers, using indicators of pay disparity to evaluate fairness and equity within salary systems. Internal fairness entails minimizing salary gaps between executives and employees within a firm (Card et al., 2012), whereas external equity implies reducing wage gaps between executives and their industry peers (Denis et al., 2020).

To operationalize this construct, we manually collect birthplace data for executives from Chinese A-share companies and cross-reference these locations with the 2012 national poverty-stricken counties list. This novel approach captures how regional economic conditions during executives' upbringing might influence their current decisions regarding compensation. Although this study uses Chinese data, the insights derived are applicable far beyond the Chinese context. Recently, governments in both developed countries such as the U.S. and developing countries such as China have acknowledged the importance of pay equity (Song et al., 2024) and are beginning to address large pay disparities by imposing salary caps on executives. Furthermore, China offers unique data on executives' experiences of poverty. By linking executives' birthplaces to historical poverty records, we identify those who grew up in economically disadvantaged areas. As a robustness check, we also identify executives born between 1947 and 1961 (i.e., those who experienced the "three-year difficult period," 1959–1961, during their childhood) as an additional proxy for early-life adversity, utilizing this historical famine as an exogenous shock.

Based on a final sample of 7793 firm-year observations from Chinese listed firms between 2007 and 2022, our baseline results show a negative correlation between executives' poverty experience and both internal (executive–employee) and external (executive–peer) pay disparities. We also examine how executives' risk preferences, negative media coverage and perks mediate the relationship between poverty experience and both internal and external pay gaps. We find that executives with poverty backgrounds exhibit higher risk aversion, which mediates the negative association between poverty experience and pay disparities. Furthermore, as these executives accumulate wealth and social standing, they tend to avoid negative online news to protect their reputation and align with public expectations, therefore adopting fairer compensation policies and narrowing pay gaps.

Our findings are robust across alternative measurements of poverty exposure and pay inequality. To address endogeneity, we employ a two-stage least squares (2SLS) approach with instrumental variables and conduct Heckman selection tests to control for sample selection bias. We also use exposure to the historical famine (executives born during 1947–1961) as an exogenous shock. The effect of poverty experience on mitigating pay gaps is particularly pronounced in state-owned enterprises (SOEs), firms in developed regions, labor intensive industries, firms with executives holding advanced degrees and firms making larger public welfare donations. In additional analyses, we examine whether the above reduction in pay gaps occurs through the curbing of excessive executive compensation or raising of employee wages. The results indicate that the mitigating effect of executives' poverty experience on pay disparities increases when executives' compensation exceeds industry benchmarks.

This study contributes to the literature in several ways. First, although there is considerable research regarding pay disparities focusing on executives' characteristics and corporate policies (Park, 2017; Tong et al., 2023), little research examines the impact of executives' early experiences, and that of individual psychological factors in general, on pay disparities and equity. By demonstrating a link between executives' early poverty experiences and their firm's pay disparities, we establish childhood poverty as a formative influence on executives' philosophy regarding compensation. Second, to the best of our knowledge, the literature only examines the impact of executives on firms' internal (executive–employee) pay gaps (Wade et al., 2006; Ridge et al., 2015; Vo and Canil, 2019; Ye et al., 2022), whereas we distinguish between intra-firm (executive–employee) and between-firm (executive–peer) compensation gaps, providing a dual perspective on pay equality. Third, probing further into the influence of executives' poverty experience on pay disparities, we identify risk tolerance and media visibility as critical boundary conditions shaping compensation decisions. Finally, we also contribute to the literature on compensation benchmarking. Our finding that executives with poverty backgrounds are associated with smaller pay gaps will be of interest to both researchers and policy-makers, as it provides empirical support for global pay equity initiatives through targeted governance frameworks.

The remainder of the paper is organized as follows. Section 2 presents the literature review and develops our hypotheses. Section 3 describes the data, variables and research design. Section 4 reports the results of the main regression and robustness tests and addresses endogeneity issues. Section 5 presents tests examining the mechanisms underlying the main results. Section 6 presents further analyses. Section 7 concludes the paper.

2. Prior research and hypothesis development

Two competing perspectives exist regarding the impact of internal pay disparities. Tournament theory (Lazear and Rosen, 1981; Chen et al., 2011) posits that individuals promoted for outstanding performance continue competing with peers, enhancing their competitiveness to further overall advancement (Hu et al., 2013). However, executives with childhood poverty experience exhibit distinctive behavioral patterns. Having internalized resource insecurity, they develop a heightened valuation of rewards (Martin et al., 2020), thus actively leveraging their bargaining power to secure performance-based compensation growth (Humphery-Jenner et al., 2016). Concurrently, their intensified drive to outperform rivals (Pepper and Gore, 2015) may inadvertently widen internal pay disparities. This occurs because performance-based compensation adjustments are typically confined to the executive level, without proportional increases for lower-level employees (Ridge et al., 2017), contradicting equity theory's egalitarian perspective (Milgrom and Roberts, 1988).

In contrast, equity theory suggests that compensation disparities between executives and employees engender perceptions of unfairness that trigger destructive competition. Substantial pay gaps increase employee distress and depression while impairing cooperation (Breza et al., 2018), diminishing morale and performance and increasing turnover (Green et al., 2019). These effects extend to the managerial levels, in which significant pay disparities correlate with turnover, resulting in labor and skill shortages as experienced employees depart (Ridge et al., 2017). Market evidence further indicates that investors' aversion to inequality acts as a channel through which high pay disparities depress firm value (Pan et al., 2022), highlighting the organizational risks associated with compensation imbalances.

Executives with poverty backgrounds exhibit distinctive psychological attributes such as lower risk tolerance and stronger empathy (Xu et al., 2024), prompting them to reduce pay disparities to mitigate these organizational risks (Mas, 2006). This reduction occurs through two primary mechanisms. First, their conscious curtailment of executive perks directly addresses consumption-based indicators of internal resource allocation. This voluntary curtailment signals organizational fairness, alleviating employee discontent and reducing turnover risks. Second, it occurs through generous and altruistic behaviors, including salary concessions during compensation conflicts (Wysocki, 2010), especially when imbalances cause organizational friction. These executives' empathy toward employees stems from a deep-seated aversion to hierarchy-driven conflict, rooted in experiences of marginalization associated with poverty. They also demonstrate stronger commitment to corporate social responsibility, prioritizing social initiatives and protecting employee rights (O'Sullivan et al., 2021), practices empirically linked to reduced executive–employee pay differentials (D'Mello et al., 2024). Therefore, when conflicts arise from unequal compensation, poverty-exposed executives are more likely to promote smaller internal pay disparities and choose self-sacrificial resolutions that benefit others.

Based on these arguments, we propose the following competing hypotheses:

H1a: Poverty experience among executives is positively associated with internal (executive–employee) pay disparity.

H1b: Poverty experience among executives is negatively associated with internal (executive–employee) pay disparity.

We integrate imprinting theory and reputation theory to explain how childhood poverty experience influences executives' compensation decisions. Imprinting theory posits that childhood poverty normalizes perceptions of scarcity, conditioning executives to interpret external pay gaps as competitive threats. As Xu et al. (2024) show, these imprints evolve over time through education, environmental changes and accumulated experience but continue to anchor executives' compensation philosophies throughout their lifetime. Compensation gaps relative to industry benchmarks serve as salient indicators of underperformance or declining mar-

ket position. Executives with experience of material deprivation exhibit heightened risk aversion and perceive excessive internal pay disparities as signals of operational inefficiency or reduced competitiveness, which lowers their tolerance for pay inequities (Jeong and Kim, 2019).

Reputation theory further enhances this perspective by highlighting poverty-exposed executives' heightened sensitivity to pay differentials. At the individual level, reputation consists of shared perceptions of a person's attributes and behaviors and motivates individuals to engage in impression management to maintain valued identities (Ranft et al., 2006). Executives from impoverished backgrounds, exemplified by figures such as Huawei's Ren Zhengfei (from Zhenning County, Guizhou), often receive amplified media attention for their societal contributions, intensifying their incentives to maintain reputation. Media scrutiny exposes compensation practices to public evaluation, wherein high pay gaps are increasingly viewed as unfair, potentially damaging corporate reputation. This prompts stronger restraint in compensation practices among executives with (verses their peers without) poverty experience (D'Mello et al., 2024). This mechanism of restraint underlying reductions in pay disparity operates in a tangible manner: negative news coverage reduces executives' compensation and increases pay–performance sensitivity in listed firms (Ang et al., 2021). Kuhnen and Niessen (2012) show that declines in option-based compensation are especially pronounced when companies and executives prioritize their reputations amid increased negative media attention. Conversely, limited negative news coverage helps maintain a stable public image, sustains stakeholder confidence, prevents investor concern over pay disputes or employee morale and ultimately avoids the erosion of corporate value due to external conflicts or regulatory interventions. Consequently, poverty-exposed executives have stronger incentives to constrain pay disparities, as media attention compels both improvements in governance (Dyck et al., 2010) and equitable compensation structures to safeguard hard-earned reputational capital. Based on this reasoning, we hypothesize as follows:

H2. Poverty experience among executives is negatively associated with external (executive–peer) pay disparity.

3. Data, variables and methodology

3.1. Data and sample

Our sample period begins in 2007, coinciding with the implementation of China's new accounting standards, which became effective on 1 January 2007. These standards replaced the previous "accrued wages" accounting item with a list of "employee benefits payable" to record various employee compensations, substantially changing financial statement formats and accounting entries. Therefore, we select A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2007 to 2022 as our initial sample and exclude the following: (a) financial firms; (b) special-treatment (ST and ST*) firms; and (c) observations with missing birthplace information for any top executive. The final sample consists of 7793 firm-year observations. All continuous variables are subjected to 1 % and 99 % truncation.

Birthplace information for top executives, including chairpersons, CEOs and actual controllers, is manually collected using two complementary methods: (1) through regulatory disclosures, using the first six digits of their national ID numbers disclosed in IPO prospectuses, cross-referenced with their resumes in annual reports; and (2) via multi-source verification, using hand-collected data from corporate websites, financial

news platforms, Baidu Baike and other credible public sources. Part of the dataset is obtained from the CSMAR, Chinese Research Data Services (CNRDS) and Chinese Deep Data (CNDD) databases, with all entries rigorously validated to ensure accuracy.¹ Additional financial data, including firm-level and control variables, are sourced from the CSMAR database.

3.2. Variable measurement

3.2.1. Dependent variables

Building on the studies of Chen et al. (2013), Rouen (2020), Javakhadze and Shelton (2022) and Song et al. (2024), we operationalize pay disparities using two constructs: internal pay disparity (*Intpay_Dis*) and external pay disparity (*Extpay_Dis*). *Intpay_Dis* quantifies the disparity between the average total compensation of top executives (encompassing chairpersons, CEOs and actual controllers) and that of general employees. Actual controllers are only included if they hold formal managerial positions (e.g., director, supervisor or senior executive), sign employment contracts, perform active duties and receive compensation directly from the company. Following D'Mello et al. (2024), executive compensation is calculated as the aggregate of salary, performance bonuses and other annual remuneration components. Employee compensation is derived using the formula $\lceil (end-of-period\ employee\ benefits\ payable - beginning-of-period\ employee\ benefits\ payable) + (cash\ paid\ to\ employees - executive\ compensation) \rceil / (total\ employees - number\ of\ executives)$. *Extpay_Dis* is calculated as the difference between top executives' average total compensation and the industry peer group mean. To ensure commensurability across firms, both *Intpay_Dis* and *Extpay_Dis* are normalized by dividing by 1,000,000, aligning with established practices in compensation research (D'Mello et al., 2024).

3.2.2. Independent variables

Following Hulme and Shepherd (2003), poverty experience is defined as experiencing prolonged periods of material deprivation or originating from impoverished regions. Such experiences profoundly shape self-efficacy trajectories. Adopting the methodological frameworks established by Hulme and Shepherd (2003) and Xu and Ma (2022), we cross-validate executives' birthplace data against the 2012 national poverty-stricken county designations published by the State Council's Leading Group Office of Poverty Alleviation and Development (LGOPAD). These designations comprise 592 administrative units, including counties, county-level cities, districts and banners, officially classified as poverty-stricken.²

Because institutional decision-making authority over executive compensation and promotion processes typically resides with management, we hypothesize that early-life poverty experience influences intra-organizational compensation disparities. We define the dependent variable representing executives' early poverty experience, *Poverty*, as a dummy variable that equals 1 if at least one top executive (chairperson, CEO or actual controller) was born in a poverty-stricken county and 0 otherwise. To ensure robust measurement, we employ an alternative specification using childhood exposure to China's three-year difficult period (1959–1961) as an instrumental variable and conduct additional robustness checks to validate our findings.

¹ Given the limited availability of executives' resumes in the "Board and Executive Characteristics" section of the CSMAR database, with disclosure rates hovering around 19 %, we implement a multi-pronged approach to mitigate data gaps. This includes manually compiling and structuring top executives' birthplace information from IPO prospectuses, financial news outlets, corporate websites, Baidu Baike and official media reports, in addition to extracting birthplace data from the first six digits of the national ID numbers disclosed in firms' IPO filings, which align with the Chinese administrative division codes (GB/T 2260). However, executives' birthplace information remains sensitive personal data subject to voluntary disclosure, and executives may exercise discretion in providing it. Our final dataset, comprising 7793 firm-year observations, reflects both the methodological rigor necessitated by and inherent constraints of this research domain.

² China's national poverty-stricken counties underwent multiple designation cycles: 331 counties were initially identified in 1986, followed by three subsequent designation cycles in 1994, 2001 and 2012, each designating 592 counties as poverty-stricken. Although this aggregate number was maintained through the latter three cycles, the State Council's LGOPAD revised the designation criteria in 2012. This revision removed all previously designated poverty-stricken counties in economically advanced coastal provinces while expanding the coverage to underdeveloped central and western provinces, maintaining the aggregate number at 592. This study adopts the 2012 list as the baseline to ensure the temporal relevance and precise measurement of the poverty-exposure variable.

3.2.3. Control variables

We build on research by Zhang (2017), Pan et al. (2022) and Xu and Ma (2022), which theoretically links pay disparity to corporate governance mechanisms. To account for potential confounders, we employ a multidimensional framework for controls comprising (1) corporate-level controls including firm size (*Size*), asset-liability ratio (*Lev*), firm age (*FirmAge*), growth rate (*Growth*), dual role (*Dual*), top shareholder ownership (*Top1*), profitability (*Loss*), board size (*Board*), price-to-book ratio (*PB*) and inventory ratio (*INV*), and (2) executive-level controls capturing managerial incentives through average team age (*TMTAge*) and gender diversity (*Gender*). These variables are selected based on established theoretical links between compensation disparities and corporate governance effectiveness. Their definitions and measurements are presented in Appendix A.

3.3. Model construction

Following D'Mello et al. (2024), we estimate the baseline regression as follows:

$$Intpay_Dis_{i,t}/ExtPay_Dis_{i,t} = \beta_0 + \beta_1 Poverty_{i,t-1} + \beta_2 Controls_{i,t-1} + \sum Industry + \sum Year + \mu_{i,t} \quad (1)$$

In Eq. (1), i denotes the company and t represents the year. The model includes two dependent variables: (1) internal pay disparity (*Intpay_Dis_{i,t}*), operationalized as the difference between top executives' compensation and the median employee pay in firm i in year t , and (2) external pay disparity (*ExtPay_Dis_{i,t}*), defined as the difference between top executives' pay and that of their industry peers. The independent variable, *Poverty_{i,t-1}*, captures the poverty experience of the firm's executives in the previous year, using a one-year lag to address potential endogeneity biases. *Controls_{i,t-1}* represent a comprehensive set of control variables, all lagged by one year.

To enhance causal identification, we include two fixed effects: (1) year fixed effects (*Year FE*), which absorb time-invariant macroeconomic shocks, and (2) industry fixed effects (*Industry FE*), which control for industry-specific compensation practices. For example, retail sectors frequently demonstrate significant pay disparities due to their reliance on minimum-wage labor (D'Mello et al., 2024). Finally, standard errors are clustered at the firm level to account for potential within-cluster correlations.

4. Empirical results

4.1. Summary statistics

Table 1 provides the summary statistics of the variables. The mean and standard deviation of internal pay disparity (*Intpay_Dis*) are 0.789 and 0.890, respectively. External pay disparity (*ExtPay_Dis*) exhibits greater variation with a standard deviation of 1.268 and values ranging from -0.210 to 25.915, indicating substantial heterogeneity in executive compensation across industry peers. Executives with poverty experience (*Poverty*) account for approximately 3.8 % of the sample, a figure consistent with that in the literature (Liu et al., 2023). The mean management team age (*TMTAge*) is 49.208 years. Female executives (*Gender*) constitute 5 % of the sample, underscoring the need for gender diversity in leadership roles. Other firm-level characteristics are generally aligned with those reported in comparable studies (Kong et al., 2021; Ye et al., 2022).

4.2. Baseline regression results

Table 2 reports the regression results for the model specified in Eq. (1). The results in columns (1) and (3), obtained by excluding executive characteristics (including *TMTAge* and *Gender*) from the control variables, reveal that the coefficient of *Poverty* is negative and significant at the 1 % level, indicating that executives with poverty experience are associated with both lower internal and lower external pay disparities. The results in column (2), incorporating executive characteristics as controls, also show a statistically significant negative relationship ($p < 0.01$) between *Poverty* and internal pay disparity, suggesting that poverty experience motivates executives to narrow pay gaps between them and employees and promote internal equity. Similarly,

Table 1
Descriptive statistics.

Variable	N	Mean	SD	Min	p50	Max
<i>Intpay_Dis_t</i>	7793	0.789	0.890	-0.070	0.506	4.811
<i>Extpay_Dis_t</i>	7793	0.706	1.268	-0.210	0.353	25.915
<i>Poverty_{t-1}</i>	7793	0.038	0.191	0	0	1
<i>Size_{t-1}</i>	7793	22.404	1.407	19.317	22.203	26.452
<i>Lev_{t-1}</i>	7793	0.450	0.204	0.027	0.450	0.908
<i>FirmAge_{t-1}</i>	7793	2.818	0.371	0.693	2.890	3.611
<i>Growth_{t-1}</i>	7793	0.183	0.404	-0.658	0.121	4.024
<i>Dual_{t-1}</i>	7793	0.378	0.485	0	0	1
<i>Top1_{t-1}</i>	7793	35.636	15.242	8.087	33.454	75.843
<i>Loss_{t-1}</i>	7793	0.090	0.286	0	0	1
<i>Board_{t-1}</i>	7793	2.148	0.207	1.609	2.197	2.708
<i>PB_{t-1}</i>	7793	3.584	3.182	0.413	2.656	44.504
<i>INV_{t-1}</i>	7793	0.152	0.137	0	0.118	0.772
<i>TMTAge_{t-1}</i>	7793	49.208	3.171	39.690	49.210	57.200
<i>Gender_{t-1}</i>	7793	0.051	0.220	0	0	1

This table presents the descriptive statistics for the main variables in the baseline regression analysis. All variables are defined in the Appendix A.

in the results in column (4) incorporating demographic controls, the coefficient of *Poverty_{t-1}* remains significant and negative, providing consistent evidence that poverty experience mitigates external pay disparities by increasing executives' inclination to reduce compensation inequities relative to peers. These findings support hypotheses H1b and H2, confirming that executives with poverty experience narrow internal and external pay disparities.

4.3. Robustness check

4.3.1. IV-2SLS with instrumental variable

Building on imprinting theory, we argue that regional economic conditions during an executive's formative years establish lasting cognitive frameworks that influence subsequent strategic preferences. Specifically, a high unemployment rate in a top executive's birthplace (*L_unemp_rate*) serves as an exogenous shock that increases the likelihood of childhood economic deprivation—whether through parental job loss, decreased household income or community-wide scarcity. This early exposure to economic hardship becomes internalized as a poverty imprint (*Poverty*), fostering persistent egalitarian values that are reflected in compensation decisions. Birthplace unemployment rate functions as a valid instrumental variable for three reasons: (1) its temporal precedence (occurring during the pre-career childhood period) rules out reverse causality with contemporary firm-level outcomes; (2) limited geographic mobility during youth results in quasi-random exposure; and (3) it affects firm behavior only through the internalization of poverty and not through ongoing corporate governance channels, thus satisfying the exclusion restriction necessary for causal inference.

As shown in Table 3, the first-stage regression results indicate a significant positive association between *L_unemp_rate* (unemployment rate in top executives' birthplaces) and *Poverty*. In the second stage, the coefficients of the instrumented variable *Poverty* in columns (2) and (3) remain significant and negative, suggesting that experience of poverty meaningfully reduces pay disparity. Notably, the first-stage F-statistics exceed the conventional threshold of 10 and the CD Wald F-statistic is 13.196 ($F > 10$), mitigating concerns regarding the instrumental variable's weakness. Overall, these results reinforce the view that early-life exposure to economic scarcity leaves a lasting imprint that translates into comparatively equitable organizational compensation practices.

Table 2
Executives' poverty experiences and dual pay disparities.

	(1) Intpay_Dis _t	(2) Intpay_Dis _t	(3) Extpay_Dis _t	(4) Extpay_Dis _t
<i>Poverty</i> _{t-1}	-0.202*** (-2.886)	-0.203*** (-2.895)	-0.309*** (-3.788)	-0.311*** (-3.846)
<i>Size</i> _{t-1}	0.366*** (11.985)	0.373*** (12.169)	0.489*** (10.123)	0.495*** (10.129)
<i>Lev</i> _{t-1}	-0.484*** (-4.930)	-0.494*** (-5.015)	-0.689*** (-4.941)	-0.697*** (-4.965)
<i>FirmAge</i> _{t-1}	0.029 (0.488)	0.039 (0.657)	0.076 (1.007)	0.084 (1.136)
<i>Growth</i> _{t-1}	0.029 (1.249)	0.022 (0.916)	0.041 (1.301)	0.034 (1.076)
<i>Dual</i> _{t-1}	0.135*** (3.321)	0.128*** (3.137)	0.118* (1.871)	0.112* (1.769)
<i>TopI</i> _{t-1}	-0.009*** (-5.982)	-0.009*** (-5.973)	-0.011*** (-5.020)	-0.011*** (-5.009)
<i>Loss</i> _{t-1}	-0.176*** (-5.735)	-0.176*** (-5.724)	-0.189*** (-4.718)	-0.188*** (-4.698)
<i>Board</i> _{t-1}	0.149 (1.439)	0.169 (1.605)	0.257* (1.652)	0.279* (1.771)
<i>PB</i> _{t-1}	0.045*** (7.324)	0.045*** (7.330)	0.063*** (6.218)	0.063*** (6.209)
<i>INV</i> _{t-1}	0.088 (0.552)	0.090 (0.567)	0.060 (0.275)	0.061 (0.278)
<i>TMTAge</i> _{t-1}		-0.010 (-1.571)		-0.009 (-1.064)
<i>Gender</i> _{t-1}		0.057 (0.638)		0.095 (0.858)
<i>Constant</i>	-7.469*** (-11.034)	-7.207*** (-10.330)	-10.551*** (-9.286)	-10.322*** (-9.020)
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	7793	7793	7793	7793
<i>Adj. R</i> ²	0.351	0.352	0.259	0.259

This table presents the regression results examining the effects of executives' poverty experience on internal and external pay disparities. Columns (2) and (4) incorporate executive characteristics as control variables, whereas columns (1) and (3) exclude these controls. Variable definitions are provided in Appendix A. T-statistics are reported in parentheses, with robust standard errors clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

4.3.2. Heckman two-stage test

Following the approach of Guo et al. (2021) and Li et al. (2024), we implement a two-stage Heckman selection model to address potential endogeneity arising from executives' early-life experience. In the first stage, we use the proportion of executives with poverty experience in the same industry, province and year as an instrumental variable. This instrument satisfies the relevance condition, as regional and industry factors such as shared economic conditions, geographic clustering of impoverished counties and identical market or regulatory environments predict individuals' exposure to poverty but are unlikely to directly affect firm-level pay disparities. Executives from the same province are subject to similar regional economic dynamics and poverty distributions, while those in the same industry experience comparable market conditions and compensation benchmarks (e.g., industry-wide salary guidelines). Thus, this instrument captures contextual variation in poverty exposure without directly affecting compensation outcomes.

The results are shown in Table 4. The first-stage regression (column [1]) reveals a statistically significant relationship between the instrument and executives' poverty experience. Columns (2) and (3) report the second-stage results incorporating the inverse Mills ratio to control for selection bias. The coefficients of *Pov*-

Table 3
Iv-2sls with instrumental variable.

	(1) Poverty _{t-1}	(2) Intpay_Dis _t	(3) Extpay_Dis _t
<i>L_unempreate_{t-1}</i>	0.016*** (3.660)		
<i>Poverty_{t-1}</i>		-5.444* (-2.118)	-4.859** (-2.307)
<i>Size_{t-1}</i>	0.005** (2.022)	0.431*** (8.508)	0.562*** (18.858)
<i>Lev_{t-1}</i>	0.060*** (4.139)	-0.180 (-0.997)	-0.367** (-2.275)
<i>FirmAge_{t-1}</i>	-0.021** (-2.328)	-0.015 (-0.137)	0.050 (0.656)
<i>Growth_{t-1}</i>	0.008 (0.915)	0.044 (0.735)	0.047 (0.753)
<i>Dual_{t-1}</i>	-0.016*** (-3.774)	0.068 (1.135)	0.087 (1.467)
<i>Top1_{t-1}</i>	0.000** (2.012)	-0.007*** (-3.645)	-0.009*** (-5.795)
<i>Loss_{t-1}</i>	0.004 (0.436)	-0.156* (-2.018)	-0.163*** (-2.832)
<i>Board_{t-1}</i>	-0.025* (-1.892)	-0.020 (-0.075)	0.143 (1.077)
<i>PB_{t-1}</i>	-0.001 (-1.310)	0.045*** (3.066)	0.068*** (7.001)
<i>INV_{t-1}</i>	-0.034* (-1.726)	-0.280 (-0.883)	-0.309* (-1.820)
<i>TMTAge_{t-1}</i>	0.001 (0.829)	-0.011 (-1.295)	-0.012* (-1.768)
<i>Gender_{t-1}</i>	0.030** (2.087)	0.210 (0.720)	0.275** (2.337)
<i>Industry</i>	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes
<i>F</i>	13.399	397.971	34.193
<i>CD Wald F</i>	13.196		
<i>Observations</i>	5251	5251	5251

T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1 %, 5 %, and 10 % significance, respectively.

erty remain significant and negative (at the 1 % level) for both internal (*Intpay_Dis*) and external (*Extpay_Dis*) pay disparities. These findings confirm the robustness of our main results to selection bias.

4.3.3. Shift in executive composition: Never-to-ever

To address potential differences between the firms with and without executives with poverty experience, and to account for transitions in the *Poverty* variable from 0 to 1, we employ a “never-to-ever” difference-in-differences (DID) design that enhances comparability between the treatment and control groups. The approach excludes firms that have never employed poverty-exposed executives, which serve as a valid control group under the DID framework. Excluding such firms would violate the counterfactual comparability assumption, as their inherent risk preferences may systematically differ from those that eventually hired executives with poverty backgrounds. Our approach thus sharpens the contrast between the firms experiencing a meaningful shift in executives’ poverty backgrounds and those that are stable in this regard. The results are shown in Table 5. The estimated coefficients of *Treat* \times *post* remain significant and negative, further supporting the robustness of our main findings.

Table 4
Heckman two-stage test.

	(1) Poverty _{t-1} First	(2) Intpay_Dis _t Second1	(3) Extpay_Dis _t Second2
<i>IV</i>	-0.966*** (-2.71)		
<i>Poverty_{t-1}</i>		-1.003*** (-2.72)	-1.339*** (-3.07)
<i>Imr</i>		0.379** (2.22)	0.476** (2.37)
<i>Size_{t-1}</i>	0.104*** (3.49)	0.384*** (12.13)	0.510*** (10.38)
<i>Lev_{t-1}</i>	0.441** (2.17)	-0.478*** (-4.68)	-0.684*** (-4.68)
<i>FirmAge_{t-1}</i>	-0.199** (-2.08)	0.020 (0.33)	0.059 (0.79)
<i>Growth_{t-1}</i>	0.028 (0.38)	0.020 (0.84)	0.045 (1.37)
<i>Dual_{t-1}</i>	-0.303*** (-4.00)	0.106** (2.54)	0.082 (1.32)
<i>TopI_{t-1}</i>	0.003 (1.57)	-0.009*** (-5.72)	-0.011*** (-4.78)
<i>Loss_{t-1}</i>	0.182* (1.82)	-0.170*** (-5.16)	-0.173*** (-4.07)
<i>Board_{t-1}</i>	-0.352** (-2.33)	0.121 (1.09)	0.216 (1.33)
<i>PB_{t-1}</i>	-0.014 (-1.20)	0.045*** (7.22)	0.063*** (6.34)
<i>INV_{t-1}</i>	-0.071 (-0.24)	0.156 (1.01)	0.147 (0.68)
<i>TMTAge_{t-1}</i>	-0.008 (-0.72)	-0.013* (-1.92)	-0.012 (-1.39)
<i>Gender_{t-1}</i>	0.145 (1.16)	0.078 (0.85)	0.112 (0.99)
<i>Constant</i>	-2.290*** (-2.94)	-7.486*** (-11.02)	-10.483*** (-9.50)
<i>VIF</i>		4.25 < 10	4.25 < 10
<i>Industry</i>	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes
<i>Observations</i>	7218	7218	7218
<i>Pseudo.R²/Adj.R²</i>	0.016	0.359	0.262

This table presents the findings from the Heckman two-stage procedure. A Probit regression is initially estimated, incorporating the instrumental variable alongside all baseline control variables, from which the inverse Mills ratio (*IMR*) is derived. This *IMR* is subsequently included in the second-stage regression analysis, which controls for industry and year fixed effects while clustering standard errors at the firm level. T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1 %, 5 %, and 10 % significance, respectively.

4.3.4. Alternative measures of dependent variables

To further validate the robustness of our conclusions, we employ alternative measures of the dependent variables. Consistent with Dai et al. (2017), internal pay disparity is redefined as the ratio of average executive compensation to mean employee wages (*Intpay_Dis1*). Similarly, external pay disparity is measured as the ratio of average executive compensation to average industry peer compensation (*Extpay_Dis1*). Table 6 presents the results. As demonstrated in columns (1) and (2), the coefficients of *Poverty* remain negative and sig-

Table 5
Shift in executives' composition.

	(1) Intpay_Dis _t	(2) ExtPay_Dis _t
<i>Treat</i> × <i>post</i>	−0.403*** (−5.108)	−0.486*** (−4.607)
<i>Size_{t-1}</i>	0.377*** (12.052)	0.502*** (10.060)
<i>Lev_{t-1}</i>	−0.498*** (−4.938)	−0.714*** (−4.945)
<i>FirmAge_{t-1}</i>	0.026 (0.425)	0.065 (0.862)
<i>Growth_{t-1}</i>	0.018 (0.727)	0.031 (0.930)
<i>Dual_{t-1}</i>	0.120*** (2.899)	0.105 (1.622)
<i>TopI_{t-1}</i>	−0.009*** (−5.777)	−0.011*** (−4.873)
<i>Loss_{t-1}</i>	−0.167*** (−5.264)	−0.178*** (−4.300)
<i>Board_{t-1}</i>	0.153 (1.402)	0.260 (1.598)
<i>PB_{t-1}</i>	0.044*** (7.110)	0.064*** (6.076)
<i>INV_{t-1}</i>	0.059 (0.368)	0.042 (0.189)
<i>TMTAge_{t-1}</i>	−0.010 (−1.522)	−0.009 (−1.041)
<i>Gender_{t-1}</i>	0.071 (0.740)	0.099 (0.844)
<i>Constant</i>	−7.220*** (−10.158)	−10.375*** (−8.886)
<i>Industry</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>Observations</i>	7531	7531
<i>Adj. R</i> ²	0.354	0.261

T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1 %, 5 %, and 10 % significance, respectively.

nificant at the 1 % level, aligning with the baseline regression results. These findings confirm the consistency of our conclusions across alternative measurement specifications.

4.3.5. Alternative measures of independent variables

First, following Zhang (2017), executives who lived through the “three-year difficult period” (1959–1962)—a time of widespread famine and severe food shortages—during their childhood are classified as having experienced poverty. Adopting the psychological definition of childhood (ages 0–14), we consider executives born between 1947 and 1961 as having been exposed to childhood poverty. We use a binary variable, *Agepoor*, which equals 1 for executives born in this interval, and 0 otherwise. Second, in line with Xu and Ma (2022), we focus on chairpersons as the key top executives. We define a new variable, *Cperson_Poverty*, which is 1 if a firm's chairperson was born in a poverty-stricken county, and 0 otherwise.

Table 7 presents the results. As shown in columns (1) and (2), the coefficients of *Agepoor* remain consistent with our main findings, supporting the robustness of the results. Columns (3) and (4) show that *Cperson_Poverty* exhibits statistically significant negative associations with internal pay disparity (*Intpay_Dis*) and external pay disparity (*ExtPay_Dis*) at the 5 % and 1 % levels, respectively, further reinforcing the conclusions of our primary analysis.

Table 6
Alternative measures of dependent variables.

	(1) Intpay_Dis1 _t	(2) ExtPay_Dis1 _t
<i>Poverty</i> _{t-1}	-0.255*** (-3.823)	-0.315*** (-3.898)
<i>Size</i> _{t-1}	0.387*** (9.139)	0.485*** (9.939)
<i>Lev</i> _{t-1}	-0.551*** (-4.589)	-0.667*** (-4.788)
<i>FirmAge</i> _{t-1}	0.103 (1.601)	0.089 (1.206)
<i>Growth</i> _{t-1}	0.035 (1.286)	0.029 (0.925)
<i>Dual</i> _{t-1}	0.089 (1.599)	0.109* (1.714)
<i>Top1</i> _{t-1}	-0.009*** (-4.481)	-0.011*** (-4.957)
<i>Loss</i> _{t-1}	-0.150*** (-4.379)	-0.173*** (-4.419)
<i>Board</i> _{t-1}	0.238* (1.817)	0.273* (1.743)
<i>PB</i> _{t-1}	0.052*** (5.814)	0.064*** (6.364)
<i>INV</i> _{t-1}	0.014 (0.073)	0.062 (0.285)
<i>TMTAge</i> _{t-1}	-0.009 (-1.261)	-0.009 (-1.092)
<i>Gender</i> _{t-1}	0.084 (0.840)	0.092 (0.835)
<i>Constant</i>	-7.884*** (-7.869)	-10.107*** (-8.847)
<i>Industry</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>Observations</i>	7793	7793
<i>Adj.R</i> ²	0.260	0.257

This table presents the findings using alternative measures of internal and external pay disparities. We introduce two new proxy variables *Intpay_Dis1* for internal pay disparity and *ExtPay_Dis1* for external pay disparity. Specifically, *Intpay_Dis1* is computed as the ratio of average executive compensation to average employee wages, capturing within-firm pay inequality. Meanwhile, *ExtPay_Dis1* is defined as the ratio of average top-executive compensation to the industry-peer average, reflecting between-firm pay differentials. T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

4.3.6. Augmented controls and province-year fixed effects

To ensure the robustness of the regression results, we make the following modifications. First, we use current-period values instead of one-period lags for both the explanatory and control variables. Second, we incorporate additional controls at the political level (political connections, *PC*) and the macroeconomic level (log-transformed GDP, *LnGDP*). Additionally, we include province-year fixed effects to account for time-varying provincial heterogeneity. The results are shown in Table 8.

As shown in Panel A of the table, the relationship between executives' poverty experience and pay disparities remains negative and significant ($p < 0.01$) even when using contemporaneous (not lagged by one period) variables. Panel B shows that after controlling for *PC*, *LnGDP* and province-year fixed effects, the coefficient of *Poverty* remains statistically significant at the 1% level. These findings confirm that our baseline results remain robust across various model specifications.

Table 7

Alternative measures of independent variables.

	(1) Intpay_Dis _t	(2) Extpay_Dis _t	(3) Intpay_Dis _t	(4) Extpay_Dis _t
<i>Agepoor</i> _{t-1}	-0.126*** (-2.976)	-0.160*** (-2.734)		
<i>Cperson_Poverty</i> _{t-1}			-0.212** (-2.451)	-0.329*** (-2.949)
<i>Size</i> _{t-1}	0.374*** (12.267)	0.497*** (10.161)	0.376*** (11.173)	0.511*** (9.188)
<i>Lev</i> _{t-1}	-0.498*** (-5.076)	-0.705*** (-5.020)	-0.469*** (-4.282)	-0.725*** (-4.398)
<i>FirmAge</i> _{t-1}	0.039 (0.663)	0.085 (1.155)	0.062 (1.007)	0.119 (1.509)
<i>Growth</i> _{t-1}	0.020 (0.828)	0.031 (0.985)	0.007 (0.234)	0.015 (0.393)
<i>Dual</i> _{t-1}	0.102** (2.534)	0.081 (1.316)	0.155*** (3.391)	0.134* (1.814)
<i>TopI</i> _{t-1}	-0.009*** (-5.888)	-0.011*** (-4.911)	-0.010*** (-5.763)	-0.012*** (-4.814)
<i>Loss</i> _{t-1}	-0.178*** (-5.772)	-0.191*** (-4.766)	-0.180*** (-5.147)	-0.203*** (-4.417)
<i>Board</i> _{t-1}	0.187* (1.771)	0.303* (1.915)	0.131 (1.156)	0.265 (1.502)
<i>PB</i> _{t-1}	0.045*** (7.382)	0.063*** (6.234)	0.046*** (6.718)	0.067*** (5.648)
<i>INV</i> _{t-1}	0.078 (0.494)	0.046 (0.213)	0.193 (1.174)	0.175 (0.738)
<i>TMTAge</i> _{t-1}	-0.008 (-1.239)	-0.007 (-0.757)	-0.014** (-2.022)	-0.014 (-1.446)
<i>Gender</i> _{t-1}	0.063 (0.702)	0.101 (0.916)	0.025 (0.274)	0.070 (0.594)
<i>Constant</i>	-7.351*** (-10.428)	-10.501*** (-9.027)	-7.097*** (-9.518)	-10.511*** (-8.149)
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	7793	7793	6474	6474
<i>Adj. R</i> ²	0.353	0.259	0.351	0.253

This table reports robustness checks for the association between executives' poverty experiences and pay disparities. Columns (1)–(2) re-examine this relationship using a refined definition of childhood poverty, aligning with psychological literature (0–14 years). Specifically, we reclassified executives born between 1947 and 1961—spanning the “Three-Year Difficult Period” (1959–1962)—as having childhood poverty exposure. Columns (3)–(4) present results using alternative measures of top executives' poverty experiences, focusing on the chairperson as the top executive. A binary variable, *Cperson_Poverty*, was created to capture chairpersons born in poverty-stricken counties (1 = yes, 0 = no). These analyses confirm the robustness of our main findings across measurement specifications. T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

4.3.7. Controlling for the effects of the salary regulation policies and global financial crisis

Two key policies were introduced to regulate executive compensation in China: (1) the “Guiding Opinions on Further Regulating the Salary Management of Central SOE Principals” (hereinafter, the “salary cap policy”), jointly issued by six ministries and commissions in 2009,³ and (2) the “Reform Plan for the Payment Packages of Executives of SOEs” (hereinafter, the “salary reform policy”), implemented by the State Council

³ The six ministries and commissions include the Ministry of Commerce, the National Development and Reform Commission, the Ministry of Finance, the General Administration of Customs, the State Taxation Administration and the State Administration for Market Regulation in China.

Table 8
Augmented controls and province-year fixed effects.

Panel A: Not lagged by one period

	(1) Intpay_Dis _t	(2) Extpay_Dis _t
<i>Poverty</i> _t	-0.198*** (-3.089)	-0.300*** (-4.073)
<i>Size</i> _t	0.359*** (13.278)	0.480*** (10.915)
<i>Lev</i> _t	-0.487*** (-5.554)	-0.709*** (-5.311)
<i>FirmAge</i> _t	0.008 (0.156)	0.047 (0.726)
<i>Growth</i> _t	-0.002 (-0.080)	-0.003 (-0.092)
<i>Dual</i> _t	0.117*** (3.483)	0.090* (1.716)
<i>TopI</i> _t	-0.008*** (-6.403)	-0.010*** (-5.406)
<i>Loss</i> _t	-0.177*** (-6.345)	-0.176*** (-4.743)
<i>Board</i> _t	0.170* (1.849)	0.268** (1.966)
<i>PB</i> _t	0.049*** (7.752)	0.071*** (5.997)
<i>INV</i> _t	0.093 (0.666)	0.082 (0.425)
<i>TMTAge</i> _t	-0.008 (-1.510)	-0.006 (-0.763)
<i>Gender</i> _t	0.063 (0.862)	0.107 (1.125)
<i>Constant</i>	-6.976*** (-11.335)	-10.099*** (-9.722)
<i>Industry</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>Observations</i>	6730	6474
<i>Adj.R</i> ²	0.376	0.351

Panel B: Controlling province \times year fixed effects and adding control variables

	(1) Intpay_Dis _t	(2) Extpay_Dis _t	(3) Intpay_Dis _t	(4) Extpay_Dis _t
<i>Poverty</i> _{t-1}	-0.182*** (-2.882)	-0.289*** (-3.718)	-0.197*** (-2.825)	-0.282*** (-3.523)
<i>Size</i> _{t-1}	0.375*** (12.949)	0.497*** (11.031)	0.372*** (11.463)	0.482*** (9.685)
<i>Lev</i> _{t-1}	-0.480*** (-4.976)	-0.710*** (-5.068)	-0.532*** (-5.159)	-0.762*** (-5.200)
<i>FirmAge</i> _{t-1}	0.053 (0.914)	0.106 (1.431)	0.048 (0.782)	0.087 (1.175)
<i>Growth</i> _{t-1}	0.007 (0.301)	0.025 (0.777)	0.029 (1.126)	0.042 (1.277)
<i>Dual</i> _{t-1}	0.077** (1.967)	0.043 (0.715)	0.118*** (2.802)	0.076 (1.251)
<i>TopI</i> _{t-1}	-0.009*** (-6.006)	-0.011*** (-5.210)	-0.010*** (-6.076)	-0.013*** (-5.625)
<i>Loss</i> _{t-1}	-0.169*** (-5.498)	-0.171*** (-4.103)	-0.169*** (-5.128)	-0.174*** (-4.083)
<i>Board</i> _{t-1}	0.201* (0.331**)	0.331** (0.151)	0.151 (0.229)	

(continued on next page)

Table 8 (continued)

Panel A: Not lagged by one period

	(1) Intpay_Dis _t	(2) Extpay_Dis _t		
<i>PB</i> _{t-1}	(1.894) 0.044*** (7.825)	(2.094) 0.062*** (6.693)	(1.345) 0.046*** (6.776)	(1.505) 0.068*** (5.780)
<i>INV</i> _{t-1}	0.003 (0.021)	0.009 (0.041)	-0.016 (-0.094)	-0.078 (-0.340)
<i>TMTAge</i> _{t-1}	-0.006 (-0.859)	-0.004 (-0.381)	-0.013* (-1.838)	-0.013 (-1.395)
<i>Gender</i> _{t-1}	0.024 (0.283)	0.032 (0.274)	0.046 (0.444)	0.065 (0.526)
<i>Pc</i> _{t-1}			-0.006 (-0.162)	-0.004 (-0.070)
<i>LnGDP</i> _{t-1}			0.013 (0.617)	0.003 (0.105)
Constant	-7.545*** (-10.969)	-10.786*** (-9.888)	-7.126*** (-9.428)	-9.711*** (-8.352)
<i>Province</i> × <i>Year</i>	Yes	Yes	Yes	Yes
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	7781	7781	6687	6687
<i>Adj. R</i> ²	0.386	0.284	0.337	0.251

T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1 %, 5 %, and 10 % significance, respectively.

in 2014. Both the policies aimed to limit excessive executive pay and reduce compensation disparities, initially targeting central SOEs in 2009 and expanding to cover all SOEs (excluding private firms) in 2014.

To address potential selection bias due to these policies, we exclude the following subgroups from the sample: (1) central SOEs from 2009 to 2011, and (2) all SOEs from 2014 to 2016. Additionally, to minimize distortion due to the 2008 global financial crisis, which significantly reduced per capita household and real income, we omit observations from before 2010. Table 9 presents the results.

As shown in columns (1)–(4) of the table, the estimated coefficients of *Poverty* remain significant and negative after controlling for the salary cap and salary reform policies. Columns (5)–(6) present the results with the financial crisis period (2008–2009) excluded. Across all these specifications, the negative association between executives' poverty experience and pay disparities remains consistent with our baseline results, underscoring the robustness of our findings.

4.4. Cross-sectional analysis

4.4.1. Different property rights

In China, enterprises are classified as SOEs or non-SOEs based on property rights, with each category being entrusted with distinct economic and social responsibilities (Liu et al., 2025). SOEs prioritize political goals and internal equity, often balancing economic growth with social and political objectives such as employment regulation and market stability. This reduces the influence of executives' personal preferences and background, including their poverty experience, on compensation systems. Additionally, the compensation of executives in SOEs is more strongly regulated, limiting pay gaps. In contrast, non-SOEs, driven by profit maximization, empower executives to make compensation decisions. Executives with poverty experience in non-SOEs may narrow pay disparities to satisfy employees and retain talent, resulting in a stronger inhibitory effect of poverty experience on pay gaps. We investigate this issue and present the results in Table 10.

Table 9

Exclusion of “salary policies” and “financial crisis” period impact.

	(1)	(2)	(3)	(4)	(5)	(6)
	Policy-2009		Policy-2014		Financial crisis	
	Intpay_Dis _t	Extpay_Dis _t	Intpay_Dis _t	Extpay_Dis _t	Intpay_Dis _t	Extpay_Dis _t
<i>Poverty_{t-1}</i>	-0.378*** (-3.899)	-0.581*** (-4.770)	-0.278** (-2.167)	-0.487*** (-2.938)	-0.229*** (-3.144)	-0.343*** (-3.956)
<i>Size_{t-1}</i>	0.459*** (12.364)	0.633*** (9.667)	0.531*** (13.229)	0.758*** (9.717)	0.394*** (12.217)	0.527*** (10.093)
<i>Lev_{t-1}</i>	-0.599*** (-5.119)	-0.911*** (-4.961)	-0.687*** (-5.553)	-1.083*** (-5.202)	-0.538*** (-5.065)	-0.764*** (-5.005)
<i>FirmAge_{t-1}</i>	0.097 (1.425)	0.168* (1.888)	-0.011 (-0.177)	0.030 (0.338)	0.051 (0.817)	0.104 (1.316)
<i>Growth_{t-1}</i>	-0.015 (-0.521)	-0.005 (-0.123)	-0.044 (-1.511)	-0.048 (-1.114)	0.026 (1.053)	0.043 (1.280)
<i>Dual_{t-1}</i>	0.039 (0.841)	-0.002 (-0.027)	0.026 (0.561)	-0.044 (-0.553)	0.134*** (3.132)	0.120* (1.799)
<i>Top1_{t-1}</i>	-0.007*** (-3.822)	-0.009*** (-3.294)	-0.005*** (-2.713)	-0.006** (-2.178)	-0.009*** (-5.817)	-0.012*** (-4.877)
<i>Loss_{t-1}</i>	-0.164*** (-4.047)	-0.169*** (-3.041)	-0.134*** (-3.091)	-0.121** (-2.009)	-0.172*** (-5.201)	-0.182*** (-4.196)
<i>Board_{t-1}</i>	0.163 (1.215)	0.298 (1.406)	0.228* (1.697)	0.364 (1.633)	0.173 (1.526)	0.295* (1.720)
<i>PB_{t-1}</i>	0.048*** (7.757)	0.073*** (6.070)	0.052*** (8.127)	0.080*** (6.255)	0.049*** (7.416)	0.070*** (6.302)
<i>INV_{t-1}</i>	-0.005 (-0.027)	0.001 (0.003)	-0.086 (-0.467)	-0.126 (-0.485)	0.054 (0.324)	0.012 (0.052)
<i>TMTAge_{t-1}</i>	-0.009 (-1.235)	-0.010 (-0.938)	0.002 (0.290)	0.006 (0.663)	-0.010 (-1.483)	-0.009 (-0.945)
<i>Gender_{t-1}</i>	0.083 (0.831)	0.161 (1.294)	0.072 (0.740)	0.126 (1.041)	0.070 (0.752)	0.112 (0.975)
<i>Constant</i>	-9.173*** (-10.435)	-13.472*** (-8.613)	-11.134*** (-12.497)	-16.706*** (-9.061)	-7.697*** (-10.349)	-11.111*** (-9.000)
<i>Industry</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	5261	5261	4555	4555	7109	7109
<i>Adj. R²</i>	0.408	0.306	0.449	0.339	0.348	0.262

This table reports the effect of executives’ poverty experiences on internal and external pay disparities after controlling for the “Salary Cap” and “Salary Reform” policies—both aimed at curbing excessive executive compensation—as well as the potential influence of the “Financial Crisis” period. Introduced in 2009, the “Salary Cap” policy targeted executives in central SOEs, while the 2014 “Salary Reform” policy extended its reach to include executives across all SOEs (including central SOEs). The latter policy applied to senior executives managed by the central government within state-owned or state-controlled enterprises, such as party committee secretaries, general managers (including CEOs), chief supervisors, and other deputy executives, in which the State Council (the Central People’s Government) acts as the state investor. T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

The association between executives’ poverty experience and pay disparities is not significant in SOEs. In non-SOEs, poverty experience exhibits significant negative correlations with both internal and external pay disparities, indicating a pronounced effect in terms of reducing compensation inequality. The differences in the coefficients between the two groups are statistically significant.

4.4.2. Industry attributes

In labor-intensive industries, which are characterized by high turnover among frontline employees and operational sensitivity to pay inequity, the moderating effect of executives’ poverty experience on internal pay gaps is likely to be more pronounced. Executives with poverty backgrounds tend to emphasize distributive

Table 10

Cross-sectional analysis: Different property rights.

	(1)	(2)	(3)	(4)
	Intpay_Dis _t		Extpay_Dis _t	
	SOE	Non-SOE	SOE	Non-SOE
<i>Poverty_{t-1}</i>	-0.090 (-1.125)	-0.278** (-2.167)	-0.122 (-1.452)	-0.487*** (-2.938)
<i>Size_{t-1}</i>	0.268*** (7.524)	0.531*** (13.229)	0.305*** (7.213)	0.758*** (9.717)
<i>Lev_{t-1}</i>	-0.489*** (-3.600)	-0.687*** (-5.553)	-0.558*** (-3.617)	-1.083*** (-5.202)
<i>FirmAge_{t-1}</i>	0.179 (1.560)	-0.011 (-0.177)	0.264* (1.903)	0.030 (0.338)
<i>Growth_{t-1}</i>	0.088** (2.297)	-0.044 (-1.511)	0.115*** (2.781)	-0.048 (-1.114)
<i>Dual_{t-1}</i>	0.094 (1.158)	0.026 (0.561)	0.073 (0.814)	-0.044 (-0.553)
<i>TopI_{t-1}</i>	-0.010*** (-4.616)	-0.005*** (-2.713)	-0.011*** (-3.479)	-0.006** (-2.178)
<i>Loss_{t-1}</i>	-0.181*** (-4.584)	-0.134*** (-3.091)	-0.195*** (-4.396)	-0.121** (-2.009)
<i>Board_{t-1}</i>	0.159 (1.155)	0.228* (1.697)	0.276* (1.718)	0.364 (1.633)
<i>PB_{t-1}</i>	0.033*** (2.969)	0.052*** (8.127)	0.034*** (2.967)	0.080*** (6.255)
<i>INV_{t-1}</i>	0.287 (1.073)	-0.086 (-0.467)	0.320 (0.916)	-0.126 (-0.485)
<i>TMTAge_{t-1}</i>	0.002 (0.150)	0.002 (0.290)	0.014 (0.895)	0.006 (0.663)
<i>Gender_{t-1}</i>	-0.003 (-0.020)	0.072 (0.740)	0.014 (0.089)	0.126 (1.041)
<i>Constant</i>	-5.917*** (-5.554)	-11.134*** (-12.497)	-7.865*** (-5.069)	-16.706*** (-9.061)
<i>coefficient difference</i>	-0.188** Industry	-0.364*** Yes		
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	3237	4555	3237	4555
<i>Adj R²</i>	0.300	0.449	0.243	0.339

This table shows the impact of executives' poverty experience on internal and external pay disparities based on different property rights. For the grouped sample results, we employed a Bootstrap-based Fisher's combined test with 500 sampling iterations to conduct an intergroup coefficient difference test. The results were $p = -0.188$ (<0.01) and $p = -0.364$ (<0.01), respectively. T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1 %, 5 %, and 10 % significance, respectively.

justice (Liu et al., 2023) and demonstrate greater empathy toward workers' economic vulnerabilities. This inclination leads them to strategically reduce pay disparities between management and employees to enhance team stability and mitigate turnover. Unlike in capital-intensive sectors, where talent retention often relies on equity incentives, management executives' lower mobility in labor-intensive industries shifts competitive dynamics toward cost control, further aligning their poverty experience with internal pay fairness.

Poverty experience among executives also influences external pay decisions through institutional norms (Pan et al., 2022) and reputational mechanisms specific to labor-intensive sectors. These industries often face closer scrutiny regarding executive compensation relative to market benchmarks, and excessive gaps threaten organizational legitimacy and perceptions of fairness among employees. Therefore, poverty-exposed executives, being more sensitive to systemic inequities, are more likely to align their compensation with industry standards to prevent labor disputes and preserve social legitimacy. This stands in contrast to capital-

Table 11
Cross-sectional analysis: Industry attributes.

	(1)	(2)	(3)	(4)
	Intpay_Dis _t		Extpay_Dis _t	
	Labor-intensive industry	Non-labor-intensive industry	Labor-intensive industry	Non-labor-intensive industry
<i>Poverty_{t-1}</i>	-0.339*** (-3.443)	-0.054 (-0.558)	-0.477*** (-4.482)	-0.166 (-1.360)
<i>Size_{t-1}</i>	0.392*** (10.256)	0.340*** (7.574)	0.505*** (8.392)	0.487*** (5.896)
<i>Lev_{t-1}</i>	-0.524*** (-4.488)	-0.472*** (-2.979)	-0.745*** (-4.398)	-0.639*** (-2.803)
<i>FirmAge_{t-1}</i>	0.001 (0.011)	0.038 (0.462)	0.013 (0.138)	0.146 (1.143)
<i>Growth_{t-1}</i>	-0.011 (-0.331)	0.041 (1.233)	0.001 (0.019)	0.049 (1.032)
<i>Dual_{t-1}</i>	0.086* (1.648)	0.182*** (2.765)	0.024 (0.331)	0.226* (1.868)
<i>Top1_{t-1}</i>	-0.009*** (-4.635)	-0.009*** (-3.620)	-0.010*** (-4.178)	-0.012*** (-2.830)
<i>Loss_{t-1}</i>	-0.198*** (-4.917)	-0.124*** (-2.688)	-0.216*** (-4.301)	-0.138** (-2.045)
<i>Board_{t-1}</i>	0.024 (0.188)	0.417*** (2.601)	-0.025 (-0.145)	0.711*** (2.718)
<i>PB_{t-1}</i>	0.051*** (6.799)	0.033*** (3.708)	0.069*** (5.627)	0.052*** (3.134)
<i>INV_{t-1}</i>	0.015 (0.060)	0.266 (1.461)	0.050 (0.155)	0.173 (0.602)
<i>TMTAge_{t-1}</i>	0.003 (0.377)	-0.025*** (-2.917)	0.004 (0.370)	-0.025** (-2.047)
<i>Gender_{t-1}</i>	0.088 (0.681)	-0.010 (-0.086)	0.118 (0.785)	0.012 (0.073)
<i>Constant</i>	-7.819*** (-8.949)	-6.348*** (-6.121)	-10.316*** (-8.134)	-10.533*** (-4.934)
<i>Coefficient difference</i>	-0.285***		-0.312***	
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	4638	3153	4638	3153
<i>Adj.R²</i>	0.375	0.358	0.282	0.261

This table shows the impact of executives' poverty experience on internal and external pay disparities based on regional development levels. T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

intensive industries, where talent retention strategies typically emphasize career development opportunities (Campanella et al., 2023). We investigate this issue and present the results in Table 11.

The correlations of executives' poverty experience with internal and external pay disparities are both significant and negative within labor-intensive industries. In other industries, no significant correlation is observed. The differences in the coefficients between the two groups are statistically significant.

4.4.3. Regional development

Due to China's vast territory and uneven regional development, significant regional differences exist in wages and pay disparities. Western and central regions, which experience relatively slower economic growth, tend to exhibit smaller wage gaps. In contrast, eastern regions, which are characterized by intense market competition and stricter legal regulations, show a stronger tendency among executives to emphasize both internal and external pay equity to maintain organizational stability. We therefore expect executives in eastern regions

Table 12

Cross-sectional analysis: Regional development level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Intpay_Dis _t			Extpay_Dis _t		
	Eastern	Central	Western	Eastern	Central	Western
<i>Poverty</i> _{t-1}	-0.249*** (-2.776)	0.019 (0.116)	-0.091 (-0.770)	-0.441*** (-4.068)	0.017 (0.102)	-0.054 (-0.363)
<i>Size</i> _{t-1}	0.421*** (11.269)	0.228*** (3.442)	0.277*** (6.292)	0.569*** (9.467)	0.344** (2.578)	0.309*** (6.226)
<i>Lev</i> _{t-1}	-0.496*** (-4.077)	-0.320 (-1.565)	-0.518*** (-3.033)	-0.795*** (-4.241)	-0.283 (-0.920)	-0.535*** (-2.827)
<i>FirmAge</i> _{t-1}	0.052 (0.721)	-0.008 (-0.064)	0.170 (1.353)	0.106 (1.183)	0.030 (0.184)	0.197 (1.373)
<i>Growth</i> _{t-1}	-0.010 (-0.322)	0.060 (1.309)	0.079** (2.126)	0.002 (0.050)	0.054 (0.669)	0.084* (1.698)
<i>Dual</i> _{t-1}	0.072 (1.446)	0.273* (1.924)	0.190** (2.579)	0.031 (0.413)	0.458 (1.519)	0.152* (1.876)
<i>TopI</i> _{t-1}	-0.009*** (-5.155)	-0.011*** (-2.896)	-0.004 (-1.628)	-0.011*** (-4.330)	-0.015** (-2.233)	-0.005* (-1.855)
<i>Loss</i> _{t-1}	-0.159*** (-3.667)	-0.146** (-2.264)	-0.122** (-2.525)	-0.155*** (-2.702)	-0.193** (-1.988)	-0.129** (-2.408)
<i>Board</i> _{t-1}	0.282** (2.039)	0.183 (0.988)	0.043 (0.332)	0.432** (2.086)	0.418 (1.079)	-0.019 (-0.106)
<i>PB</i> _{t-1}	0.054*** (7.325)	0.033** (2.346)	0.036*** (3.377)	0.078*** (6.155)	0.051* (1.956)	0.040*** (3.182)
<i>INV</i> _{t-1}	0.139 (0.710)	-0.059 (-0.117)	-0.202 (-0.641)	0.174 (0.661)	-0.212 (-0.244)	-0.216 (-0.666)
<i>TMTAge</i> _{t-1}	-0.012 (-1.451)	0.009 (0.951)	-0.019** (-2.059)	-0.012 (-1.033)	0.019 (1.412)	-0.022* (-1.928)
<i>Gender</i> _{t-1}	0.160 (1.421)	-0.069 (-0.465)	-0.077 (-0.827)	0.188 (1.487)	-0.111 (-0.394)	0.003 (0.020)
<i>Constant</i>	-8.402*** (-9.895)	-4.983*** (-2.972)	-4.972*** (-4.187)	-12.124*** (-8.941)	-8.759** (-2.341)	-5.605*** (-4.616)
<i>Coefficient difference</i>	0.213***			0.411***		
<i>Industry</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	5256	1014	1421	5256	1014	1421
<i>Adj. R</i> ²	0.379	0.327	0.345	0.283	0.244	0.271

This table shows the impact of executives' poverty experience on internal and external pay disparities based on regional development levels. In this table, we divide the entire sample into eastern, central, and western regions. The eastern region includes 11 provinces/municipalities: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes 9 provinces/autonomous regions: Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes 9 provinces/autonomous regions: Sichuan, Guizhou, Yunnan, Xizang, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

to be more motivated to narrow wage disparities both within their firms and relative to industry peers. We investigate this conjecture and present the results in Table 12.

Columns (1) and (4) show that the coefficients of *Poverty* are negative and significant at the 1% level for both internal and external pay disparities among eastern firms. The associations for central and western firms—reported in columns (2)–(3) and (5)–(6), respectively—are not significant. Tests for intergroup differences in the coefficients further confirm that the effect of executives' poverty experience is more pronounced among enterprises in the eastern region.

Table 13
Cross-sectional analysis: executives' education background.

	(1)	(2)	(3)	(4)
	Intpay_Dis _t		Extpay_Dis _t	
	Advanced academic degrees	Lower academic degrees	Advanced academic degrees	Lower academic degrees
<i>Poverty_{t-1}</i>	-0.244*** (-3.760)	-0.015 (-0.085)	-0.365*** (-4.365)	-0.066 (-0.409)
<i>Size_{t-1}</i>	0.367*** (12.305)	0.372*** (7.155)	0.504*** (9.893)	0.449*** (6.758)
<i>Lev_{t-1}</i>	-0.559*** (-5.258)	-0.237 (-1.266)	-0.801*** (-5.188)	-0.304 (-1.252)
<i>FirmAge_{t-1}</i>	-0.013 (-0.210)	0.158 (1.555)	0.026 (0.345)	0.237* (1.825)
<i>Growth_{t-1}</i>	0.041 (1.525)	-0.027 (-0.599)	0.059 (1.575)	-0.024 (-0.437)
<i>Dual_{t-1}</i>	0.108*** (2.669)	0.209*** (2.662)	0.106 (1.565)	0.144 (1.519)
<i>Top1_{t-1}</i>	-0.008*** (-5.058)	-0.011*** (-3.765)	-0.010*** (-4.703)	-0.012*** (-2.664)
<i>Loss_{t-1}</i>	-0.139*** (-4.160)	-0.283*** (-4.313)	-0.143*** (-3.217)	-0.315*** (-3.971)
<i>Board_{t-1}</i>	0.104 (1.030)	0.406* (1.858)	0.182 (1.190)	0.619** (1.977)
<i>PB_{t-1}</i>	0.049*** (7.526)	0.027*** (2.747)	0.071*** (6.344)	0.035*** (2.631)
<i>INV_{t-1}</i>	0.041 (0.232)	0.205 (0.823)	-0.030 (-0.123)	0.298 (0.843)
<i>TMTAge_{t-1}</i>	-0.015** (-2.315)	0.005 (0.384)	-0.016* (-1.806)	0.011 (0.711)
<i>Gender_{t-1}</i>	0.069 (0.667)	0.103 (0.895)	0.123 (0.927)	0.109 (0.867)
<i>Constant</i>	-6.581*** (-9.841)	-8.764*** (-7.414)	-9.834*** (-8.508)	-11.481*** (-6.748)
<i>Coefficient difference</i>	0.229***		0.300***	
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	5944	1848	5944	1848
<i>Adj R²</i>	0.367	0.357	0.259	0.294

T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

4.4.4. Education background

We next classify executives by their degrees. The *advanced academic degree* group represents executives with bachelor's degrees or higher (including master's and doctoral degrees). These individuals typically receive more systematic training in logical reasoning and the social sciences, which fosters a deeper understanding of societal issues such as the importance of equity relative to that of efficiency and inclusive prosperity. Poverty experience may heighten these executives' sense of social responsibility and moral commitment, leading them to view pay equity as a strategic mechanism to enhance corporate stability and social reputation. Consequently, they may be more inclined to reduce pay disparities to improve employees' loyalty. The *lower academic degree* group represents executives with lower educational attainment. These individuals often have limited access to social resources and industry insights and rely more on traditional compensation models. Therefore, insecurities rooted in poverty experience may lead them to perceive salaries as a marker of status and security, reducing their willingness to narrow pay gaps with employees or industry peers. We investigate this conjecture and present the results in Table 13.

As shown in columns (2) and (4), the coefficients of *Poverty* are not statistically significant for the lower academic degree group. Columns (1) and (3) show a significant negative correlation between executives' poverty experience and both internal and external pay disparities among those with advanced academic degrees. The intergroup differences in these coefficients are significant (Table 13).

4.4.5. Social responsibility expenditure

Firms that make larger donations tend to demonstrate stronger commitments to social equity, which systematically influences their selection and compensation of executives (Burbano, 2016). These firms often recruit leaders whose childhood poverty experiences align with their philanthropic values, fostering a governance environment aligned with those values. Executives with personal experience of economic hardship or exposure to social inequality internalize the link between corporate conduct and social responsibility. This cognitive framework motivates them to proactively allocate resources for corporate social responsibility expenditures, including public welfare donations, thus assertively reducing pay gaps to reflect shared norms of equity. Conversely, in firms that make limited donations, the absence of institutionalized mechanisms to promote equity constrains executives' ability to translate personal values into equitable pay structures.

To investigate this issue, we categorize firms based on the median value of their public welfare contributions. The results are presented in Table 14. The significant and negative coefficients of *Poverty* in columns (1) and (3) indicate that poverty experience reduces pay gaps more strongly in firms with larger donations. In comparison, columns (2) and (4) show statistically nonsignificant effects of poverty experience on external pay disparity and weaker effects on internal pay disparity, respectively, among firms with smaller donations. The between-group differences in these coefficients (0.121 and 0.140) are statistically significant, empirically confirming that among firms with large donations, the influence of executives' poverty experience on equalizing pay is amplified.

5. Mechanism tests

Drawing on Di Giuli and Laux's (2022) methodological approach, we adopt sequential regression to examine the mechanisms underlying the poverty experience–pay disparity link. First, we estimate the relationship between *Poverty* and a mediating variable *M*, which is described below. Next, we assess how the predicted values of *M* (generated from the first stage) influence internal and external compensation gaps. This two-stage procedure is formally operationalized through the following equations:

$$M_{i,t} = \beta_0 + \beta_1 Poverty_{i,t-1} + \beta_2 Controls_{i,t-1} + \sum Industry + \sum Year + \mu_{i,t} \quad (2)$$

$$Intpay_Dis_{i,t}/Extpay_Dis_{i,t} = \beta_0 + \beta_1 M_{hat,i,t} + \beta_2 Controls_{i,t-1} + \sum Industry + \sum Year + \mu_{i,t} \quad (3)$$

In Eq. (2), *M* represents the mechanism variables, comprising *Managerisk*, *Negnews* and *Excessperks*; Eq. (3) shows the predicted values of *M*, with all the control variables held constant as in Model (1). Consistent with March and Shapira (1987), we operationalize *Managerisk* as the year-end ratio of risk investments (comprising trading financial assets, accounts receivable, held-to-maturity investments, available-for-sale financial assets and investment properties) to total assets. *Negnews* captures negative online media coverage, measured as the natural logarithm of total stock forum posts; executives from impoverished regions may avoid stimulating negative online media coverage due to reputational concerns. *Excessperks* represents the deviation between actual and projected normal executive perks. Actual executive perks are calculated as *administrative expenses* – (*total executive compensation* + *bad debt provisions* + *inventory impairments* + *annual intangible asset amortization*) – *executive non-monetary private benefits*.

5.1. Managerial risk preference as an underlying mechanism

Executives who have experienced material adversity in early life tend to exhibit heightened risk aversion. These leaders perceive large internal compensation gaps as risk signals indicating potential operational inefficiencies or declining competitiveness. Compensation inequities that provoke internal dissatisfaction undermine organizational stability, further reinforcing risk aversion among these executives (Long et al., 2020).

Table 14
Cross-sectional analysis: social responsibility expenditures.

	(1)	(2)	(3)	(4)
	Intpay_Dis _t		Extpay_Dis _t	
	Larger donation amounts	Smaller donation amounts	Larger donation amounts	Smaller donation amounts
<i>Poverty</i> _{t-1}	-0.240*** (-3.806)	-0.119 (-1.143)	-0.358*** (-4.576)	-0.218** (-1.974)
<i>Size</i> _{t-1}	0.354*** (11.897)	0.406*** (10.058)	0.475*** (9.053)	0.535*** (9.018)
<i>Lev</i> _{t-1}	-0.509*** (-5.235)	-0.492*** (-3.474)	-0.720*** (-5.106)	-0.682*** (-3.519)
<i>FirmAge</i> _{t-1}	0.008 (0.143)	0.100 (1.226)	0.051 (0.726)	0.143 (1.414)
<i>Growth</i> _{t-1}	0.032 (1.041)	0.008 (0.187)	0.032 (0.786)	0.049 (0.838)
<i>Dual</i> _{t-1}	0.130*** (3.231)	0.126** (2.230)	0.126* (1.830)	0.092 (1.138)
<i>Top1</i> _{t-1}	-0.009*** (-6.781)	-0.009*** (-4.261)	-0.012*** (-5.403)	-0.011*** (-3.420)
<i>Loss</i> _{t-1}	-0.172*** (-5.295)	-0.180*** (-3.318)	-0.190*** (-4.256)	-0.179*** (-2.630)
<i>Board</i> _{t-1}	0.217** (2.232)	0.086 (0.586)	0.346** (2.349)	0.154 (0.722)
<i>PB</i> _{t-1}	0.043*** (6.593)	0.050*** (5.189)	0.062*** (5.210)	0.068*** (4.952)
<i>INV</i> _{t-1}	0.201 (1.354)	-0.116 (-0.508)	0.149 (0.720)	-0.116 (-0.378)
<i>TMTAge</i> _{t-1}	-0.008 (-1.255)	-0.015 (-1.618)	-0.007 (-0.833)	-0.013 (-1.104)
<i>Gender</i> _{t-1}	0.029 (0.351)	0.097 (0.855)	0.069 (0.611)	0.129 (0.960)
<i>Constant</i>	-6.946*** (-10.398)	-7.682*** (-8.262)	-10.015*** (-8.003)	-10.912*** (-8.113)
<i>Coefficient difference</i>	0.121***		0.140**	
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	4904	2888	4904	2888
<i>Adj R</i> ²	0.357	0.340	0.261	0.250

T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1 %, 5 %, and 10 % significance, respectively.

Moreover, significant compensation gaps relative to industry benchmarks serve as salient indicators of under-performing leadership or deteriorating market positioning. Executives with childhood experiences of material scarcity often display strong positional insecurity, leading to cautious and risk-averse decision-making when confronted with pay disparities (Zhang et al., 2022). Xu and Ma (2022) further observe that executives from socioeconomically disadvantaged backgrounds often exhibit a strong normative commitment rooted in their early adversity, which motivates them to mitigate compensation-related risks and narrow pay disparities as these are crucial for restoring organizational equity.

We investigate the role of risk tolerance and present the results in Table 15. In column (1), the coefficient of *Poverty* is significant and negative, indicating that executives with poverty experience are more risk-averse. In columns (2) and (3), the estimated values of *Managerisk* (denoted as *Managerisk_hat*) exhibit positive and significant coefficients at the 1 % level, suggesting that lower risk tolerance drives these executives to actively narrow both internal and external pay disparities in response to perceived concerns regarding fairness.

Table 15
The Mechanisms test of managerial risk preference.

	(1) Managerisk _t	(2) Intpay_Dis _t	(3) Extpay_Dis _t
<i>Poverty</i> _{t-1}	-0.014** (-2.032)		
<i>Managerisk_hat</i>		15.468*** (2.985)	23.425*** (3.874)
<i>Size</i> _{t-1}	-0.009*** (-5.190)	0.510*** (8.298)	0.703*** (8.297)
<i>Lev</i> _{t-1}	0.006 (0.532)	-0.587*** (-5.561)	-0.842*** (-5.525)
<i>FirmAge</i> _{t-1}	0.003 (0.545)	-0.006 (-0.099)	0.015 (0.200)
<i>Growth</i> _{t-1}	-0.000 (-0.008)	0.022 (0.894)	0.034 (1.044)
<i>Dual</i> _{t-1}	0.012*** (2.854)	-0.056 (-0.747)	-0.166* (-1.690)
<i>TopI</i> _{t-1}	-0.000 (-0.308)	-0.009*** (-5.614)	-0.010*** (-4.663)
<i>Loss</i> _{t-1}	-0.007 (-1.576)	-0.064 (-1.362)	-0.019 (-0.320)
<i>Board</i> _{t-1}	-0.027*** (-2.934)	0.598*** (3.638)	0.927*** (4.206)
<i>PB</i> _{t-1}	0.000 (0.274)	0.044*** (6.880)	0.062*** (5.875)
<i>INV</i> _{t-1}	-0.032* (-1.842)	0.575*** (2.655)	0.797*** (2.832)
<i>TMTAge</i> _{t-1}	0.001 (0.903)	-0.020*** (-2.810)	-0.024** (-2.511)
<i>Gender</i> _{t-1}	-0.006 (-0.663)	0.145 (1.487)	0.229* (1.939)
<i>Constant</i>	0.311*** (7.383)	-12.075*** (-6.350)	-17.693*** (-7.092)
<i>Industry</i>	Yes	Yes	Yes
<i>Year</i>	Yes	Yes	Yes
<i>Observations</i>	7697	7697	7697
<i>Adj. R</i> ²	0.178	0.353	0.260

T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1 %, 5 %, and 10 % significance, respectively.

5.2. Excessive consumption as an underlying mechanism

Executives with poverty experience demonstrate a unique propensity to reduce perquisite consumption, thereby aligning shareholder interests with organizational welfare. This behavioral pattern reflects their stewardship-oriented leadership, which prioritizes long-term value creation over short-term material gains. Internally, their enhanced empathy toward employees' socioeconomic challenges drives resource reallocation from executive perquisites (e.g., luxury business trips and extravagant entertainment) to employee welfare programs. This redistribution demonstrates a commitment to fair resource allocation and restores perceptions of organizational equity among staff. We investigate this mechanism and present the results in Table 16.

Column (1) reveals a statistically significant negative relationship between *Poverty* and *Excessperks*, indicating that executives with poverty experience tend to curtail excessive perquisite consumption. Column (2) demonstrates that the predicted *Excessperks* (*Excessperks_hat*) exhibits a positive regression coefficient with *Intpay_Dis* that is significant at the 1 % level, indicating an inverse relationship between excessive perquisites among executives and staff pay. This result implies that executives with poverty experience consciously limit their perks as a strategic measure to reduce internal pay inequality.

Table 16
The Mechanisms tests of excessive consumption.

	(1) Excessperks _t	(2) Intpay_Dis _t
<i>Poverty</i> _{t-1}	-0.362** (-2.075)	
<i>Excessperks_hat</i>		0.503*** (2.582)
<i>Size</i> _{t-1}	-0.299*** (-6.441)	0.517*** (6.974)
<i>Lev</i> _{t-1}	-0.464* (-1.675)	-0.270** (-2.002)
<i>FirmAge</i> _{t-1}	-0.185 (-1.073)	0.150** (2.130)
<i>Growth</i> _{t-1}	0.041 (0.479)	-0.000 (-0.002)
<i>Dual</i> _{t-1}	-0.043 (-0.386)	0.130*** (3.151)
<i>TopI</i> _{t-1}	0.001 (0.306)	-0.010*** (-5.912)
<i>Loss</i> _{t-1}	0.150 (1.275)	-0.253*** (-5.747)
<i>Board</i> _{t-1}	0.021 (0.077)	0.176 (1.617)
<i>PB</i> _{t-1}	0.053** (2.523)	0.021* (1.757)
<i>INV</i> _{t-1}	-0.124 (-0.281)	0.139 (0.852)
<i>TMTAge</i> _{t-1}	0.022 (1.209)	-0.020*** (-2.737)
<i>Gender</i> _{t-1}	-0.119 (-0.458)	0.122 (1.190)
<i>Constant</i>	5.981*** (4.730)	-10.215*** (-6.756)
<i>Industry</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>Observations</i>	7199	7199
<i>Adj. R</i> ²	0.066	0.345

T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1 %, 5 %, and 10 % significance, respectively.

5.3. Negative news coverage as an underlying mechanism

Increasing corporate transparency has led to heightened public scrutiny of executives' compensation, with elevated pay levels increasingly being perceived as unfair (D'Mello et al., 2024). Consequently, modern executives face growing concerns over reputational damage and disciplinary costs due to negative media exposure. Chinese executives with origins in economically underdeveloped regions, such as Ren Zhengfei (CEO of Huawei, from Zhenning County, Guizhou), Yu Chengdong (CEO of Huawei's Automotive Unit, from Huoqiu County, Anhui) and Liu Teng (CEO of a fiber optics firm, from Qidong County, Hunan), receive considerable media attention for their active social engagement. After assuming leadership roles, these executives often undertake poverty alleviation and charitable and rural development initiatives and provide educational support for disadvantaged students. Their philanthropic engagement creates a self-reinforcing cycle wherein increased media coverage enhances public approval of both the leaders and their firms. Consequently, these executives become more sensitive to compensation-related risks and take active measures to mitigate regulatory and reputational threats to safeguard their hard-earned reputational capital.

Table 17
The Mechanisms test of negative news coverage.

	(1) Negnews _t	(2) Extpay_Dis _t
<i>Poverty_{t-1}</i>	−0.266*** (−3.160)	
<i>Negnews_hat</i>		1.173*** (3.846)
<i>Size_{t-1}</i>	0.468*** (13.999)	−0.054 (−0.412)
<i>Lev_{t-1}</i>	−0.695*** (−4.366)	0.118 (0.496)
<i>FirmAge_{t-1}</i>	−0.126 (−1.466)	0.232*** (2.764)
<i>Growth_{t-1}</i>	−0.049 (−1.136)	0.092*** (2.646)
<i>Dual_{t-1}</i>	0.076 (1.467)	0.023 (0.338)
<i>Top1_{t-1}</i>	−0.008*** (−4.386)	−0.001 (−0.392)
<i>Loss_{t-1}</i>	0.342*** (5.546)	−0.590*** (−5.224)
<i>Board_{t-1}</i>	0.163 (1.279)	0.087 (0.514)
<i>PB_{t-1}</i>	0.085*** (10.543)	−0.037 (−1.396)
<i>INV_{t-1}</i>	−0.095 (−0.433)	0.172 (0.787)
<i>TMTAge_{t-1}</i>	−0.018** (−2.120)	0.012 (1.213)
<i>Gender_{t-1}</i>	0.286** (2.118)	−0.240* (−1.719)
<i>Constant</i>	−7.847*** (−9.532)	−1.115 (−0.484)
<i>Industry</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>Observations</i>	7793	7793
<i>Adj.R²</i>	0.215	0.259

Our methodology involves systematic data curation of executive-related stock forum discourse from the CNRDS and GUBA¹ databases. This process includes three stages: (1) eliminating off-topic content using keyword filtering, (2) applying natural language processing (NLP) techniques for sentiment classification, and (3) conducting rigorous manual validation of ambiguous posts. We operationalize *Negnews* by log-transforming the raw count of negative-toned executive forum posts (after adding 1 to handle zero values). T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1 %, 5 %, and 10 % significance, respectively.

¹ The GUBA database (comprising online discussions about stocks of Chinese listed companies) is a specialized financial text database. It offers unique advantages through its comprehensive coverage of investor interactions, enabling real-time analysis of sentiment dynamics regarding both intra-day and after-hours market events. This capability facilitates the examination of how sentiment-driven market microstructure effects propagate to equity prices. Its timestamped records allow precise tracking of negative sentiment surges during critical corporate events, providing superior explanatory power compared with traditional media indices.

Executives with poverty experience avoid excessive external pay disparities not out of altruism but to avoid negative publicity and reputational harm. By keeping their compensation close to industry medians, they mitigate social comparisons stemming from deviations from peer firms (Kuhnen and Niessen, 2012), while also minimizing regulatory attention, strengthening organizational legitimacy and reducing public skepticism regarding governance quality. Highlighting this behavioral pattern, Mas (2017) finds that executives with greater transparency and visibility in online forums not only experience favorable public perceptions of their

pay but also curb compensation disparities. As argued by Kuhnen and Niessen (2012), we contend that negative media coverage (proxied by the volume of social media posts) reflects the extent of public discourse regarding top executives' pay. We investigate this issue and present the results in Table 17.

As shown in column (1), the coefficient of *Poverty* is significant and negative at the 1 % level, indicating that executives with early-life material hardship are associated with lower negative news coverage. This result suggests that these executives actively manage organizational reputation to reduce public criticism. In column (2), the variable *Negnews_hat* exhibits a positive and statistically significant coefficient (at the 1 % level), confirming that greater media criticism is associated with larger external (executive-to-peer) pay disparities. Reduced negative media exposure creates a virtuous cycle: by tempering public criticism, executives with poverty experience gain greater latitude to narrow compensation gaps.

6. Additional analysis

6.1. Executives' poverty experience, excessive compensation and average employee compensation

Jensen and Murphy (2010) argue that "how to pay is more important than how much to pay." When individual contributions are poorly aligned with performance metrics, executive compensation may become inflated. Empirical evidence from our analysis suggests that executives' poverty experience helps narrow pay disparities between the top management and employees. However, the mechanism behind this phenomenon remains unclear: does it result from reduced executive pay, increased employee remuneration or a combination of both? Considering that compensation budgets are often constrained, excessive executive pay may create a zero-sum dynamic that compromises employee welfare (Kraus and Rubin, 2010).

Motivated by the increasing public scrutiny of extreme executive compensation, we propose that executives with poverty experience may emphasize equity by restraining excessive pay. This view is consistent with findings that these executives exhibit higher levels of socially responsible behavior, potentially mitigating employee perceptions of unfairness (D'Mello et al., 2024). Following Core et al. (2008), we measure excessive compensation using both residuals from predicted compensation models and absolute pay levels. Accordingly, we specify Eq. (4) as follows:

$$\begin{aligned} \text{Compens}_{i,t} = & \beta_0 + \beta_1 \text{Size}_{i,t-1} + \beta_2 \text{Lev}_{i,t} + \beta_3 \text{Roa}_{i,t} + \beta_4 \text{Roa}_{i,t-1} + \beta_5 \text{Ia}_{i,t} + \beta_6 \text{Board}_{i,t} + \beta_7 \text{Indep}_{i,t} \\ & + \beta_8 \text{Dual}_{i,t} + \beta_9 \text{Top1}_{i,t} + \Sigma \text{Industry} + \Sigma \text{Year} + \varepsilon_{i,t} \end{aligned} \quad (4)$$

where *Compens* denotes the natural logarithm of the average compensation of executives; *Roa* represents the return on assets, measured as net profit divided by the average of beginning-of-period and end-of-period owners' equity; *Ia* is the ratio of intangible assets to total assets; and other variables are as defined previously. Excessive compensation is defined as the residual ε obtained from estimating Model (4), which captures unexplained compensation deviations after controlling for observable factors.

The results are reported in Table 18. Column (1) shows a significant and negative coefficient of *Poverty*, indicating that executives with poverty experience systematically receive lower excessive compensation. Column (2) reveals no statistically significant relationship between *Poverty* and employee pay (*Staffpay*). These results suggest that the poverty experience-driven reduction in pay disparities operates mainly through restraining executive pay rather than raising employee compensation.

6.2. Executives' poverty experience, peer comparison and external pay disparity

When executives' compensation exceeds industry averages, early-life poverty experience may heighten their sensitivity to social comparisons (Sandberg and Andersson, 2022). Drawing on behavioral agency theory, we theorize that executives from impoverished backgrounds place greater emphasis on fairness in pay and view excessive compensation as "unearned gains" that trigger aversion to loss. This perception motivates them to reduce unnecessary perks to restore fairness and strategically curb managerial agency behaviors (Malmendier et al., 2011). Conversely, when pay falls below industry benchmarks, mental accounting alters their evaluation of their compensation. These executives are more likely to perceive their salary as meeting basic needs rather

Table 18

Executives' poverty experience, excessive compensation and average employee compensation.

	(1) Overpay _t	(2) Staffpay _t
<i>Poverty</i> _{t-1}	-0.147** (-2.116)	-0.016 (-0.356)
<i>Size</i> _{t-1}	0.039** (2.491)	-0.200*** (-11.612)
<i>Lev</i> _{t-1}	-0.109 (-1.323)	-0.484 (-1.634)
<i>FirmAge</i> _{t-1}	0.005 (0.110)	-0.007 (-0.093)
<i>Growth</i> _{t-1}	0.017 (0.976)	0.195 (0.865)
<i>Dual</i> _{t-1}	0.059** (1.980)	0.061 (0.621)
<i>TopI</i> _{t-1}	-0.003*** (-2.688)	-0.000 (-0.093)
<i>Loss</i> _{t-1}	0.025 (0.910)	0.232 (1.495)
<i>Board</i> _{t-1}	0.159** (2.280)	-0.137 (-1.253)
<i>PB</i> _{t-1}	0.015*** (3.646)	0.025*** (2.979)
<i>INV</i> _{t-1}	0.048 (0.394)	-1.228 (-0.967)
<i>TMTAge</i> _{t-1}	-0.000 (-0.062)	-0.007 (-0.348)
<i>Gender</i> _{t-1}	0.001 (0.012)	-0.031 (-0.573)
<i>Constant</i>	-1.114*** (-2.776)	5.761*** (4.037)
<i>Industry</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>Observations</i>	7793	7793
<i>Adj.R</i> ²	0.023	0.020

This table shows relations among executives' poverty experience, excess compensation, and average employee compensation. Results further confirm that poverty experiences manifest their inhibitory effect on wage gaps by reducing excessive compensation rather than increasing employee compensation. T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1%, 5%, and 10% significance, respectively.

than themselves as being disadvantaged compared with peers. Lower pay is framed as "fair compensation for work" rather than inequitable treatment, reducing their inclination to further decrease their own compensation. This demonstrates that the influence of poverty experience on compensation decisions varies significantly depending on whether the compensation is above or below industry norms (Mueller et al., 2017).

We examine this issue and present the results in Table 19. The regression results on the relationship between executives' poverty experience and peer comparison-based pay disparities indicate that the coefficient of *Poverty* is significant and negative in column (1) but nonsignificant in column (2). These findings suggest that the effect of poverty experience on restraining external pay disparities is more pronounced when executives' compensation exceeds that of their industry peers in the same year.

Table 19
Executives' poverty experience, peer comparison and pay disparities.

	(1)	(2)
	Extpay_Dis _t	
	Executives' pay > peer pay	Executives' pay \leq peer pay
<i>Poverty</i> _{t-1}	-0.346*** (-4.045)	0.006 (0.316)
<i>Size</i> _{t-1}	0.488*** (9.502)	0.004 (1.067)
<i>Lev</i> _{t-1}	-0.609*** (-4.143)	-0.009 (-0.512)
<i>FirmAge</i> _{t-1}	0.091 (1.176)	-0.011 (-0.804)
<i>Growth</i> _{t-1}	0.033 (0.961)	0.006 (1.011)
<i>Dual</i> _{t-1}	0.099 (1.451)	-0.007 (-1.063)
<i>TopI</i> _{t-1}	-0.011*** (-4.876)	-0.000 (-0.946)
<i>Loss</i> _{t-1}	-0.177*** (-3.979)	-0.011* (-1.825)
<i>Board</i> _{t-1}	0.273* (1.646)	0.004 (0.206)
<i>PB</i> _{t-1}	0.068*** (6.004)	-0.002*** (-2.904)
<i>INV</i> _{t-1}	0.023 (0.094)	-0.027 (-1.047)
<i>TMTAge</i> _{t-1}	-0.009 (-1.036)	0.002 (1.491)
<i>Gender</i> _{t-1}	0.092 (0.777)	-0.001 (-0.077)
<i>Constant</i>	-10.149*** (-8.501)	-0.194* (-1.720)
<i>Industry</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>Observations</i>	7128	665
<i>Adj.R</i> ²	0.258	0.219

T-statistics are reported in parentheses, and robust standard errors are clustered at the firm level. ***, **, and * indicate 1 %, 5 %, and 10 % significance, respectively.

7. Conclusion

As the world's most populous nation, China has historically prioritized equity over absolute equality. Our study investigates how executives' childhood poverty experience influences both internal (executive–employee) and external (executive–peer) pay disparities. Although the study's empirical setting is China, the findings hold broader relevance for economies experiencing persistent wage inequalities.

Our results indicate that executives with impoverished backgrounds actively reduce both internal and external pay gaps. Those who have experienced childhood poverty show a stronger tendency to narrow compensation differentials with both employees and industry peers. Consistent with behavioral imprinting theory, these executives exhibit higher risk aversion and adopt more prudent compensation strategies. Notably, when they reach senior positions, their philanthropic engagement is associated with reduced negative media coverage and fewer excessive perks, which reinforce their reputational incentives for ensuring equitable pay structures. These findings are robust to endogeneity concerns, addressed through instrumental variable estimation.

The poverty experience-induced reduction in pay disparities is more pronounced in SOEs, firms in eastern regions, labor-intensive industries, among executives with advanced degrees and in firms with larger donations. Further analysis reveals no significant association between top executives' poverty experience and average employee compensation levels. However, the effect of poverty experience on narrowing external pay gaps is stronger when executive pay exceeds industry benchmarks. Additionally, executives with poverty experience pursue pay equity through a dual pathway: internal resource reallocation and external reputation management.

Our study offers valuable insights for regulators and firms seeking to promote fairer executive compensation practices. First, governments and corporate boards should emphasize diversity in the recruitment and promotion of executives, especially in SOEs, labor-intensive industries and regions with high inequality. Our findings indicate that executives with childhood poverty experience exhibit a stronger commitment to equitable compensation than their peers. Policy measures to promote equitable compensation may include targeted quotas, mentorship programs and professional development initiatives to improve the representation of candidates from more socioeconomically disadvantaged backgrounds in senior management, as these individuals may demonstrate greater motivation to narrow pay gaps and advance equity.

Second, regulators should enhance disclosure requirements regarding executive–employee and executive–peer pay ratios, particularly in industries where compensation exceeds benchmark levels. Public disclosure requirements could capitalize on executives' sensitivity to media scrutiny, as reflected in the risk-averse compensation strategies of poverty-exposed leaders. Transparency frameworks should also oblige firms to justify pay disparities through clear links to performance-based compensation structures.

Third, policymakers could introduce tax incentives or subsidies for firms that align corporate social responsibility expenditures with measurable reductions in internal and external pay gaps. Linking donation levels to equity metrics may motivate more firms to adopt socially responsible compensation structures, irrespective of their executives' backgrounds (Choi et al., 2023). Such approaches are essential for balancing the interests of employees and executives while promoting fairness and sustainable corporate development.

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.

Appendix A. Variable definitions

Variable	Definition	Source
<i>Intpay_Dis</i>	The difference between the average salaries of the top executives (including chairpersons, CEOs, and actual controllers) and the average salary of employees; the values is normalized by dividing by 1,000,000.	Author calculation
<i>Extpay_Dis</i>	The difference between top executives (including chairpersons, CEOs, and actual controllers) and the average salary of top executives in the same industry, the values is normalized by dividing by 1,000,000.	Author calculation
<i>Poverty</i>	Compared with the list of national poverty-stricken counties in 2012, if any top executives within the team (including chairpersons, CEOs, and actual controllers) was born in a poverty-stricken county, the top executives' poverty experience is considered present, and “ <i>Poverty</i> ” takes the value of 1; otherwise, it takes 0.	Hand-Collection, IPO prospectuses, CSMAR, CNRDS, CNDD

Appendix A (continued)

Variable	Definition	Source
<i>Size</i>	Natural logarithm of total assets	CSMAR
<i>Lev</i>	Total liabilities divided by total assets	CSMAR
<i>FirmAge</i>	Natural logarithm of the current year minus the year the company was established, plus one	CSMAR
<i>Growth</i>	Increase in operating income for the current year divided by the operating income for the previous year	CSMAR
<i>Dual</i>	Takes the value of 1 if the chairperson and CEO are the same person; otherwise, it takes 0	CSMAR
<i>Top1</i>	Number of shares held by the top shareholder divided by total shares	CSMAR
<i>Loss</i>	Takes the value of 1 if the net profit for the year is less than 0; otherwise, it takes 0	CSMAR
<i>Board</i>	Natural logarithm of the number of board members	CSMAR
<i>PB</i>	Price per share divided by book value per share	CSMAR
<i>INV</i>	Net inventory at the end of the year divided by total assets at the end of the year	CSMAR
<i>TMTAge</i>	Average age of management team members	CSMAR
<i>Gender</i>	Takes the value of 1 if the executive is female; otherwise, it takes 0	CSMAR

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Contents lists available at ScienceDirect

China Journal of Accounting Research

journal homepage: www.elsevier.com/locate/cjar



Fund cliques and firms' information environment: information efficiency or noise trading?



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ARTICLE INFO

Article history:

Received 23 October 2023

Accepted 1 December 2025

Available online 5 January 2026

JEL classification:

G12

G23

G30

Keywords:

Fund clique

Stock price synchronicity

Firm information environment

ABSTRACT

Fund cliques (i.e., mutual funds holding the same stocks) are a common feature of global financial markets, raising the question: How do fund cliques shape firms' information environment? Do they improve information efficiency or amplify noise trading? Using a sample of Chinese A-share listed companies from 2004 to 2020, we explore the impact of fund cliques on firms' information environment (measured by stock price synchronicity). Research has found that the increase in the degree of fund clique significantly reduces stock price synchronicity. Our evidence supports the noise trading channel, showing that fund cliques amplify noise trading by reducing the marginal returns of private information acquisition or distorting price signals. Using the unique characteristics of the Chinese market, our paper enriches research on stock price synchronicity and institutional investor behavior, and provides references for emerging capital markets to optimize institutional investor supervision and improve firms' information environment.

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1. Introduction

The term "fund clique" refers to the practice of different fund managers concentrating their holdings on the same stocks over the same period, thus forming a network of fund groups. The objective drivers of fund cliques stem from the complex social connections inherent in fund managers: they exchange private information

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through direct communication (Pool et al., 2015; Shen et al., 2016). The subjective drivers stem from the pressure of short-term performance rankings and reputation anxiety, leading fund managers to imitate the investment decisions of star managers to attract more capital inflows (Liu and Su, 2016; Feng et al., 2025). Regarding their economic consequences, the literature suggests that fund cliques have various effects, including improving information efficiency, influencing corporate governance mechanisms and fostering irrational trading (Crane et al., 2019; Crawford et al., 2017). However, there is no consensus on the relationship between fund cliques and fund manager performance (Ozsoylev et al., 2014; Luo et al., 2020).

In studies on the economic consequences of fund cliques, their impact on the information environment of listed companies remains to be clarified: Can fund cliques, leveraging their capital and information advantages, improve information disclosure and optimize the information environment of listed companies? Or do they send aggressive signals to the market, fostering noise trading and worsening the information environment of listed companies?

Some scholars use stock price synchronicity metrics to measure firms' information environment (Kelly, 2014; Wang et al., 2014; Li and Wang, 2016). This metric has two properties: it incorporates information efficiency, reflecting firm-specific information, and noise trading, reflecting investor irrationality. Two competing hypotheses exist: the information efficiency hypothesis posits that investors rationally incorporate firm-specific information into stock prices through arbitrage, thereby reducing stock price synchronicity (Gul et al., 2010; Tang et al., 2011); in contrast, the noise trading hypothesis suggests that increased noise trading, due to limitations in individual investors' ability to discern and analyze firm-specific information, reduces stock price synchronicity (West, 1988; Kumar and Lee, 2006). To accurately identify the impact of fund cliques on the information environment of listed companies, we deconstruct fund cliques from the dual perspectives of information efficiency and noise trading, exploring how interactions between fund holdings influence companies' stock price synchronicity.

There are significant differences in the development level and operating characteristics of capital markets in emerging and developed countries, which makes understanding the phenomenon of fund cliques in domestic and emerging capital markets more practical. Take the example of the Chinese and American markets.

First, capital concentration is higher in the US capital market than in the Chinese capital market, and the asset management industry exhibits a pronounced concentration of capital, with a small number of large institutions controlling most of the market capital flows. In contrast, individual investors represent a higher proportion of all investors in the Chinese capital market, and their ability to access and analyze information is limited, leading to a greater impact of noise trading on the information environment of listed companies. Furthermore, the high degree of equity concentration in Chinese listed companies makes it less likely that a single fund will exert regulatory authority. This may encourage funds to form networks to increase their influence on corporate decision-making (Feng et al., 2025).

Second, leading US asset management institutions exhibit significant divergences in investment styles, often relying on different strategies to establish their market positioning. In contrast, the Chinese fund industry faces prominent homogeneous competition, with strategy convergence being prevalent. From a market perspective, with increasing concentration, passive investment products (such as index funds and ETFs) in the US have absorbed the vast majority of capital flows, while the domestic market remains dominated by active investment, with mutual funds playing a key role. This difference has two implications: (1) the high frequency of trading in Chinese mutual funds makes fund flows more influential on investment decisions, making fund holdings and group-buying more likely to trigger extreme price fluctuations, thereby affecting stock price synchronicity (Liu et al., 2024). (2) Chinese investors rely more heavily on fund managers' research capabilities and investment decisions, and investor protection in emerging markets is relatively inadequate, making the economic consequences of fund group-buying more pronounced for investors (Feng et al., 2025).

The above differences constitute an important background for the frequent occurrence of fund cliques in the domestic capital market and highlight the importance of studying the relationship between fund cliques and the information environment of listed companies in China for the development of capital markets in emerging countries.

In addition to the current state of market development, China's recent strengthening of regulatory oversight of firms' information environment provides a unique institutional context for this study (Feng et al., 2025). According to statistics, in 2023, 32 listed companies were investigated by the China Securities

Regulatory Commission (CSRC) for financial fraud. Typical cases, such as Kangmei Pharmaceutical, Zhangzi Island and Furen Pharmaceutical, have severely infringed on the rights and interests of minority shareholders, disrupted capital market order and caused adverse social impacts.¹ In response, regulators have continued to strengthen governance. On 18 March 2021, the CSRC issued the “Measures for the Administration of Information Disclosure of Listed Companies” to strengthen the development of firms’ information environment; the Shanghai and Shenzhen stock exchanges simultaneously updated their information disclosure regulatory guidelines to optimize the information environment from a regulatory perspective; and in April 2022, the CSRC issued the “Opinions on Accelerating the High-Quality Development of the Public Fund Industry,” proposing to focus on improving core review capabilities for investment studies and reversing the development model that relies too heavily on “star fund managers.”

This paper uses as a sample non-financial listed companies in the Chinese capital market from 2004 to 2020. Based on whether two funds hold a significant number of shares in a listed company, a network of connected funds is established and fund groups are extracted using the Louvain algorithm to explore the impact of fund cliques on firms’ stock price synchronicity. The results reveal that (1) an increase in the proportion of fund group holdings significantly reduces stock price synchronicity; (2) the possible mechanism by which fund cliques affect stock price synchronicity is to weaken the quality of information disclosure and reduce investors’ information capabilities; and (3) when economic policy uncertainty and investor sentiment are high, fund cliques have a more pronounced inhibitory effect on stock price synchronicity. These research conclusions are robust.

Our paper makes the following contributions. First, it enriches research on stock price synchronicity by leveraging the perspective of social networks. Research on stock price synchronicity primarily explores the impact of factors such as the institutional environment, analyst behavior and the quality of accounting information on stock price synchronicity (You et al., 2006; Zhu et al., 2007; Hutton et al., 2009), paying less attention to the behavior of institutional investors. We use the Louvain algorithm to extract the clique behavior of fund managers during their active stock selection process and explore the impact of this behavior on stock price synchronicity from the perspectives of information efficiency and noise trading. Given that the formation of fund cliques is deeply linked to the underlying environment and institutional conditions of the capital market, our findings have important implications not only for the domestic capital market but also for international investment markets, particularly in emerging economies.

Second, this paper extends research on institutional investor cliques from the perspective of firms’ information environment. This line of research primarily explores the impact of cliques on capital market stability, by analyzing participation in corporate governance (Crane et al., 2019; Wu et al., 2019; Guo et al., 2020), paying less attention to the potential damage of institutional investor behavior on firms’ information environment. From the perspective of firms’ information environment, we explore the possible mechanisms by which fund cliques influence stock price synchronicity. On the one hand, cooperation and sharing of advances and setbacks among fund group members can weaken the governance effects of “voting with their feet” and “exit threats,” reduce the quality of firms’ information disclosure and hinder the incorporation of idiosyncratic information into stock prices, thus leading to an increase in stock price synchronicity. On the other hand, fund cliques can be seen as a “favorable” signal for grouped stocks, fostering irrational investor sentiment, weakening investors’ ability to make investment decisions based on company fundamentals and promoting noise trading in the stock market, thus leading to a decrease in stock price synchronicity.

2. Research hypothesis

2.1. Causes of fund cliques

Fund cliques refer to the practice of fund managers selecting and holding the same stocks over a specific period of time, forming a network of fund managers through these shared holdings. Fund cliques exist both within and outside fund companies. Yu et al. (2015) find that fund companies and their affiliated funds in the

¹ Source: The Beijing News, <https://baijiahao.baidu.com/s?id=1776013060574875025&wfr=spider&for=pc>.

Chinese capital market all heavily invest in “hot” and “clustered” stocks, failing to demonstrate independent stock selection and professional investment capabilities. Pareek (2012) finds that even after controlling for the overall trading behavior of departments, mutual funds still trade with other funds in their network, and the investment behavior of closely connected investors is significantly positively correlated (Colla and Mele, 2010).

Why do funds form groups?

From an objective perspective, fund managers communicate directly and share private information. Pool et al. (2015) find that shared ownership is significantly correlated with direct communication and social interaction among investors, and that fund managers tend to communicate with managers who hold the same stocks, trusting private information shared between them more than public information (Xiao et al., 2012). Furthermore, fund managers naturally have complex social connections. Pool et al. (2015) and Shen et al. (2016) find that geographical and academic connections, such as alumni connections, residential distance and ethnic background, significantly influence fund managers’ behavioral decisions, and that socially connected fund managers make more homogeneous transactions.

In addition, the objective reasons for the formation of fund cliques may include the following. (1) As it is not uncommon for fund managers and their teams to manage multiple funds at the same time, the energy allocated to stock selection for each fund is limited; (2) fund managers may have the same private sources of information, such as sharing the same research team within the company, and thus be influenced by the research reports of the same analysts; (3) the training systems of fund managers are converging, which may lead them to have the same methods and preferences for stock selection; and (4) the market has limited high-quality targets to choose from, forcing fund managers to make the same choices.

From a subjective perspective, fund managers often face severe short-term performance pressure and turnover risk. Therefore, they may choose to emulate the investment decisions of star fund managers due to performance pressure or to attract capital flows. Liu and Su (2016) find that capital flows between funds in the same network have significant spillover effects and that network-driven capital flows are significantly positively correlated with excess fund returns.

Unlike herd behavior, fund cliques aim to capture the network of relationships and information exchanges between fund managers. In practice, stock prices are often influenced by a variety of factors, such as fundamentals, technicals and liquidity, with the weight of each factor varying over time. Traditional value investing posits that stock prices are primarily influenced by fundamentals, with investment returns derived from differences in market perception. Herd behavior and fund cliques correspond to technical and liquidity factors, respectively. Herd behavior emphasizes imitation and following among institutional investors. This imitation and following is primarily based on technical analysis, observing the trading strategies of other institutional investors in the market to adjust their own trading decisions, resulting in identical or similar capital flows. In contrast, fund cliques focus on analyzing the network of relationships and information exchanges between fund managers, with imitation and following being only one of the contributing factors. This network fosters the convergence of investment decisions among fund managers within the same group, manifesting as identical or similar holdings.

2.2. *The economic consequences of fund cliques*

Based on the above discussion, fund cliques may lead to the following economic consequences. First, regarding their impact on investment behavior, the literature suggests that fund cliques can improve information efficiency, affect corporate governance and promote irrational trading. (1) Crawford et al. (2017) propose that investors share information on the Internet mainly for arbitrage purposes, which helps to speed up the price discovery process and is less susceptible to the influence of noise traders. Shen et al. (2016) find that homogeneous investment behavior within the “small circle” of fund managers formed through alumni relationships improves performance, and that the mechanism relies on the sharing of private information within the relationship network. Ali and Miller (2013) and Pareek (2012) show that the faster the speed of information dissemination between members of a highly concentrated group, the higher the efficiency of cooperation. (2) Crane et al. (2019) find that cliques can both strengthen governance by enhancing the collective voice and worsen governance by weakening the “exit threat.” On the one hand, individual investors with a low shareholding ratio can form a group to make a “collective voice,” that is, through cooperation and the same

investment decisions, they can better supervise corporate governance (Crane et al., 2019); on the other hand, Crane et al. (2019) and Wu et al. (2019) find that cooperation between institutional investors reduces the degree of competition between individuals, that is, “joint entry and exit” produce a “bundling effect,” delaying the incorporation of negative information about the company into its stock price, thus weakening the governance effect of “exit threats.” (3) Concentrated information networks lead to greater volatility of individual stocks in the cross-section (Pareek, 2012). For example, when asset management institutions adopt joint investment, their suppression of underinvestment and their promotion of overinvestment are stronger than when they invest independently (Cai and He, 2015).

However, research has yet to reach a consensus on the impact of information on fund manager performance. On the one hand, assuming that each portfolio is constructed independently, Cohen et al. (2008) find that the greater the similarity between portfolios of high-quality funds, the better their future performance will be. Fund managers invest more in heavily weighted stocks within their network, which also outperform other holdings. Furthermore, investors at the center of the network can trade earlier and achieve higher returns than those on the periphery (Ozsoylev et al., 2014). On the other hand, Luo et al. (2020) find that funds with lower levels of information use within fund networks perform significantly better than their counterparts. This excess return is primarily due to fund managers’ superior stock selection skills. The degree of information use within a network directly reflects the amount of private information contained within the fund. Furthermore, some studies show that cliques have a limited impact on fund performance, meaning that group stock selection can only improve the performance of fund managers with weak stock selection skills and poor historical performance to a certain extent (Yu et al., 2015).

2.3. Factors affecting stock price synchronicity

The stock price synchronicity metric, α , used to measure a company’s information environment, is derived from the goodness of fit of the CAPM model. There are currently two main theoretical approaches in the field of stock price synchronicity: the information efficiency hypothesis and the noise trading hypothesis. Information transmission in the securities market can be divided into three stages: disclosure, dissemination and utilization. The information efficiency hypothesis focuses on the disclosure and dissemination stages, explaining stock price synchronicity using the coefficients of the CAPM model, that is, abnormal returns derived from firm-specific information. The noise trading hypothesis focuses on the utilization stage, arguing that market noise influences the disturbance term of the CAPM model, thus affecting stock price synchronicity.

2.3.1. Information efficiency hypothesis

In the context of corporate governance, “exit threats” and “voting with one’s feet” are two typical patterns of investor behavior that influence corporate decision-making. Exit threats refer to the use of stock sales by non-major shareholders as leverage to pressure management into improving governance; voting with one’s feet occurs when investors directly express negative opinions about management’s governance capabilities through actual share reductions. The bundling effects within investor networks further shape group behavior: interconnected investor groups form a coordinated decision-making mechanism, and individual investment behavior often conforms to group strategies, leading to significant convergence of investments. For example, institutional investors often exhibit a “joint entry and exit” trading pattern. This group behavior can weaken the governance effectiveness of individual “exit threats”; when sales behavior becomes consistent, the threat signal from individual institutions is diluted by the group’s actions (Wu et al., 2019). More fundamentally, the phenomenon of cliques within investor networks can foster the risks of collusion. Guo et al. (2020) find that the higher the degree of grouping, the lower the efficiency of information transmission between investors and management. This manifests in the following ways: information asymmetry increases, making it difficult for management to accurately identify true governance requirements, while inefficient investment problems worsen, as group decision-making biases may obscure the true value of projects. From the perspective of market signal transmission, Lin et al. (2012) find that the behavior of investor groups reduces the information content of stock prices: future earnings information is less reflected in stock prices, while the correlation between stock prices and overall market fluctuations increases. Stock price synchronicity then increases significantly, which means that the explanatory power of information specific to individual stocks decreases and that the

market's homogeneous fluctuations become more prominent. These studies reveal the dual effect of investor networks on corporate governance: they can strengthen supervision through collective action, but they can also weaken governance efficiency due to group irrationality. Their mechanism of action still needs to be further explored in the context of specific market environments.

Therefore, according to the information efficiency hypothesis, the possible transmission mechanism by which fund cliques lead to synchronized changes in company stock prices is as follows: to gain recognition from capital flows, fund cliques adopt similar investment strategies, "advancing and retreating together," which reduces the intensity of competition among funds within the group, can weaken governance effects such as "voting with their feet" and "exit threats," delays the integration of negative information into stock prices, worsens the quality of firms' information disclosure, reduces information efficiency and thus improves the synchronicity of company stock prices.

Based on the above analysis, we hypothesize the following:

Ha: When other conditions remain unchanged, the higher the proportion of shares held by fund cliques, the stronger the synchronicity of company stock prices.

2.3.2. Noise trading hypothesis

The noise trading hypothesis posits that investors' limited ability to identify and analyze firm-specific information promotes noise trading in the market, thereby reducing stock price synchronicity (Zhang and Wang, 2024). West (1988) argues that the R^2 of the CAPM model primarily reflects noise, bubbles, investor biases and irrational behavior. DeLong et al. (1989) demonstrates that high stock price volatility is primarily driven by market noise. Kumar and Lee (2006) find that retail investors' trading behavior is highly imitative, contagious and driven by emotions, such that retail investors are likely to become noise traders. Currently, academics generally argue that due to the immaturity of the Chinese capital market, the large proportion of retail investors and the high level of market speculation (Zhang and Wang, 2024), stock price synchronicity primarily reflects market noise unrelated to firm value. Lin et al. (2012) argue that the R^2 of the Chinese stock market primarily reflects market noise rather than information efficiency and that stock price synchronicity should not be simply viewed as a measure of firm-level information. Wang et al. (2009) suggest that Chinese companies have less idiosyncratic information and more market noise than other companies and that stock price fluctuations are primarily driven by noise rather than information. Jiang and Kim (2015) argue that Chinese listed companies have a high degree of equity concentration, a low proportion of institutional investors and are primarily short-term speculators. Compared with Western capital markets, China's market information efficiency and stock research levels are low, making it easier for herd behavior and fund cliques to distort market price signals and worsen the information environment (Cao et al., 2015; Dai et al., 2015).

Therefore, according to the noise trading hypothesis, the possible transmission mechanism by which fund cliques lead to synchronized changes in company stock prices is as follows. On the one hand, due to the relatively immature and noisy nature of the capital market, investors' independent stock selection ability is limited. Their emotions may be more easily swayed by phenomena such as market overheating, leading them to blindly follow fund managers in selecting "group stocks." On the other hand, fund cliques may promote irrational trading, driving overinvestment or discouraging underinvestment, thereby increasing stock price volatility and amplifying trading noise. Both factors promote noise trading in the market, thus reducing the synchronicity of company stock prices.

Based on the above analysis, we propose the following opposing hypothesis:

Hb: When other conditions remain unchanged, the higher the proportion of shares held by fund cliques, the lower the synchronicity of company stock prices.

3. Research design

3.1. Data source and sample selection

The research sample for this paper consists of Chinese A-share companies listed from 2004 to 2020, excluding those in the financial industry.² The CSMAR database provides detailed data on annual fund holdings,³ company financials, stock prices and other data, while the CNRDS database provides investors' online search indices. Following previous research, all continuous variables are winsorized with a margin of 1 % to mitigate the influence of outliers on the results. This process results in 34,311 data points collected from 3536 A-share listed companies from 2004 to 2020.

3.2. Variable definition

3.2.1. Measurement of group holdings of fund cliques

Following Crane et al. (2019), Pareek (2012) and Wu et al. (2019), we use two indicators to characterize the group shareholding of fund cliques (*CliqueOwn*): the fund clique group shareholding ratio of stocks (*CliqueOwnership*) and the Herfindahl index of the fund clique group shareholding ratio (*Herfindahl*).

The specific construction method is as follows:

(1) Construction of fund network connections: If, at the end of the year, among all holdings of funds i and j , there are n companies whose shares each account for more than 5 % of the net asset value of the funds, then the connection between these two funds is established as $X_{i,j} = n$ (Pareek, 2012; Xiao et al., 2012).⁴ Next, calculate the connections between $X_{i,j}$ and all N funds and construct an $N \times N$ row adjacency matrix, called M.

(2) Extraction of fund groups: Blondel et al. (2008) and other scholars designed and developed the Louvain community discovery algorithm. This algorithm can determine the degree of connectivity between funds based on their holdings and extract specific fund groups from those funds. The adjacency matrix M is introduced into the Louvain algorithm to obtain the fund group extraction results.

(3) Calculate the shareholding ratio of each fund group, where $\lambda_{i,j,t}$ is the ratio of the shares of company i held by fund j at the end of year t to the total number of outstanding shares of company i ; $IfClique_{j,t}$ is a dummy variable indicating whether fund j belongs to a certain fund group.⁵

$$CliqueOwnership_{i,t} = \sum_{j=1}^N \lambda_{i,j,t} \times IfClique_{j,t} \quad (1)$$

where *CliqueOwnership_{i,t}* represents the proportion of company i held by the funds in the group in year t , and the Herfindahl index *Herfindahl_{i,t}* represents the shareholding ratio of the fund group, which is equal to the sum of the squares of the shareholding ratios of all members of each fund group.

3.2.2. Stock price synchronicity

Following previous studies, we use Formula (2) to estimate the R^2 of individual stocks to measure stock price synchronicity:

$$r_{i,t} = \beta_0 + \beta_1 r_{m,t} + \beta_2 r_{l,t} + \varepsilon_{i,t} \quad (2)$$

where $r_{i,t}$ is the return of individual stocks in week t , $r_{m,t}$ is the market return in week t and $r_{l,t}$ is the industry return in week t . $r_{l,t}$ is calculated by taking the weighted average of individual stock returns $r_{i,t}$, using the company's market capitalization as the weight, in accordance with the 2012 edition of the CSRC industry classification standards.

² We choose 2004 as the starting date because some pre-2004 data are missing from the CSMAR and CNRDS databases.

³ Fund holdings data include shareholding details appearing in the annual reports of all active mutual funds after excluding index funds, covering the active stock selection behavior of all fund managers.

⁴ For example, Fund A and Fund B jointly held shares in Company M and Company N at the end of 2010, and their holdings accounted for more than 5 % of the net value. Thus, $X_{A,B} = 2$.

⁵ If the fund belongs to a group fund, this variable takes a value of 1 and otherwise 0.

Table 1

Definition and measurement of main variables.

Variable Type	variable name	Variable Definition
Explained variables variable	$SYN_{i,t}$	The stock price synchronicity of stock i in year t
Explanatory variables	$CliqueOwnership_{i,t}$	The proportion of fund groups holding stock i shares at the end of year t
	$Herfindahl_{i,t}$	Herfindahl index of the proportion of fund groups holding stock i at the end of year t
Control variables	$Big4_{i,t}$	Is the auditor from one of the Big Four accounting firms?
	$BM_{i,t}$	Company growth, measured by book-to-market ratio
	$Levi_{i,t}$	Financial leverage, measured as the company's debt-to-asset ratio
	$Oturnover_{i,t}$	Monthly average excess turnover rate
	$ROA_{i,t}$	Profitability, measured by return on total assets
	$Size_{i,t}$	Company size, measured as the natural logarithm of the company's total assets at the end of the year
	$SOE_{i,t}$	Is the company owned by a state-owned enterprise?
	$TOP1_{i,t}$	Shareholding ratio of the largest shareholder at the end of the year
		Shareholding ratio of the largest shareholder at the end of the year

We then use Formula (3) to take the logarithm of the goodness of fit of Formula (2) to make it normally distributed. The final indicator obtained is our measure of stock price synchronicity.

$$SYN_{i,t} = \ln \left(\frac{R_{i,t}^2}{1 - R_{i,t}^2} \right) \quad (3)$$

where $SYN_{i,t}$ is the stock price synchronicity of stock i in year t and $R_{i,t}^2$ is the goodness of fit of Formula (2).

3.3. Empirical model

To test our competing hypotheses, we construct Eq. (4) to examine the impact of fund cliques on stock price synchronicity. If β_1 is significant and positive, Ha holds; if β_1 is significant and negative, Hb holds.

$$SYN_{i,t} = \alpha + \beta_1 CliqueOwn_{i,t} + \lambda X_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \quad (4)$$

where $SYN_{i,t}$ is the stock price synchronicity of company i in year t ; $CliqueOwn_{i,t}$ is the level of fund group ownership of company i in year t , measured by $CliqueOwnership_{i,t}$ and $Herfindahl_{i,t}$; and $X_{i,t}$ is a set of control variables. Following previous research, we control for Big Four status ($Big4_{i,t}$), book-to-market ratio ($BM_{i,t}$), debt-to-asset ratio ($Levi_{i,t}$), monthly average excess turnover rate ($Oturnover_{i,t}$), return on total assets ($ROA_{i,t}$), company size ($Size_{i,t}$), state-owned status ($SOE_{i,t}$) and the shareholding ratio of the largest shareholder ($TOP1_{i,t}$). We also control for year and company fixed effects, denoted by $\eta_{i,t}$, and use company-level robust standard errors.

The definitions and measures of the main variables are presented in Table 1.

3.4. Descriptive statistics

Table 2 reports the descriptive statistics of our main variables. Overall, the proportion of group holdings by Chinese funds is not high. The mean percentage of $CliqueOwnership_{i,t}$ is 0.034, with a median of 0.002. This means that the average proportion of group holdings by funds in a single stock is only 3.34 %, while the maximum is 35.2 %.⁶

⁶ Wu et al. (2019) calculate an average shareholding ratio of institutional investors of 8.46 % from 1999 to 2016, with a maximum of 58 %. Guo et al. (2020) calculate an average shareholding ratio of institutional investors of 7 % from 2000 to 2017, with a maximum of 55.8 %. These results are approximately two to three times the group shareholding ratio of funds obtained in our article. Because institutional investors pool several funds, their shareholding ratio is relatively large. We believe that the difference in group shareholding ratios is reasonable.

Table 2

Descriptive statistics of main variables.

	N	Mean	P50	Sd	Min	P10	P90	Max
SYN	34,311	-0.252	-0.187	0.919	-3.042	-1.439	0.863	1.784
CliqueOwnShip	34,311	0.034	0.002	0.067	0.000	0.000	0.115	0.352
Herfindahl	34,311	0.002	0.000	0.005	0.000	0.000	0.004	0.030
Big4	34,311	0.058	0.000	0.234	0.000	0.000	0.000	1.000
BM	34,311	0.571	0.549	0.265	0.088	0.231	0.947	1.179
Lev	34,311	0.453	0.453	0.207	0.057	0.171	0.726	0.999
Turnover	34,311	0.026	0.021	0.020	0.003	0.007	0.054	0.111
ROA	34,311	0.032	0.034	0.069	-0.380	-0.008	0.098	0.195
Size	34,311	22.050	21.880	1.296	19.320	20.550	23.790	26.030
SOE	34,311	0.443	0.000	0.497	0.000	0.000	1.000	1.000
Top1	34,311	0.351	0.328	0.152	0.087	0.168	0.566	0.748

4. Empirical results

Table 3 reports the results of our baseline regression. Regression ① shows that after controlling for firm and year fixed effects, when holding conditions such as firm size, return on total assets and turnover rate constant, a 1 % increase in fund cliques (measured by *CliqueOwnship*) is associated with a 0.578 decrease in stock price synchronicity (*SYN*). This result is significant at the 1 % level, validating Hb and supporting the noise trading hypothesis. Specifically, the results suggest that in the immature Chinese capital market, stock price synchronicity reflects more market noise unrelated to firm value (Wang et al., 2009; Lin et al., 2012). Compared with independent investors, individual investors are more likely to blindly “follow the trend” and buy “clustered” stocks. Furthermore, fund cliques may promote irrational trading, increase stock price volatility and amplify noise. This, in turn, fosters noise trading in the market, thus reducing stock price synchronicity.

Among the control variables, the coefficients for *BM* and *Size* are significant and positive, indicating that larger book-to-market ratios and companies are associated with higher stock price synchronicity. The coefficients for *Lev* and *Turnover* are significant and negative, indicating that higher debt-to-asset ratios and monthly average excess turnover are associated with lower stock price synchronicity. The regression results for these variables are generally consistent with those of previous research.

5. Robustness tests

To test the robustness of our conclusions and solve the endogeneity problem of the model, we conduct the following tests.

5.1. Alternative variable construction

5.1.1. Replacement of the stock price synchronicity index

(1) In the original industry classification standard, most companies belong to the manufacturing industry. We refine the industry classification used to calculate the stock price synchronicity index by basing it on the secondary industry of the CSRC industry classification standards, thereby avoiding the impact of this classification on our results. The results are shown in Table 4, regressions ① and ②.

(2) We use the yield indicators of the Shanghai and Shenzhen stock exchanges instead of the overall market yield indicators when calculating the fitting coefficient R^2 . The results are shown in regressions ③ and ④ of Table 4.

(3) We replace the weekly rate of return with the daily rate of return when calculating the stock price synchronicity index. The results are shown in regressions ⑤ and ⑥ of Table 4.

All of these results are significant at the 1 % level.

Table 3
Benchmark regression results.

	(1) SYN	(2) SYN
CliqueOwnership	−0.578*** (−7.10)	
Herfindahl		−9.040*** (−8.72)
Big4	0.029 (0.86)	0.030 (0.89)
BM	0.807*** (23.67)	0.825*** (25.21)
Lev	−0.597*** (−15.73)	−0.594*** (−15.68)
Turnover	−7.336*** (−24.59)	−7.313*** (−24.60)
ROA	−0.102 (−1.36)	−0.103 (−1.38)
Size	0.099*** (10.31)	0.093*** (9.86)
SOE	0.019 (0.81)	0.019 (0.81)
Top1	−0.055 (−0.95)	−0.046 (−0.80)
_cons	−2.396*** (−12.17)	−2.295*** (−11.74)
Firm fixed effects	yes	yes
Year fixed effects	yes	yes
N	34,106	34,106
F	272,85	275,91
Adj.R ²	0.42	0.42

Note: The T-values in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

Table 4
Change of stock price synchronicity index (1).

	(1) Industry refinement	(2) Industry refinement	(3) Market segments	(4) Market segments	(5) Daily Rate of Return	(6) Daily Rate of Return
CliqueOwnership	−2.859*** (−14.41)		−0.700*** (−5.87)		−0.996*** (−11.34)	
Herfindahl		−28.926*** (−11.42)		−11.350*** (−7.47)		−13.771*** (−12.30)
Control variables	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
N	34,091	34,091	34,106	34,106	34,149	34,149
F	301,68	292,40	272,27	274,81	504,47	507,34
Adj.R ²	0.46	0.45	0.39	0.39	0.54	0.54

Note: The T-values in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

Table 5
Change of stock price synchronicity index (2).

	① Two-period yield	② Two-period yield	③ Rise and fall together	④ Rise and fall together
CliqueOwnership	−0.735*** (−6.89)		−0.599*** (−13.96)	
Herfindahl		−10.047*** (−7.39)		−6.010*** (−10.97)
Control variables	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
N	34,091	34,091	34,091	34,091
F	312,54	313,41	160,74	152,12
Adj.R ²	0.38	0.38	0.36	0.36

Note: The T-values in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

(4) To avoid the time lag between individual stock returns and market returns, we perform a regression of returns lagged by one period and current returns when calculating the stock price synchronicity index. The results are shown in Table 5, regressions ① and ②.

(5) Based on the literal meaning of “rising and falling together,” we measure stock price synchronicity by using the number of days during which the price change of a stock is consistent with the total number of days during which the market price changes over a 1-year time window. The results are shown in regressions ③ and ④ of Table 5.

All of these results are significant at the 1 % level.

5.1.2. Replacement of fund group indicators

We then use the shareholding ratio of the largest group, *CliqueTop1*, to measure the degree of group cohesion between fund cliques, replacing *CliqueOwnership* and *Herfindahl*. The results are shown in Table 6, regression ①, where the coefficient is negative and significant at the 1 % level, so our conclusion remains robust.

5.1.3. Change the connection standard for fund clusters

We reconstruct our fund group measure by requiring that funds collectively hold more than 3 % and 7 % of each stock’s net asset value.⁷ The results are shown in regressions ② through ⑤ of Table 6. The coefficients are all negative and significant at the 1 % level, so our conclusion remains robust.

5.2. Consideration of institutional or fund holdings

In addition to fund groups, the holdings of institutional investors, such as fund companies, may affect stock price synchronicity. Fund companies and other institutional investors also interact. For example, institutional investor holdings can significantly reduce the occurrence of sharp rises and falls in stock prices (Gao et al., 2017). To exclude the possibility that the impact of fund group holdings on stock price synchronicity is actually the influence of institutional investor holdings such as fund companies, we add the following control variables: ① the proportion of the circulating market value of the shares held by all funds at the end of the year (*FundPosition_{i,t}*); ② the proportion of the circulating market value held by all institutional investors (*InstPosition_{i,t}*); ③ the holdings of institutional investors other than funds (*OthInstPst_{i,t}*); and ④ the holdings of both funds and institutional investors. After adding the holdings of funds and institutional investors, we

⁷ To construct the original fund group measure, we use a fund’s joint holding of more than 5 % of the net value of each stock to indicate network connections.

Table 6

Change fund clique measurement and connection standard for change fund clique.

	① SYN	② SYN	③ SYN	④ SYN	⑤ SYN
CliqueTop1	−1.467*** (−8.04)				
CliqueOwnership3		−0.441*** (−7.34)			
CliqueOwnership7			−0.649*** (−4.48)		
Herfindahl13				−9.706*** (−9.38)	
Herfindahl7					−12.472*** (−5.74)
Control variables	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
N	34,106	34,106	34,106	34,106	34,106
F	274,55	273,25	269,21	277,35	270,75
Adj.R ²	0.42	0.42	0.42	0.42	0.42

Note: The T-values in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

rerun the regression. As shown in Table 7, fund group holdings remain negative and significant at the 1 % level.

5.3. The impact of industry fund cliques

To explore the relationship between fund cliques and stock price synchronicity at the industry level, the fund clique variable is weighted according to the circulating market value at the individual stock level to construct the industry-level fund clique index to reflect the overall situation of listed companies in the industry held by clique funds. Similarly, the synchronicity index is weighted by the circulating market value of individual stocks to construct the industry-level synchronicity index. In terms of industry-level control variables, we obtain the industry financial performance indicators of A-share companies listed on the Shanghai and Shenzhen stock exchanges from the CSMAR “Industry Financial Indicators” database and select variables such as the number of companies in the industry, industry market value, industry financial leverage, industry book-to-market ratio and industry debt-to-asset ratio to reflect the overall financial pressure, profitability and growth of the industry. We also add year fixed effects to the regression.

The regression results show that, when other things remain constant, an increase in the level of industry fund cliques reduces industry stock price synchronicity (SYN). This result is significant at the 1 % level. This result is similar to the regression results of individual stocks, suggesting that industry-level fund cliques reduce stock price synchronicity. The information efficiency hypothesis posits that when investors incorporate firm-specific information into stock prices through rational arbitrage, it reduces stock price synchronicity. This path, which reduces stock price synchronicity by reducing idiosyncratic information, occurs primarily at the firm level. The main regression, controlling for firm and industry fixed effects, shows that firm-level fund cliques reduce stock price synchronicity, confirming the possibility of this pathway. Therefore, we believe that industry-level fund cliques may reduce stock price synchronicity by exacerbating noise trading, which also reflects the current state of the Chinese A-share market (Table 8).

Table 7
Results of considering institutional holdings or fund holdings.

	① Fund Holdings	② Institutional holdings	③ Other institutional holdings	④ Fund and institutional holdings
CliqueOwnership	-0.841*** (-7.84)		-0.658*** (-8.09)	
Herfindahl		-5.735*** (-5.34)		-8.742*** (-7.21)
FundPosition	0.002*** (2.70)			0.003*** (4.24)
InstitutionPosition		-0.006*** (-11.60)		-0.006*** (-10.94)
othInsttPst			-0.007*** (-13.62)	
Control variables	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
N	30,551	34,053	34,053	30,549
F	211,65	262,26	264,98	205,74
Adj.R ²	0.42	0.43	0.43	0.43

Note: The T-values in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

5.4. Changes in the regression model

5.4.1. Instrumental variable regression

The complex social connections between fund managers are a key factor in their sharing of private information and the formation of homogeneous transactions (Xiao et al., 2012; Pool et al., 2015; Shen et al., 2016). Therefore, factors such as alumni connections and work experience within the same financial institution will form a network of relationships and influence their stock holdings. Therefore, the network developed through fund managers' social connections should be closely linked to the network constructed based on their stock holdings, meeting the correlation assumption of instrumental variables. Regarding exogeneity, fund managers' social connections are weakly correlated with the control variables reflecting individual stock financial characteristics (firm growth, financial leverage, profitability, firm size) and are more likely to influence stock price

Table 8
Considers the impact of industry fund clique.

	① Weighted Industry SYN	② Weighted Industry SYN	③ Weighted Industry SYN	④ Weighted Industry SYN
Weighted Industry CliqueOwn	-17.630*** (-3.25)	-25.624*** (-3.74)		
Weighted Industry Herfinddahl			-17.630*** (-3.25)	-25.624*** (-3.74)
Industry control variables	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
N	1024	847	1024	847
F	10,59	9,92	10,59	9,92
Adj.R ²	0.21	0.33	0.21	0.33

T-values in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

synchronicity through the level of fund group cohesion, thus meeting the exogeneity requirement. Similar to our construction of the fund group holding variable discussed above, the fund network connection criterion is replaced by whether a fund manager has alumni connections or work experience within the same financial institution. The fund manager's connected groups are extracted and the proportion of these groups' holdings in each stock is calculated to construct the instrumental variable, as follows:

(1) Construction of group network connections: If the managers of funds i and j are alumni (graduates of the same university, bachelor's degree, master's degree or doctoral degree programs) at the end of the year, their educational backgrounds are connected, denoted by $Y_{i,j} = 1$; if the managers of funds i and j have worked at the same financial institution in the past, their work experience is connected, denoted by $Z_{i,j} = 1$. Furthermore, we obtain the $N \times N$ adjacency matrices P and Q .

(2) Extraction of fund groups: We import the adjacency matrices P and Q into the Louvain algorithm to obtain the connected groups.

(3) Calculate the group shareholding ratio of each stock: $\lambda_{i,j,t}$ is the ratio of the shares of company i held by fund j at the end of year t to the total number of outstanding shares of company i ; $IfYClique_{j,t}$ indicates whether fund j belongs to the connected group obtained by the adjacency matrix P , which takes a value of 1 if yes and 0 otherwise; $IfZClique_{j,t}$ indicates whether fund j belongs to the connected group obtained by the adjacency matrix Q .

$$edubg_{i,t} = \sum_{j=1}^N \lambda_{i,j,t} \times IfYClique_{j,t} \quad (5)$$

$$pastwork_{i,t} = \sum_{j=1}^N \lambda_{i,j,t} \times IfZClique_{j,t} \quad (6)$$

Regressions ①–④ of Table 9: The regression coefficients of the fund group shareholding ratio and Herfindahl index are both negative and significant at the 1 % level, and the instrumental variable passes the under-identification and over-identification tests, proving that it meets the correlation and exogeneity assumptions.

5.4.2. Fama–Macbeth regression

The two-step interface regression test, namely Fama–Macbeth regression, can eliminate the influence of cross-sectional correlation on standard errors, making the regression results more robust. The results of the Fama–Macbeth regression are presented in regressions ① and ② of Table 10, showing that our conclusions remain robust.

Table 9
Regression results of instrumental variables.

	① 1stage	② 2stage	③ 1stage	④ 2stage
CliqueOwnhat		−0.622*** (−6.86)		
Herfindahlhat				−9.090*** (−6.82)
edubg	0.180*** (30.52)		0.008*** (11.78)	
pastwork	0.598*** (130.28)		0.044*** (86.60)	
Control variables	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
N	34,149	34,106	34,149	34,106
F	15474,37	272,44	5403,19	272,38
Adj.R ²	0.89	0.42	0.73	0.42

Z-scores in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

Table 10
Fama-Macbeth regression results.

	(1) Fama-Macbeth	(2) Fama-Macbeth
CliqueOwnership	−0.568*** (−3.335)	
Herfindahl		−9.022*** (−4.751)
Control variables	yes	yes
Firm fixed effects	yes	yes
Year fixed effects	yes	yes
N	34,311	34,311
F	304.92	342.72
Adj.R ²	0.197	0.197

Note: The T-values in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

5.4.3. PSM regression

Because fund managers' investment selection is not random, fund groups have a greater information advantage than small and medium-sized investors. They may exploit this information advantage to select stocks with low information quality to attract small and medium-sized investors to join the group, thereby increasing noise trading and reducing stock price synchronicity. This can lead to sample self-selection bias. To eliminate the impact of this issue on the regression results, the following PSM test is conducted. Companies with high fund group holdings ($Dum = 1$) and those with low fund group holdings ($Dum = 0$) are matched based on company characteristics using propensity scores, and then the regression is performed. The results show that companies with high fund group holdings have low stock price synchronicity, which proves that our regression results are robust (Table 11).

Table 11
PSM regression results.

	(1) SYN	(2) SYN
CliqueOwn_Dum	−0.043** (−2.18)	
Herfindahl_Dum		−0.043** (−2.28)
Control variables	yes	yes
Firm fixed effects	yes	yes
years	yes	yes
N	10,293	11,044
F	47.20	53.69
Adj.R ²	0.44	0.45

Note: The Z-scores in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

Table 12
Quantile regression results.

	① SYN	② SYN	③ SYN	④ SYN	⑤ SYN	⑥ SYN
CliqueOwnership	−0.64*** (−5.87)	−0.51*** (−5.38)	−0.51*** (−5.38)			
Herfindahl				−9.98*** (−7.23)	−8.92*** (−9.27)	−8.02*** (−6.68)
Control variables	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
N	34,311	34,311	34,311	34,311	34,311	34,311

Note: The data in brackets are the Z values of quantile regression; *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

5.4.4. Quantile regression

We use quantile regression at quantile values of 0.25, 0.5 and 0.75 to examine the relationship between fund cliques and stock price synchronicity at different quantile levels, to eliminate the impact of left-skewed data. Table 12 presents the results of the quantile regression, demonstrating that even after accounting for distributional imbalances and outliers, fund cliques still significantly suppress stock price synchronicity for companies with varying levels of fund cliques.

6. Impact mechanism tests

Our baseline regression results demonstrate a significant negative correlation between fund cliques and stock price synchronicity. To further explore the mechanism influencing fund clique-induced stock price synchronicity, this section examines the role of information disclosure quality and investors' information capabilities based on the information efficiency hypothesis and the noise trading hypothesis, respectively.

6.1. The role of information disclosure quality

Information disclosure quality refers to the degree to which firm information is accepted, interpreted and disseminated by external investors. Listed companies' information disclosure is the primary channel for the market to obtain information about these companies (Zeng and Lu, 2006; Xu and Xu, 2015). According to Crawford et al. (2012) and Ke and Petroni (2004), analysts and institutional investors are important information producers in the capital market and constitute a vital component of the capital market. Therefore, within the corporate information environment, corporate information disclosure encompasses both the narrow definition of announcements by listed companies and the broader definition of interactions between listed companies, analysts and institutional investors. However, given the current reality of imperfect market mechanisms, a fragile market base and the immature development of institutional investors, fund holdings may increase earnings management and reduce the quality of information disclosure by investee companies (Koh, 2007; Yang et al., 2012).

Referring to the method of Kim and Verrecchia (2001), we adopt the KV measurement method to measure the quality of information disclosure. This method helps to avoid a series of problems caused by the use of accounting variables such as arbitrary accruals and earnings management. The KV measurement model is as follows:

$$\ln \left| \frac{P_t - P_{t-1}}{P_{t-1}} \right| = \alpha + \lambda_1 \left(\frac{Vol_t}{Vol_0} - 1 \right) + \varepsilon \quad (7)$$

Table 13
Channel Effects of Information Disclosure Quality.

	① KV1	② KV1	③ KV2	④ KV2
CliqueOwnership	0.065*** (3.77)		0.253*** (16.20)	
Herfindahl		-0.335 (-1.53)		3.879*** (19.55)
Control variables	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
N	34,149	34,149	34,149	34,149
F	203,62	202,22	300,55	314,91
Adj.R ²	0.41	0.41	0.44	0.44

Note: The T-values in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

$$\ln \left| \frac{P_t - P_{t-1}}{P_{t-1}} \right| = \alpha + \lambda_2 (Vol_t - Vol_0) + \varepsilon \quad (8)$$

where P_t is the closing price on day t , Vol_t is the number of shares traded on day t and Vol_0 is the average daily trading volume for all trading days during the study period. The sums λ_2 obtained by least squares regression λ_1 (negative β cases are not considered) are taken as $KV1$ and $KV2$. The smaller the value of λ , the smaller the KV value and the more complete the information disclosed by the company; that is, the KV value is inversely proportional to the quality of information disclosure. Referring to the methods of Dell (2010) and Jiang (2022), we construct Formula (9) to test the effect of information disclosure quality:

$$KV_{i,t} = \alpha + \beta_1 CliqueOwn_{i,t} + \lambda X_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \quad (9)$$

The empirical results are presented in Table 13. The coefficients β_1 for regressions ①, ③ and ④ are all positive and significant at the 1 % level, indicating that fund cliques significantly reduce the quality of information disclosure. Combined with the baseline regression results, the transmission mechanism of information disclosure quality under the information efficiency hypothesis is established, but its explanatory power remains weak. Therefore, the noise trading hypothesis should be adopted to explain stock price synchronicity in the Chinese capital market.

6.2. The role of investors' information capabilities

An investor's information capability refers to their ability to acquire and process information to gain an information advantage or avoid an information disadvantage (Kalay, 2015; Tan et al., 2015). Better information capabilities means that individual investors are more likely to base their investment decisions on company fundamentals. The main reason for individual investors' irrational investment behavior is their lack of resources and their tendency to rely on their own experience and past experiences. They are also easily influenced by "rumors" from various channels, leading them to make impulsive decisions and frequently trade, thus becoming noise traders (Peng and Xiong, 2006). Investors' information search behavior through the internet can reduce bias in their investment behavior and mitigate stock price correlation anomalies (Liu and Kong, 2017).

Drawing on previous research, we use the investor network search index to measure the degree of change in investors' information capabilities. A higher investor network search index indicates investors' greater motivation and ability to proactively acquire information on listed companies. Retail investors and non-core institutional investors are key drivers of the synchronized stock price fluctuations caused by fund cliques. The network search index fully captures the information acquisition methods of retail investors and non-core institutional investors in the capital market. The vast majority of retail investors lack direct access to listed com-

panies, analysts and institutional investors, and online searches are an essential way to obtain information. Non-core institutional investors may have the opportunity to communicate directly with listed companies, analysts and other institutional investors, but they lack access to private information within the cluster. The information they possess is essentially equivalent to the public information available to retail investors. Therefore, the network search index fully captures the information boundaries of retail investors and non-core institutional investors.

We define investor information capabilities as the natural logarithm of the sum of the number of searches for the stock code, company abbreviation and company full name, plus 1 (SVI_1).⁸ Referring to the methods of Dell (2010) and Jiang (2022), we construct Formula (10) to test the role of investor information capability:

$$SVI_{i,t} = \alpha + \beta_1 CliqueOwn_{i,t} + \lambda X_{i,t} + \eta_{i,t} + \varepsilon_{i,t} \quad (10)$$

The empirical results are presented in Table 14. The coefficients β_1 for regressions ① through ④ are all negative and significant at the 1% level, indicating that fund cliques significantly weaken investors' information capabilities. This is consistent with the hypothesis that fund cliques attract other investors to follow suit and promote noise trading. Therefore, the transmission mechanism of investors' information capabilities is consistent with the assumptions underlying the noise trading hypothesis.

According to Cohn et al. (2022), log-linear models may affect the validity of estimation results. We further use information opacity⁹ to measure investors' information capabilities to test the noise trading hypothesis. The empirical results, shown in Table 15, support the noise trading hypothesis.

7. Heterogeneity tests

Based on the mechanism influencing investors' information capabilities under the noise trading hypothesis, this section studies the moderating role of economic policy uncertainty and investor sentiment in the relationship between fund cliques and stock price synchronicity.

7.1. The regulatory role of economic policy uncertainty

Economic policy uncertainty refers to the uncertainty surrounding macroeconomic policies, including fiscal, regulatory and monetary policies (Wan et al., 2024). It indicates the inability of economic entities to accurately predict whether, when and how the government will change its current economic policies (Gulen and Ion, 2016). Policy uncertainty can increase stock risk through factors such as corporate cash flows, discount factors and correlation coefficients and may well explain the long-term volatility of the Chinese stock market (Lei et al., 2018). Furthermore, Chen Guojin et al. (2017) argue that policy uncertainty influences corporate book value and stock prices by influencing corporate profit margins, household consumption and the proportion of investments in risky assets. When policy uncertainty is high, stock market volatility increases, further exacerbating risks. Faced with high policy uncertainty, individual investors become more cautious and are more likely to view fund cliques as a "positive" signal, exacerbating noise trading in the stock market and further reducing stock price synchronicity. Based on the above analysis, we predict that when economic policy uncertainty is high, the inhibitory effect of fund cliques on stock price synchronicity will be more pronounced.

Following the methodology of Baker et al. (2016), we calculate an index based on keyword searches of the South China Morning Post (SCMP). This index measures economic policy uncertainty, EPU_t , as the proportion of SCMP articles that simultaneously include the keywords "China," "economy," "uncertainty" and "policy" in the total number of articles that month.¹⁰ To examine the heterogeneity of economic policy uncer-

⁸ We use SVI_2 , measured as the natural logarithm of the sum of the number of searches with only stock codes as keywords, plus 1, as a robustness test.

⁹ Drawing on the methods of Hutton et al. (2009) and Pan et al. (2011), we estimate total discretionary accruals using the modified Jones model (Dechow et al., 1995) by industry and year. A company's information transparency is measured by adding the absolute value of total discretionary accruals over the previous three periods (*Opaque*). A higher value indicates less transparency of information, implying a weakening of investors' information capabilities.

¹⁰ The data come from the website https://www.policyuncertainty.com/china_monthly.html, which regularly publishes monthly economic policy uncertainty indexes for different countries and regions. Annual data are obtained by averaging monthly data.

Table 14
Channel effects of investor information capabilities.

	① SVI1	② SVI1	③ SVI2	④ SVI2
CliqueOwnership	−1.143*** (−21.32)		−1.324*** (−36.24)	
Herfindahl		−11.930*** (−17.30)		−14.151*** (−29.93)
Control variables	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
N	24,101	24,101	24,101	24,101
F	642.77	621.23	1085.67	1021.62
Adj.R ²	0.84	0.84	0.99	0.99

Note: The T-values in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

Table 15
Channel effects of investor information capabilities.

	① Opaque	② Opaque
CliqueOwn	0.191*** (5.25)	
Herfindahl		2.230*** (4.54)
Control variables	yes	yes
Firm fixed effects	yes	yes
Year fixed effects	yes	yes
N	26,845	26,845
F	23.09	22.31
Adj.R ²	0.27	0.27

Note: The T-values in brackets are adjusted for stock clique; *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

tainty, we divide the sample into two groups, namely high and low economic policy uncertainty groups, and conduct separate regressions for each group.

The empirical results are presented in Table 16. The coefficients for *CliqueOwnership* and *Herfindahl* are −0.540 and −9.810, respectively, in the high economic uncertainty group, while the coefficients are −0.053 and −1.511 in the low economic policy uncertainty group. This suggests that when economic policy uncertainty is high, fund cliques have a greater inhibitory effect on stock price synchronicity. The Chow test results indicate that this structural difference is significant.

7.2. The regulatory role of investor sentiment

Investor sentiment is a systemic risk that influences pricing in the capital market (DeLong et al., 1990). Behavioral finance argues that investors with heterogeneous beliefs and preferences are often irrational. Furthermore, due to the influence of social interaction mechanisms, such as emotional contagion and imitative

Table 16

The moderating effect of economic policy uncertainty.

	① SYN (High EPU)	② SYN (Low EPU)	③ SYN (High EPU)	④ SYN (Low EPU)
CliqueOwn	−0.540*** (−6.62)	−0.053 (−0.39)		
Herfindahl			−9.810*** (−8.99)	−1.511 (−0.87)
Chow test	(9.61)***		(9.89)***	
Control variables	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
N	30,095	4707	30,095	4707
F	665,18	86,21	670,10	86,28
Adj.R ²	0.38	0.25	0.38	0.25

Note: The values in brackets are T-values adjusted for stock clique and F-values of Chow test; *, **, *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

learning, and the existence of limited arbitrage, asset prices often deviate from normal levels. In the Chinese stock market, investor sentiment has a positive impact on market liquidity: higher investor sentiment leads to greater market liquidity. Furthermore, investors who trade in the Chinese stock market are more likely to exhibit cognitive deficiencies when confronted with new information (Liu et al., 2016; He et al., 2021). When investor sentiment is high, the capital market as a whole is more eager to explore investment opportunities, and the dissemination of information through channels such as commercial media influences investor decision-making (Miao et al., 2024). When investor sentiment is high, individual investors are more likely to view fund cliques as a “positive” signal. Due to irrational behavioral biases, individual investors are more likely to trade based on market data and “favorable” information, weakening their own information analysis capabilities and further reducing stock price synchronicity. Based on the above analysis, we predict that when investor sentiment is high, the inhibitory effect of fund cliques on stock price synchronicity will be more pronounced.¹¹

Drawing on the method of Yi and Mao (2009), we improve the BW index construction method by incorporating indicators that reflect changes in investor sentiment in the domestic stock market, namely closed-end fund discounts, trading volume, the number of IPOs and first-day returns, the consumer confidence index and the number of new investor accounts. Furthermore, we control for macroeconomic variables such as the consumer price index, the factory price index for industrial products, industrial value added and the macroeconomic prosperity index. We construct a monthly index of the China Stock Market Investor Sentiment Composite Index (*CICSI_t*) and use its arithmetic mean as the annual index. To examine the heterogeneity of investor sentiment, we divide the sample into two groups, namely a high investor sentiment group and a low investor sentiment group, and conduct separate regressions for each group.

The empirical results are presented in Table 17. The coefficients for *CliqueOwnership* and *Herfindahl* are −0.501 and −9.467, respectively, in the high investor sentiment group, while the coefficients are −0.401 and −7.050 in the low investor sentiment group. This indicates that when investor sentiment is high, fund cliques have a more pronounced inhibitory effect on stock price synchronicity. The Chow test results indicate that this structural difference is significant.

¹¹ According to the method used to construct investor sentiment indicators, low investor sentiment indicates low levels of market trading volume, confidence index and new account openings. During such periods, retail investors are more likely to withdraw from the capital market and invest in other sectors rather than imitate fund managers and join the group. This differs from the wait-and-see attitude of retail investors during periods of high economic policy uncertainty.

Table 17

The moderating effect of investor sentiment in 7 markets.

	① SYN (High CICSI)	② SYN (low CICSI)	③ SYN (High CICSI)	④ SYN (low CICSI)
CliqueOwn	−0.501*** (−4.95)	−0.401*** (−4.23)		
Herfindahl			−9.467*** (−6.68)	−7.050*** (−5.86)
Chow test	(15.56)***		(15.48)***	
Control variables	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
N	21,430	13,370	21,430	13,370
F	426,37	346,11	429,01	348,36
Adj.R ²	0.34	0.42	0.34	0.42

Note: The values in brackets are T-values adjusted for stock clique and F-values of Chow test; *, **, *** represent significance levels of 10 %, 5 %, and 1 %, respectively.

8. Conclusion and implications

The 20th National Congress of the Communist Party of China provided clear guidance for the development of the capital market and formulated new requirements. As Yi Huiman, Chairman of the CSRC, pointed out at the 2022 Financial Street Forum Annual Meeting, the number of individual investors exceeds 200 million. This is a key source of market vitality and crucial support for its normal functioning. It is essential to determine how to leverage the role of institutional investors to improve the capital market.

In recent years, the phenomenon of fund cliques has emerged in both domestic and international investment markets. This phenomenon is common in mature international capital markets and is likely to become a common problem in emerging capital markets. This research topic has universal reference value for domestic and international investment markets, and its findings can reveal common characteristics and patterns of change in the behavior of institutional investors in capital markets at different stages of development. By studying fund managers' clique behavior in stock selection, we obtain the following findings. First, the increase in the proportion of fund group holdings significantly reduces stock price synchronicity; second, the possible mechanism by which fund cliques affect stock price synchronicity is by weakening the quality of information disclosure and reducing investors' information capabilities; third, when economic policy uncertainty and investor sentiment are high, the inhibitory effect of fund cliques on stock price synchronicity is more pronounced.

This paper makes the following contributions. From an information disclosure perspective, excessive clique behavior by funds reduces information efficiency and is not conducive to the integration of company-specific information into stock prices. Therefore, we must remain vigilant about the damage that fund cliques can cause to the capital market, and any excessive clique behavior by funds must be taken seriously by market participants.

Our paper also has some limitations. For example, it does not address the mechanism influencing the dissemination of information, an aspect that will need to be explored in future research.

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.

Acknowledgments

The author acknowledges support from the National Natural Science Foundation of China: “Rescue” or “Bailout”: A Study on the Motivations, Mechanisms, and Effects of Government Bailout Funds (72272157), and Financial Society of Guangdong Basic Research Project (JCKT202404).

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