China Journal of Accounting Research
Volume 17, 3 (2024)

Media coverage and price reactions to earnings news
Miao Yu, Hangsoo Kyung, Albert Tsang 100379

Does investor communication improve corporate social responsibility? A machine learning-based textual analysis
Siyu Fan, Dongmin Kong, Jie Lu, Honghai Yu 100370

Artificial intelligence and corporate risk-taking: Evidence from China
Hong Chen, Mengyun Zhang, Jun Zeng, Wenhua Wang 100372

Does big data tax administration expand bank credit loans?
Xinwu Li, Zixi Ling, Zhe Li, Liyi Zhu 100374

The impact of big data tax administration on corporate ESG—A quasi-natural experiment based on Golden Tax Project III
Jingbo Luo, Jiayi Xu 100378

Is audit materiality informative? Evidence from China
Lei Zhu, Qianwen Zheng, Yubin Li 100373

Spillover effect of digital transformation along the supply chain: From the perspective of suppliers' audit fees
Lu Li, Wen Bo, Libin Qin 100363

Peer effect on climate risk information disclosure
Yanxi Li, Duo Wang, Delin Meng, Yunge Hu 100375

The spillover effect of customers' ESG performance on suppliers' green innovation quality
Yani Sun, Yuezhe Shen, Qingmei Tan 100362

Corrigendum to ''Real effects of greenhouse gas disclosures'' [China Journal of Accounting Research, 17(2), (2024) 100360]
Tong Lu, Lijun Ruan, Yanyan Wang, Lisheng Yu 100371

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17
3
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Media coverage and price reactions to earnings news

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ABSTRACT

In this study, we find that relative to firms with less media coverage, stock price sensitivity to positive (negative) earnings surprises in earnings announcements of firms with greater media coverage is stronger (weaker). This asymmetry in the effect of media coverage on stock price sensitivity to positive versus negative earnings surprises suggests that greater media coverage of earnings announcements intensifies stock price reactions to positive earnings surprises but attenuates reactions to negative earnings surprises. Moreover, we find that negative earnings news is less persistent for firms with greater media coverage. Overall, our findings support the conjecture that greater media coverage increases managers' incentive to avoid future negative news, thereby reducing the persistence of poor financial performance and weakening price reactions to negative earnings news.

1. Introduction

An important stream of empirical studies in accounting, finance and economics suggests that news media play an important role in capital markets by alerting capital market participants to firm events. As a result, media coverage can significantly affect investors' reactions to firms' information disclosures, such as earnings releases (Peress, 2008; Griffin et al., 2011; Pinnuck, 2014; Miller and Skinner, 2015; Kong et al., 2017; Huang et al., 2018; Bonsall et al., 2020; Cao et al., 2020; Kyung and Tsang, 2022; Tsang et al., 2024). In support of this view, studies provide strong evidence that news media influence stock price reactions to earnings news by creating and disseminating information (Bushee et al., 2010; Drake et al., 2014; Guest, 2021), disciplining manager behavior (Miller, 2006; Dai et al., 2015) and influencing investor sentiment (Tetlock, 2007).

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In summary, studies conclude that high levels of media dissemination of earnings news reduce information asymmetry and enhance price discovery (e.g., Engelberg and Parsons, 2011; Blankespoor et al., 2018).[1]

Another stream of literature examines whether and how stock market reactions to firms' information disclosures vary depending on the content of the information disclosed, namely positive or negative earnings news. These studies generally show that the stock market responds more strongly to negative news than to positive news (e.g., Kothari et al., 2009; Mian and Sankaraguruswamy, 2012; Williams, 2015). Research also suggests that differences in stock market reactions to firms' information disclosures can have important capital market implications and provide possible explanations for asymmetric market reactions to good and bad news.[2] For example, whereas Kothari et al. (2009) attribute this asymmetry to managers withholding bad news, Mian and Sankaraguruswamy (2012) suggest that stock market reactions to earnings news can be affected by differences in investor sentiment.

Surprisingly, despite the crucial role of the media in investors' reactions to firms' information disclosures and the large difference in price reactions to positive and negative earnings news,[3] studies to date have not explored whether and how the level of media coverage of firms affects stock market reactions to positive and negative earnings news. Thus, the main objective of this study is to examine whether and how investors' reactions to firms' earnings announcements containing positive and negative earnings surprises vary depending on the level of media coverage of these announcements.

Based on a large sample of quarterly earnings announcements from U.S. firms, we first demonstrate the existence of asymmetric stock price reactions to negative and positive earnings surprises in firms' earnings announcements, consistent with prior studies (e.g., Kothari et al., 2009; Mian and Sankaraguruswamy, 2012; Williams, 2015). Second, we present robust evidence that stock price reactions to positive and negative earnings surprises in quarterly earnings announcements are influenced by the level of media coverage. Specifically, we find that stock price sensitivity to positive earnings surprises becomes stronger when the level of media coverage of a firm in the pre-earnings announcement period is high; conversely, stock price sensitivity to negative earnings surprises is weakened when the level of media coverage of a firm in the pre-earnings announcement period is high. In other words, we find that the impact of media coverage on price reactions to earnings news varies depending on the direction of earnings surprises. Our finding that greater media coverage intensifies stock price reactions to positive earnings surprises is consistent with research showing that greater media coverage of firms can lead to stronger stock market reactions (Peress, 2008; Engelberg and Parsons, 2011; Li et al., 2011; Twedt, 2016). However, our finding that media coverage mitigates stock price reactions to negative earnings surprises runs counter to the expectation that increased media coverage strengthens price reactions to earnings news, regardless of the nature of the earnings surprises.[4]

Further analysis shows that our main findings are robust across (1) earnings- and non-earnings-related news, (2) different types of media coverage (i.e., full articles, news flashes and press releases) and (3) media coverage with varying emotional tones. Our findings are also robust to an array of additional tests, such as examining yearly earnings announcements instead of quarterly earnings announcements, testing within-firm variations in different levels of media coverage associated with corporate earnings announcements instead of cross-firm variations in media coverage, using an alternative measure of earnings surprises and controlling

[1] Price discovery is generally defined as "the process through which prices converge toward earnings information" (Guest, 2021, p. 1029).

[2] For example, Huang et al. (2018) show that firms influence investors' reactions to positive earnings surprises by manipulating the salience of earnings announcements. Other evidence suggests that managers may be incentivized to limit negative stock price responses by bundling non-earnings press releases with negative earnings news during the earnings announcement period (Liu et al., 2017) or by strategically scheduling and timing their earnings announcements (deHaan et al., 2015). For example, Michaely et al. (2016) show that managers opportunistically disclose bad news on Friday evenings to attenuate negative stock price reactions. Aherna and Sosyura (2014) show that during merger negotiations, bidders tend to publish more news stories in the financial press to manipulate their stock prices.

[3] Research suggests that earnings announcements constitute a major mechanism through which investors receive information about firms (e.g., Holstein, 2008; Solomon and Soltes, 2012; Michaely et al., 2016).

[4] To enhance the robustness of our findings, we use various measures of media coverage derived from the RavenPack database. These measures include media coverage variables that are assessed using a range of pre-earnings announcement windows (e.g., the 90-, 60- and 30-day windows preceding a firm's quarterly earnings announcement). Additionally, we use abnormal levels of media coverage during the pre-earnings announcement window (defined as the residuals from regressing the total level of media coverage during the 90-day pre-earnings announcement window on firm-level determinants identified by Engelberg and Parsons (2011) as an alternative measure of media coverage.

for the potential effects of other information intermediaries on stock price reactions to earnings news. Overall, our findings support the conjecture that media coverage plays an important but asymmetric role in investors' reactions to positive versus negative earnings news.

Finally, we examine the possible underlying channel that contributes to weaker stock price reactions to negative earnings news from firms with greater media coverage. Specifically, we conduct tests to examine two possible channels. First, studies suggest that losses are less persistent than profits (Hayn, 1995) and that loss avoidance is important for both managers and investors (Degeorge et al., 1999; Matsumoto, 2002; Graham et al., 2005). Suk et al. (2021) argue that the boards of directors of firms with lower earnings persistence are more likely to view poor earnings performance as a transitory shock and are therefore less likely to fire CEOs with poor earnings performance.[5] According to these studies, one possible explanation for our finding is that a higher level of media coverage increases a firm's incentive to avoid losses and/or avoid reporting negative news in future periods. Accordingly, we predict that firms with higher levels of media coverage are more likely than their counterparts to exhibit lower levels of negative news persistence, thereby increasing investors' sentiment/optimism about the transient nature of negative earnings news.

Second, research shows that financial media and the business press are more likely to cover firms with deteriorating (versus improving) performance and that greater media coverage foreshadows poor performance and negative earnings surprises (Niessner and So, 2017). Other studies find that the media can play an important corporate governance role and can therefore discipline managers' behavior.[6] In line with this view, research suggests that greater media coverage can increase firms' accounting conservatism (i.e., recognizing bad news in a timely manner while delaying recognition of gains; Kong et al., 2017). The conclusions drawn from these studies regarding the information and/or monitoring role of the media thus suggest another possible explanation for our finding of a weaker stock market reaction to negative earnings news when firms' media coverage is higher. Specifically, for firms with greater media coverage, investors may be aware of declining earnings performance well before the earnings announcement date (e.g., firms may release bad news earlier due to media coverage[7] or the media may release bad news to the market more quickly). As a result, investors may exhibit weak price reactions to negative earnings news released on the earnings announcement date.

Consistent with the first conjecture proposed above (i.e., investors tend to perceive firms with greater media coverage as having lower negative news persistence), our evidence indicates that negative earnings news is less persistent for firms with greater media coverage in the pre-earnings announcement period than for other firms. In contrast, contrary to our second conjecture (i.e., firms with greater media coverage tend to release negative earnings news earlier), repeating our tests using different pre-earnings announcement windows (i.e., –4 days to –2 days, –7 days to –2 days, –30 days to –2 days and –60 days to –2 days) provides no evidence that the weaker stock price response to bad news documented in our study is driven by a stronger market response to bad news before the earnings announcement date.

Our study makes several contributions to the literature. First, a growing body of research documents the significant capital market benefits associated with media coverage. These benefits may take the form of reduced information asymmetry, greater investor responsiveness to information, higher analyst forecast accuracy and reduced incidence of mispricing (Bushee et al., 2010; Engelberg and Parsons, 2011; Drake et al., 2014; Cao et al., 2020).[8] We contribute to this literature by showing that media coverage increases stock price sensitivity to earnings news when the news is positive, but reduces this sensitivity when firms report negative earnings news.

[5] In contrast, they show that CEOs with poor performance are more likely to be fired if their firm's earnings persistence is high (i.e., when poor earnings performance in the current period is more likely to carry forward to future periods).

[6] Given the considerable influence of the media as information intermediaries in capital markets, many studies focus on the role of the media in corporate governance (e.g., Dyck et al., 2008; Griffin et al., 2011; Drake et al., 2014; Hillert et al., 2014; Dai et al., 2015; Rogers et al., 2016).

[7] Kothari et al. (2009) and Baginski et al. (2018) infer the level to which managers withhold bad news by noting differences in the magnitude of stock price sensitivity to bad news relative to good news. They argue that stronger stock price reactions to bad news (than to good news) following earnings announcement dates suggest that managers tend to withhold bad news.

[8] Other studies highlight the importance of the media by showing that firms have incentives to influence media coverage. For example, Bushee and Miller (2012) reveal that hiring investor relations firms increases firms' media coverage. Aherna and Sosyura (2014) show that bidders tend to publish more news stories in the financial press during merger negotiations to manipulate their stock prices.

Second, beginning with Ball and Brown (1968), a substantial number of accounting studies demonstrate asymmetric stock price reactions to negative versus positive corporate news (i.e., stock price sensitivity to earnings surprises is conditional on the sign of the unexpected earnings). This literature identifies various factors that promote asymmetric market responses to good versus bad news (e.g., Soffer et al., 2000; Conrad et al., 2002; Francis et al., 2002; Skinner and Sloan, 2002; Hutton et al., 2003; Kothari et al., 2009; Mian and Sankaraguruswamy, 2012; Williams, 2015). Our study adds to this literature by providing evidence that asymmetric stock market reactions to positive versus negative earnings news can also be attributable to the effect of media coverage on different types of earnings news. Additionally, this study adds to the literature on the value relevance and/or informativeness of earnings (Radhakrishnan and Tsang, 2011; Kim et al., 2019; Martins and Barros, 2021) by providing evidence supporting the importance of the level of media coverage associated with earnings news.

The remainder of this study is organized as follows. Section 2 provides a literature review and develops the study's hypotheses. Section 3 describes the research design. Section 4 presents the data and sample selection. Section 5 discusses the key findings. Section 6 offers our conclusions.

2. Literature review and hypothesis development

The media play an important intermediary role in financial markets by collecting, aggregating, interpreting and disseminating firm-related news. These activities reduce information asymmetry between firms and capital market participants (Miller, 2006; Bushee et al., 2010; Solomon and Soltes, 2012; Solomon et al., 2014; Cao et al., 2020; Tsang et al., 2024). Studies suggest that the business press tends to exert greater influence on capital markets than do other major information intermediaries, such as financial analysts, because the business press has a wider audience base (Fang and Peress, 2009) and greater credibility and timeliness (Kothari et al., 2009). Consistent with this view, studies show that by widely disseminating information to capital market participants, the business press can significantly influence investors' decision-making processes (e.g., Huberman and Regev, 2001; Tetlock, 2007; Peress, 2008; Tetlock et al., 2008; Bushee et al., 2010; Tetlock, 2011; Chen et al., 2013; Drake et al., 2014; Solomon et al., 2014).[9]

Kothari et al. (2009) examine whether the impact of earnings disclosures on capital markets is conditional on news content. They find that favorable (unfavorable) disclosures from the business press can decrease (increase) the costs of capital and stock return volatility. Kuhnen (2015) conducts a laboratory experiment and finds that people tend to form overly pessimistic beliefs based on negative financial news reports and that they react more strongly to negative news than to positive news. Following this reasoning, managers who report negative earnings surprises in their earnings announcements are expected to face stronger negative stock reactions to such information when their firms receive greater media coverage. That is, although a high level of media coverage can intensify stock price reactions to positive news, it can also intensify stock price reactions to negative news.

In addition, many theoretical and empirical studies on capital markets implicitly assume that the media collect, process and disseminate corporate news in a homogeneous, neutral and symmetrical way, without being affected by the nature or sign of the news. This assumption may not be warranted because media reporters (like many other capital market participants) are economic entities in the financial market. Their decisions are therefore affected by numerous factors, such as the nature of corporate news (Mullainathan and Shleifer, 2005; Reuter and Zitzewitz, 2006; Kothari et al., 2009; Gurun and Butler, 2012). For instance, Hamilton (2004) suggests that media decisions regarding news coverage are often driven by the perceived level of audience appeal. In line with this view, studies postulate that media managers have incentives to cover and disseminate more negative news than positive news and even to report negative news more negatively (e.g.,

[9] As Bushee et al. (2010, p. 2) explain, "[t]he business press is perhaps the broadest and most widely disseminated of all potential information intermediaries, reaching both sophisticated and unsophisticated investors, as well as managers, regulators, and other market participants.".

Baumeister et al., 2001; Mullainathan and Shlefier, 2005; Holstein, 2008; Solomon and Soltes, 2012). Niessner and So (2017) reinforce the argument about media bias towards negative financial news.[10] Overall, these studies suggest that capital market participants (e.g., journalists and investors) are likely to pay more attention to negative news than to positive news.[11]

However, research also suggests that firms' poor financial performance can significantly increase the likelihood of CEO turnover and reduce CEOs' chances of obtaining comparable employment opportunities at other firms after their departure (e.g., Cannella et al., 1995; Huson et al., 2001; Dai et al., 2021). In their recent study, Suk et al. (2021) provide evidence that earnings persistence is one of the most important earnings attributes in explaining the sensitivity of CEO turnover to a firm's financial performance. Specifically, they show that negative news disclosed by firms with lower levels of earnings persistence has a weaker influence on CEO turnover decisions made by the board of directors. Following this observation, to the extent that greater media coverage of poor corporate financial performance increases managers' career concerns, we conjecture that managers of firms reporting negative (versus positive) earnings news, particularly those of firms with greater media coverage, have stronger incentives to avoid reporting negative news in a future period. This in turn may increase investor sentiment regarding the future financial performance of firms. In support of this claim, Mian and Sankaraguruswamy (2012) find that although investor sentiment/optimism intensifies stock price reactions to positive news, it weakens stock price reactions to negative news. Analogously, we predict that a higher level of media coverage will weaken stock price reactions to negative news and intensify stock price reactions to positive news, resulting in asymmetric price reactions to positive versus negative earnings news.

Studies also suggest that the media not only affect investors' decision-making processes but also managers' behavior. For example, managers' decisions to pursue acquisitions may be affected by the level and tone of media attention given to the proposed transactions (Liu and McConnell, 2013; Cihan et al., 2017). Dai et al. (2015) show that the dissemination of corporate insider trading news by the media constrains managers' future trading activities by reducing the profitability of insider trading. Dyck and Zingales (2002) show that greater media coverage increases the responsiveness of the private sector to environmental concerns. They conclude that the media play an important role in shaping corporate policy and should not be ignored when analyzing a country's corporate governance system. Kong et al. (2017) find that media coverage increases firms' incentives to adopt conservative accounting practices to avoid public scrutiny.[12] These conclusions again suggest that a higher level of media coverage attenuates stock market reactions to negative earnings news disclosed on earnings announcement dates, because firms with greater media coverage are likely to disclose negative news more quickly. In other words, investors may be aware of declining earnings performance well before firms' earnings announcement dates, especially for firms with greater media coverage.

Overall, *ex ante*, it is unclear whether and how media coverage differently affects stock market reactions to firms' earnings announcements that contain positive and negative earnings news. Given the potentially different role of media coverage in stock price reactions to positive versus negative earnings news, we put forward the following hypotheses:

Hypothesis 1a. Greater media coverage **intensifies** stock price reactions to **negative** earnings news disclosed on the earnings announcement date.

[10] A rational explanation for why the media pay more attention to negative news is provided by psychological research, which confirms that negative events have more significant effects on individual learning and information processing than do positive events (Skowronski and Carlston, 1989; Baumeister et al., 2001; Rozin and Royzman, 2001). For example, studies show that negative news attracts more attention (Fiske, 1980), is easier to remember (Wentura et al., 2000) and is more carefully processed (Klinger et al., 1980) than positive news.

[11] Additionally, research suggests that newspaper readers prefer to read positive news about the firms they own, leading newspapers to skew their coverage toward positive information (Kindleburger, 1989; Galbraith, 1990; Schiller, 2000). In line with this view, the model proposed by Mullanaithan and Shleifer (2002) assumes that the newspaper has an incentive to change a story to match the reader's prior beliefs. Thus, to the extent that readers prefer to read and thus react more strongly to (are likely to discount) positive (negative) news (Jensen, 1979; Mullanaithan and Shleifer, 2002), we also predict that media coverage has an effect on investors' asymmetric responses to good and bad news.

[12] Research suggests that media coverage is positively associated with corporate visibility (e.g., Wartick, 1992; Carroll and McCombs, 2003; Kiousis et al., 2007; Moon and Hyun, 2014).

Hypothesis 1b. Greater media coverage **weakens** stock price reactions to **negative** earnings news disclosed on the earnings announcement date.

3. Research design

3.1. Determinants of media coverage

Our study aims to determine whether greater media coverage of corporate news released through earnings announcements intensifies or attenuates stock market reactions to this news. However, media coverage is not random (Bushee et al., 2010; Soltes, 2010). Both observable and unobservable factors related to the media's decision to cover a particular firm's earnings announcements may be associated with the stock market valuation of the information given in the announcements.[13]

To alleviate the possibility of selection bias in media coverage decisions, we use a Heckman (1979) two-stage selection model. In the first stage, we estimate the following logistic regression model regarding the choice of media coverage:

$$\begin{aligned} Coverage_{i,q} = {} & \alpha_0 + \alpha_1 Dum\_Press\_year(t-1)_{i,q} + \alpha_2 BadNews_{i,q} + \alpha_3 SUE_{i,q} + \alpha_4 BadNews \times SUE_{i,q} \\ & + \alpha_5 LnMVE_{i,q} + \alpha_6 Leverage_{i,q} + \alpha_7 MB_{i,q} + \alpha_8 InstitutionHolding_{i,q} + \alpha_9 NumInstitution_{i,q} \\ & + \alpha_{10} NumAnalyst_{i,q} + \alpha_{11} NumEmployee_{i,q} + \alpha_{12} SP1500_{i,q} + \alpha_{13} PriorReturn_{i,q} \\ & + \alpha_{14} PriorTurnover_{i,q} + \alpha_{15} NumLawsuit_{i,q} + \alpha_{16} Zscore_{i,q} + \alpha_{17} HighTech_{i,q} \\ & + \alpha_{18} Regulate_{i,q} + Industry\ and\ Year - Quarters\ Fixed\ Effects + \varepsilon_{i,q} \end{aligned} \quad (1)$$

The dependent variable $Coverage_{i,q}$ is an indicator variable (e.g., *Dum_Press_90day*) used to measure firm *i*'s media coverage during the (approximately) 90-day window preceding the firm's quarterly earnings announcement in fiscal quarter *q*. Specifically, this variable is measured from 1 day after a firm's earnings announcement date in quarter *q*–1 to 1 day before its earnings announcement date in quarter *q*. The Heckman (1979) two-stage selection model requires an instrument to satisfy the exclusion restriction. We examine whether our instrument is an exogenous variable in the first-stage model but does not affect the dependent variables in the second-stage regressions. For our instrumental variable, we use $Dum\_Press\_year(t-1)$, which is an indicator variable equal to 1 if the business press covers a firm during fiscal year *t*–1 and 0 otherwise. A firm's media coverage in the previous year is likely to be associated with its current media coverage but is unlikely to affect its stock price in response to a current earnings announcement. We calculate the inverse Mills ratio (IMR) from Eq. (1) and include IMR in the second-stage regressions.[14]

We include a set of factors that may affect the business press's decision to cover a firm's earnings announcements. First, we include unexpected earnings to control for the information content of earnings announcements, because the business press is more likely to cover news with a greater impact on investors. To proxy for unexpected earnings, we follow Mian and Sankaraguruswamy (2012) and use seasonally differenced earnings surprises as a measure of earnings surprises. Our proxy for unexpected earnings surprises (SUE) is thus defined as earnings per share before extraordinary items in quarter *q* minus earnings per share before extraordinary items in quarter *q*–4 (i.e., the same quarter of the previous year), scaled by the stock price at the end of

[13] For example, managers who have less incentive to withhold bad news (e.g., managers of firms with weaker stock price reactions to their earnings announcements) are more likely than others to attract media attention. If this conjecture is valid, the research question examined in our study may be subject to selection bias.

[14] We acknowledge the weakness of using media coverage in the previous year as an instrumental variable in our test. For example, firms that received extensive media coverage in the previous year may have acquired a larger shareholder base and analyst following. This prior media coverage may in turn affect investors' responses to the firms' earnings news in subsequent periods. We thus conduct additional tests to determine the validity of our instrument, following Lennox (2012). First, we test the validity of the exclusion restriction. We find that our instrument is associated with media coverage in the current fiscal quarter but is not associated with current stock returns on the earnings announcement dates. In an additional robustness test, we use an alternative instrumental variable and find that our conclusion remains unchanged. Specifically, we define an indicator variable, *Media_Competitor*, equal to 1 if the business press covers a firm's major competitor in its industry during fiscal year *t*–1 and 0 otherwise.

quarter q.[15] In a robustness test, instead of assuming that market earnings expectations follow a random walk model and measuring earnings surprises as seasonally differenced earnings, we define an alternative measure of unexpected earnings surprises, *SUE_Analyst*, using analysts' consensus forecasts as the benchmark.

Studies suggest that the media have a greater incentive to cover negative news than positive news because negative news tends to attract more attention (Baumeister et al., 2001; Mullainathan and Shlefier, 2005; Holstein, 2008; Solomon and Soltes, 2012). Thus, we define the indicator variable *BadNews*, which takes the value of 1 if a firm-quarter's *SUE* is negative and 0 otherwise. We interact this variable with *SUE* to control for possible media negativity bias. We control for firm size (*LnMVE*), leverage (*Leverage*), and growth opportunity (*MB*), because the market demand for information is greater for larger firms, more leveraged firms and faster-growing firms than for their respective counterparts (Bushee et al., 2010). Firms with higher institutional ownership are also more likely than others to receive greater media coverage, because institutional investors are the main clientele of news services (Soltes, 2010). We therefore include institutional ownership (*InstitutionHolding*) and the number of institutional investors (*NumInstitution*) in our analysis. We also include analyst following (*NumAnalyst*) to control for the potential substitution effect between analyst coverage and media coverage (Fang and Peress, 2009).

In addition, as media coverage may be positively related to the potential economic impact of a particular firm in society, we control for the number of employees (*NumEmployee*) as a proxy for the economic impact of the firm. As firms included in major market indexes are of particular interest to the business press (Li et al., 2011), we include an indicator variable for the S&P 1500 Index (*SP1500*). To control for investor attention, we also include stock returns from the previous quarter (*PriorReturn*) and market-adjusted share turnover from the previous quarter (*PriorTurnover*). Kothari et al. (2009) show that litigation costs, managerial career concerns and information asymmetry are all associated with incentives to withhold bad news. Therefore, we include the number of class action lawsuits in each industry (*NumLawsuit*) to control for litigation costs and the Z-score (*Zscore*) to control for managerial career concerns. We also include a classification of high-tech industries (*HighTech*) and a classification of regulated industries (*Regulate*) to control for information asymmetry. The variables are defined in detail in Appendix I.

3.2. Stock price sensitivity to positive versus negative earnings surprises

To examine whether and how media coverage affects investors' responses to earnings announcements that contain positive versus negative earnings news, we follow Mian and Sankaraguruswamy (2012) and create two indicator variables, *Goodnews* and *Badnews*, where *Goodnews* (*Badnews*) equals 1 if a firm's unexpected earnings are positive (negative) and 0 otherwise. We then multiply unexpected earnings surprises (*SUE*) by these indicator variables and obtain *SUEGoodNews* and *SUEBadNews* (i.e., our measures of good and bad earnings surprises, respectively). We further multiply *SUEGoodNews* and *SUEBadNews* by the level of media coverage, *Coverage*, around the earnings announcement dates to create the interaction terms *SUEGoodNews* × *Coverage* and *SUEBadNews* × *Coverage*. These variables allow us to test whether the earnings response coefficient of positive versus negative earnings news varies depending on the level of media coverage. We include the indicator variable *BadNews* as a stand-alone variable to account for the difference in intercepts for good and bad earnings news (Bartov et al., 2002).[16] Furthermore, we include industry and quarter fixed effects to control for time-invariant industry- and quarter-specific effects that may affect stock returns surrounding earnings announcements. We then regress the 3-day cumulative abnormal returns surrounding a firm's quarterly earnings announcements (*CAR (–1, +1)*) on *SUEGoodNews* × *Coverage* and *SUEBadNews* × *Coverage*.[17]

The model is specified as follows:

[15] We adjust earnings when a stock split is observed for better comparison over the years. In an additional test, instead of using quarterly earnings announcements, we examine the role of media coverage using yearly earnings announcements. Although we have a much smaller number of observations, our results remain unchanged.

[16] Following Mian and Sankaraguruswamy (2012), we also include two additional control variables, *NonlGood*, measured as the square of *SUEGoodnews*, and *NonlBad*, measured as the square of *SUEBadnews* multiplied by –1.

[17] In a robustness test, we use the 7-day cumulative abnormal returns surrounding earnings announcements, *CAR (–3, +3)*, instead of the 3-day cumulative abnormal returns, *CAR (–1, +1)*. We find that our inferences remain unchanged.

$$
\begin{aligned}
CAR(-1,+1)_{i,q} = {} & \beta_0 + \beta_1 BadNews_{i,q} + \beta_2 SUEGoodNews_{i,q} + \beta_3 SUEGoodNews \times Coverage_{i,q} \\
& + \beta_4 SUEBadNews_{i,q} + \beta_5 SUEBadNews \times Coverage_{i,q} + \text{Control Variables} \\
& + IndustryandYear - QuartersFixedEffect + \varepsilon_{i,q} \qquad (2)
\end{aligned}
$$

where *Coverage* is our proxy for media attention, measured in the period preceding a firm's quarterly earnings announcement. Given the positive association between stock prices and earnings surprises (Ball and Brown, 1968), we expect that$\beta_2 > 0$ and$\beta_4 > 0$. Our variables of interest in this regression model are β_3 and β_5.

If greater media coverage increases investors' attention to corporate earnings news contained in earnings announcements, then we would expect β_3 and β_5 to be significant and positive (H1a). In contrast, if greater media coverage of negative news in the current period provides more incentive for managers to avoid reporting negative news in future periods, thereby reducing investors' concerns about the persistence of poor financial performance, we predict that firms with negative earnings news will experience less negative stock price reactions if they have higher media coverage, compared to firms with similar negative earnings surprises but less media coverage. In other words, we expect that$\beta_5 < 0$ (H1b).

All of the control variables in Eq. (1), but not the instrumental variable, are included in Eq. (2), with *IMR* as an additional control. Furthermore, we include industry and quarter fixed effects to control for time-invariant industry- and quarter-specific effects that may affect stock returns surrounding earnings announcements.[18]

4. Data and sample selection

We identify quarterly earnings announcement dates using data from the Compustat and I/B/E/S (Institutional Brokers' Estimate System) databases, following Dellavigna and Pollet (2009) and Mian and Sankaraguruswamy (2012). Our primary data source for firm press releases and media coverage is the RavenPack database, which provides comprehensive coverage of press articles for a large number of publicly traded U.S. firms. RavenPack offers access to all Dow Jones (DJ) news sources, including DJ Newswires and *The Wall Street Journal*. Given this data coverage, studies (e.g., Drake et al., 2014) suggest that RavenPack media data provide a valid approximation of public news for market participants. As a result, RavenPack data are widely used by researchers to examine the role of the media in capital markets (e.g., Dang et al., 2015). We require that all news articles obtained from RavenPack have a relevance score of 100 for (i.e., are highly relevant to)[19] a given firm to ensure that we only include news articles that are relevant to the firms in our sample.

For each quarterly earnings announcement, we define a 3-day event window centered on the quarterly earnings announcement date. Next, we calculate the total number of news articles published during each measurement window before a firm's quarterly earnings announcement date. Other data used in our study come from Compustat, CRSP (Center for Research in Security Prices), I/B/E/S, Thomson Reuters 13F and Securities Class Action Clearinghouse. Our final sample for the main analysis comprises 112,787 firm-quarter observations that are associated with 5,640 firms over the 2000–2014 period. All of the continuous variables are winsorized at the top and bottom 1 % to minimize the influence of outliers.

Table 1 presents the descriptive statistics. More than 77.2 % of the firms in our sample receive media coverage, with an average of 18.41 news articles published in the fiscal quarter preceding a firm's quarterly earnings announcement (i.e., the period from 1 day after a firm's earnings announcement in quarter q–1 to 1 day before its earnings announcement in quarter q). During the 3-day earnings announcement window, an average of 6.96 news articles are published (including both earnings- and non-earnings-related news articles).

[18] The results for Equation (2) are qualitatively similar whether the equation controls for firm fixed effects or industry fixed effects.

[19] RavenPack uses a relevance score ranging from 0 (not relevant) to 100 (highly relevant) to indicate the relevance of a news article to a particular firm. For example, news articles focused on a firm's industry in general (instead of focusing on the firm specifically) will have a low relevance score. However, even if a news article is not classified by the database as highly relevant, news articles with a relevance score below 100 can arguably play an important role in attracting investors' attention if this news is related to a particular firm. Thus, in a robustness test, we repeat our analyses using all news articles with a relevance score of 75 and above and find that our conclusion remains unchanged.

Table 1
Descriptive Statistics.

Variables	N	Mean	25 %	Median	75 %	Std. Dev.
CAR(−1,+1)	112,787	0.000	−0.045	−0.001	0.045	0.089
Num_Press_90day	112,787	18.408	2	11	25	23.140
Num_Press_60day	112,787	10.552	0	6	14	14.853
Num_Press_30day	112,787	4.861	0	2	6	7.447
Num_Press_3day	112,787	6.957	0	6	10	6.314
Abn_Num_Press	112,787	−0.026	−9.917	−1.581	7.322	17.731
Num_Press_Earnings	112,787	1.765	0	0	3	2.834
Num_Press_NonEarnings	112,787	16.609	1	9	22	21.867
Num_Press_Pos	112,787	5.688	0	3	7	9.490
Num_Press_Neg	112,787	3.800	0	1	4	7.192
Num_Press_Full	112,787	5.532	0	2	7	9.328
Num_Press_Flash	112,787	6.980	0	3	8	11.791
Num_Press_PR	112,787	2.990	0	2	4	3.357
Negative_News_Ratio	112,787	0.183	0.043	0.152	0.273	0.172
SUE	112,787	0.000	−0.005	0.001	0.006	0.033
BadNews	112,787	0.395	0	0	1	0.489
LnMVE	112,787	6.713	5.478	6.572	7.822	1.710
Leverage	112,787	0.194	0.007	0.164	0.322	0.186
MB	112,787	2.157	1.158	1.594	2.467	1.680
InstitutionHolding	112,787	0.614	0.409	0.660	0.832	0.274
NumInstitution	112,787	4.598	4.025	4.654	5.226	0.989
NumAnalyst	112,787	1.814	1.099	1.792	2.398	0.736
NumEmployee	112,787	11.801	11.782	11.794	11.820	0.020
SP1500	112,787	0.439	0	0	1	0.496
PriorReturn	112,787	0.000	−0.013	−0.001	0.012	0.029
PriorTurnover	112,787	0.009	0.004	0.007	0.012	0.008
NumLawsuit	112,787	6.150	0	1	7	17.326
Zscore	112,787	4.946	1.116	2.302	4.928	13.211
HighTech	112,787	0.287	0	0	1	0.452
Regulate	112,787	0.058	0	0	0	0.233

RavenPack also classifies news articles into (1) full articles, (2) news flashes and (3) press releases. Full articles may include editorial content generated by reporters or other information generated by firms. News flashes generally do not contain editorial content; instead, they simply rebroadcast information generated by firms or other information intermediaries such as analysts. Press releases mainly comprise news generated by firms. On average, 5.53 full news articles, 6.98 news flashes and 2.99 press releases are published in the fiscal quarter preceding a firm's quarterly earnings announcement.[20]

Table 2 presents the Pearson correlation matrix for the main variables. The significant and positive correlations among all of the media coverage variables suggest that these variables capture a similar construct. Consistent with Mian and Sankaraguruswamy (2012), *SUE* and *CAR(–1, +1)* are positively correlated. In addition, *LnMVE*, *MB*, *InstitutionHolding* and *NumAnalyst* are all positively associated with our media coverage variables. The results of Spearman's non-parametric correlation analysis are similar and are therefore not tabulated for the sake of brevity.

[20] Table 1 also shows a difference between the level of *Num_Press_Pos* (5.688) and *Num_Press_Neg* (3.800). Although this difference seems inconsistent with the view that the media tend to have greater incentives to cover negative news, it is intuitively reasonable because, overall, more firms report positive earnings surprises than negative earnings surprises. Our results below (reported in Table 3) suggest that when the absolute level of earnings surprises is kept constant, relative to positive earnings surprises, negative earnings surprises do indeed tend to attract greater media attention, consistent with prior studies (Tetlock et al., 2008; Kothari et al., 2008; Bushee et al., 2010).

Table 2
Pearson Correlation Matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) *CAR(−1,+1)*															
(2) *Dum_Press_90day*	**0.018**														
(3) *Num_Press_90day*	**0.008**	**0.443**													
(4) *Num_Press_Earnings*	**0.022**	**0.371**	**0.502**												
(5) *Num_Press_NonEarnings*	**0.006**	**0.422**	**0.993**	**0.402**											
(6) *Num_Press_Pos*	**0.008**	**0.346**	**0.755**	**0.421**	**0.744**										
(7) *Num_Press_Neg*	**0.006**	**0.290**	**0.783**	**0.367**	**0.782**	**0.516**									
(8) *Num_Press_Full*	**0.004**	**0.333**	**0.798**	**0.360**	**0.798**	**0.580**	**0.690**								
(9) *Num_Press_Flash*	**0.010**	**0.336**	**0.858**	**0.488**	**0.845**	**0.699**	**0.685**	**0.518**							
(10) *Num_Press_PR*	**0.005**	**0.492**	**0.715**	**0.502**	**0.691**	**0.651**	**0.484**	**0.462**	**0.624**						
(11) *BadNews*	**−0.140**	**−0.019**	**−0.035**	**−0.007**	**−0.036**	**−0.038**	**−0.013**	**−0.046**	**−0.013**	**−0.025**					
(12) *SUE*	**0.118**	**0.005**	0.001	**−0.004**	0.001	**0.003**	**−0.012**	**0.011**	**−0.012**	**0.006**	**−0.524**				
(13) *LnMVE*	**0.009**	**0.132**	**0.507**	**0.206**	**0.510**	**0.398**	**0.378**	**0.383**	**0.460**	**0.358**	**−0.094**	**0.014**			
(14) *MB*	**−0.040**	**0.017**	**0.039**	−0.001	**0.041**	**0.017**	**0.054**	**0.083**	**−0.005**	**0.016**	**−0.077**	**0.041**	**0.115**		
(15) *InstitutionHolding*	**0.029**	**0.245**	**0.321**	**0.174**	**0.317**	**0.196**	**0.219**	**0.244**	**0.232**	**0.285**	**−0.035**	**−0.006**	**0.448**	−0.002	
(16) *NumAnalyst*	**0.013**	**0.138**	**0.456**	**0.198**	**0.456**	**0.339**	**0.344**	**0.348**	**0.408**	**0.319**	**−0.018**	**−0.021**	**0.671**	**0.059**	**0.469**

Entries in ***Bold*** denotes a significance level of at least 0.05. Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in the Appendix.

5. Empirical results

5.1. Determinants of media coverage

As studies indicate that the business press is more likely to cover and/or tends to cover more negative corporate news than positive news (e.g., Niessner and So, 2017), our study does not retest this assumption. Nevertheless, we validate it as a first step in our study. The results of estimating Eq. (1) to test the plausibility of this assumption are reported in Table 3. We find significant and negative (positive) coefficients on *SUE* (*BadNews* × *SUE*) across all models with and without the instrumental variable, which is consistent with the findings of previous studies (e.g., Niessner and So, 2017). These results suggest that business-focused media are more likely to cover and/or tend to cover more negative earnings news than positive earnings news.

5.2. Media coverage and asymmetric stock price sensitivity to positive versus negative earnings surprises

Table 4 reports the results of estimating Eq. (2), which allow us to examine the effects of media coverage on the sensitivity of stock prices to positive versus negative earnings surprises. We use five proxies (i.e., *Num_Press_90day*, *Num_Press_60day*, *Num_Press_30day*, *Num_Press_3day* and *Abn_Num_Press*) for the level of pre-earnings announcement media coverage to examine whether and how the number of news articles published before a firm's earnings announcement date affects the intensity of stock price reactions to an earnings surprise, and whether and how this effect varies depending on the direction of the earnings surprise. Using our five proxies, consistent with Mian and Sankaragursuswamy (2012), we find significant and positive coefficients on *SUEGoodNews*, supporting the notion that earnings surprises are value relevant for investors.

Our main variables of interest are the coefficients on *SUEGoodNews* × *Coverage* and *SUEBadNews* × *Coverage*, which measure the effects of media coverage on the sensitivity of stock prices to positive and negative earnings news, respectively. We find a significant and positive coefficient on *SUEGoodNews* × *Coverage*, suggesting that greater media coverage of a firm strengthens positive stock price reactions to the firm's positive earnings surprises. More importantly, the significant and negative coefficient on *SUEBadNews* × *Coverage* across all columns of Table 4 strongly supports H1b that greater media coverage in the period before a firm's earnings announcement attenuates (i.e., weakens) investors' reactions to negative earnings surprises in the earnings announcement.

Table 3
Determinants of Media Coverage.

Dependent Variable Model	*Coverage = Dum_Press_90day* *Logistic* (1)	*Coverage = Dum_Press_90day* *Logistic* (2)
Dum_Press_Year(t-1)		6.322***
		(0.000)
BadNews	−0.048*	−0.208***
	(0.078)	(0.000)
SUE	**−3.903*** **	**−4.106*** **
	(0.000)	**(0.000)**
BadNews × SUE	**8.669*** **	**6.560*** **
	(0.000)	**(0.000)**
LnMVE	−0.413***	0.082*
	(0.000)	(0.060)
Leverage	−0.430**	−0.303
	(0.020)	(0.158)
MB	0.113***	0.041**
	(0.000)	(0.042)
InstitutionHolding	0.931***	−0.023
	(0.000)	(0.904)
NumInstitution	0.679***	−0.117
	(0.000)	(0.140)
NumAnalyst	0.216***	0.489***
	(0.000)	(0.000)
NumEmployee	−1.548	−3.731
	(0.231)	(0.123)
SP1500	0.196**	−0.393***
	(0.035)	(0.000)
PriorReturn	0.176	0.214
	(0.483)	(0.549)
PriorTurnover	−23.348***	−9.401**
	(0.000)	(0.019)
NumLawsuit	0.001	−0.004***
	(0.789)	(0.003)
Zscore	0.002	−0.002
	(0.462)	(0.130)
HighTech	0.108	0.112
	(0.448)	(0.462)
Regulate	0.397	0.318
	(0.294)	(0.271)
Constant	17.071	44.537
	(0.262)	(0.119)
Industry&Year-Quarters Fixed Effect	Yes	Yes
Firm Clustering	Yes	Yes
Observations	112,787	112,787
Pseudo R-squared	0.119	0.629

*, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively (two-tailed). Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in the Appendix.

By measuring the level of media coverage using different measurement windows (i.e., 90, 60 and 30 days before a firm's earnings announcements), we can also determine the relative magnitude of the estimated coefficients on $BadNews \times SUE \times Coverage$. We find statistically different magnitudes, with a larger magnitude when the measurement window is shorter and closer to a firm's earnings announcement date. This finding suggests that when media coverage is closer to the earnings announcement date, it tends to more strongly weaken stock price reactions to negative earnings surprises (–0.014 in column 4 and –0.005 in column 1). Similarly, using an additional measure of media coverage based on the abnormal number of news articles surrounding a firm's quarterly earnings announcement date (defined as the residual of the model regressing the total level of

Table 4
Media Coverage and Asymmetric Stock Price Reactions to Positive versus Negative Earnings Surprises.

Dependent variable	***CAR(−1,+1)***				
Coverage =	***Num_Press_90day***	***Num_Press_60day***	***Num_Press_30day***	***Num_Press_3day***	***Abn_Num_Press***
Model	***OLS***	***OLS***	***OLS***	***OLS***	***OLS***
	(1)	(2)	(3)	(4)	(5)
BadNews	−0.017***	−0.017***	−0.017***	−0.017***	−0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SUEGoodNews	0.423***	0.426***	0.438***	0.415***	0.452***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SUEGoodNews × Coverage	**0.002****	**0.002****	**0.002**	**0.005***	**0.003*****
	(0.029)	**(0.028)**	**(0.300)**	**(0.060)**	**(0.004)**
SUEBadNews	0.348***	0.341***	0.336***	0.364***	0.285***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SUEBadNews × Coverage	**−0.005*****	**−0.007*****	**−0.013*****	**−0.014*****	**−0.004*****
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
NonlGood	−3.125***	−3.134***	−3.150***	−3.117***	−3.160***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NonlBad	−1.217***	−1.206***	−1.203***	−1.240***	−1.182***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LnMVE	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Leverage	0.001	0.001	0.002	0.002	0.001
	(0.427)	(0.421)	(0.393)	(0.411)	(0.429)
MB	−0.002***	−0.002***	−0.002***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
InstitutionHolding	0.014***	0.014***	0.014***	0.013***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NumInstitution	−0.004***	−0.004***	−0.004***	−0.004***	−0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NumAnalyst	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
NumEmployee	−0.135**	−0.133**	−0.133**	−0.131**	−0.132**
	(0.012)	(0.013)	(0.013)	(0.014)	(0.014)
SP1500	0.004***	0.003***	0.004***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PriorReturn	−0.008	−0.008	−0.008	−0.008	−0.008
	(0.488)	(0.480)	(0.471)	(0.480)	(0.500)
PriorTurnover	−0.332***	−0.330***	−0.324***	−0.308***	−0.314***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NumLawsuit	0.000	0.000	0.000	0.000	0.000
	(0.212)	(0.220)	(0.229)	(0.182)	(0.206)
Zscore	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.030)	(0.029)	(0.028)	(0.030)	(0.026)
HighTech	0.002	0.002	0.002	0.002	0.002
	(0.186)	(0.182)	(0.180)	(0.196)	(0.184)
Regulate	−0.002	−0.002	−0.002	−0.002	−0.002
	(0.354)	(0.351)	(0.361)	(0.380)	(0.387)
Constant	1.598**	1.579**	1.576**	1.558**	1.559**
	(0.011)	(0.012)	(0.013)	(0.014)	(0.014)
Industry&Year-Quarters Fixed Effect	Yes	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes	Yes
Observations	112,787	112,787	112,787	112,787	112,787
R-squared	0.029	0.029	0.029	0.029	0.029

Goodnews (*Badnews*) equals 1 if the unexpected earnings is positive (negative), and 0 otherwise. We then multiply unexpected earnings surprises (*SUE*) by these indicator variables to yield *SUEGoodNews* and *SUEBadNews* (i.e., our measures of good and bad earnings surprises), respectively. *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively (two-tailed). Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in the Appendix.

Table 5
Media Coverage and Stock Price Reactions to Positive versus Negative Earnings Surprises.

Panel A. Media Coverage by Content—Earnings-Related versus *Non-Earnings-Related News Articles.*

Dependent variable		***CAR(−1, +1)***	
	Earnings-Related News	**Non-Earnings-Related News**	**All News**
Coverage =	***Num_Press_Earnings***	***Num_Press_NonEarnings***	
Model	***OLS***	***OLS***	***OLS***
	(1)	**(2)**	**(3)**
BadNews	−0.021***	−0.022***	−0.022***
	(0.000)	(0.000)	(0.000)
SUE	0.031*	0.039**	0.021
	(0.098)	(0.050)	(0.296)
BadNews × SUE	0.142***	0.147***	0.174***
	(0.000)	(0.000)	(0.000)
Num_Press_Earnings	0.001*		0.001***
	(0.065)		(0.002)
BadNews × Num_Press_Earnings	0.001		−0.000
	(0.489)		(0.845)
SUE × Num_Press_Earnings	**0.030*** **		**0.027*** **
	(0.000)		**(0.000)**
BadNews × SUE × Num_Press_Earnings	**−0.055*** **		**−0.042*** **
	(0.000)		**(0.000)**
Num_Press_NonEarnings		−0.001***	−0.001***
		(0.003)	(0.000)
BadNews × Num_Press_NonEarnings		0.001***	0.001**
		(0.008)	(0.010)
SUE × Num_Press_NonEarnings		**0.002*** **	**0.001**
		(0.008)	**(0.222)**
BadNews × SUE × Num_Press_NonEarnings		**−0.006*** **	**−0.004*** **
		(0.000)	**(0.000)**
All Other Controls	Yes	Yes	Yes
Industry&Year-Quarters Fixed Effect	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes
Observations	112,787	112,787	112,787
R-squared	0.028	0.028	Yes

Panel B. Media Coverage by Type—Full News Articles, Flash News Articles, and Press Releases

Dependent variable	***CAR(−1,+1)***			
	Full News Articles	**Flash News Articles**	**Press Release News Articles**	**All Types**
Coverage =	***Num_Press_Full***	***Num_Press_Flash***	***Num_Press_PR***	
Model	**OLS**	**OLS**	**OLS**	**OLS**
	(1)	**(2)**	**(3)**	**(4)**
BadNews	−0.021***	−0.022***	−0.022***	−0.022***
	(0.000)	(0.000)	(0.000)	(0.000)
SUE	**0.050*** **	**0.047** **	**0.035* **	**0.030**
	(0.009)	**(0.014)**	**(0.095)**	**(0.162)**
BadNews×SUE	**0.115*** **	**0.132*** **	**0.154*** **	**0.162*** **
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
Num_Press_Full	−0.001**			−0.001
	(0.011)			(0.250)
BadNews× Num_Press_Full	0.001*			0.001
	(0.052)			(0.521)
SUE×Num_Press_Full	**0.004** **			**0.003**
	(0.027)			**(0.240)**
BadNews×SUE×Num_Press_Full	**−0.012*** **			**−0.003**
	(0.000)			**(0.391)**
Num_Press_Flash		−0.001**		−0.001
		(0.011)		(0.372)
BadNews×Num_Press_Flash		0.001***		0.001***

(*continued on next page*)

Table 5 (*continued*)

Panel B. Media Coverage by Type—Full News Articles, Flash News Articles, and Press Releases

Dependent variable	***CAR(−1,+1)***			
	Full News Articles	**Flash News Articles**	**Press Release News Articles**	**All Types**
Coverage =	***Num_Press_Full***	***Num_Press_Flash***	***Num_Press_PR***	
Model	**OLS**	**OLS**	**OLS**	**OLS**
	(1)	**(2)**	**(3)**	**(4)**
		(0.000)		(0.008)
SUE×Num_Press_Flash		**0.003****		**0.000**
		(0.026)		**(0.796)**
BadNews×SUE×Num_Press_Flash		**−0.010*****		**−0.006****
		(0.000)		**(0.040)**
Num_Press_PR			−0.001**	−0.001
			(0.019)	(0.464)
BadNews×Num_Press_PR			0.001**	−0.001
			(0.050)	(0.783)
SUE×Num_Press_PR			**0.012****	**0.009**
			(0.016)	**(0.177)**
BadNews×SUE×Num_Press_PR			**−0.034*****	**−0.018***
			(0.000)	**(0.069)**
All Other Controls	Yes	Yes	Yes	Yes
Industry&Year-Quarters Fixed Effect	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes
Observations	112,787	112,787	112,787	112,787
Adjusted R-Squared	0.028	0.028	0.028	0.028

Panel C. Media Coverage by Tone—Positive/Negative News Articles

Dependent variable	***CAR(−1,+1)***		
	News with Positive Tone	**News with Negative Tone**	**News with All Tones**
Coverage =	***Num_Press_Pos***	***Num_Press_Neg***	
Model	**OLS**	**OLS**	**OLS**
	(1)	**(2)**	**(3)**
BadNews	−0.022***	−0.021***	−0.022***
	(0.000)	(0.000)	(0.000)
SUE	**0.037***	**0.043****	**0.030**
	(0.053)	**(0.022)**	**(0.124)**
BadNews×SUE	**0.123*****	**0.132*****	**0.147*****
	(0.000)	**(0.000)**	**(0.000)**
Num_Press_Pos	−0.001***		−0.001**
	(−0.004)		(−0.023)
BadNews×Num_Press_Pos	0.001***		0.001*
	(0.001)		(0.055)
SUE×Num_Press_Pos	**0.007*****		**0.005****
	(0.000)		**(0.012)**
BadNews×SUE×Num_Press_Pos	**−0.012*****		**−0.007****
	(0.000)		**(−0.046)**
Num_Press_Neg		−0.001	0.001
		(−0.338)	(0.937)
BadNews× Num_Press_Neg		0.001**	0.001
		(0.025)	(0.314)
SUE× Num_Press_Neg		**0.009*****	**0.005**
		(0.005)	**(0.136)**
BadNews×SUE×Num_Press_Neg		**−0.022*****	**−0.017*****
		(−0.000)	**(−0.001)**
All other controls	Yes	Yes	Yes
Industry&Year-Quarters Fixed Effect	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes

Table 5 (*continued*)

Panel C. Media Coverage by Tone—Positive/Negative News Articles

Dependent variable	***CAR(−1,+1)***		
	News with Positive Tone	**News with Negative Tone**	**News with All Tones**
Coverage =	***Num_Press_Pos***	***Num_Press_Neg***	
Model	**OLS**	**OLS**	**OLS**
	(1)	**(2)**	**(3)**
Observations	112,787	112,787	112,787
Adjusted R-Squared	0.028	0.028	0.028

*, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively (two-tailed). Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in the Appendix.

media coverage (*Num_Press_90day*) on the control variables included in Eq. (1)), we again find a significant and negative coefficient on the interaction term $SUEBadNews \times Coverage$ (column 5). This result confirms our previous findings.

Information intermediaries such as institutional investors, financial analysts and news media shape firms' information environment and play a crucial role in disseminating firms' information to other capital market participants (e.g., Piotroski and Roulstone, 2004; Bushee et al., 2010). It is therefore important to control for the potential effects of these variables when examining the influence of media coverage on stock price reactions to positive and negative earnings news. Rather than simply controlling for the main effects of these variables in Model (2), in an additional test we include their interaction terms with SUE and $BadNews \times SUE$. In untabulated results, after controlling for the potential effects of $LnMVE$, *NumAnalyst* and *InstitutionHolding* in the differential market response to positive versus negative news, we find that a firm's level of media coverage remains an incrementally important factor affecting stock price reactions to positive and negative earnings surprises.

In addition to using the Heckman (1979) two-stage selection model, we adopt the propensity score matching method to mitigate potential media self-selection issues. Specifically, we identify a sample of firms that do not receive media coverage but are otherwise similar (across all observable dimensions) to those that do receive media coverage. Each firm with media coverage is matched with the firm without media coverage that has the closest propensity score within a maximum distance of 1 % (in the same year). This procedure yields 24,205 firm-year observations in the sample with media coverage and 24,205 observations in the matched sample without media coverage (a total of 48,410 observations). We obtain results that corroborate our finding that stock price reactions to negative earnings surprises are attenuated for firms with greater media coverage.

5.3. Media coverage by content: Earnings-related versus non-earnings-related news articles

In this section, we investigate whether the effects of media coverage on stock price reactions to negative earnings surprises vary depending on the content of media coverage in the pre-earnings announcement period. Previous studies suggest that investors tend to have limited attention spans regarding firm-specific information (Peng and Xiong, 2006; Hirshleifer et al., 2009) and that the media play an important intermediary role in the dissemination of information released in earnings announcements (Fang and Peress, 2009; Bushee et al., 2010; Tetlock, 2010). Consistent with previous findings, we predict that investors' attention to earnings-related news articles will have a greater effect on stock price reactions to earnings surprises during the earnings announcement period.

Table 6
Media Coverage and Persistence of Negative Earnings.

Dependent variable	$BadNews_{i,q+1}$			
Coverage =	*Num_Press_90day*	*Num_Press_60day*	*Num_Press_30day*	*Abn_Num_Press*
Model	*Logistic*	*Logistic*	*Logistic*	*Logistic*
	(1)	(2)	(3)	(4)
$BadNews_{i,q}$	**1.601*** **	**1.602*** **	**1.593*** **	**1.573*** **
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
$BadNews_{i,q} \times Coverage_{i,q}$	**−0.002*** **	**−0.004*** **	**−0.008*** **	**−0.003*** **
	(0.000)	**(0.000)**	**(0.000)**	**(0.001)**
$Coverage_{i,q}$	0.001**	0.003***	0.008***	0.001**
	(0.013)	(0.000)	(0.000)	(0.022)
$LnMVE_{i,q}$	−0.237***	−0.239***	−0.240***	−0.250***
	(0.000)	(0.000)	(0.000)	(0.000)
$Leverage_{i,q}$	0.199***	0.202***	0.204***	0.245***
	(0.000)	(0.000)	(0.000)	(0.000)
$MB_{i,q}$	−0.116***	−0.115***	−0.115***	−0.126***
	(0.000)	(0.000)	(0.000)	(0.000)
$InstitutionHolding_{i,q}$	−0.374***	−0.365***	−0.359***	−0.407***
	(0.000)	(0.000)	(0.000)	(0.000)
$NumInstitution_{i,q}$	0.129***	0.122***	0.117***	0.154***
	(0.000)	(0.000)	(0.000)	(0.000)
$NumAnalyst_{i,q}$	0.257***	0.254***	0.252***	0.267***
	(0.000)	(0.000)	(0.000)	(0.000)
$NumEmployee_{i,q}$	3.748***	3.670***	3.669***	3.899***
	(0.000)	(0.000)	(0.000)	(0.000)
$SP1500_{i,q}$	0.024	0.024	0.025	0.022
	(0.209)	(0.198)	(0.179)	(0.254)
$PriorReturn_{i,q}$	−0.586**	−0.588**	−0.592**	−0.577**
	(0.014)	(0.014)	(0.013)	(0.019)
$PriorTurnover_{i,q}$	5.501***	5.539***	5.562***	5.419***
	(0.000)	(0.000)	(0.000)	(0.000)
$NumLawsuit_{i,q}$	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
$Zscore_{i,q}$	0.005***	0.005***	0.005***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
$HighTech_{i,q}$	0.094***	0.093***	0.092***	0.102***
	(0.000)	(0.000)	(0.000)	(0.000)
$Regulate_{i,q}$	0.139***	0.139***	0.138***	0.156***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−44.521***	−43.564***	−43.540***	−46.306***
	(0.000)	(0.000)	(0.000)	(0.000)
Industry&Year-Quarters Fixed Effect	Yes	Yes	Yes	Yes
Firm Clustering	Yes	Yes	Yes	Yes
Observations	112,553	112,553	112,553	112,553
Pseudo R-squared	0.123	0.124	0.124	0.127

*, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively (two-tailed). Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in the Appendix.

To examine whether the effects of media coverage on stock price sensitivity to bad news vary depending on the content of media coverage,[21] we separately examine whether the level of financial news items (*Num_Press_Earnings*) and that of non-financial news items (*Num_Press_NonEarnings*) affect stock market

[21] RavenPack classifies each news article based on its topic, which allows us to identify the content of each article. We treat an article as financial or earnings-related news if it falls into one of the following categories: mergers and acquisitions, analyst ratings, asset news, balance of payments, bankruptcy, credit, credit ratings, dividends, earnings, equity actions, insider trading, target prices, revenues, securities, stock prices or taxes. Any news article that does not belong to the financial news group is classified as non-financial or non-earnings-related news (e.g., news related to corporate social responsibility, regulations or products).

reactions to negative earnings news. As we focus on stock market reactions to bad news, we interact these two variables with *SUE* and *BadNews* and compare their estimated coefficients. The results are presented in Panel A of Table 5. We find that increasing levels of both financial and non-financial news coverage attenuate stock price reactions to negative earnings surprises. The coefficients on $BadNews \times SUE \times Coverage$ are significant and negative whether *Coverage* is measured based on earnings-related or non-earnings-related news articles. However, the coefficient on $BadNews \times SUE \times Coverage$ in column 1 (with *Coverage* measured by the total number of financial news items) is significantly larger than the coefficient in column 2 (with *Coverage* measured by the total number of non-financial news items). The coefficients are –0.055 and –0.006, respectively. Specifically, these results show that the coefficient on $BadNews \times SUE \times Num\_Press\_Earnings$ is significantly larger than the coefficient on $BadNews \times SUE \times Num\_Press\_NonEarnings$. Similar patterns are observed for the effects of media coverage on stock price reactions to positive earnings news. Thus, the findings reported here support our prediction that relative to non-earnings-related news, earnings-related news coverage tends to play a more important role in attenuating stock market reactions to firms' bad news disclosures.

5.4. Media coverage by type: Full news articles, news flashes and press releases

In this section, we explore whether the effects of media coverage on stock price reactions to negative earnings surprises vary depending on the type of media coverage in the pre-earnings announcement period. Specifically, we investigate whether different types of news articles (i.e., full news articles, news flashes and press releases) have different effects on stock price reactions to earnings surprises. The results are presented in Panel B of Table 5. Across the three types of news articles, we find that the coefficients on $BadNews \times SUE \times Coverage$ are all significant and negative. Overall, these findings align with our argument that investors are likely to be affected by media coverage in their reactions to bad news earnings announcements.

5.5. Media coverage by tone: News articles with a positive versus negative tone

Studies suggest that not only the level of media coverage but also the tone of media coverage can significantly affect the decision-making of capital market participants (e.g., Liu and McConnell, 2013; Cihan et al., 2017; Bradshaw et al., 2021). RavenPack assigns each news article a sentiment score ranging from 0 to 100, with a score of 50 indicating neutrality, a score below 50 indicating a more negative tone and a score above 50 indicating a more positive tone.[22] Thus, we further examine whether the effects of media coverage on stock price reactions to negative versus positive earnings surprises vary depending on the tone of media coverage in the pre-earnings announcement period. The results are presented in Panel C of Table 5. We find that regardless of tone, greater media coverage attenuates stock price reactions to negative earnings surprises during earnings announcements.

5.6. Additional test

News from unreliable sources can misinform capital market participants, leading them to form false beliefs. Thus, we classify a news source as reliable if its reliability is coded 1 by RavenPack and as less reliable otherwise.[23] The results (untabulated) show that the number of news articles from more reliable news providers (vs.

[22] The composite sentiment score created by RavenPack measures news sentiment in a given story by combining five sentiment analysis techniques. Composite sentiment scores are determined by assessing emotionally charged words and phrases embedded in news stories and are typically rated by experts as having short-term positive or negative effects on stock prices.

[23] RavenPack rates the influence and trustworthiness of each news provider on a scale of 1 to 10, with 1 indicating the most trusted sources. According to RavenPack's definition, a news source assigned a score of 1 is considered fully accountable, reputable and impartial. News providers with a score of 1 include highly reliable news media organizations and blogs. News media organizations in this category include *The Washington Times*, *The New York Times*, *The Financial Times*, *The Times*, The Heritage Foundation, *Barrons*, Marketwatch, Bloomberg News, Forbes.com and *The New York Daily News*. A "blog" is defined as "a discussion or informational website with discrete entries or posts." (Walker Rettberg, 2008, p.18). Blogs with a score of 1 include the Blog Herald, Green Technology, Drugs.com, Gig News, Mediapost and Media Creativity.

that from less reliable providers) does indeed tend to play a more important role in stock price reactions to negative earnings surprises.

A possible explanation for our main finding is that wider media dissemination of a firm's poor financial performance increases its CEO's career concerns, which, in turn, increases the firm's incentives to avoid reporting negative news in future periods. In this section, we directly test this potential explanation by examining whether and how media coverage affects the correlation between the likelihood of reporting negative news in the current period and the likelihood of reporting negative news in the future. Specifically, we regress *BadNews* in quarter $q+1$ on *BadNews* in quarter q and the interaction term between *BadNews* in quarter q and *Coverage.* The results are reported in Table 6. Consistent with our conjecture, we find that the coefficient on the interaction term *BadNews* $\times$ *Coverage* is significant and negative, indicating that greater media coverage weakens the persistence of negative news.

5.7. Additional robustness tests

In our study, we attempt to address the potential endogeneity of media coverage by using the Heckman (1979) two-stage selection model to explain the media's decisions to cover a firm. In this section, we conduct additional tests to better address the identification issue. Instead of comparing firms, we compare earnings announcements made by the same firm in the same year that generate the same (or similar) earnings surprises, when one announcement receives more media coverage than the other. We again find that relative to negative earnings announcements issued by a firm with less media coverage, negative earnings announcements issued by the same firm with greater media coverage tend to elicit a lesser stock market reaction. Finally, we conduct additional tests to ensure that our findings are robust to yearly earnings announcements. The findings of our study do not seem to be affected by this choice.

6. Conclusion

In this study, we use multiple variables to measure the level of media coverage in the period preceding firms' earnings announcements. We find consistent and robust evidence that although increased media coverage causes an increase in stock price sensitivity to positive earnings surprises, it causes a reduction in stock price sensitivity to negative earnings surprises. Our additional analyses reveal that these findings are robust to yearly earnings announcements, earnings- and non-earnings-related news, different types of media coverage (i.e., full articles, news flashes and press releases) and media coverage with varying emotional tones. Our findings are also robust after controlling for the potential effects of other major information intermediaries, namely institutional investors and financial analysts, on stock price sensitivity to earnings surprises. Overall, our findings suggest that media coverage plays an important but asymmetric role in investors' reactions to positive versus negative earnings news.

Further evidence indicates that negative earnings news is less persistent for firms with greater media coverage than for other firms. This finding supports the conjecture that greater media coverage increases managers' incentives to avoid future negative news, thereby reducing the persistence of poor financial performance and weakening price reactions to firms' negative earnings news.

We acknowledge that our results should be interpreted with caution. Indeed, the relationship between media coverage and asymmetric investor responses to good and bad news may be endogenously determined. For example, to the extent that firms reporting bad news are likely to provide more information across various channels (e.g., corporate websites or social media) to attenuate investors' strong reactions to bad news, our findings may be attributable to increased firm disclosures bundled with bad news. Such a conjecture is worthy of future investigation.

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 1. Variable definitions

Variable	Definition	Data Source
CAR(–1,+1)	Cumulative abnormal returns over a 3-day window (from day –1 to day + 1, with day 0 being the quarterly earnings announcement date) surrounding a firm's quarterly earnings announcement date;	CRSP
CAR (–3, +3)	Cumulative abnormal returns over a 7-day window (from day –3 to day + 3) surrounding a firm's quarterly earnings announcement date;	CRSP
Num_Press_90day	The total number of news articles (***all articles***) specifically related to firm *i* published during the ***90-day*** window preceding the firm's quarterly earnings announcement date (the period from 1 day after the earnings announcement date in quarter *q*–1 to 1 day before the earnings announcement date in quarter *q*);	RavenPack
Num_Press_60day	The total number of news articles (***all articles***) specifically related to firm *i* published during the ***60-day*** window preceding the firm's quarterly earnings announcement date;	RavenPack
Num_Press_30day	The total number of news articles (***all articles***) specifically related to firm *i* published during the ***30-day*** window preceding the firm's quarterly earnings announcement date;	RavenPack
Num_Press_3day	The total number of news articles (***all articles***) specifically related to firm *i* published in the ***3-day window*** (from day –1 to day + 1, with day 0 being the firm's quarterly earnings announcement date) surrounding the firm's quarterly earnings announcement date;	RavenPack
Dum_Press_90day	An indicator variable equal to 1 if the total number of news articles (i.e., *Num_Press_90day*) published during the ***90-day*** window preceding the firm's quarterly earnings announcement date is greater than 0, and 0 otherwise;	RavenPack
Dum_Press_Year(t–1)	An indicator variable equal to 1 if the total number of news articles published in year *t*–1 is greater than 0, and 0 otherwise;	RavenPack
Abn_Num_Press	The level of ***abnormal*** media coverage measured during the ***90-day*** window preceding a firm's quarterly earnings announcement date. It is defined as the residual from regressing the level of media coverage (i.e., *Num_Press_90day*) on firm-level determinants identified by Engelberg and Parsons (2011) (i.e., all control variables included in Equation (1));	RavenPack
Num_Press_Earnings	The total number of news articles (particularly ***earnings-related news articles***) specifically related to firm *i* published during the ***90-day*** window preceding the firm's quarterly earnings announcement date;	RavenPack

(*continued on next page*)

Appendix 1 (*continued*)

Variable	Definition	Data Source
Num_Press_NonEarnings	The total number of news articles (particularly ***non-earnings-related news articles***) specifically related to firm *i* published during the ***90-day*** window preceding the firm's quarterly earnings announcement date;	RavenPack
Num_Press_Pos	The total number of news articles with a sentiment score of 50 or above (i.e., positive tone) specifically related to firm *i* published during the ***90-day*** window preceding the firm's quarterly earnings announcement date;	RavenPack
Num_Press_Neg	The total number of news articles with a sentiment score below 50 (i.e., negative tone) specifically related to firm *i* published during the ***90-day*** window preceding the firm's quarterly earnings announcement date;	RavenPack
Num_Press_Full	The total number of ***full news articles*** specifically related to firm *i* published during the ***90-day*** window preceding the firm's quarterly earnings announcement date;	RavenPack
Num_Press_Flash	The total number of ***news flashes*** specifically related to firm *i* published during the ***90-day*** window preceding the firm's quarterly earnings announcement date;	RavenPack
Num_Press_PR	The total number of ***press releases*** specifically related to firm *i* published during the ***90-day*** window preceding the firm's quarterly earnings announcement date;	RavenPack
Num_Press_MoreReliable	The total number of ***news articles from reliable news sources*** specifically related to firm *i* published during the ***90-day*** window preceding the firm's quarterly earnings announcement date; the reliability of each article is defined using the reliability score provided by RavenPack's Web Edition database; news articles with a reliability score of 1 are defined as reliable;	RavenPack
Num_Press_LessReliable	The total number of ***news articles from less reliable news sources*** specifically related to firm *i* published during the ***90-day*** window preceding the firm's quarterly earnings announcement date; the reliability of each article is defined using the reliability score provided by RavenPack's Web Edition database; news articles with a reliability score of 2, 3, 4 or 5 are defined as less reliable;	RavenPack
Negative_News_Ratio	The ratio of the number of negative news articles to the total number of news articles, measured as the total number of ***negative news articles*** (news articles with a sentiment score < 50) divided by the total number of news articles issued during the ***90-day*** window preceding a firm's quarterly earnings announcement date;	RavenPack
SUE	A measure of earnings surprise, defined as actual earnings per share before extraordinary items in quarter *q* minus actual earnings per share before extraordinary items in quarter *q*–4 (i.e., the same quarter of the previous year), scaled by the stock price at the end of the quarter, following Livnat and Mendenhall (2006);	Compustat

Appendix 1 (*continued*)

Variable	Definition	Data Source
BadNews	An indicator variable equal to 1 if *SUE* defined above is less than 0 and 0 otherwise;	Compustat
LnMVE	The natural logarithm of the market value of equity at the end of the quarter (in millions);	Compustat
Leverage	The leverage ratio defined as long-term debt plus debt in current liabilities, divided by total assets;	Compustat
MB	The ratio of the market value of equity to the book value of equity;	Compustat/CRSP
InstitutionHolding	The percentage of institutional ownership at the end of the fiscal quarter;	Thomson Reuter 13f
NumInstitution	The natural logarithm of 1 plus the total number of institutional holders at the end of the fiscal quarter;	Thomson Reuter 13f
NumAnalyst	The natural logarithm of 1 plus the number of analysts who issue quarterly earnings forecasts for a specific firm during a given quarter, as captured in the I/B/E/S database;	Compustat
NumEmployee	The natural logarithm of 1 plus the total number of employees;	Compustat
SP1500	an indicator variable equal to 1 if a firm is part of the S&P 1500 Index in year *t* and 0 otherwise;	Compustat
PriorReturn	A firm's cumulative market-adjusted returns over 50 trading days ending on *t*–10;	CRSP
PriorTurnover	The mean ratio of daily trading volume to the total number of shares outstanding over 50 trading days ending on *t*–10;	CRSP
NumLawsuit	The number of class action lawsuits in an industry, following Field, Lowry and Shu (2005);	Securities Class Action Clearing House
Zscore	The Altman Z-score (which captures a firm's bankruptcy risk);	Self-measured
HighTech	A, variable for high-tech industries, classification of high-tech industries following Kothari, Shu and Wysocki (2008);	Compustat
Regulate	A variable for regulated industries, classification of regulated industries following Kothari, Shu and Wysocki (2008).	Compustat

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Does investor communication improve corporate social responsibility? A machine learning-based textual analysis

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ABSTRACT

In this study, we take a machine learning-based approach to measure institutional investor attention to corporate social responsibility (CSR) issues when communicating with firms during site visits. We find that institutional investors can effectively enhance CSR performance through CSR-related communication. This effect remains robust to various checks and is more pronounced for non-state-owned enterprises and firms with lower levels of institutional ownership and in periods following the issuance of Green Investment Guidelines. We also identify information asymmetry and financing constraints as the two mechanisms underlying this effect. Overall, our findings highlight the importance of private interactions between management and institutional investors in promoting CSR.

1. Introduction

Socially responsible investing (SRI) has grown rapidly in recent years, with institutional investors increasingly incorporating environmental, social and governance (ESG) factors into their investment decisions. These investors now manage trillions of dollars in assets under sustainable investment strategies to better manage risks and generate long-term returns (Renneboog et al., 2008; Nofsinger et al., 2019; Hoepner et al., 2023).

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As major providers of capital in financial markets, they have both the incentive and power to influence corporate social responsibility (CSR) activities[1] (Dyck et al., 2019; Kim et al., 2019; Chen et al., 2020; Liu et al., 2023). While many studies examine the mechanisms through which investors can engage with management and influence firms' CSR performance, such as shareholder proposals and voting (Dimson et al., 2015; Dyck et al., 2019; Kim et al., 2019; Dikolli et al., 2022; Hwang et al., 2022; Hoepner et al., 2023), few investigate the role of private meetings between managers and institutional investors. Survey evidence suggests that institutional investors actively engage in private communications with firms to express their concerns about the environment, labor relations, human rights and other topics related to social performance (Hockerts and Moir, 2004; Ziek, 2009; Du et al., 2010). In April 2022, the China Securities Regulatory Commission revised the Guidelines for Investor Relations Management of Listed Companies for the first time, requiring sustainable information to be included in communications between listed companies and investors. Anecdotal evidence also reveals that Chinese investors increasingly consider corporate sustainability and any relevant information, as this can be essential when they interact with firms.[2] However, private communication, as a channel through which institutional investors can influence CSR performance, remains understudied. We use a unique Chinese corporate site visit dataset to examine whether investors can effectively enhance CSR performance through direct interactions.

Previous studies show that institutional investors play an important role in shaping CSR. Although numerous studies explore the relationship between institutional ownership and CSR performance based on total institutional shareholder holdings, the empirical findings remain mixed (Borghesi et al., 2014; Fernando et al., 2017; Dyck et al., 2019; Chen et al., 2020; Hwang et al., 2022; Kim and Yoon, 2022), partly because institutional investors do not monitor all of their holdings equally. This variation may thus not accurately reflect institutional investors' monitoring behavior regarding CSR issues, as their preferences, objectives and strategies will differ (Gloßner, 2019; Nofsinger et al., 2019). Other studies mainly focus on shareholder activism or voting on shareholder proposals and present direct evidence of institutional investors' influence (Dimson et al., 2015; Barko et al., 2022; Hoepner et al., 2023). However, shareholder activism is an infrequent form of costly intervention and often only involves (and therefore can only influence) a few firms (Chapman et al., 2022). The generalizability of these findings may then be limited, warranting cautious interpretation.

Our focus in this study is on private interactions between institutional investors and firms, thus filling an important gap in the literature. Institutional investors can enhance the transparency of CSR policies, risks and impacts by engaging with firms on CSR issues, thus enabling better monitoring and advocacy for improvement (Hockerts and Moir, 2004; Jiang et al., 2022). Communication also helps to reduce the uncertainty around CSR practices, thus reducing investors' perceptions of risk and firms' capital costs. This provides firms with more resources to invest in CSR (Lins et al., 2017; Chapman et al., 2022). However, communication can serve investors' interests in terms of influencing firms, or may lack constraining power compared with activist tactics such as shareholder proposals (Chapman et al., 2022; Heath et al., 2023). Thus, whether communications lead to CSR improvements remains debatable.

Using the context of site visits to examine institutional investors' CSR-related communications offers several advantages. First, site visit transcripts capture real-time interactions between company managers and investors and avoid post-editing or embellishment, thus reflecting institutional investors' authentic concerns over CSR issues. Second, compared with regular investor communication (e.g., earnings conference calls), site visits can be initiated whenever investors deem them necessary.[3] The transcripts can therefore promptly capture investors' concerns regarding CSR issues. Third, unlike interactive platforms aimed at retail investors

[1] According to the Global Sustainable Investment Review (2022), $30.3 trillion is invested globally in sustainable investing assets. The market size for major types of responsible investments in China was approximately CNY 31.59 trillion.

[2] According to the manager of the Investor Service Department at the Shanghai Stock Exchange, "CSR has emerged as one of the critical areas of focus for investors when evaluating companies." (News source: https://www.amac.org.cn/hdjl/esgtzlt/2020lt/2020ltzjgd/202101/t20210125_24199.html).

[3] According to the "Investor Relations Management Guidelines" published by the Shenzhen Stock Exchange, listed companies typically do not decline site visit requests from investors and only advise rescheduling if the timing coincides with sensitive periods (e.g., before profit announcements or other significant corporate event disclosures).

(Lee and Zhong, 2022), site visits primarily involve expert analysts and institutional investors, whose expertise, research resources and market influence better position them to analyze CSR performance and drive changes.

We introduce a machine learning-based approach to capture CSR-related communication during site visits. First, we use *word2vec*, a neural network-based word embedding model, to identify words that are semantically related to our selected CSR seed words, and construct a CSR lexicon tailored to Chinese-listed firms. Next, we perform a content analysis on the discussions between managers and institutional investors, utilizing our CSR lexicon to identify CSR-related communication in the site visit transcripts, and construct two key independent variables. The first variable computes the cosine similarity between two vectors: one representing the transcript text and the other the CSR lexicon. This provides a quantifiable measure of the semantic alignment between the transcripts and CSR vocabulary. The second variable evaluates the relative frequency of CSR keywords in the transcripts by normalizing the total keyword count by the total word count. Higher values for these two variables indicate institutional investors' increased emphasis on CSR issues during site visits.

Using Chinese A-share firms listed in the Shenzhen Stock Exchange (SZSE) from 2013 to 2021, we first explore whether institutional investors can effectively enhance CSR performance through CSR-related communication. We find that this communication significantly enhances firms' subsequent CSR performance. A one-standard-deviation increase in CSR-related communication results in an approximate 2 % improvement in CSR performance in the following year. We also find positive and significant correlations between five CSR communication sub-dimensions and future CSR performance. Our results indicate that site visits represent an interactive communication channel through which institutional investors influence CSR. The results are robust to several checks, including using alternative measures of CSR performance and CSR-related communication, controlling for firm fixed effects, using alternative model specifications and accounting for possible endogeneity issues.

We then investigate cross-sectional variation in how the effect of CSR communication on CSR performance varies with state ownership, institutional shareholdings, and regulatory environment. We find that the effect is more pronounced for non-state-owned enterprises and firms with lower institutional shareholdings in periods following the issuance of the Green Investment Guidelines. Finally, we identify two channels through which institutional investors' CSR communication can improve firms' CSR performance: enhancement of the information environment and alleviation of financial constraints.

This study makes several contributions to the literature. First, it provides insights into the effect institutional investors can have on CSR performance. Whether institutional investors can truly improve corporate sustainability remains a matter of debate. Some argue that institutional investors can improve CSR through engagement and monitoring (Dimson et al., 2015; Gloßner, 2019), but others suggest that they may lack the motivation or capability to affect CSR change across large portfolios or consider short-term financial priorities (Gloßner, 2019). "Greenwashing," a situation in which there is no actual ESG impact, may also be an issue (Gibson Brandon et al., 2022; Heath et al., 2023). Our study provides evidence of the positive influence of institutional investors on CSR performance. In addition, most studies focus on ownership, shareholder proposals and voting, and only a few report that site visits can affect CSR performance, despite the prevalence and importance of private interactions between investors and managers. They also examine the impact of site visits or their frequency on CSR ratings without considering the communication content (Hu et al., 2020; Jiang et al., 2022). As investors' horizons and preferences differ (Gloßner, 2019; Hwang et al., 2022), the frequency of their site visits may not accurately capture the levels of CSR monitoring they engage in. We address this limitation by conducting a content analysis of CSR-related communication based on site visit transcripts, thus providing richer insights into the channel through which institutional investors influence CSR performance.

Second, our study enriches the literature on the economic consequences of investor–manager communication. Investors can communicate with public firms through various channels such as earnings calls, capital market conferences, non-deal roadshows and site visits. Prior studies indicate that these interactions provide information advantages (Cheng et al., 2016; Liu et al., 2017; Bushee et al., 2018; Chapman et al., 2022; Rennekamp et al., 2022), reduce information asymmetry (Brown et al., 2004; Jiang and Yuan, 2018) and facilitate the scrutiny and monitoring of firms (Reiter, 2021), but they do not explore the impact of such communications on CSR. Our study is the first to provide empirical evidence that investor–manager communications significantly influence firms' CSR performance specifically through site visits.

Finally, our study makes important methodological contributions to analyses of investor engagement in CSR. We innovatively apply a machine learning-based textual analysis approach, including seeded word embedding and bag-of-words-based content analysis techniques, to quantify CSR-related communication during site visits. We develop a specific Chinese CSR lexicon, which incorporates both common CSR terms and China-specific CSR vocabulary and concepts. This enables us to more effectively analyze investor engagement in CSR issues in China's unique institutional context (Shen et al., 2023).

2. Literature review and hypothesis development

2.1. Institutional investors' corporate site visits

Site visits are important channels through which both shareholding and non-shareholding institutional investors can privately interact with firms (Soltes, 2014; Cheng et al., 2016; Bowen et al., 2018). However, these private meetings are generally unobservable, so information regarding such meetings in U.S. public firms is limited. By contrast, the mandatory disclosure regulations introduced in China by the SZSE in 2009 mean that investor relationship management reports are available and private meetings observable. We can therefore examine these previously unobservable activities. Through site visits, institutional investors can observe firms' operating and production activities first-hand and have the opportunity to engage in face-to-face discussions with managers (Cheng et al., 2016). These private interactions facilitate institutional investors' information acquisition and provide them an informational advantage, that enables them to make better investment decisions and more accurate forecasts (Cheng et al., 2016; Liu et al., 2017; Han et al., 2018; Hong et al., 2019). The information gained from site visits is eventually conveyed to the market and incorporated into stock prices (Cheng et al., 2018). Site visits also enable institutional investors to more effectively monitor managers, thus helping to mitigate their myopic decisions (Jiang et al., 2022). Although some studies suggest that site visits can affect firms' activities related to social responsibility (Hu et al., 2020), they only examine whether or not institutional investors conduct site visits or the frequency of their visits, without considering the communication content. We analyze the CSR-related communications in site visit transcripts to address this limitation.

2.2. Institutional investors and CSR performance

Institutional investors are often known as "universal owners" due to their large, diversified and long-term equity holdings. They play an important external governance role as they can influence management via "voice" and "the threat of exit" (Hirschman, 1970; Gillan and Starks, 2000; Chen et al., 2007; McCahery et al., 2016). Due to their importance in financial markets, a substantial body of literature has examined whether and how institutional investors affect corporate social performance. Some studies indicate that institutional shareholders can help to improve the social impact of their portfolio firms (Dyck et al., 2019; Chen et al., 2020). As major equity owners, they can directly engage with firms to address environmental protection, employee rights and other social issues (Dimson et al., 2015; Barko et al., 2022; Hwang et al., 2022). Through their monitoring role, they can also ensure that managers pursue CSR strategies in the shareholders' interests (Gloßner, 2019). Numerous studies indicate that active CSR engagement allows investors to reduce the risk of costly incidents (Nofsinger and Varma, 2014; Nofsinger et al., 2019; Hoepner et al., 2023), generate social benefits (Kim et al., 2019) and ultimately enhance firm value (Gloßner, 2019).

However, institutional investors may not attempt to change firms' CSR practices and may even have negative effects. They may lack the ability or resources to effectively monitor CSR practices across all of their portfolio firms, and the costs of extensive monitoring may outweigh the expected benefits. Moreover, some institutional investors may also have pecuniary motives for prioritizing financial performance over CSR. For example, Gloßner (2019) finds that short-term investors induce managerial short-termism, in which CSR spending is reduced to increase short-term profits. Furthermore, socially responsible investment (SRI) funds themselves may engage in "greenwashing" or "impact washing," limiting their influence on firms'

CSR practices. Empirical evidence suggests that SRI funds attract capital but do not exhibit better ESG performance than traditional funds (Gibson Brandon et al., 2022; Kim and Yoon, 2022), or they simply select firms that already have high environmental and social performance without significantly changing firm behavior (Heath et al., 2023).

Thus, it remains an open question whether institutional investors successfully improve the CSR performance of their portfolio firms. Investors' preferences and investment horizons regarding CSR will also differ. Some may aim to maximize the financial performance of their portfolios, while others may have broader objectives that encompass social responsibility. This heterogeneity among institutional investors can determine the extent to which they actively pursue and achieve CSR improvements across the firms they have invested in.

2.3. Hypothesis development

We propose that institutional investors have the potential to influence firms' CSR performance through CSR-related communication. First, through effective communication, these investors can make CSR information more transparent, which then improves the monitoring of management and leads to CSR performance improvements. Institutional investors can obtain detailed, timely and accurate information about firms' CSR policies, impacts, risks and opportunities by engaging with them, and thus can confidently advocate for improvements (Hockerts and Moir, 2004). For example, conversations with executives can inform assessments of how to implement CSR strategies, while conversations with operations managers can provide insights into resource usage and waste. Discussions with staff can elicit their perspectives on working conditions and employee safety. Such increased transparency enables institutional investors to better fulfill their monitoring role and thus pushes managers to improve their sustainability performance (Jiang et al., 2022). Issues highlighted by institutional investors also gain attention from the public and regulators, increasing the scrutiny firms face regarding their social responsibility activities. Institutional investors' engagement in CSR also provides a signal that such issues are material to long-term value creation, which incentivizes firms to improve their CSR practices (Chen et al., 2020; Barko et al., 2022). In summary, CSR-related communication promotes transparency, which helps to improve corporate sustainability.

Second, communication can reduce investors' uncertainty about CSR practices, thus reducing the perceived investment risks. Firms will then face fewer financing constraints and can direct more resources toward CSR initiatives. Chapman et al. (2022) find that direct and ongoing interactions can help increase investors' understanding of a firm's strategy and build mutual trust, resulting in greater alignment with and support from management. Firms regarded as more trustworthy by investors may also receive valuation premiums from them (Guiso et al., 2008; Lins et al., 2017). Through proactive CSR engagement, investors can gain more clarity about firms' policies, impacts and exposure to risk. If lower risk premiums are factored into capital costs, firms will face fewer restrictions when accessing affordable capital from investors and lenders (Dhaliwal et al., 2011; Lins et al., 2017). This reduction in financing constraints will provide firms with more resources and the flexibility to further invest in CSR initiatives.

Nevertheless, whether institutional investors can truly improve corporate sustainability through CSR-related communication remains debatable. First, they may engage in such communication primarily because their investments and performance metrics involve social responsibility, rather than to influence corporate practices (Heath et al., 2023). Second, compared with litigation and shareholder proposals, communication represents a relatively mild form of intervention that may lack management constraining power (Chapman et al., 2022). Executives may simply react with superficial responses or temporary actions to satisfy investors' transient CSR concerns.

In summary, the net effect of institutional investors' CSR-related communication on CSR performance is an empirical question. Therefore, we propose the following null hypothesis:

H1: Institutional investors' CSR-related communication with firms has no effect on the CSR performance of these firms.

3. Data and methodology

3.1. Sample and data sources

We first assess firms listed on the SZSE between 2013 and 2021 and select our sample according to the following criteria.[4] We exclude (1) financial firms and B-share (foreign share) firms; (2) site visits involving non-institutional investors[5]; (3) transcripts in which any questions or answers do not consist of at least two tokens; and (4) firm-year observations missing data for the variables used in our analysis. Our final sample consists of 7,781 firm-year observations. To alleviate the potential influence of extreme observations, all continuous variables are winsorized at the 1 % level in each tail.

The transcripts of site visits for Chinese listed firms and firm characteristics are collected from the China Stock Market and Accounting Research (CSMAR) database. Corporate social responsibility data are retrieved from Huazheng ESG ratings, accessed through the WIND database. This leading Chinese ESG rating agency has several advantages over other mainstream sustainability rating frameworks. First, it provides comprehensive ratings dating back to 2009 for all A-share listed firms. Second, it ensures the accuracy of these ratings by issuing quarterly updates and timely adjustments in response to major ESG incidents. Consequently, the Huazheng rating score is applied extensively in studies of ESG performance (see, e.g., Lin et al., 2021; Jiang et al., 2022). We manually collected the signatories of the Chinese Principles of Responsible Investment (PRI) from the online United Nations PRI signatory directory, and matched them with institutional investor names in the site visit transcripts using fuzzy matching.[6]

3.2. Measuring CSR-related communication

We introduce a machine learning-based approach using *word2vec*, a neural network-based word embedding model, to identify words semantically related to CSR seed words and construct a CSR lexicon.[7] We then use this lexicon to quantify institutional investors' considerations of CSR issues when communicating with firms.

First, following the literature (Li et al., 2021; Wu, 2023), we initiated the construction of a dictionary by identifying relevant seed words. The Company Law of 2006 requires Chinese companies to undertake social responsibilities in their business activities, and in 2008 the SZSE mandated companies in the Shenzhen 100 Index to release CSR reports. These should include at least the following dimensions: (1) protection of the interests of shareholders and creditors; (2) protection of workers' rights; (3) protection of suppliers, customers and consumers; (4) environmental protection and sustainable development; and (5) public relations and social welfare services. We selected seed words for our initial CSR dictionary construction based on these five dimensions, as our sample consisted of SZSE-listed companies. We reviewed 100 randomly selected CSR reports from Shenzhen 100 Index companies and took an independent extraction and cross-validation approach to ensure seed word quality. From this, we compiled a seed word repository containing 563 words, with 108 related to "shareholders and creditors," 119 to "employees", 112 to "suppliers, customers and consumers", 118 to "environmental protection and sustainability" and 106 related to "public relations and social welfare." Table IA1 in the presents the list of selected seed words in Chinese across all CSR dimensions.

[4] The sample period begins in 2013 because the SZSE updated the requirements on the timeliness of the information disclosure related to site visits of listed companies in 2012. Since 2013, all listed companies have standardized the disclosure of investors' site visit activities following the requirements of the SZSE. As our model uses lagged CSR communication data, the CSR performance data span 2014–2021, while the CSR communication and control variables span 2013–2020.

[5] Site visits include various visitors such as individual investors, institutional investors and other market participants. Among them, institutional investors are the primary participants. The literature shows that the participation of non-institutional investors, such as media, in site visits could also have an impact on corporate social responsibility. To avoid confounding our results, we exclude site visits involving non-institutional investors.

[6] Data source: https://www.unpri.org/signatories/signatory-resources/signatory-directory.

[7] For lack of space, we are unable to report all details of our textual analysis in this section. Technical details of the natural language processing pipeline and machine learning methods are provided in the online.

Next, we scraped CSR reports released on cninfo.com[8] from 2006 to 2020 and preprocessed the raw CSR report text to train the embedding model. As these reports focus specifically on CSR issues, they are likely to contain more domain-specific words around the relevant CSR concepts than are more general texts, thus providing more finely tuned and precise word vector representations than models trained on generic corpora. Preprocessing involved text tokenization, named entity recognition, stopword removal and phrase extraction to prepare the data for effective model training. We applied the same preprocessing procedures used for the CSR reports to the site visit transcripts we used for constructing our text-based measures to ensure consistency in the text processing.

We then used the textual corpus of these CSR reports to train a word2vec model, a widely used embedding algorithm that converts words into word vectors (Mikolov et al., 2013), to capture semantic similarities between words based on their co-occurrence patterns. word2vec is based on a neural network model that builds a vocabulary from the training corpus and learns vector representations of words. It trains word vectors using either the continuous bag-of-words or skip-gram architecture. Both methods work to capture semantic similarity through vector cosine distance, and words with similar meanings will have closer vectors. We divided the preprocessed CSR reports into three training rounds to feed into the word2vec model to generate word embeddings. The model maps the tokens to 300-dimensional vectors, constructing a vector space where each unique token is assigned a specific vector representation. Words with similar semantic meanings have a smaller cosine distance between them in this vector space. Using our selected seed words, we first constructed a CSR dictionary by searching for semantically similar words. We used the average word vector of all seed words within the same dimension to represent that dimension. We then identified semantically similar words by calculating the cosine similarity between this averaged dimension vector and the vectors of other words. We then expanded the CSR lexicon by incrementally adding synonyms in three rounds of training. In each iteration, based on cosine similarity, words most similar to the seed word vectors were selected to expand the dictionary for each dimension. Finally, after manually checking the output dictionaries, we constructed a CSR lexicon containing 3,879 words. Table IA3 in the illustrates the expansion of the dictionary in each round and the number of words in each dimension.

Using the constructed CSR lexicon, we performed a content analysis of dialogues between managers and institutional investors to quantify the relevant CSR-related communication in the site visit transcripts, and then aggregated these measures at the firm-year level. This involved creating two independent variables to measure institutional investor attention to CSR issues when communicating with firms during site visits.

First, CSR_cosine_k is the cosine similarity between the TF-IDF weighted[9] word vectors that represent the site visit transcripts and the CSR dictionary, formulated as in Eq. (1).

$$CSR\_cosine_k = \cos(V_k, V_{CSR}) \tag{1}$$

where V_k is the TF-IDF weighted word vector of the k^{th} transcript and V_{CSR} is the CSR dictionary vector. For expositional purposes, we multiplied all variables based on cosine similarity by 100.

Second, CSR_freq_k measures the relative frequency of the TF-IDF weighted CSR dictionary words appearing in transcript k. This is calculated as the weighted count of CSR words divided by the total number of words in the transcript, formulated as in Eq. (2).

$$CSR\_freq_k = \frac{\sum_{j=1}^{N} I\left(w_j \in W_{\mathrm{CSR}}\right) \cdot \mathrm{tfidf}\left(w_j, k\right)}{\sum_{i=1}^{M} \mathrm{tfidf}(w_i, k)} \tag{2}$$

where w_j is a word appearing in the transcript,W_{CSR} is the CSR dictionary, $I(\cdot)$ is an indicator function that equals 1 if w_j is in W_{CSR} and 0 otherwise, $tfidf\left(w_j, k\right)$ is the TF-IDF weight of w_j in the k^{th} transcript and M is the total number of words in the k^{th} transcript.

[8] The official website designated by the China Securities Regulatory Commission for public companies disclosure.

[9] The TF-IDF weighting technique aims to highlight words that are frequent within a specific document but relatively rare across the entire corpus. By multiplying the term's frequency (TF) by its inverse document frequency (IDF), TF-IDF assigns higher weights to terms that are both prominent in the current document and distinctive across the broader dataset.

We aggregated these two measures to the firm-year level using Eqs. (3) and (4), where $N_{i,t}$ is the number of meeting transcripts for company i in year t. By construction, the $CSR\_cosine_{i,t}$ and $CSR\_freq_{i,t}$ measures quantify the extent to which institutional investors consider CSR issues. Increased values for these two independent variables indicate a higher level of consideration of CSR issues during site visits.

$$CSR\_cosine_{i,t} = \sum\nolimits_{k=1}^{N_{i,t}} CSR\_cosine_k \tag{3}$$

$$CSR\_freq_{i,t} = \sum\nolimits_{k=1}^{N_{i,t}} CSR\_freq_k \tag{4}$$

In addition, as CSR is a multi-dimensional concept encompassing many issues, we created variables to measure institutional investor attention toward each specific CSR dimension in communications. We calculated both the cosine similarity $CSR\_cosine_{d,i,t}$ and the relative frequency $CSR\_freq_{d,i,t}$ for each CSR dimension d. These are formulated similarly to Eqs. (1)–(4) but use the words of the sub-dimensions instead of the full CSR lexicon. We labeled these dimension-specific CSR communication variables with suffixes indicating each dimension: "share" for shareholder and creditor interests; "emp" for employees; "ssc" for suppliers, customers and consumers; "env" for environmental protection and sustainability; and "social" for public relations and social welfare services. Higher values of these variable indicate greater attention to issues within the specific dimension.

To assess the robustness of our main results, we constructed several alternative measures. First, we created equally weighted versions without TF-IDF weighting to evaluate whether term importance affects the measures. Second, we restricted our identification to only the question portion of the transcripts rather than the full questions and answers, as this provided us with institutional investors' initiations. Third, we calculated the average of the TF-IDF weighted CSR communication across all transcripts of firms i in year t. Together, these variants enabled us to evaluate whether our main CSR communication measures are sensitive to the weighting method, text section or aggregation level. All of the variables are defined in Appendix A.

3.3. Measuring CSR performance

Huazheng ESG ratings are updated and released quarterly (at the end of January, April, July and October each year). The evaluated firms are assigned one of nine rating grades from "AAA" to "C." We quantified the rating levels by assigning 100 points to an AAA grade with a decrement of 10 points for each lower grade, down to 20 points for a C grade. To calculate the CSR score for each firm-year, we took the average of the four quarterly rating scores:

$$Score_{i,t} = \frac{1}{4}\sum\nolimits_{q=1}^{4} RawScore_{i,q,t} \tag{5}$$

where $RawScore_{i,q,t}$ is company i's rating score for the q quarter of year t.

3.4. Control variables

Following the literature (Dyck et al., 2019; Gloßner, 2019; Chen et al., 2020), we included numerous firm-level variables to control for factors that may affect CSR performance: firm size (*Size*), firm age (*Age*), asset tangibility (*Tangible*), leverage ratio (*Lev*), return on equity (*ROE*), Tobins' Q(*Tobinq*), institutional ownership (*Inshold*), state ownership (*SOE*), board independence (*Indp*) and CEO duality (*Dual*). We provide detailed definitions in Appendix A.

3.5. Empirical model

We estimated the following baseline regression model to examine whether investors can effectively enhance CSR performance through CSR-related communication:

$$Score_{i,t+1} = \beta_0 + \beta_1 * CSR\_Communication_{i,t} + Controls_{i,t} + IndustryFE + YearFE + \varepsilon_{i,t} \tag{6}$$

Table 1
Summary Statistics.

Panel A CSR-related communication variables

	Obs	P25	Mean	Median	P75	SD
CSR_cosine	7781	1.5304	5.5445	3.3293	7.0936	6.2028
cosine_share	7781	0.5638	2.5413	1.4277	3.2306	3.1284
cosine_emp	7781	0.0903	0.8986	0.3726	1.0776	1.3663
cosine_scc	7781	1.2898	5.6460	3.0327	6.8812	7.2361
cosine_env	7781	0.1633	2.7042	0.7027	2.7342	5.0835
cosine_social	7781	0.0000	0.5875	0.1877	0.6831	1.0323
CSR_freq	7781	1.9653	7.0417	4.2642	9.0043	7.7974
freq_share	7781	0.3068	1.2392	0.7182	1.5728	1.4599
freq_emp	7781	0.0823	0.5045	0.2438	0.6158	0.7032
freq_scc	7781	0.8761	3.6156	1.9836	4.4624	4.5119
freq_env	7781	0.1187	1.3732	0.4207	1.4184	2.4384
freq_social	7781	0.0000	0.2103	0.0781	0.2479	0.3567

Panel B Other Variables

	Obs	P25	Mean	Median	P75	SD
Score	7781	45.0000	50.9857	50.0000	60.0000	9.9820
Size	7781	21.3084	22.0905	21.9659	22.7219	1.0991
Age	7781	1.6094	1.9895	1.9459	2.3979	0.6745
Tangible	7781	0.8849	0.9072	0.9459	0.9723	0.1022
Lev	7781	0.2321	0.3862	0.3775	0.5243	0.1881
ROE	7781	0.0367	0.0700	0.0731	0.1170	0.1030
Tobinq	7781	1.3972	2.2526	1.8502	2.6495	1.3208
Inshold(%)	7781	14.5509	37.7714	38.0032	58.5055	24.6086
SOE	7781	0.0000	0.2109	0.0000	0.0000	0.4080
Dual	7781	0.0000	0.3380	0.0000	1.0000	0.4731
Indp(%)	7781	33.3300	37.6471	33.3300	42.8600	5.3695

This table presents summary statistics for the sample of 7,781 firm-year observations over 2013–2021. Panel A reports descriptive statistics for the CSR communication measures. Panel B shows descriptive statistics for the dependent variable and control variables. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A.

where the dependent variable $Score_{i,t+1}$ represents firm *i*'s annual average CSR rating score in the following year. $CSR\_Communication_{i,t}$ refers to a series of text-based measures of CSR-related communication for firm *i* in year *t*. *Controls* are a set of firm-specific characteristics. We included industry- and year-fixed effects to absorb time-invariant industry differences and common time trends, respectively. The coefficient estimate of β_1 captures the impact of CSR-related communication on firms' subsequent CSR performance, when controlling for other factors. A positive and statistically significant β_1 would suggest that increased CSR-related communication is associated with improvements in future CSR performance. The model is estimated using OLS with standard errors clustered at the firm level.

4. Empirical results

4.1. Descriptive statistics

Table 1 provides the descriptive statistics for the CSR-related communication measures and fundamental firm characteristics included in our regression models. Panel A demonstrates that the median values of our CSR communication metrics are generally lower than the mean, suggesting a right-skewed distribution. This indicates that a majority of firms exhibit limited CSR-related communication. The mean values for the independent variables *CSR_cosine* and *CSR_freq* are 5.5445 and 7.0417, respectively. By comparing the statistics

Table 2
Institutional Invests' CSR Communication and CSR Performance: Baseline Results.

	Depend Variable = $Score_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
CSR_cosine	0.232***	0.239***	0.155***			
	(0.025)	(0.026)	(0.026)			
CSR_freq				0.183***	0.188***	0.118***
				(0.020)	(0.020)	(0.020)
Size			2.057***			2.063***
			(0.271)			(0.271)
Age			−0.993***			−0.992***
			(0.334)			(0.334)
Tangible			8.506***			8.481***
			(1.631)			(1.632)
Lev			−11.060***			−11.071***
			(1.165)			(1.165)
ROE			21.437***			21.418***
			(1.563)			(1.566)
Tobinq			−0.371***			−0.374***
			(0.136)			(0.137)
Inshold			−0.028***			−0.028***
			(0.009)			(0.009)
SOE			2.530***			2.535***
			(0.566)			(0.566)
Dual			−0.521			−0.534
			(0.366)			(0.367)
Indp			0.154***			0.153***
			(0.031)			(0.031)
Constant	49.700***	46.616***	−5.506	49.694***	46.809***	−5.418
	(0.251)	(2.137)	(6.279)	(0.252)	(2.150)	(6.289)
Industry Fixed	No	Yes	Yes	No	Yes	Yes
Year Fixed	No	Yes	Yes	No	Yes	Yes
Observations	7781	7781	7781	7781	7781	7781
Adjusted R^2	0.021	0.058	0.178	0.020	0.057	0.177

This table reports the estimation results for the effect of institutional investors' CSR communication on firms' subsequent CSR performance. Columns (1)-(3) present results using the CSR communication variable based on cosine similarity. Columns (4)-(6) show results based on the relative frequency of CSR keywords. The dependent variable is the firms' CSR rating score in year $t+1$, with all independent and control variables measured in year t. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

across the specific dimensions, we find that "public relations and social welfare services" has the lowest mean values of 0.59 for *cosine_social* and 0.21 for *freq_social*.[10] In Panel B, the average CSR rating score is 51 out of 100, and other firm-level control variables are consistent with the samples of SZSE A-share companies used in other studies.

4.2. Baseline multivariate regression results

Table 2 reports the main results of our regressions. Columns (1) to (3) show that the independent variable is CSR-related communication calculated using the cosine similarity method. Columns (4) to (6) show CSR-related communication calculated by the relative frequency method. Columns (1) and (4) show a significant correlation between the independent and dependent variables when no control variables are added. Fixed effects are added in Columns (2) and (5), and the estimates persist with statistical significance. Control variables and controls for industry- and year-fixed effects are added in Columns (3) and (6). The coefficients of

[10] In the descriptive statistics of Table 1, Panel A, the sum of the relative frequency means of the five dimensions should theoretically equal the mean of *csr_freq*. However, as these variables are winsorized separately, a slight discrepancy arises.

CSR_cosine and *CSR_freq* are positive and significant at the 1 % level, suggesting that institutional investors can improve CSR performance through CSR-related communication during site visits. This effect has both statistical and economic significance. The coefficient estimates of 0.155 in Column (3) and 0.118 in Column (6) suggest that a one-standard-deviation increase in CSR-related communication leads to an improvement in CSR performance of 1.9 % (=0.155*6.20/50.99) in the following year and 1.8 % (=0.118*7.79/50.99) if all other variables are controlled. In summary, the baseline model results show that CSR-related communication during site visits can lead to subsequent improvements in firms' CSR performance, and thus our null hypothesis is rejected.

Table 3
Dimension-specific CSR Communication and CSR Performance.

Panel A Cosine Similarity Communication Measures

	Depend Variable $=Score_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
cosine_share	0.145***				
	(0.049)				
cosine_emp		0.341***			
		(0.101)			
cosine_scc			0.099***		
			(0.022)		
cosine_env				0.187***	
				(0.034)	
cosine_social					0.621***
					(0.133)
Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes
Observations	7781	7781	7781	7781	7781
Adjusted R^2	0.171	0.171	0.174	0.178	0.173

Panel B Relative Frequency Communication Measures

	Depend Variable $= Score_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
freq_share	0.351***				
	(0.106)				
freq_emp		0.769***			
		(0.201)			
freq_scc			0.163***		
			(0.035)		
freq_env				0.411***	
				(0.069)	
frq_social					2.016***
					(0.388)
Controls	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes
Observations	7781	7781	7781	7781	7781
Adjusted R^2	0.172	0.172	0.174	0.178	0.174

This table presents the estimation results for the effects of dimension-specific CSR communication on firms' overall CSR performance. Panel A reports findings using the cosine similarity communication variables, while Panel B shows analyses based on relative frequency measures. All models include control variables, industry fixed effects, and year fixed effects. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.3. Dimension-specific CSR communication

We further examined the effect of sub-dimension CSR communication on firms' CSR performance. Panel A of Table 3 reports the results of estimating model (6) using the cosine similarity measures for CSR communication related to each dimension. We find positive and significant coefficients on all CSR dimension variables. Increased discussions of shareholder and creditors' rights (*cosine_share*), employee relations (*cosine_emp*), supplier/consumer/product issues (*cosine_scc*), environmental protection (*cosine_env*) and public welfare services (*cosine_social*) during site visits lead to improvements in firms' CSR scores. The relative frequency measures in Panel B produce consistent results. In summary, more dimension-specific CSR communication during site visits is related to better CSR performance. This illustrates that site visits can be a useful channel for various forms of CSR-related communication and suggests that institutional investors can effectively engage firms across various aspects of CSR through direct interaction and communication during site visits.

5. Robustness tests

We performed the following robustness tests to further verify the reliability of our main results.

5.1. Alternative CSR performance measure

Firms' CSR performance may be partly related to resource availability and thus to firm size. We addressed this following Hwang et al. (2022) and constructed an alternative CSR performance measure, *adjustedScore*, by removing size effects from the raw CSR scores. We subtracted the mean score of firms in the same total asset quintile. As shown in Table 4, our main conclusions remain robust when using this size-adjusted dependent variable.

5.2. Alternative CSR communication proxies

We assessed the robustness of our baseline results using three alternative proxies for institutional investors' CSR communication.

First, we constructed equal-weighted versions of our key variables *CSR_cosine* and *CSR_freq*. Compared with the baseline TF-IDF weighted measures, these equal-weighted variants exclude any effects of word importance, thus providing a sensitivity test to the weighting scheme. As Columns (1) and (2) of Table 5 show,

Table 4
Robustness Checks: An Alternative Proxy for CSR Performance.

	Depend Variable $=adjustedScore_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
CSR_cosine	0.214***	0.217***	0.160***			
	(0.026)	(0.026)	(0.026)			
CSR_freq				0.171***	0.170***	0.122***
				(0.020)	(0.020)	(0.020)
Constant	−1.185***	−5.229***	−35.566***	−1.202***	−5.055**	−35.467***
	(0.247)	(1.991)	(6.244)	(0.249)	(2.004)	(6.254)
Controls	No	No	Yes	No	No	Yes
Industry Fixed	No	Yes	Yes	No	Yes	Yes
Year Fixed	No	Yes	Yes	No	Yes	Yes
Observations	7781	7781	7781	7781	7781	7781
Adjusted R^2	0.018	0.051	0.156	0.018	0.050	0.155

This table reports the estimation results using an alternative CSR performance measure adjusted for firm size. The dependent variable is the firm's CSR rating in year $t+1$ minus the quintile mean rating, with all independent and control variables measured in year t. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 5
Robustness Checks: Alternative Proxies for Institutional Investors' CSR Communication.

	Depend Variable = $Score_{t+1}$					
	Equal-weighted		Only Questions		Average Values	
	(1)	(2)	(3)	(4)	(5)	(6)
CSR_cosine	0.058***		0.183***		1.057***	
	(0.011)		(0.034)		(0.301)	
CSR_freq		0.885***		0.207***		1.123***
		(0.169)		(0.037)		(0.291)
Constant	−6.132	−6.201	−6.546	−6.321	−9.831	−9.791
	(6.289)	(6.284)	(6.226)	(6.235)	(6.191)	(6.196)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7781	7781	7781	7781	7781	7781
Adjusted R^2	0.176	0.175	0.176	0.176	0.173	0.173

This table reports the estimation results using three alternative constructions of the CSR communication variable. The dependent variable is the firms' CSR rating in year $t+1$, with all independent and control variables measured in year t. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

the coefficients remain positive and statistically significant at the 1 % level when using these equal-weighted measures.

We then solely considered the question portions of the transcripts rather than the full question-and-answer section. In our baseline regression, the CSR communication measures are built using the Q&A sessions from the site visit transcripts. Interactions in site visits are dynamic, and questions posed by institutional investors are often uncertain and are not predetermined. Although this helps to ensure the accuracy and authenticity of managers' responses, some may engage in excessive self-marketing when answering. The CSR-related information we capture in investor–management conversations is then expected to be boilerplate language or "cheap talk" with no real impact. By assessing only investor questions we isolate institutional investors' initiations and thus mitigate concerns about biased manager responses. We substituted *CSR_cosine* and *CSR_freq* in our baseline model with the measures constructed from only the questions to address these concerns. The results reported in Columns (3) and (4) of Table 5 show a persistent and significant positive correlation between institutional investors' CSR communication and firms' CSR performance.

Finally, we redefined the CSR communication measures of a given firm by averaging the cosine similarity and relative frequency across all site visit transcripts for that firm in year t, thus quantifying the average proportion of CSR-related communication in the firm-year level. As Columns (5) and (6) of Table 5 show, the coefficient estimates on alternative measures are all significant and positive and thus consistent with our main results in Table 2.

In summary, the regression results are consistent with our main findings, indicating that they are robust to alternative measures and are unlikely to be driven by the method used to calculate CSR-related communication.

5.3. Endogeneity issues

Our findings demonstrate that institutional investors' CSR communications can improve firms' CSR performance. However, our results may suffer from endogeneity problems because the direct consideration of CSR-related issues by institutional investors during their interactions is not likely to be random. Endogeneity may thus occur due to potential factors simultaneously affecting CSR-related communication and firms' CSR performance. Reverse causality may also be a problem as the consideration of CSR-related issues by institutional investors during communications may be driven by changes in a firm's CSR performance. We therefore applied several procedures to address these potential problems.

Table 6
Robustness Checks: Controlling for Firm Fixed Effects.

	Depend Variable $=Score_{t+1}$			
	(1)	(2)	(3)	(4)
CSR_cosine	0.074***	0.035*		
	(0.021)	(0.020)		
CSR_freq			0.067***	0.035**
			(0.016)	(0.015)
Size		1.442***		1.437***
		(0.458)		(0.457)
Age		−0.955		−0.939
		(0.762)		(0.762)
Tangible		2.031		2.021
		(1.768)		(1.768)
Lev		−6.295***		−6.308***
		(1.367)		(1.366)
ROE		15.724***		15.671***
		(1.312)		(1.311)
Tobinq		−0.143		−0.145
		(0.123)		(0.123)
Inshold		0.014		0.014
		(0.014)		(0.014)
SOE		0.957		0.958
		(1.060)		(1.059)
Dual		−0.026		−0.024
		(0.377)		(0.377)
Indp		0.117***		0.117***
		(0.035)		(0.035)
Constant	51.373***	16.040	51.299***	16.104
	(0.251)	(10.206)	(0.250)	(10.196)
Firm Fixed	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Observations	7781	7781	7781	7781
Adjusted R^2	0.013	0.081	0.014	0.082

This table reports the estimation results after controlling for firm fixed effects. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.3.1. Controlling for firm-fixed effects

Although we controlled for a set of firm-level control variables in the baseline model, unobservable firm-level time-invariant variables may drive our results. To mitigate this concern, we re-estimated the main specifications with firm fixed effects. As Table 6 shows, the coefficients for the CSR communication measures remain positive and significant, although with smaller magnitudes. These results indicate that time-invariant firm-specific characteristics do not drive the positive relationship between institutional investors' CSR-related communication and CSR performance.

5.3.2. Controlling for CSR reports and communication tone

Various communication channels can convey information about a company's CSR activities or records (Ziek, 2009; Du et al., 2010), and annual CSR reports represent one of the most important channels. These CSR disclosures provide details of a firm's CSR activities and communicate CSR information to stakeholders, which may simultaneously determine the level of attention that institutional investors give to CSR issues and firms' future CSR practices. Investors can obtain a comprehensive picture of firms' CSR practices from these reports, and consequently can identify firms that could be persuaded to increase their CSR performance. Moreover, Chen et al. (2018) find that firms are often under pressure to increase their commitment to social responsibility when they are required to publish their CSR reports, which ultimately improves their corporate social responsibility practices. Therefore, the presence of CSR reports could be simultaneously associated with

Table 7
Endogeneity: Additional Controlling Variable.

	Depend Variable $=Score_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
CSR_cosine	0.126***	0.155***	0.126***			
	(0.023)	(0.026)	(0.023)			
CSR_freq				0.098***	0.118***	0.098***
				(0.018)	(0.020)	(0.018)
Report_cosine	2.592***		2.592***			
	(0.151)		(0.151)			
Report_freq				2.002***		2.002***
				(0.116)		(0.116)
Tone		0.173	0.225		0.031	−0.018
		(0.803)	(0.757)		(0.805)	(0.760)
Constant	20.765***	−5.620	20.619***	19.775***	−5.439	19.787***
	(6.002)	(6.340)	(6.055)	(5.990)	(6.355)	(6.050)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7781	7781	7781	7781	7781	7781
Adjusted R^2	0.252	0.178	0.252	0.253	0.177	0.253

This table presents the estimation results after controlling for additional variables. In Columns (1) and (4), we employed textual analysis on firms' CSR reports in year *t* to measure public CSR disclosure and additionally controlled for *Report_cosine* and *Report_freq*, corresponding to the two independent variables. In Columns (2) and (5), we include *Tone* to proxy for the sentiment in communications in year *t*. Columns (3) and (6) show the results after controlling for both additional variables. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

both the firm's CSR communication and its future CSR performance. To control for this potential confounding effect, we include CSR reporting as a control variable in our analysis.

In addition, our results may be driven by the tone conveyed rather than the specific content of the communication. The literature suggests that sentiment, as a form of non-verbal expressive behavior, can provide rich out-of-text information and have economic consequences (Loughran and McDonald, 2011; Price et al., 2012). Such omitted variables may affect the main results of our study.

We thus considered additional control variables in Eq. (6) to mitigate the endogeneity resulting from the omitted variables of firms' CSR report disclosures and the average tone of communications. Using the same CSR lexicon and textual analysis methodology, we constructed two measures for each annual CSR report, *Report_cosine* and *Report_freq*, to quantify the cosine similarity and relative frequency of the CSR information of the annual CSR report, respectively. We also controlled for the sentiment tone of the communications using a validated Chinese sentiment dictionary.[11] The sentiment is averaged across site visit transcripts to compute a firm-year level variable.

We then re-estimated the regressions with the expanded regression model. Table 7 shows the results. The coefficients on CSR communication remain significant and positive, consistent with the baseline model results. The consistency across these tests suggests that our findings are robust after further controlling for plausible omitted variables.

5.3.3. Change model analyses

Our findings may also be influenced by reverse causality, as institutional investors are more likely to discuss CSR issues with firms that already have strong CSR performance. Thus, the observed relationship may be correlational rather than causal. To account for this potential endogeneity, we estimated a change model as

[11] We measure the sentiment in a conversation as the share of positive tone words minus negative tone words using the sentiment dictionary developed by the National Taiwan University, one of the most commonly used sentiment dictionaries in Chinese natural language processing.

Table 8
Change Model Analyses.

	Depend Variable $=\Delta Score_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔCSR_cosine	0.042***	0.041***	0.034**			
	(0.014)	(0.014)	(0.014)			
ΔCSR_freq				0.037***	0.037***	0.031***
				(0.011)	(0.011)	(0.011)
Constant	−0.108	−1.524**	−4.537*	−0.104	−1.538**	−4.599*
	(0.072)	(0.676)	(2.603)	(0.072)	(0.674)	(2.603)
Controls	No	No	Yes	No	No	Yes
Industry Fixed	No	Yes	Yes	No	Yes	Yes
Year Fixed	No	Yes	Yes	No	Yes	Yes
Observations	5111	5111	5111	5111	5111	5111
Adjusted R^2	0.001	0.019	0.058	0.002	0.020	0.058

This table presents the estimation results of change model analyses. The dependent variable is the annual change in firms' CSR ratings from year t to $t+1$ ($\Delta Score_{i,t+1}$). The independent variables are annual changes in CSR communication measures (ΔCSR_cosine and ΔCSR_freq). Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

an additional robustness test, in which we use the differences of the variables rather than their levels. The dependent variable is the firm's CSR performance change from year t to $t+1$. The independent variable is the change in CSR communication. These analyses filter out time-invariant unobservable firm heterogeneity and thus better identify the causal effect and alleviating endogeneity issues.

Table 8 shows that after considering the differences in the variables, the relationship between changes in CSR-related communication (*ΔCSR_cosine* and *ΔCSR_freq*) and changes in firms' CSR ratings (*ΔScore*) remains significant and positive. This indicates that even after accounting for time-invariant unobservable firm heterogeneity, CSR communication is significantly associated with improvements in CSR performance.

5.3.4. Instrumental variable

Institutional investors' consideration of CSR-related issues may be driven by changes in firms' CSR performance, leading to a reverse causality problem. Potential endogeneity may then remain a concern after applying the above procedures. Thus, we used a two-stage least squares (2SLS) analysis to further address the endogeneity problem, in which we introduced an instrumental variable for the CSR-related communication of institutional investors in site visits.

We considered the number of non-top-10 shareholding institutional investors who participated in the site visits and are signatories to the United Nations' PRI as an instrumental variable for CSR communication.

PRI is a global initiative of the United Nations aimed at encouraging financial institutions to consider ESG factors in their investment decisions, with the goal of promoting sustainable development and long-term value creation. Signatories of the PRI must regularly report on their progress in integrating ESG factors and how they are advancing sustainability goals in their investment practices. The PRI also encourages institutional investors to engage in dialogue with the firms they invest in to promote better environmental and social responsibility practices (Gibson Brandon et al., 2022). Thus, institutional investors who are PRI signatories are likely to devote more attention to CSR issues when communicating with firms. Therefore, the proportion of CSR-related issues in the conversations may increase with the number of PRI signatories among visiting institutional investors.

The choice to become a PRI signatory is at the discretion of each institutional investor. Their decision is unlikely to be influenced by any specific firm, as investors often have diversified portfolios spanning multiple firms. To reinforce the exogeneity of our instrumental variable, we only considered the number of non-top-10 shareholding institutional investors among the site visit participants. Although comprehensive shareholder data are not available, by restricting our sample to these shareholders we only consider institutional investors with limited influence over firms' CSR practices. Investors with large shareholdings may affect CSR by exercising shareholder rights, either through voting or threatening divestment. By limiting the instrument to these

Table 9
Endogeneity: An Instrumental Variables Approach.

	1st Stage		2nd Stage	
	CSR_cosine	*CSR_freq*	$Score_{t+1}$	
	(1)	(2)	(3)	(4)
CSR_cosine			0.533***	
			(0.180)	
CSR_freq				0.411***
				(0.138)
PRI	0.292***	0.379***		
	(0.046)	(0.058)		
Constant	−23.627***	−31.719***	3.893	4.346
	(4.537)	(5.841)	(7.758)	(7.851)
Controls	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Observations	7781	7781	7781	7781
Adjusted R^2	0.085	0.085	0.127	0.129

This table reports the estimation results of the two-stage least squares (2SLS) analysis by using *PRI* as an instrumental variable. Columns (1) and (2) show the results for the first stage, in which we examine the relationship between PRI and CSR communication measures. Columns (3) and (4) report the results for the second stage regression. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 10
Institutional investors' CSR Communication, State-owned enterprises, CSR performance.

	Depend Variable = $Score_{t+1}$			
	SOE	*non-SOE*	*SOE*	*non-SOE*
	(1)	(2)	(3)	(4)
CSR_cosine	0.048	0.185***		
	(0.041)	(0.030)		
CSR_freq			0.053*	0.135***
			(0.032)	(0.024)
Constant	−24.933**	1.752	−24.359**	1.856
	(10.809)	(7.764)	(10.811)	(7.802)
Controls	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Observations	1641	6140	1641	6140
Adjusted R^2	0.223	0.168	0.223	0.166
Comparison coefficients	Observed difference = 0.138 p-value = 0.000		Observed difference = 0.082 p-value = 0.004	

This table reports the effects of institutional investors' CSR communication on CSR performance for both state-owned and non-state-owned enterprises. The last row shows the significance of the differences in coefficient estimates between two groups. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

non-top-10 shareholding institutional investors, we exclude such potential channels of influence. We manually collected the names of Chinese institutions that had joined before 2020 from the online PRI signatory directory,[12] and thus obtained a list of Chinese investment managers. We used fuzzy matching to compare these signatories against the names of the non-top-10 institutional shareholders participating in site visits.

Table 9 presents the results of the 2SLS analysis. Columns (1) and (2) show the results of the first stage, in which the instrumental variable is significantly and positively correlated with the endogenous explanatory

[12] https://www.unpri.org/signatories.

variables. This suggests that PRI signatories involved in site visits are likely to place a greater emphasis on CSR issues during their interactions. The Cragg–Donald Wald F statistics (80.28 and 85.33, respectively) indicate no problem of weak instrumental variables. The second stage regression results in Columns (3) and (4) reveal that the coefficients corresponding to the fitted CSR communication are significant and positive at the 1 % level. Thus, our main findings remain robust even after considering potential endogeneity issues through the instrumental variable approach.

6. Cross-sectional implications and plausible mechanisms

The baseline regression confirms that the CSR communication of institutional investors may be a driver of future improved CSR performance. In this section, we report our investigation of changes in this effect. We considered three situations: state-owned enterprises (SOEs), periods following the issuance of Green Investment Guidelines, and firms with low institutional ownership. We then explore the potential mechanisms for the effect of CSR-related communication on firms' CSR performance.

6.1. SOEs

Previous research finds that unlike non-SOEs, whose primary goal is to maximize profits or shareholder wealth, SOEs have additional social responsibilities as required by the government, including infrastructure construction, addressing employment problems and participating in poverty alleviation programs (Piotroski and Wong, 2012). SOEs therefore recognize the strategic significance of CSR and may be more willing to undertake relevant endeavors. However, as non-SOEs do not face such institutional pressure, they may lack the incentive to engage in sustainable development. Therefore, the expectations of and attention from institutional investors may play a more effective role in non-SOEs that have scope for CSR improvement.

We define SOEs as firms in which the government is the ultimate controlling owner. We divided the sample into two subsamples based on whether a firm is an SOE, and re-ran our baseline model. Table 10 shows a significant effect of institutional investors' CSR communication on the CSR score of a firm that is a non-SOE. In addition, a comparison of the coefficients of CSR communication measures for the two subsamples suggests that the differences between them are statistically significant. Overall, non-SOEs do not face the same

Table 11
Institutional Investors' CSR Communication, Policy Implementation, CSR Performance.

	Depend Variable $=Score_{t+1}$			
	Before 2018	*After 2018*	*Before 2018*	*After 2018*
	(1)	(2)	(3)	(4)
CSR_cosine	0.141***	0.200***		
	(0.026)	(0.045)		
CSR_freq			0.106***	0.155***
			(0.021)	(0.034)
Constant	−1.324	−20.726**	−1.397	−20.564**
	(6.540)	(9.471)	(6.541)	(9.482)
Controls	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Observations	5098	2683	5098	2683
Adjusted R^2	0.170	0.180	0.169	0.179
Comparison coefficients	Observed difference = −0.060		Observed difference = −0.050	
	p-value = 0.047		p-value = 0.033	

This table reports the effects of institutional investors' CSR communication on CSR performance across the periods before and after the issuance of the Green Investment Guidelines. The last row shows the significance of the differences in coefficient estimates between two groups. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

external pressure from the government's sustainable development strategies as SOEs, and the attention from institutional investors regarding CSR issues can make up for this lack of external drive.

6.2. Implementation of Green Investment Guidelines

Changes in the regulatory environment may lead to differences in the effectiveness of institutional investor communication in different periods. The China Securities Investment Fund Industry Association introduced the "Green Investment Guidelines (Trial)" in 2018, which represents the first comprehensive and systematic set of green investment self-regulatory standards. Institutional investors are required to prioritize investments in sustainable firms, engage in responsible investment and use their rights to urge investee firms to improve E&S performance and corporate information disclosure. This policy has strengthened the incentives for institutional investors to implement green investment, thus encouraging asset managers to focus on sustainability. Therefore, we expect the effect of institutional investors' CSR communication on CSR performance to be greater after the introduction of these guidelines.

We therefore divided the samples into two subsamples before and after 2018, as the time of the policy release. We re-estimated our baseline model using these subsamples. The results presented in Table 11 indicate that the positive correlation between CSR communication measures and CSR scores is high for the period following the implementation of the Green Investment Guidelines (Trial), and the difference between the coefficients of the two groups has statistical significance.

6.3. Institutional ownership

Chen et al. (2020) provide evidence that institutional investors can push for high firm-level E&S performance and generate real social impact by influencing the CSR policies of their portfolio firms through the rights that come with their shareholdings. Our main results show that the voice of institutional investors in private communication can affect CSR performance. We also find that this influence is not limited to shareholding institutional investors. Those who do not yet hold shares can also impact CSR improvement if they participate in private meetings. Thus, we further examine whether institutional investor communication in

Table 12
Institutional Investors' CSR Communication, Institutional Ownership, CSR Performance.

	Depend Variable = $Score_{t+1}$			
	High Institutional Shareholding	*Low Institutional Shareholding*	*High Institutional Shareholding*	*Low Institutional Shareholding*
	(1)	(2)	(3)	(4)
CSR_cosine	0.121***	0.204***		
	(0.036)	(0.036)		
CSR_freq			0.102***	0.144***
			(0.028)	(0.029)
Constant	−16.702**	19.542**	−16.401**	19.463**
	(8.004)	(8.947)	(8.009)	(9.010)
Controls	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Observations	3864	3917	3864	3917
Adjusted R^2	0.180	0.184	0.181	0.181
Comparison coefficients	Observed difference = −0.083 p-value = 0.006		Observed difference = −0.042 p-value = 0.047	

This table shows the relationship between Institutional investors' CSR Communication and CSR performance for firms with high and low levels of institutional shareholding, partitioned based on the median value of institutional ownership. The last row shows the significance of the differences in coefficient estimates between two groups. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

general can be an alternative mechanism for institutional ownership and affect CSR performance by assessing whether it can produce a marginal effect in firms with low levels of institutional ownership and promote the improvement of their CSR performance.

We divided the sample based on the median of institutional ownership and compared the impact of CSR communication on high- and low-institutional shareholding groups. Table 12 reports the results. Columns (1) and (2) show that the coefficients on CSR communication are positive and significant at the 1 % level in both the high and low ownership groups. This indicates a robust relationship between CSR communication and performance, regardless of institutional ownership characteristics. The coefficient is higher for the low institutional ownership group (0.204) than for the high group (0.121), and the difference is significant at 1 %. This suggests CSR communication has a greater impact with a lower level of institutional shareholding. Engagement through private communication may be the investors' primary channel of influence when the stakes are lower. Those with higher stakes can also leverage shareholder rights. Overall, these results support the substitutive relationship between institutional ownership and communication.

6.4. Underlying mechanism

Thus far, we have documented that CSR-related communication during site visits can lead to subsequent improvements in firms' CSR performance. We further investigate potential channels for our results. One potential mechanism is that through effective communication, these investors can enhance the transparency of CSR information, which then leads to CSR performance improvements. Chen et al. (2018) suggest that firms face pressure to strengthen their CSR commitments when they are required to disclose their CSR activities. Investor–manager interactions regarding CSR provide additional relevant disclosures to the market. This may garner further attention from stakeholders (e.g., suppliers, consumers and communities) and the government, thereby disciplining firms and improving their corporate behavior. Research also shows that a firm's information environment affects its sustainability (Burke, 2022). Therefore, institutional investors can support firms' CSR efforts by increasing public access to information. The attention given to CSR issues by institutional investors can strengthen external oversight, attract the attention of other stakeholders and promote the firm's sustainable development by improving corporate information transparency.

Alleviating financing constraints may serve as another potential mechanism through which communication can improve CSR practices. Previous studies highlight that financial constraints have a major impact on sustainable corporate policies. Financially unconstrained firms are more likely to invest in a sustainable

Table 13
Underlying Mechanism.

	(1)	(2)	(3)	(4)
	Information environment	*Information environment*	*Financing Constraint*	*Financing Constraint*
CSR_cosine	0.007***		−0.008***	
	(0.001)		(0.003)	
CSR_freq		0.006***		−0.007***
		(0.001)		(0.002)
Constant	−2.607***	−2.581***	4.620***	4.584***
	(0.227)	(0.226)	(0.607)	(0.608)
Controls	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Observations	7781	7781	7781	7781
Adjusted R^2	0.141	0.143	0.522	0.522

This table presents results examining the underlying mechanisms institutional investors' CSR communication may influence corporate sustainability. Columns (1) and (2) analyze the effect on firms' information environments, proxied by annual information disclosure ratings. Columns (3) and (4) examine impacts on financing constraints, measured using the KZ Index. CSR communication is captured by the variables *CSR_cosine* and *CSR_freq*. Standard errors reported in parentheses are clustered at the firm level. Variable definitions are provided in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

development strategy, as this requires a solid financial base and resource input (Xu and Kim, 2022). Chapman et al. (2022) suggest that direct and ongoing dialogue between management and investors is essential for mutual understanding and trust. Effective communication between firms and investors can reduce investors' uncertainty about CSR initiatives, thus lowering perceived investment risks. Therefore, firms may face fewer financing constraints and can allocate more resources toward CSR activities.

We measured the information environment and financing constraint using two proxies to test these two potential channels. We first considered the annual information disclosure ratings of listed companies in the SZSE to measure their information environments. The SZSE categorizes firms into four annual grades (A, B, C and D) based on the quality of their information disclosure. A firm receiving an "A" grade is considered to have a high-quality information environment. We thus assigned these firms an *information environment* variable value of 1. We also used the KZ Index, as proposed by Kaplan and Zingales (1997), as a proxy for financial constraint. A high KZ index value indicates a great degree of financial constraint.

Table 13 presents the results of examining the mechanisms underlying the influence of institutional investors' CSR communication on corporate sustainability. Columns (1) and (2) give the results from analyzing the effect on firms' information environments, proxied by annual information disclosure ratings. Columns (3) and (4) give those from examining the impacts on financing constraints, measured using the KZ Index. The coefficients on *CSR_cosine* and *CSR_freq* in Columns (1) and (2) are positive and significant, indicating that firms with a higher level of CSR communication have superior information environments. This supports the mechanism of investor–manager CSR dialogue, which improves corporate transparency.

Similarly, the negative and significant coefficients on the CSR communication variables in Columns (3) and (4) suggest that CSR discussions between investors and managers reduce firms' financing constraints. This is consistent with the mechanism of CSR communication, which reflects investor support and the ease of access to resources. Overall, our empirical results provide evidence for both proposed channels. CSR communication with institutional investors enhances corporate information environments and relaxes financing constraints. This enables firms to devote greater resources and commitment to sustainability initiatives.

7. Conclusion

In this study, we explore the impact of institutional investors' communication on CSR. We examine site visit transcripts of Chinese A-share firms in the SZSE from 2013 to 2021 and conduct a machine learning-based textual analysis to quantify the level of attention institutional investors give to CSR issues when communicating with management. Our results provide strong evidence that CSR communication during site visits can effectively enhance subsequent CSR performance. We also analyze the cross-sectional characteristics affecting the strength of the impact of CSR communication. The effect is more pronounced for non-state-owned firms than for SOEs, indicating that institutional investors play a more crucial monitoring role in the absence of state oversight. In addition, the impact increases following the introduction of green policies such as the Green Investment Principles, suggesting that such frameworks encourage and empower investors to engage in sustainability. Firms with lower levels of institutional ownership also exhibit a more substantial effect, implying that private and direct communication has a more important role in improving CSR when shareholders' monitoring is limited.

Our study has meaningful implications for both policy and practice. It highlights the need for institutional investors to proactively communicate their CSR priorities during private interactions. Their monitoring role should involve going beyond financial metrics and engaging with CSR issues that can lead to long-term value creation. For market regulators, enabling institutional investor access and promoting CSR communication norms can lead to improved accountability regarding sustainability practices. Although we focus on Chinese firms, future research can examine other locations, as investors worldwide increasingly prioritize sustainability; thus, understanding how they can effectively foster CSR improvements remains an important topic.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Claude in order to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) 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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Appendix A. Variable Definitions

Variables	Definitions
TF-IDF weighted CSR-related Communication Measures	
$CSR\_cosine_{i,t}$	The sum of cosine similarities between the TF-IDF weighted word vector of each transcript and the TF-IDF weighted average vector of the CSR dictionary across all transcripts of the firm i in year t.
$CSR\_freq_{i,t}$	The sum of the relative frequencies of TF-IDF weighted CSR words in each transcript across all transcripts of the firm i in year t.
Dependent Variables	
$Score_{i,t}$	The annual average of the quarterly ESG rating scores of firm i in year t.
TF-IDF weighted CSR-related Communication Measures by Dimension	
$cosine\_share_{i,t}$	The sum of cosine similarities between the TF-IDF weighted word vector of each transcript and the TF-IDF weighted average vector for the "shareholders and creditors" dimension across all transcripts of firm i in year t.
$cosine\_emp_{i,t}$	The sum of cosine similarities between the TF-IDF weighted word vector of each transcript and the TF-IDF weighted average vector for the "employees" dimension across all transcripts of firm i in year t.
$cosine\_scc_{i,t}$	The sum of cosine similarities between the TF-IDF weighted word vector of each transcript and the TF-IDF weighted average vector for the "suppliers, customers and consumers " dimension across all transcripts of firm i in year t.
$cosine\_env_{i,t}$	The sum of cosine similarities between the TF-IDF weighted word vector of each transcript and the TF-IDF weighted average vector for the "environmental protection and sustainable development" dimension across all transcripts of firm i in year t.
$cosine\_social_{i,t}$	The sum of cosine similarities between the TF-IDF weighted word vector of each transcript and the TF-IDF weighted average vector for the "public relations and social welfare services" dimension across all transcripts of firm i in year t.
$freq\_share_{i,t}$	The sum of relative frequencies of TF-IDF weighted words for the "shareholders and creditors" dimension in each transcript across all transcripts of firm i in year t.
$freq\_emp_{i,t}$	The sum of relative frequencies of TF-IDF weighted words for the "employees" dimension in each transcript across all transcripts of firm i in year t.

Appendix A. (*continued*)

Variables	Definitions
$freq\_scc_{i,t}$	The sum of relative frequencies of TF-IDF weighted words for the "suppliers, customers and consumers" dimension in each transcript across all transcripts of firm *i* in year *t*.
$freq\_env_{i,t}$	The sum of relative frequencies of TF-IDF weighted words for the "environmental protection and sustainable development" dimension in each transcript across all transcripts of firm *i* in year *t*.
$freq\_social_{i,t}$	The sum of relative frequencies of TF-IDF weighted words for the "public relations and social welfare services" dimension in each transcript across all transcripts of firm *i* in year *t*.
Variables in Robustness Tests	
$adjustedScore_{i,t}$	$adjustedScore_{i,t}$ is defined as CSR rating score adjusted for the effect of firm size. It is constructed by subtracting the average CSR score of firms in the same size quintile from each firm's CSR rating score.
Unweighted CSR-related Communication Measures	
$CSR\_cosine_{i,t}$	The sum of cosine similarities between the unweighted word vector of each transcript and the unweighted CSR dictionary vector across all transcripts of company *i* in year *t*.
$CSR\_freq_{i,t}$	The sum of relative frequencies of unweighted CSR dictionary words in each transcript across all transcripts of company *i* in year *t*.
Questions-Only CSR Communication Measures	
$CSR\_cosine_{i,t}$	The sum of cosine similarities between the TF-IDF weighted word vector of the questions portion of each transcript and the TF-IDF weighted average vector of the CSR dictionary across all transcripts of the firm *i* in year *t*.
$CSR\_freq_{i,t}$	The sum of relative frequencies of TF-IDF weighted CSR words appearing only in the questions portion of each transcript across all transcripts of the firm *i* in year *t*.
Average CSR Communication Measures	
$CSR\_cosine_{i,t}$	The average cosine similarity between the vector representation of each transcript and the CSR dictionary vector across all transcripts of the company *i* in year *t*.
$CSR\_freq_{i,t}$	The average relative frequency of CSR dictionary words across all transcripts of the company *i* in year *t*.
CSR Communication Measures on CSR Report	
$Report\_cosine_{i,t}$	The cosine similarity between the TF-IDF weighted word vector of the CSR report and the TF-IDF weighted word vector of the CSR dictionary for the company *i* in year *t*.
$Report\_freq_{i,t}$	The relative frequency of TF-IDF weighted CSR dictionary words in the CSR report for company *i* in year *t*.
Communication Tone	
$Tone_{i,t}$	The average relative frequency of positive versus negative tone words in the site visit transcripts of the company *i* in year *t*.
Control Variables	
$Size_{i,t}$	Natural logarithm of total assets.
$Age_{i,t}$	Natural logarithm of the number of years firm *i* has been listed on a stock exchange at the end of year *t* plus one.
$Tangible_{i,t}$	The ratio of property, plant, and equipment to total assets.
$Lev_{i,t}$	The ratio of total debt to total assets.
$ROE_{i,t}$	The ratio of net income to shareholders' equity.
$Tobinq_{i,t}$	The ratio of the firm's market value to its book value.
$Inshold_{i,t}$	The proportion of shares held by institutional investors.
$SOE_{i,t}$	A dummy variable equals one if the firm is state-owned and 0 otherwise.
$Indp_{i,t}$	The percentage of independent directors on the board.
$Dual_{i,t}$	A dummy variable equals one if the firm's CEO also holds the position of chairman of the board of the same firm and 0 otherwise.

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Artificial intelligence and corporate risk-taking: Evidence from China

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ABSTRACT

The deep integration of artificial intelligence (AI) into enterprises presents both opportunities and challenges, making it a focal point of current research. This study explores the impact of AI on corporate risk-taking, using data spanning 2010–2019 from A-share listed companies in China. Our findings suggest that AI significantly heightens companies' level of risk-taking. Furthermore, financing constraints can amplify the relationship between AI and risk-taking, enhancing their sensitivity correlation. AI also significantly improves firms' investment efficiency and mitigates their underinvestment issues. Finally, mediation tests indicate that AI enhances risk-taking by diminishing firms' risk perception. Overall, we offer valuable insights into and references for accelerating the deep integration of AI into enterprises.

1. Introduction

Artificial intelligence (AI) has risen to prominence with advancements in AI-related technologies, serving as a crucial driver of productivity growth in today's digital era (Wamba, 2022). This strategic technology, which plays a pivotal role in the latest technological revolution and industrial progress, has transcended research to receive real economic applications. It has infiltrated sectors such as transportation, healthcare and education, engendering novel intelligent practices spanning diverse domains. It offers significant support for management and decision-making (Galaz et al., 2021; Pietronudo et al., 2022).

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The profound integration of AI into the real economy is gaining both theoretical and practical attention, with AI being framed as an essential facilitator of high-quality economic growth. The emergence of AI has led to a surge in novel technologies, products, industries and models, thereby providing a substantial boost to enterprise development (Farrokhi et al., 2020). AI also plays an instrumental role in enhancing supply chain management in enterprises (Toorajipour et al., 2021) and improving customer relations (Perez-Vega et al., 2021). Numerous studies demonstrate the overall ability of AI to enhance efficiency and reduce firm costs (Wilson and Daugherty, 2018; Baryannis et al., 2019). However, traditional industries are facing unprecedented challenges due to the advent of AI. Consequently, the effective promotion of deep AI integration into the real economy and the empowerment of actual enterprises to improve quality and efficiency have become key AI development factors.

As AI and real enterprises become intertwined, the application of related technologies is likely to significantly affect enterprises. From a business perspective, risk and return are matched. Companies are inevitably bound to undertake certain risks to garner profits (Wang and Mao, 2015). Thus, studies commonly categorize corporate risk-taking as enterprises' inclination to incur costs in pursuit of high profits amid the uncertainty of the internal and external environments (Lumpkin and Dess, 1996).

The risk-taking level of a firm mirrors the firm's risk appetite in making investment decisions. A higher level of risk-taking reflects a firm's inclination toward risky investment projects. A firm's risk-taking level is influenced not only by its management's willingness to take risks but also by its resource procurement ability (Si and Li, 2022). Therefore, investigating corporate risk-taking levels can offer insights into firms' investment tendencies and provide a more comprehensive understanding of corporate behaviors. Studies reveal that numerous factors can affect firms' corporate risk-taking levels. At the macro level, political and economic factors (Mao and Xu, 2016; Luo et al., 2022), socio-cultural factors (Jin et al., 2017; Huang et al., 2022; Shen et al., 2022) and environmental factors (Zhou et al., 2022; Zhu et al., 2022) may affect corporate risk-taking levels. At the micro level, aspects such as corporate equity structure (Su, 2016), equity incentives (Li and Zhang, 2014) and managerial characteristics (Yu et al., 2013; Lv et al., 2015; He et al., 2016; Tan et al., 2022) can also affect corporate risk-taking level. Nevertheless, with the deep integration of AI-related technologies into real enterprises, attention to the potential influence of these technologies on corporate risk-taking level is noticeably lacking.

In this study, we begin by exploring the effects of AI adoption in enterprises. The corporate risk-taking level is analyzed to comprehend the economic repercussions of integrating AI into real enterprises. The subject of our study is Chinese A-share listed companies from 2010 to 2019, and we use a blend of theoretical and empirical research. First, we delve into the issue through a literature review and theoretical analysis. Subsequently, the relationships between the defined variables are analyzed through relevant indicator quantification and empirical research methods (e.g., descriptive statistics, correlation analysis and regression analysis). We find that enterprises' adoption of AI significantly increases their risk-taking. Furthermore, financing constraints play a moderating role in this relationship. Specifically, the severity of financing constraints amplifies the positive relationship between AI adoption and risk-taking.

This paper makes two primary contributions. First, we expand the firm-level study of AI. Research is progressively shifting focus toward the impact of digital technology on economic activities, as this impact continues to grow (Goldfarb and Tucker, 2019). Studies thus far primarily concentrate on economic development (Lin et al., 2020; Yang and Hou, 2020) and the labor market (Graetz and Michaels, 2018; Cheng et al., 2019; Wang and Dong, 2020) from a macro-level perspective. Some explore duopoly competition in AI technologies using game theory models, and others emphasize the positive effects of AI integration into real firms (Johnson et al., 2022). However, the relationship between AI adoption and corporate risk-taking receives insufficient attention. Using risk-taking as a focal point, we examine the specific impact of AI adoption on corporate investment decisions. This allows us to provide evidence of the impact of AI on firms at the micro level, supplementing related AI and risk-taking research.

Second, our findings will help to promote the application of AI at the enterprise level, fostering deeper enterprise integration of AI. AI is a strategic apex in the new round of technological revolution and industrial competition. It has become a critical element of technological innovation in production and daily life and a focus of extensive attention at the enterprise level. Through this study, we help elucidate the positive effects of AI on enterprises, addressing whether enterprises should adopt AI. We also demonstrate that the effects of AI adoption on enterprises can be influenced by financing constraints, offering a more comprehensive understanding of the impacts of AI on enterprises.

2. Literature review and hypothesis development

Corporate risk-taking, denoting the trade-off between risk and return (i.e., the level of risk a firm is willing to assume to generate profits; Wang and Mao, 2015), represents a prevalent research concern. At the firm level, a firm's risk-taking level indicates whether it can fully utilize investment opportunities. The higher a firm's risk-taking level, the greater its motivation to invest, which can promote its future development (Yu et al., 2013). However, from the management perspective, agency theory proposes that managers aim to minimize investment failure possibilities to protect their personal reputations and improve their career prospects and income levels. Internal and external uncertainties limit management's knowledge, time and energy, thus making them more conservative and leading to the abandonment of projects that are risky but have positive net present value (NPV; Zhang et al., 2015).

2.1. Artificial intelligence and corporate risk-taking

The development and application of AI have transformed the business processes, production and operation modes of traditional industries, significantly influencing their development and transformation (Wamba, 2022). AI, characterized by high levels of integration and empowerment, assists enterprises in automating and intellectualizing business processes using big data resources and machine learning technologies. It allows for adjustments to and innovations in the original organizational structure and enhances enterprise management efficiency (Złotowski et al., 2017; Wilson and Daugherty, 2018). The network externality of AI can also boost information communication efficiency between external entities, such as suppliers and customers (Min, 2010), thus reducing enterprise transaction costs and improving resource allocation efficiency. However, the integration of AI into real enterprises remains in the exploratory stage, potentially inducing moral hazards in management and exacerbating agency conflicts. This could worsen the problems that may arise during enterprises' decision-making (Miller, 2018; Gacanin and Wagner, 2019). Therefore, investigating how corporate risk-taking levels change in response to AI integration into real enterprises is timely and holds profound theoretical significance.

AI, a technology and application system, simulates, extends and enhances human cognitive behaviors using new-generation information technology such as supercomputing, cloud computing and big data. The ultimate aim of AI is to emulate human thinking with computers, following the fundamental mechanism of intelligence formation (Min, 2010). The application of AI allows managers to progressively optimize their decisions, transitioning from satisfactory to optimal decisions. It allows managers to better grasp internal and external information when making decisions, thereby enhancing their investment risk-taking capacity.

First, AI can serve as an advanced assistant for managers. Using computerized in-depth algorithms, AI integrates data from inside and outside organizations. It aids in analyzing, deducing and processing complex problems, such as by constructing scenario simulations. AI technology can complete complex logical thinking processes, substantially augmenting an enterprise's capacity to handle massive amounts of information (Tian et al., 2022). AI helps managers transcend the limitations of knowledge, effort and time, allowing them to create multiple alternatives based on past case records. This provides managers with a broader and more reliable basis for their decisions, aiding decision-makers in making more scientifically sound decisions (Edwards et al., 2000).

Second, the development of AI enables machines to mirror the intelligence of the human brain, simulating certain human cognitive processes and intelligent behaviors (Min, 2010). Consequently, computers can execute higher-level applications with enhanced analytical and decision-making abilities, proposing visionary decision-making solutions. In such a decision-making environment, comprising AI employees and AI technology, conditions, information and thinking processes are controllable. The existence of absolutely rational decision-makers and a deterministic decision-making environment facilitate the achievement of optimal decisions (Wilson and Daugherty, 2018).

Dynamic capability theory defines dynamic capability as the higher-order capacity of an enterprise to reconfigure internal and external resources. The objective of dynamic capability is to assist an enterprise in creating and maintaining a competitive edge in a dynamically evolving environment (Teece, 2012). As the application of AI in enterprises intensifies, companies can integrate internal and external information and resources more effectively, thereby fortifying their dynamic capabilities. In essence, satisfactory decision-making is hindered by limited human rationality and inadequate and asymmetric information. The development of AI significantly mitigates these constraints. Its immense information processing capacity and absolute rationality traits enable more scientific analysis and integration of data. It optimizes managers' decision-making environments, overcomes physiological limitations imposed by the human factor and executes management activities based on the principle of optimal decision-making. Such capabilities allow managers to make decisions with enhanced information integration and utilization capacities, reducing the uncertainties they face. Consequently, companies can make superior decisions tailored to their situations, further assisting in diminishing excessively risk-averse inclinations. Therefore, we propose the following hypothesis:

H1: AI enhances the level of corporate risk-taking, thus enabling firms to undertake more risky projects.

2.2. Moderating effect of financing constraints

Financing represents a fundamental aspect of corporate finance, as it is an activity that firms undertake to fulfill their investment needs (Jiang et al., 2020). The presence of information asymmetry and unavoidable transaction costs in the market inevitably implies that companies' utilization of external funds incurs higher costs. This gives rise to corporate financing constraints (Lu and Zhang, 2014).

Ideally, a company should invest in all positive NPV projects despite their limited numbers. However, firms and their managers cannot precisely predict the expected NPV of invested projects. This leads them to overlook NPV-positive projects or invest in NPV-negative projects, resulting in inefficient investment. When firms face high financing constraints, their investment decisions become more important and the decision-making process more cautious. As a result, listed firms' investment expenditures fall below the optimal level, indicating underinvestment (Zhang and Zheng, 2012; Pan et al., 2016). When the problem of financing constraints is not significant (i.e., when a firm's financing environment is relatively positive), the firm has the capacity to choose from a wider range of investment projects; hence, underinvestment is not a concern. Conversely, when firms face harsher financing constraints, they exercise more caution in utilizing funds, increasing the likelihood of a conservative bias in the investment process, which often results in underinvestment. Therefore, for enterprises facing greater financing constraints, the integration of AI can assist in achieving more accurate analysis of the internal and external environments and information. It helps firms precisely assess the NPV of projects, greatly reducing the chance of overlooking NPV-positive projects. This alleviates the issue of underinvestment and decreases the conservative tendency of firms during the investment process. This is reflected in a stronger correlation between AI and risk-taking. Hence, we propose the following hypothesis:

H2: The greater the financing constraints a firm faces, the stronger the link between AI and corporate risk-taking.

3. Research design

3.1. Research sample and data source

The research sample comprises data on A-share listed companies in Shanghai and Shenzhen from 2010 to 2019. We choose 2010 as the starting point of the study for two reasons. First, according to the 2018 China Artificial Intelligence Industry White Paper, China began investing in AI research and development (R&D) after 2010 and exhibited an annual growth trend, only recently shifting from R&D to industrial applications. Second, the data distribution indicates that the firms in the sample have reported on their level of AI adoption since 2010. The onset of COVID-19 in 2020 led to major changes in the macroenvironment faced by companies, which may bias the results of the data analysis. Consequently, we define the research period as 2010–2019. The AI data used in this study are obtained from the annual reports of the listed companies, using a combination of text location and manual research.

The data on financial metrics and corporate governance status are obtained from the China Stock Market & Accounting Research database. Of the 28,905 company-year instances obtained from the initial retrieval, 1,581 instances undergoing special treatment are removed. A further 788 instances from the financial and insurance sectors are omitted. The calculation of risk-taking necessitates 5 years of data before and after, leading to the exclusion of some instances due to inadequate market exposure or gaps in the data sequence. Consequently, 9,921 additional instances are excluded on account of incomplete information. The final panel consists of 16,615 firm-year observations. To ensure that bias and extreme values do not influence the test results, all continuous variables in this study are subject to 1 % winsorization at the upper and lower ends.

3.2. Variables

3.2.1. Dependent variable: RiskTaking

Following the method of Zhang et al. (2015), we measure corporate risk-taking levels using the volatility of stock returns. This is equivalent to the standard deviation of firms' industry-adjusted annual stock returns over a 5-year period (from t–2 years to $t + 2$ years).[1] Higher stock return volatility indicates a higher level of firm risk-taking.

3.2.2. Independent variable: AI

AI data are sourced from the annual reports of listed companies. Following the method of Wu et al. (2021), we adopt an approach combining text location and manual reading to obtain enterprise-level AI data. In the text location stage, we mainly reference a series of institutional documents on AI issued by the state, the 19th Party Congress report and research reports from various institutions. With the assistance of Python, we locate AI-related keywords in annual reports,[2] and the adoption of AI by a company is determined through manual research. The dummy variable Dummy_AI is first constructed to measure AI at the enterprise level. Dummy_AI takes a value of 1 if a company demonstrates AI adoption, and 0 otherwise. The depth of a company's AI adoption is measured by the frequency of relevant keyword mentions in its annual report. We define AI as the number of keyword occurrences plus 1, then logarithmically transformed.

3.2.3. Moderating variable: KZ

Drawing from Kaplan and Zingales (1997) and Wei et al. (2014), we construct a composite index (KZ index) to measure a firm's degree of financing constraints based on the firm's financials. The methodology for the calculation involves several steps. First, the ratios of net operating cash flow to total assets, cash dividends to total assets and cash holdings to total assets, as well as the gearing ratio and Tobin's Q, are calculated for all each sample, followed by the determination of the median value for each of these indicators. Second, each sample's values for these five indicators are compared against their respective medians. A value higher than the median is assigned a value of 1, while a value lower than the median receives a value of 0. These binary values are then aggregated to compute the KZ index. Third, an ordered logistic regression model is applied, with the previously calculated KZ index acting as the dependent variable and the five indicators serving as independent variables. This model is used to estimate the coefficients for each variable. Finally, based on the coefficients derived from the regression model, the KZ index indicating financing constraints is calculated for each sample. Studies suggest that a higher value of the KZ index indicates a higher degree of financing constraint.

[1] We conduct all tests using monthly returns as a metric for assessing risk-taking, yielding qualitatively consistent results. Appendix A presents the results.

[2] We define the following terms as AI-related keywords: "artificial intelligence," "business intelligence," "image understanding," "investment decision support system," "intelligent data analysis," "intelligent robot," "machine learning," "deep learning," "semantic search," "biometric technology," "face recognition," "speech recognition," "identity verification," "autonomous driving," and "natural language processing.".

3.2.4. Control variables

Referring to the control variables typically used in risk-taking studies (Mao and Xu, 2016), we control for firm-level factors, including firm size (Size), leverage (Lev), profitability (Roa), shareholding of the largest shareholder (Sh1), chairman and CEO duality (Dual), board size (Board), directorship independence (Indep), cash flow position (CF), nature of ownership (State) and the macroeconomy (GDP). These factors affect risk-taking at the firm level, and controlling for them can help us study the impact of AI on risk-taking. We also control for industry effects and year effects in the regressions. Table 1 provides detailed definitions of all of the variables.

3.3. Model construction

Following previous studies (Li and Zhang, 2014; Lv et al., 2015), we use the model below to investigate the impact of AI adoption on firms' risk-taking levels:

$$Risk\ Taking_{i,t} = \alpha + \beta_1 AI_{i,t} + \beta_2 Controls + \sum Year + \sum Ind + \varepsilon_{i,t} \tag{1}$$

To investigate the moderating role of financing constraints (Mao and Xu, 2016), we use the following model:

$$Risk\ Taking_{i,t} = \alpha + \beta_1 AI_{i,t} + \beta_2 \mathrm{KZ}_{i,t} + \beta_3 \mathrm{AI}_{i,t} + *\mathrm{KZ}_{i,t} + \beta_4 Controls + \sum Year + \sum Ind + \varepsilon_{i,t} \tag{2}$$

In both models, the dependent variable is RiskTaking and the independent variable is AI. The subscript i represents the firm and t represents the year, such that $\mathrm{RiskTaking}_{i,t}$ represents the risk-taking level of firm i in year t. In model (1), the primary focus is on the coefficient of β_1. We expect this coefficient to be positive and significant, suggesting that AI adoption significantly increases firms' risk-taking levels. In model (2), we focus on the coefficient of the cross-product term, β_3. We also expect this coefficient to be positive and significant. This would suggest that the positive impact of AI on firms' risk-taking level increases with the severity of their financing constraints.

4. Empirical results

4.1. Descriptive statistics and correlation analysis

Table 2 reports the descriptive statistics of the primary variables. The mean value of RiskTaking is 0.061, which is generally consistent with previous research (Zhang et al., 2015), despite differences across samples.

Table 1
Variable definitions.

Variable properties	Variable	Definition
Dependent variable	RiskTaking	Level of risk-taking, as measured by the stock return volatility
Independent variables	AI	Equal to ln(1 + the number of keyword occurrences in the annual report)
	Dummy_AI	Equal to 1 if the company demonstrates AI adoption, and 0 otherwise
Moderatingvariable	KZ	Financing constraints
Control variables	Size	Company size, measured as the natural logarithm of total assets at the end of the year
	Lev	Asset to liability ratio
	Roa	Return on total assets
	Sh1	Shareholding ratio of the largest shareholder
	Dual	Dummy variable that equals 1 if the chairman and CEO are the same person, and 0 otherwise
	Board	Board size, measured as the natural logarithm of the number of board members
	Indep	Proportion of independent directors, measured as the ratio of the number of independent directors to the number of directors
	CF	Cash flow position, measured as the corporate cash flow divided by total assets
	State	Nature of property rights; equal to 1 if it is a state-owned enterprise, and 0 otherwise
	GDP	Macroeconomic factor, measured as the natural logarithm of the GDP of the province in which the listed company is located

Table 2
Descriptive statistics of the main variables.

Variable	Obs.	Mean	SD	Min.	Median	Max.
RiskTaking	16,615	0.061	0.024	0.026	0.055	0.163
AI	16,615	0.209	0.579	0.000	0.000	4.812
Dummy_AI	16,615	0.157	0.363	0.000	0.000	1.000
KZ	16,615	0.546	1.734	–7.865	0.787	5.893
Size	16,615	22.275	1.290	19.771	22.089	26.080
Lev	16,615	0.406	0.198	0.051	0.400	0.902
Roa	16,615	0.053	0.040	–0.265	0.045	0.188
Sh1	16,615	0.360	0.149	0.088	0.343	0.748
Dual	16,615	0.269	0.443	0.000	0.000	1.000
Board	16,615	2.143	0.196	1.609	2.197	2.708
Indep	16,615	0.374	0.053	0.333	0.333	0.571
CF	16,615	0.052	0.068	–0.179	0.051	0.236
State	16,615	0.369	0.483	0.000	0.000	1.000
GDP	16,615	10.456	0.725	6.229	10.474	11.587

The mean value of AI is 0.209, but the median remains 0, suggesting that the majority of the listed companies have not adopted AI. However, the maximum value is 4.812, indicating that some of them mention AI-related keywords over 100 times in their annual reports, thus revealing significant discrepancies among the companies. The dummy variable indicating AI adoption (Dummy_AI) shows that only 15.7 % of the companies have adopted AI technology; the majority have not. The degree of financing constraint (KZ) also varies considerably among the companies. Other control variables generally align with the data distribution in other studies.

Table 3 reports how the companies have adopted AI across various years and industries. In Panel A, "Obs." represents the total count of companies for each year. Both AI and Dummy_AI indicate an annual upward trend and a significant increase after 2015, a year Bloomberg rates as a milestone for AI, stating that "computers are getting smarter, and they are learning at an unprecedented rate.[3]" In 2016, the proportion of companies demonstrating AI adoption surpassed 10 % of the total for the first time and increased further to over 30 % in 2018. This significant increase is largely due to the rapid development and maturation of AI-related technologies, leading to their wider application in companies. Panel B presents the application of AI by industry. The information transmission, software and IT services companies demonstrate the highest degree of AI adoption, indicating that technology-oriented industries are more sensitive to the use of AI technology. Their already strong technological capabilities provide them with an edge in adopting AI. The education sector has the highest proportion of companies demonstrating AI adoption. This suggests that companies in the education sector value staying current and reflects the sector's pioneering role. In contrast, service-oriented industries, such as residential services, repair and other services as well as accommodation and catering, demonstrate a relatively low degree of AI adoption, suggesting that the application of AI in the service sector requires enhancement.

Table 4 reports the correlation coefficients among the main variables. The Pearson correlation coefficient matrix is illustrated in the lower left triangle, and the Spearman correlation coefficient matrix is presented in the upper right triangle. Both methods yield largely consistent results. Focusing on the Pearson correlation coefficient matrix, a positive and significant correlation exists between the adoption of AI and risk-taking in firms. With a correlation coefficient of 0.024, significant at the 1 % level, these findings partially confirm our main hypothesis. Additionally, correlations exist between other control variables and the dependent variables, thereby validating the choice of control variables in this study.

[3] Clark, J., 2015. Why 2015 was a breakthrough year in artificial intelligence. https://www.bloomberg.com/news/articles/2015–12-08/why-2015-was-a-breakthrough-year-in-artificial-intelligence.

Table 3
Artificial intelligence by year and industry.

Panel A

Year	Obs.	AI	Dummy_AI
2010	855	0.018	1.52 %
2011	1,207	0.017	1.99 %
2012	1,538	0.024	2.41 %
2013	1,682	0.028	3.03 %
2014	1,551	0.047	4.38 %
2015	1,475	0.090	8.47 %
2016	1,728	0.175	14.12 %
2017	2,012	0.359	25.30 %
2018	2,279	0.432	30.93 %
2019	2,288	0.494	36.15 %

Panel B

IND	Industry	Obs.	AI	Dummy_AI
A	Agriculture, forestry, animal husbandry and fishery	177	0.023	3.39%
B	Mining	398	0.049	5.03%
C	Manufacturing	10,693	0.169	14.07%
D	Electricity, heat power, gas and water production and supply	570	0.029	2.98%
E	Construction	504	0.095	9.33%
F	Wholesale and retail	887	0.147	14.66%
G	Transportation, warehousing and postal	615	0.128	11.54%
H	Accommodation and catering	45	0.024	2.22%
I	Information transmission, software and IT services	1,090	1.020	53.49%
K	Real estate	733	0.127	11.73%
L	Leasing and business services	190	0.172	14.74%
M	Research and technical services	150	0.187	15.33%
N	Water conservancy, environment and public facilities management	188	0.064	4.79%
O	Residential services, repair and other services	13	0.000	0.00%
P	Education	6	0.645	66.67%
Q	Healthcare	31	0.473	38.71%
R	Culture, sports and entertainment	209	0.259	22.97%
S	Conglomerates	116	0.112	12.07%

4.2. Regression analysis

4.2.1. Artificial intelligence and corporate risk-taking

Table 5 reports the results of the tests for H1, probing the relationship between AI and corporate risk-taking. Column (1) incorporates the control variables, and the regression results are significant at the 1 % level. The regression analysis reveals that the firms implementing AI exhibit an increase in their risk-taking level by 0.004 units relative to those that do not implement AI. Given the average RiskTaking value of 0.061, the positive influence of AI adoption on increasing risk-taking is deemed economically significant. This suggests that a firm's likelihood to engage in riskier ventures increases by 6.56 % following the adoption of AI. Considering the broader positive impact of AI development on macroeconomic growth, which is estimated to be between 0.55 % and 1.14 %, and its contribution to technological advancement, which ranges from 2.51 % to 4.96 % (Lin et al., 2020), the impact of AI on the business sector is considerable. Column (2) includes both the control variables and industry and year fixed effects, and the regression results remain positive and significant at the 1 % level. These results demonstrate the positive and significant effect of AI on corporate risk-taking levels. Columns (3) and (4) use the degree of AI adoption as the main independent variable. A higher value of this variable suggests a greater extent of AI adoption within a firm. Column (3) incorporates the control variables, and the regression results are significant at the 1 % level. This finding demonstrates that for each unit increase in AI adoption by a firm, there is a corresponding rise of 0.003 units in its level of risk-taking. Comparatively, the effect of managerial competence on risk-taking is 0.032 (He et al., 2016) and the impact of cultural factors on risk-taking is 0.001 (Jin et al., 2017). Therefore, we assert that the impact of our study's

Table 4
Correlation coefficients[1].

	RiskTaking	Beta	AI	Size	Lev	Roa	Sh1	Dual	Board	Indep	Cf	State	GDP
RiskTaking	1	0.332***	0.028***	–0.285***	–0.096***	–0.029***	–0.085***	0.098***	–0.126***	0.027***	–0.082***	–0.157***	0.031***
Beta	0.239***	1	0.101***	–0.126***	–0.028***	–0.096***	–0.094***	0.044***	–0.058***	0.003	–0.120***	–0.035***	0.035***
AI	0.026***	0.134***	1	0.033***	–0.037***	0.035***	–0.092***	0.073***	–0.078***	0.055***	–0.013*	–0.088***	0.160***
Size	–0.242***	–0.143***	0.018**	1	0.598***	–0.164***	0.154***	–0.208***	0.233***	0.003	0.014*	0.383***	–0.065***
Lev	–0.081***	–0.032***	–0.049***	0.600***	1	–0.429***	0.080***	–0.149***	0.146***	–0.002	–0.163***	0.295***	–0.081***
Roa	–0.052***	–0.108***	0.015*	–0.133***	–0.407***	1	0.049***	0.068***	–0.029***	–0.021***	0.418***	–0.164***	0.046***
Sh1	–0.082***	–0.096***	–0.108***	0.193***	0.086***	0.060***	1	–0.039***	–0.002	0.044***	0.073***	0.232***	–0.077***
Dual	0.084***	0.044***	0.079***	–0.197***	–0.148***	0.058***	–0.047***	1	–0.198***	0.115***	–0.010	–0.297***	0.129***
Board	–0.120***	–0.064***	–0.077***	0.254***	0.155***	–0.031***	0.015*	–0.186***	1	–0.556***	0.036***	0.282***	–0.140***
Indep	0.028***	0.003	0.045***	0.032***	0.006	–0.009	0.059***	0.119***	–0.521***	1	–0.012	–0.057***	0.020***
Cf	–0.060***	–0.114***	–0.024***	0.011	–0.179***	0.447***	0.072***	–0.010	0.035***	–0.011	1	0.010	0.031***
State	–0.139***	–0.040***	–0.093***	0.388***	0.297***	–0.140***	0.235***	–0.297***	0.287***	–0.054***	0.003	1	–0.260***
GDP	0.027***	0.034***	0.137***	–0.059***	–0.074***	0.023***	–0.078***	0.123***	–0.119***	0.008	0.022***	–0.238***	1

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

[1]It is crucial to understand that the financing constraints variable functions as a moderating variable in this study, affecting the relationship between variables x and y indirectly rather than having a direct impact on them. The correlation test primarily aims to confirm the relationships between the univariate variables, making it unsuitable for examining the impact of a moderating variable such as the financing constraints variable. Consequently, the KZ index is not incorporated into the correlation table.

Table 5
Artificial intelligence and corporate risk-taking.

	(1)	(2)	(3)	(4)
	RiskTaking	RiskTaking	RiskTaking	RiskTaking
Dummy_AI	0.004***	0.002***		
	(9.697)	(4.447)		
AI			0.003***	0.001***
			(12.488)	(5.741)
Size	–0.006***	–0.006***	–0.006***	–0.006***
	(–41.074)	(–40.587)	(–41.340)	(–40.719)
Lev	0.013***	0.014***	0.013***	0.014***
	(14.595)	(15.684)	(14.888)	(15.746)
Roa	–0.003	–0.005	–0.003	–0.005
	(–0.713)	(–1.326)	(–0.689)	(–1.304)
Sh1	–0.000	0.001	0.000	0.001
	(–0.154)	(0.921)	(0.315)	(1.054)
Dual	0.001***	0.001***	0.001***	0.001***
	(4.033)	(3.644)	(3.822)	(3.559)
Board	–0.003***	–0.003***	–0.003***	–0.003***
	(–4.035)	(–3.905)	(–3.981)	(–3.862)
Indep	0.003	0.000	0.003	0.000
	(1.073)	(0.064)	(1.029)	(0.075)
Cf	–0.019***	–0.015***	–0.018***	–0.015***
	(–8.867)	(–7.322)	(–8.628)	(–7.205)
State	–0.002***	–0.001***	–0.002***	–0.001***
	(–5.318)	(–3.554)	(–5.231)	(–3.517)
GDP	–0.000	0.000	–0.000	0.000
	(–0.535)	(0.766)	(–0.472)	(0.750)
_Cons	0.189***	0.187***	0.189***	0.187***
	(49.250)	(46.956)	(49.382)	(47.058)
Year	Yes	Yes	Yes	Yes
Ind	No	Yes	No	Yes
R2_a	0.538	0.551	0.539	0.551
N	16,615	16,615	16,615	16,615

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

focus is equally economically significant. Column (4) includes both control variables and industry and year fixed effects, and the regression results remain positive and significant at the 1 % level. This indicates that the more extensively a firm adopts AI, the higher its risk-taking level becomes. Overall, these results validate H1.

4.2.2. Artificial intelligence, financing constraints and corporate risk-taking

Table 6 introduces financing constraints as a moderating variable and performs a regression analysis. In column (1), the coefficient of the cross-product term, generated by multiplying the dummy variable for AI adoption with the variable for financing constraints, is positive and significant. This suggests that as financing constraints become more severe, the positive effect of AI on corporate risk-taking becomes more significant. In Table 5, our analysis reveals that the firms adopting AI exhibit a 0.004-unit increase in their propensity to take risks compared to those that do not. Furthermore, the data presented in Table 6 indicate that with each unit increase in financing constraints, the impact of AI adoption on risk-taking increases by 0.00049. This figure is derived from the coefficient of the cross-product term in column (1) of Table 6. Notably, this incremental effect constitutes 12.25 % of the total effect ([0.00049/0.004]x100%), underscoring the significant economic impact that financing constraints have on the relationship between AI adoption and risk-taking behavior in firms. In column (2), after incorporating the control variables and industry and year fixed effects, the coefficient of the cross-product term remains positive and significant at the 1 % level. In columns (3) and (4), where the cross-product is generated by multiplying the variable for the degree of AI adoption with that for financing

Table 6
Artificial intelligence, financing constraints and corporate risk-taking.

	(1)	(2)	(3)	(4)
	RiskTaking	RiskTaking	RiskTaking	RiskTaking
Dummy_AI	0.003***	0.001***		
	(8.866)	(3.692)		
KZ	0.000*	0.000**	0.000*	0.000**
	(1.713)	(2.373)	(1.857)	(2.479)
Dummy_AI*KZ	0.000**	0.001***		
	(2.364)	(2.678)		
AI			0.003***	0.001***
			(11.545)	(4.844)
AI*KZ			0.000*	0.000**
			(1.657)	(2.337)
Size	–0.006***	–0.006***	–0.006***	–0.006***
	(–40.316)	(–39.650)	(–40.558)	(–39.747)
Lev	0.012***	0.013***	0.012***	0.013***
	(11.155)	(11.703)	(11.423)	(11.771)
Roa	–0.001	–0.003	–0.001	–0.003
	(–0.242)	(–0.738)	(–0.251)	(–0.742)
Sh1	0.000	0.001	0.000	0.001
	(0.041)	(1.180)	(0.496)	(1.312)
Dual	0.001***	0.001***	0.001***	0.001***
	(4.132)	(3.789)	(3.921)	(3.707)
Board	–0.003***	–0.003***	–0.003***	–0.003***
	(–4.075)	(–3.934)	(–4.008)	(–3.881)
Indep	0.003	0.000	0.003	0.000
	(1.062)	(0.041)	(1.011)	(0.045)
Cf	–0.016***	–0.012***	–0.015***	–0.011***
	(–6.496)	(–4.722)	(–6.354)	(–4.679)
State	–0.002***	–0.001***	–0.002***	–0.001***
	(–5.440)	(–3.741)	(–5.368)	(–3.709)
GDP	–0.000	0.000	–0.000	0.000
	(–0.515)	(0.792)	(–0.463)	(0.765)
_Cons	0.189***	0.186***	0.189***	0.186***
	(48.819)	(46.387)	(48.931)	(46.456)
Year	Yes	Yes	Yes	Yes
Ind	No	Yes	No	Yes
R2_a	0.538	0.552	0.540	0.552
N	16,615	16,615	16,615	16,615

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

constraints, the coefficients of the cross-product terms are all significant at the 5 % level. This supports H2, which posits that the positive relationship between AI adoption and firms' risk-taking becomes stronger as firms' financing constraints intensify.

The results of the variance inflation factor test reveal the absence of multicollinearity among the variables.

4.3. Robustness testing

4.3.1. Endogeneity problem

Based on the previous analysis, we posit that firms' AI adoption aids management in decision-making, allows for a better understanding of internal and external environments and mitigates adverse effects caused by uncertainty. This helps alleviate conservative tendencies in the investment process and enhances the corporate risk-taking level. However, given that adopting AI may itself be an investment decision, reverse causality may be an issue, such that firms with higher levels of risk-taking are those that adopt technologies such as AI.

Table 7
Robustness test.

	(1)	(2)	(3)	(4)
	RiskTaking	RiskTaking	RiskTaking	RiskTaking
L.Dummy_AI	0.002***		0.002***	
	(4.536)		(3.945)	
L.KZ			–0.000**	–0.000**
			(–2.191)	(–2.145)
L.Dummy_AI*L.KZ			0.001**	
			(2.031)	
L.AI		0.002***		0.002***
		(5.357)		(4.775)
L.AI*L.KZ				0.000*
				(1.724)
L.Size	–0.005***	–0.005***	–0.005***	–0.005***
	(–32.258)	(–32.348)	(–32.132)	(–32.200)
L.Lev	0.010***	0.010***	0.011***	0.011***
	(9.243)	(9.301)	(8.847)	(8.900)
L.Roa	–0.043***	–0.042***	–0.044***	–0.044***
	(–9.767)	(–9.714)	(–9.916)	(–9.882)
L.Sh1	0.002**	0.002**	0.002*	0.002**
	(2.098)	(2.192)	(1.914)	(2.012)
L.Dual	0.001***	0.001***	0.001***	0.001***
	(3.321)	(3.310)	(3.234)	(3.221)
L.Board	–0.003***	–0.003***	–0.003***	–0.003***
	(–3.095)	(–3.078)	(–3.098)	(–3.077)
L.Indep	0.003	0.003	0.003	0.003
	(0.796)	(0.803)	(0.873)	(0.866)
L.Cf	–0.015***	–0.015***	–0.018***	–0.018***
	(–6.327)	(–6.283)	(–6.370)	(–6.369)
L.State	–0.001***	–0.001***	–0.001***	–0.001***
	(–2.900)	(–2.852)	(–2.634)	(–2.587)
L.GDP	0.000	0.000	0.000	0.000
	(1.224)	(1.216)	(1.267)	(1.243)
_Cons	0.165***	0.165***	0.166***	0.166***
	(36.670)	(36.733)	(36.642)	(36.691)
Year & Ind	Yes	Yes	Yes	Yes
R2_a	0.594	0.594	0.594	0.594
N	12,028	12,028	12,028	12,028

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

To counteract this potential endogeneity problem due to reverse causality, all of the independent and control variables are treated with a one-period lag and the regressions are repeated.

Table 7 displays the results of the repeated regression analysis of the relationship between AI and corporate risk-taking, with all of the independent variables treated with a one-period lag. The main regression coefficients of interest remain positive and significant at the 1 % level, validating the robustness of H1. In columns (3) and (4), we reanalyze the moderating effect of financing constraints. All of the coefficients of the cross-product terms remain positive and significant at the 10 % level at least, across all four columns. This confirms the robustness of the original results for H2.

4.3.2. Propensity score matching

Considering that only 15 % of the sample firms demonstrate AI adoption, a low proportion relative to the total sample, propensity score matching (PSM) is used.[4] This approach allows for a 1:1 nearest-neighbor matching for the sample demonstrating AI adoption, followed by a repeat of the regression analysis.

[4] Appendix B presents the results of the PSM and matching effect tests.

Table 8
Robustness test.

	(1) PSM	(2)	(3)	(4)	(5)
	RiskTaking	Beta	Beta	Beta	Beta
Dummy_AI	0.002***	0.045***		0.021***	
	(3.611)	(7.393)		(2.909)	
AI			0.046***		0.043***
			(11.753)		(8.517)
Size	–0.006***	–0.050***	–0.051***	0.002	–0.003
	(–24.332)	(–22.566)	(–23.012)	(0.274)	(–0.510)
Lev	0.018***	0.115***	0.116***	0.005	0.007
	(10.850)	(7.880)	(8.028)	(0.202)	(0.287)
Roa	–0.014**	–0.614***	–0.613***	–0.024	0.002
	(–2.051)	(–10.111)	(–10.111)	(–0.306)	(0.026)
Sh1	–0.003*	–0.065***	–0.060***	–0.015	–0.009
	(–1.671)	(–4.652)	(–4.337)	(–0.398)	(–0.243)
Dual	0.001**	0.006	0.005	–0.009	–0.010
	(2.271)	(1.342)	(1.118)	(–1.245)	(–1.330)
Board	–0.000	–0.026**	–0.025*	–0.007	–0.005
	(–0.008)	(–2.037)	(–1.928)	(–0.290)	(–0.223)
Indep	–0.007*	–0.065	–0.065	–0.084	–0.071
	(–1.691)	(–1.459)	(–1.449)	(–1.155)	(–0.984)
Cf	–0.001	–0.180***	–0.170***	–0.009	–0.007
	(–1.547)	(–5.365)	(–5.075)	(–0.230)	(–0.186)
State	–0.004**	0.047***	0.048***	0.076***	0.079***
	(–2.499)	(9.502)	(9.631)	(3.703)	(3.868)
GDP	0.000	0.005*	0.005*	0.031	0.021
	(0.769)	(1.823)	(1.742)	(1.070)	(0.719)
_Cons	0.188***	2.110***	2.127***	0.858**	1.057***
	(20.720)	(33.318)	(33.673)	(2.503)	(3.085)
Year & Ind	Yes	Yes	Yes	Yes	Yes
Firm FE				Yes	Yes
R2_a	0.533	0.294	0.297	0.140	0.144
N	5,206	16,508	16,508	16,508	16,508

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

In column (1) of Table 8, the post-PSM sample is regressed. The findings illustrate that the regression coefficients between the dummy variable representing AI adoption (Dummy_AI) and RiskTaking is significant at the 1 % level. This suggests the robustness of our results.

4.3.3. Variable substitution and model replacement

To further validate the robustness of our results, Beta is next utilized as a measure of corporate risk-taking. This Beta is estimated from the capital asset pricing model using the most recent year of data. Stock returns are based on individual stock returns at the date of reinvestment of cash dividends, and the market portfolio returns are the daily market returns at the date of reinvestment of cash dividends (the market capitalization-weighted average method). In columns (2) and (3) of Table 8, the dependent variable is replaced and the regressions are repeated. The regression coefficients demonstrate a positive and significant correlation at the 1 % level between AI and Beta, irrespective of whether control variables are included. This again confirms the robustness of the results. We use firm fixed effects models for the regressions reported in column (4). All of the regressions are significant at the 1 % level. The same process is applied for the regressions reported in column (5), with consistent results, further verifying the robustness of the findings.

4.3.4. Alternative sample period

In the previous sections, we define the sample period as ranging from 2010 to 2019. As the $t + 2$ period for 2019 encompasses 2020 and 2021, years that were both significantly influenced by the pandemic, this might affect stock considerations. For robustness testing, the sample period is adjusted to 2010–2017 to exclude the pandemic years. Table 9 presents the regression results, which remain significant. This suggests that altering the sample period does not affect the robustness of our findings.

4.3.5. Instrumental variable approach

To alleviate potential endogeneity issues, an instrumental variable approach is used. The digital economy development index of the province in which a firm is located is selected as the instrumental variable, as suggested in the literature (Chen et al., 2022). This variable exhibits a strong correlation with firms' level of AI adoption but does not directly affect their risk-taking level, making it a suitable instrumental variable. A two-stage least squares regression is conducted using the instrumental variable. Table 10 reports the results. The regression results in columns (1) and (3) demonstrate a high correlation between the firms' level of AI adoption and the degree of digital economic development in their province. The second-stage regression results reported in columns (2) and (4) indicate that the regression coefficients remain significant at the 1 % level after using the instrumental variable. This mitigates potential endogeneity issues, further solidifying the reliability of our findings.

Table 9
Alternative sample period.

	(1)	(2)	(3)	(4)
	RiskTaking	RiskTaking	RiskTaking	RiskTaking
Dummy_AI	0.003***	0.001**		
	(6.481)	(2.323)		
AI			0.003***	0.001***
			(7.381)	(2.582)
Size	–0.006***	–0.006***	–0.006***	–0.006***
	(–35.308)	(–35.322)	(–35.413)	(–35.343)
Lev	0.012***	0.013***	0.012***	0.013***
	(11.989)	(12.690)	(12.122)	(12.719)
Roa	–0.005	–0.009**	–0.005	–0.009**
	(–1.182)	(–2.000)	(–1.111)	(–1.970)
Sh1	0.002**	0.003***	0.002**	0.003***
	(2.118)	(2.700)	(2.273)	(2.737)
Dual	0.001***	0.001***	0.001***	0.001***
	(3.395)	(3.184)	(3.303)	(3.155)
Board	–0.003***	–0.002***	–0.003***	–0.002***
	(–2.678)	(–2.667)	(–2.683)	(–2.665)
Indep	0.005	0.002	0.005	0.002
	(1.433)	(0.501)	(1.464)	(0.520)
Cf	–0.021***	–0.017***	–0.020***	–0.017***
	(–8.749)	(–7.153)	(–8.688)	(–7.130)
State	–0.002***	–0.001***	–0.002***	–0.001***
	(–5.367)	(–3.799)	(–5.339)	(–3.792)
GDP	–0.000	0.000	–0.000	0.000
	(–1.173)	(0.090)	(–1.121)	(0.101)
_Cons	0.191***	0.188***	0.191***	0.188***
	(43.007)	(41.127)	(43.045)	(41.143)
Year	Yes	Yes	Yes	Yes
Ind	No	Yes	No	Yes
R2_a	0.605	0.617	0.605	0.617
N	12,048	12,048	12,048	12,048

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 10
Instrumental variable approach.

	(1)	(2)	(3)	(4)
	Dummy_AI	RiskTaking	AI	RiskTaking
Tool_variable	0.097***		0.150***	
	(5.492)		(5.468)	
Dummy_AI		0.047***		
		(3.869)		
AI				0.030***
				(3.881)
Size	0.024***	–0.007***	0.043***	–0.007***
	(8.511)	(–19.095)	(9.840)	(–17.643)
Lev	–0.017	0.015***	–0.055*	0.016***
	(–0.897)	(12.079)	(–1.895)	(12.141)
Roa	0.102	–0.010*	0.060	–0.007
	(1.316)	(–1.828)	(0.494)	(–1.302)
Sh1	–0.074***	0.004***	–0.174***	0.006***
	(–4.122)	(2.688)	(–6.247)	(3.252)
Dual	0.020***	0.000	0.042***	–0.000
	(3.339)	(0.173)	(4.441)	(–0.442)
Board	–0.025	–0.002	–0.054**	–0.001
	(–1.522)	(–1.644)	(–2.122)	(–1.194)
Indep	0.043	–0.002	0.030	–0.001
	(0.759)	(–0.479)	(0.338)	(–0.189)
Cf	–0.186***	–0.007*	–0.398***	–0.003
	(–4.347)	(–1.847)	(–5.966)	(–0.817)
State	–0.009	–0.001	–0.019*	–0.000
	(–1.474)	(–1.347)	(–1.929)	(–1.010)
GDP	–0.004	–0.001*	–0.009	–0.000
	(–0.698)	(–1.810)	(–1.113)	(–1.568)
_Cons	–0.519***	0.218***	–0.804***	0.217***
	(–6.047)	(22.088)	(–6.011)	(22.174)
Year & Ind	Yes	Yes	Yes	Yes
R2_a	0.216	0.167	0.250	0.172
N	16,614	16,614	16,614	16,614

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

4.4. Further research

4.4.1. Artificial intelligence and investment efficiency

Following the previous analysis, we argue that AI can enhance a firm's risk-taking capacity, which is closely linked to its investment behaviors. Thus, we further explore the relationship between AI and investment efficiency. As previously discussed, AI significantly improves investment efficiency due to its role in supporting managerial decision-making, which is primarily manifested in alleviating underinvestment.

To measure investment efficiency, we refer to the model established by Richardson (2006):

$$Invest_t = \beta_0 + \beta_1 Growth_{t-1} + \beta_1 Lev_{t-1} + \beta_1 Cash_{t-1} + \beta_1 Age_{t-1} + \beta_1 Size_{t-1} + \beta_1 \mathrm{R}eturns_{t-1} + \beta_1 Invest_{t-1} + \varepsilon \tag{3}$$

where Invest represents a firm's investment expenditure, which equals the cash expended on acquiring fixed assets, intangible assets and other long-term assets minus the net cash recouped from the disposal of these assets, divided by the total assets at the beginning of the year. Growth represents the firm's growth capability, as measured by Tobin's Q. Lev, Cash, Age, Size and Return correspond to gearing, cash holding position, the number of years a firm has been listed, asset size and stock return, respectively. The model also accounts for year effects and industry effects. The absolute value of the residuals after regression serves as a measure of investment efficiency (Inv), with larger values indicating lower efficiency. A positive residual signifies overinvestment and a negative residual indicates underinvestment. For clarity, the results are expressed as absolute values; as such, higher values of Over_Inv and Under_Inv indicate less efficient investment.

Table 11 presents the regression results. In column (1), it is evident that AI significantly reduces inefficient investment, thereby improving a firm's investment efficiency, validating this study's assumptions. In column (2), the regression coefficient is nonsignificant, implying that AI does not significantly affect overinvestment. In contrast, column (3) shows that the regression coefficient between AI and underinvestment is negative and significant, suggesting that AI notably mitigates firms' underinvestment issues. This aligns with the prior analysis and reconfirms the positive effect of AI on firms' investment behaviors.

4.4.2. Mediation analysis

Above we argue that AI has the capacity to gather and organize information, significantly enhancing firms' management and resource allocation efficiency. This allows for a more scientific analysis and integration of data, optimizing managers' decision-making environment. Hence, AI adoption reduces the uncertainty risk faced by firms. In this study, we utilize the uncertainty perception index (Fepu) as a mediating variable to explore the relationship between AI adoption, uncertainty perception and risk-taking behavior in firms. Following the approach outlined by Nie et al. (2020), economic policy uncertainty within a firm is identified when both policy-related and uncertainty-related words appear within a single sentence of its annual report's Management Discussion and Analysis section. The level of economic policy uncertainty is quantified by calculating the proportion of uncertainty-related words to the total word count extracted from this section. Similarly, in alignment with the mediation effect testing framework proposed by Wen and Ye (2014), a variable X is con-

Table 11
Artificial intelligence and investment efficiency.

	(1)	(2)	(3)
	Inv	Over_Inv	Under_Inv
AI	–0.002**	–0.002	–0.002**
	(–2.245)	(–1.327)	(–2.457)
Size	–0.003***	–0.002***	–0.004***
	(–6.059)	(–2.917)	(–8.432)
Lev	0.012***	0.025***	–0.003
	(4.003)	(4.465)	(–0.941)
Roa	0.080***	0.033	0.108***
	(6.660)	(1.326)	(9.461)
Sh1	0.001	0.004	0.004
	(0.352)	(0.662)	(1.423)
Dual	0.003***	0.005***	0.001
	(2.647)	(2.676)	(0.605)
Board	–0.003	–0.002	–0.001
	(–1.023)	(–0.364)	(–0.496)
Indep	0.016*	0.019	0.018**
	(1.792)	(1.133)	(1.989)
Cf	–0.015**	0.009	–0.031***
	(–2.194)	(0.666)	(–4.688)
State	–0.011***	–0.019***	–0.005***
	(–11.658)	(–10.637)	(–4.596)
GDP	–0.000	0.000	–0.001
	(–0.751)	(0.022)	(–0.955)
_Cons	0.104***	0.098***	0.117***
	(8.312)	(4.132)	(9.279)
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
R2_a	0.076	0.060	0.139
N	14,845	6,285	8,560

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 12
Mediation analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
	RiskTaking	Fepu	RiskTaking	RiskTaking	Fepu	RiskTaking
Dummy_AI	0.002***	–0.011***	0.002***			
	(4.447)	(–5.186)	(4.323)			
AI				0.001***	–0.008***	0.001***
				(5.741)	(–5.301)	(5.390)
Fepu			–0.008***			–0.008***
			(–5.225)			(–5.177)
Size	–0.006***	0.003***	–0.006***	–0.006***	0.003***	–0.006***
	(–40.587)	(4.296)	(–38.593)	(–40.719)	(4.356)	(–38.705)
Lev	0.014***	0.024***	0.015***	0.014***	0.024***	0.015***
	(15.684)	(4.738)	(15.316)	(15.746)	(4.703)	(15.359)
Roa	–0.005	0.004	–0.006	–0.005	0.003	–0.006
	(–1.326)	(0.194)	(–1.525)	(–1.304)	(0.151)	(–1.493)
Sh1	0.001	–0.003	0.001	0.001	–0.003	0.001
	(0.921)	(–0.593)	(1.107)	(1.054)	(–0.685)	(1.229)
Dual	0.001***	–0.001	0.001***	0.001***	–0.001	0.001***
	(3.644)	(–0.532)	(3.510)	(3.559)	(–0.499)	(3.450)
Board	–0.003***	–0.007	–0.003***	–0.003***	–0.007*	–0.003***
	(–3.905)	(–1.634)	(–4.208)	(–3.862)	(–1.657)	(–4.176)
Indep	0.000	–0.048***	–0.001	0.000	–0.048***	–0.001
	(0.064)	(–3.066)	(–0.271)	(0.075)	(–3.083)	(–0.261)
Cf	–0.015***	0.017	–0.016***	–0.015***	0.017	–0.016***
	(–7.322)	(1.492)	(–7.389)	(–7.205)	(1.440)	(–7.309)
State	–0.001***	0.007***	–0.001***	–0.001***	0.007***	–0.001***
	(–3.554)	(4.051)	(–3.499)	(–3.517)	(4.048)	(–3.484)
GDP	0.000	–0.008***	0.000	0.000	–0.008***	0.000
	(0.766)	(–8.001)	(0.096)	(0.750)	(–8.015)	(0.080)
_Cons	0.187***	0.055**	0.187***	0.187***	0.055**	0.187***
	(46.956)	(2.487)	(45.696)	(47.058)	(2.474)	(45.784)
Year & Ind	Yes	Yes	Yes	Yes	Yes	Yes
R2_a	0.551	0.094	0.573	0.551	0.094	0.573
N	16,615	15,264	15,264	16,615	15,264	15,264

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

sidered to exert its influence on another variable Y through a mediator M if changes in X lead to changes in M, which in turn affect Y. This establishes M as the mediating variable. The general analytical model used is as follows: (1) $Y = \alpha X + \varepsilon$, (2) $M = \beta X + \xi$ and (3) $sY = \varphi X + \delta M + \zeta$.

Table 12 reports the regression results. Column (1) presents the regression results for the total effect, indicating that AI can increase firms' risk-taking levels. Column (2) presents the regression results for the relationship between AI and firms' uncertainty perception. The regression coefficient is positive and significant at the 1 % level, suggesting that AI significantly reduces firms' uncertainty perception. Column (3) shows that the impact of firms' uncertainty perception on risk-taking is negative, indicating that their risk-taking level significantly increases when they face lower levels of uncertainty. In columns (4)–(6), the regression results consistently display AI as the independent variable. These outcomes suggest that given the information collection and organization capabilities associated with AI adoption, it can significantly reduce the uncertainty that firms face. These firms can then more accurately comprehend internal and external information and resources, markedly increasing their risk-taking levels.

5. Conclusion

With advancements in AI technologies, its deep integration into the real economy has led to increased research attention in terms of both theory and practice. We contribute to this dialogue by exploring the relationship between AI and corporate risk-taking. Merging theoretical and empirical research, we arrive at the following conclusions.

First, firms' AI adoption and integration significantly elevates their risk-taking levels. The deeper enterprises' involvement with AI, the greater its impact on their risk-taking. In our study, the firms adopting AI show a 6.56 % greater propensity to undertake risky projects. This observation aligns with the previous finding that AI development contributes to macroeconomic growth by between 0.55 % and 1.14 % (Lin et al., 2020), underscoring the considerable impact of AI on business operations, as demonstrated in this study. This suggests that AI significantly improves firms' management efficiency and resource allocation, fosters more scientific data analysis and integration, optimizes managers' decision-making environment, assists companies in making better-informed decisions and helps reduce overly risk-averse tendencies.

Second, the association between AI and risk-taking is also influenced by financing constraints. As enterprises' financing constraints intensify, the positive effect of integrating AI on risk-taking also increases. Specifically, for every unit increase in financing constraints, the influence of AI on risk-taking intensifies by 12.25 % above the baseline level for the firms in this study. This indicates that adopting AI technology can better mitigate firms' conservative investment tendencies due to financing constraints, reiterating the positive effects of firms' implementation of AI technology.

Lastly, the adoption of AI technology significantly improves enterprises' investment efficiency, particularly by alleviating underinvestment issues. Overall, the results of this study substantiate the beneficial role of AI in supporting corporate decision-making.

We contribute to research on AI at the firm level. Contrary to literature focusing on the macro level (Lin et al., 2020), we examine risk-taking and explore the specific impact of AI on firms' investment decisions, providing evidence for the impact of AI on enterprises at the micro level. We not only confirm the capacity of AI to replicate human cognitive processes (Min, 2010) and enhance enterprises' information processing capabilities (Tian et al., 2022) but also further highlight its role in shaping enterprise investment decisions. Therefore, the findings of this study support the deep integration of AI into the real economy.

AI is a strategic apex in the most recent wave of technological revolution and industrial competition, and it has become crucial in technological innovation in production and life. A new generation of AI is leading a fresh surge in information technology development, heralding a new technological and industrial revolution. Hastening the development of a new generation of AI and promoting its deep integration into the real economy are vital engines for achieving technological leaps, industrial optimization and upgrading, supply-side structural reform and the Made in China 2025 strategy. The findings of this study may also serve as a significant reference and inspiration for further deepening supply-side structural reform, realizing the Made in China 2025 strategy and promoting high-quality economic 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.

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Appendix A. Robustness tests

The explanatory variables are constructed using the standard deviation of monthly returns and used to re-evaluate the regression outcomes. The results, displayed in the table below, reaffirm H1 and H2.

Robustness tests

	(1)	(2)	(3)	(4)
	RiskTaking (Monthly)	RiskTaking (Monthly)	RiskTaking (Monthly)	RiskTaking (Monthly)
Dummy_AI	0.005***		0.004***	
	(4.298)		(3.479)	
AI		0.003***		0.003***
		(4.316)		(3.192)
KZ			0.002***	0.002***
			(4.610)	(4.636)
Dummy_AI*KZ			0.002***	
			(2.951)	
AI*KZ				0.001***
				(3.212)
Size	–0.011***	–0.011***	–0.011***	–0.011***
	(–25.690)	(–25.717)	(–24.589)	(–24.580)
Lev	0.032***	0.032***	0.022***	0.023***
	(11.129)	(11.162)	(6.592)	(6.639)
Roa	0.002	0.002	0.014	0.014
	(0.153)	(0.181)	(1.132)	(1.141)
Sh1	0.003	0.003	0.004	0.005*
	(1.141)	(1.212)	(1.603)	(1.675)
Dual	0.001	0.001	0.001	0.001
	(1.090)	(1.053)	(1.342)	(1.314)
Board	–0.006**	–0.006**	–0.006**	–0.006**
	(–2.486)	(–2.465)	(–2.525)	(–2.496)
Indep	–0.000	–0.000	–0.001	–0.001
	(–0.034)	(–0.020)	(–0.089)	(–0.079)
Cf	–0.029***	–0.028***	–0.007	–0.007
	(–4.300)	(–4.243)	(–0.907)	(–0.909)
State	–0.003***	–0.003***	–0.004***	–0.004***
	(–3.353)	(–3.337)	(–3.748)	(–3.722)
GDP	0.001	0.001	0.001	0.001
	(1.565)	(1.584)	(1.593)	(1.604)
_Cons	0.364***	0.364***	0.357***	0.357***
	(28.968)	(28.968)	(28.268)	(28.234)
Year & Ind	Yes	Yes	Yes	Yes
R2_a	0.341	0.341	0.342	0.342
N	16,615	16,615	16,615	16,615

***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively.

Appendix B. Propensity score matching and matching effect test results

The following table presents the results of 1:1 nearest neighbor matching. A significant difference is observed between the experimental and control groups post-matching, demonstrating a significant disparity in the effect of adopting AI on corporate risk-taking.

PSM Results

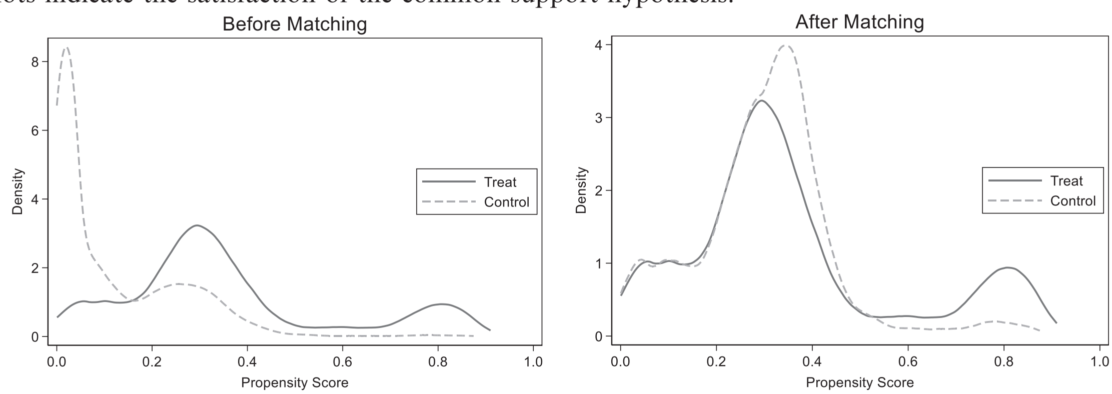
Variable	Sample	Treated	Control	Difference	SE	t-stat
RiskTaking	Before matching	0.060972	0.060423	0.000549	0.000504	1.09
	After matching	0.060972	0.058621	0.002352	0.000645	3.65

In the following table, the matching effect of PSM is examined. Post-matching, no significant difference exists between the mean values of the variables, indicating effective matching and the satisfaction of the PSM's parallel hypothesis.

Matching effect test

Variable	Treated	Control	%bias	t	p > t
Size	22.38	22.435	–4.2	–1.52	0.129
Lev	0.39067	0.39814	–3.9	–1.44	0.151
Roa	0.05513	0.05543	–0.8	–0.27	0.787
Sh1	0.33045	0.33623	–3.9	–1.46	0.145
Board	0.33846	0.34383	–1.2	–0.41	0.682
Dual	2.1089	2.1025	3.2	1.16	0.248
Indep	0.37894	0.37999	–2	–0.71	0.48
Cf	0.05094	0.05294	–3	–1.09	0.274
State	0.27622	0.27699	–0.2	–0.06	0.951
GDP	10.72	10.768	–7.1	–2.78	0.005

The figure below plots the density function before and after matching. The post-matching density function plots indicate the satisfaction of the common support hypothesis.



Density function plots

Overall, all of the findings suggest an effective PSM matching result.

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Does big data tax administration expand bank credit loans?

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ABSTRACT

The application of big data technology to global tax management is becoming increasingly widespread. China has been implementing increasingly mature technologies for tax governance using big data systems in recent years. By collecting data through web scraping on the earliest implementation times of big data tax administration in various provinces of China, we explore the relationship between big data tax administration and corporate bank credit in emerging markets. Our results show that big data tax administration enhances firms' ability to obtain bank loans. Mechanism tests indicate that big data tax administration improves the quality of corporate information disclosure, facilitating access to bank credit loans. We find that big data tax administration improves the corporate financing environment, enhancing the efficiency of resource allocation in the credit market.

1. Introduction

The digital economy has expanded rapidly around the world. Driven by continuous upgrades in Internet functionality and the widespread application of big data, significant changes are occurring in governments, corporate business models and in people's daily lives (Chen and Srinivasan, 2024). Taxation departments provide a good example of such changes, as big data technology is expanding the traditional auditing model. "Big data tax administration" combines big data with tax auditing; it involves acquiring big data from Internet platforms and integrating and comparing multiple sources of data (Bassey et al., 2022). Its implementation, which has become a new trend in national tax governance, reflects the modernization of national governance

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capabilities and systems within the tax system and significantly enhances the efficiency of governments' tax collection (Canares, 2016). A key question is whether, looking beyond strict tax enforcement, modernized tax governance can guide firms to improve the quality of their information disclosure, thereby enhancing the efficiency of resource allocation in capital markets? Examining this question yields insights relevant to governments worldwide who are implementing governance based on big data technology.

Bank loans are an important financial resource and whether they are allocated in a timely and appropriate manner is an important issue from both theoretical and practical perspectives. An extensive body of research discusses the various factors that influence firm credit, including corporate characteristics and the policy environment. However, few studies explore whether innovations and modernizations within the tax governance system can improve the financing environment for firms. Studying the effects and mechanisms of big data tax administration on corporate bank credit enhances the understanding of the social effects of modernized governance and provides empirical evidence for the motivational impact of "tax administration with data" on firms.

This paper examines the impact of big data tax administration on corporate bank credit in China. China is selected as the research setting for two reasons. First, developing countries such as China face greater difficulties than developed countries in successfully implementing e-government practices, such as big data tax administration. Indeed, Heeks (2005) suggests that the failure rate for e-government initiatives in developing countries could be as high as 85 %. Therefore, developing countries need successful case studies to build their confidence in e-governance based on big data technology. China is the largest developing country in the world and is actively promoting big data technology. The 14th Five-Year Plan elevates big data to a national strategy[1] and, in 2022, the State Council issued documents specifically emphasizing 'using big data to strengthen economic monitoring and early warning' and 'enhancing the precision level of supervision with digital means' to strengthen the construction of a digital government.[2] Thus, choosing China as a research setting provides an analysis of the impact of e-government on the allocation of credit resources in a representative developing country.

Second, the allocation of financial resources in China's capital markets is heavily influenced by government macro-level controls. For instance, China's state-owned banks frequently help the government implement its planned investment policies (Carpenter et al., 2021). However, high levels of information asymmetry between the government and enterprises can result in the misallocation of resources when implementing planned investment policies. Therefore, it is worthwhile exploring whether enhancing the digital capabilities of tax departments with big data technology can open up multiple channels of information and make corporate information more public than at present. Increasing the transparency of corporate information will enhance the government's ability to optimize decisions on corporate planned investments. Therefore, choosing China as a setting for this research allows us to elucidate the achievement of optimal resource allocation in the capital market from the perspective of government macro-control.

Initially, to verify the practicality of our research, we conducted interviews with relevant enterprises on the topic of big data tax administration. Notably, during one interview with a financial technology firm, we asked about the impact of big data tax administration on micro-enterprises. The interviewee mentioned that it facilitated enterprises in obtaining bank credit, explaining the reasons as follows: "After big data tax administration, corporate information for tax and accounting has become much more standardized ... Banks are actually very sensitive to the credibility of information. Once they detect an increase in the credibility of information, they feel much more at ease in granting loans ... Big data governance methods have improved the social credit environment."

Building on this information about a potential correlation between big data tax administration and bank credit, we conduct theoretical analysis and collect practical evidence. We find that the impact of big data tax administration on firm credit may involve opposing effects. From the perspective of optimizing the information environment, in the context of big data tax administration, firms' motives to make opaque disclosures to conceal tax evasion behaviors decline. Moreover, firms develop corporate digitalization strategies when inter-

[1] Data source: https://www.gov.cn/zhengce/2021-12/01/content_5655197.htm.
[2] Data source: https://www.gov.cn/zhengce/content/2022-06/23/content_5697299.htm.

facing with tax authority systems, which improves the quality of their information disclosure. Simultaneously, the tax authorities achieve a system of "bilateral" integration with banks, which are third-party financial institutions. Banks can utilize part of the tax-related information about enterprises provided by the tax authorities, which reduces the information asymmetry between the banks and the enterprises, in turn relaxing the loan approval conditions for enterprises and promoting a more efficient allocation of credit resources. Therefore, enterprises will be able to obtain more bank credit after the implementation of local big data tax administration.

In addition, big data tax administration may encourage enterprises to obtain more bank credit by increasing their motivation to obtain funding. It curbs tax evasion by enterprises and increases their tax expenditure, which then reduces their operational cash flow. Under these circumstances, enterprises need more funds than before to meet cash flow expenditure, which could lead to them needing more credit financing from banks. As such, big data tax administration may positively impact firms' access to bank credit through improving the quality of information disclosure and strengthening the need for funding.

Conversely, however, the reduction in free cash flow could weaken enterprises' debt repayment capacity. Banks that can identify the increased risk associated with enterprise debt repayment may lower the credit limits for these enterprises, which could ultimately lead to a decrease in bank credit for the enterprises.

It should be clarified that big data tax administration is fundamentally different in nature from China's 'Golden Tax Phase III' tax collection and management project. The 'Golden Tax Phase III' is known as 'tax administration with invoices' and involves digitizing paper invoices to achieve an 'Internet-based' tax administration system, which allows all paper invoices and related tax activities to be monitored via the Internet. For instance, tax authorities can track input and output invoices under the same taxpayer identification number via the Internet to check if an enterprise is engaged in illegal activities, such as issuing false invoices. In contrast, big data tax administration employs big data technologies and applications to implement "tax administration with data," which breaks away from the traditional reliance on invoices and shifts from tracking tax-related activities to tracking economic activities. As an example, illegal "public-to-private" transfers do not generate invoices and cannot be detected and tracked by the Golden Tax project due to the lack of invoice documentation. However, under big data tax administration, when bank data are integrated with the tax system, the tax authorities can quickly capture such anomalous economic behaviors. Therefore, the "tax administration with data" that we discuss differs fundamentally from the "tax administration with invoices" of the Golden Tax Phase III project because the mechanisms of their effects on micro-enterprises are essentially distinct.

We explore the impact of big data tax administration on corporate credit acquisition. Our results show that big data tax administration can expand corporate bank loans, especially short-term bank loans. Mechanism tests reveal that big data tax administration affects bank credit by improving the corporate information environment. Further research suggests that the effects are more pronounced in firms subject to stronger (vs. weaker) financial constraints. Our conclusions provide empirical evidence for tax authorities to strengthen their cooperation with online third parties and actively promote big data tax administration. In addition, we uncover the unexpected effects of big data tax administration on micro-enterprises.

Our research makes three main contributions. First, in contrast with studies that focus on the direct expected effects of big data tax administration on the fairness of regional tax burdens and on corporate tax compliance, our study explores the spillover effects of big data tax administration. To the best of our knowledge, it is the first study to do so. Our research finds that big data tax administration can enhance enterprises' ability to obtain bank loans. We enrich the research on the economic consequences of big data tax administration and provide the first empirical evidence of the economic consequences of modernizing the governance system.

Second, whereas some studies examine the impact of existing micro-behaviors on enterprises' ability to obtain bank loans, our paper is one of the few to explore the impact of tax governance modernization, driven by the digital economy, on corporate credit capacity. We provide a new perspective on the factors affecting corporate financing capabilities.

Third, from a practical perspective, our paper explores the sustainability of strengthening modern tax administration, which has significant real-world relevance. Studies mainly focus on the benefits of big data tax administration to tax authorities, but we uncover the unexpected benefits for the corporate financing environment. We show that stricter tax supervision can have beneficial effects on enterprises, providing a theoretical basis for emerging market countries to implement "tax administration with data" practices.

2. Theoretical analyses and development of hypotheses

Big data tax administration can enhance enterprises' ability to obtain bank credit by reducing information asymmetry and improving the quality of information disclosure. We suggest that in the context of big data tax administration, firms will reduce opportunistic disclosure behavior and enhance digital infrastructure, thereby improving the quality of information disclosure. Banks will achieve "bilateral" integration with the information channels of the tax authorities, allowing them to conveniently access high-quality enterprise disclosures. Hence, the big data tax administration may ultimately enhance the efficiency of banks' credit resource allocation and promote the ability of enterprises to obtain more bank credit financing than in the absence of such a tax administration system.

First, under a big data tax administration system, enterprises' incentives to conceal tax evasion activities through opaque information disclosure will decline. When information asymmetry exists, executives can hide complex tax evasion activities within opaque information disclosures, allowing covert tax evasion to go unnoticed by external information users (Desai and Dharmapala, 2009). However, with the implementation of big data tax administration, tax authorities regulate corporate tax behavior more strictly, which improves corporate tax compliance (Pomeranz, 2015). In this scenario, the transparency of the corporate information environment is enhanced (Sun and Shi, 2022), making complex tax evasion behaviors more detectable, and illegal tax evasion and avoidance activities easier to discover than under a traditional tax administration system. Consequently, there is an increased likelihood of enterprises being penalized for tax violations. When concealing information related to tax evasion does not reduce corporate tax expenses, the motivation for enterprises to enhance transparency in information disclosure increases. Research reveals that higher transparency in information disclosure can improve enterprises' financing capabilities and reduce the interest rates on their bank loans (Chiu et al., 2018; Wang and Zeng, 2019). Therefore, big data tax administration can enhance enterprises' ability to obtain bank loans by strengthening their motivation to make high-quality information disclosures.

Second, big data tax administration enhances the digitalization level of enterprises, thereby raising the quality of information. Big data tax administration cannot be achieved solely through government efforts, but also requires the cooperation of enterprises. The government, by acquiring big data platforms and auditing technologies through procurement and other means, aims to better integrate its tax administration system with the data systems of enterprises. To align with the tax authorities' big data tax administration, enterprises must enhance their own digitalization level to integrate their data systems with the tax authorities' auditing systems (Du and Wang, 2023). As enterprises improve their digitalization, previously unstandardized data embedded in various processes are excavated and transformed into effective, comparable information outputs, enhancing the quality of information disclosure. The higher the quality of an enterprise's information disclosure, the greater is its creditworthiness in the eyes of banks and the lower its debt financing costs (Li and Wang, 2011). Thus, in the context of a big data tax administration that includes tax-related information, the more comprehensive and higher quality the corporate information disclosures made by enterprises, the more likely it is that the enterprises will be favored by banks when they seek to obtain credit.

Thus, we ask the following question: after enterprises have improved the quality of their information disclosure, will banks be able to access tax-related and other relevant information about enterprises more conveniently through the big data tax administration system? We obtain evidence to answer this question by searching online media sources and interviewing tax authority personnel.

From the perspective of the tax authorities, we find that tax authorities actively share tax-related information with third-party agencies and financial service institutions by leveraging big data technology. For instance, according to a report by the China Taxation News on big data tax administration in Shandong Province,[3] the Shandong Provincial Department of Finance started building an integrated tax information-

[3] Data source: https://news.sdufe.edu.cn/info/1022/15589.htm.

sharing platform in 2016, breaking down the information barriers between tax authorities and third parties. In 2017, the Shandong Provincial Local Taxation Bureau collaborated with the Provincial Insurance Regulatory Bureau to optimize the process of collecting and paying vehicle and vessel taxes, partnered with the Provincial Department of Housing and Urban–Rural Development to link online second-hand house contract prices directly with tax collection data and worked with the Provincial Price Bureau to establish a third-party public welfare tax dispute and relief mechanism. Banks, as important financial service institutions, are naturally part of this information-sharing network. The director of the financial bureau in a prefecture-level city in Shandong Province states that banks are authorized to use corporate tax credit rating information from the shared platform to identify quality clients. As of December 2017, the Shandong Local Taxation Bureau had signed "tax–bank interaction" agreements with 17 municipal bureaus, 178 county (city, district) bureaus and development zone branches and 895 banks, enabling 11,400 enterprises to secure loans worth 39.28 billion yuan.

In addition, we interviewed tax authority personnel in a prefecture-level city in Jiangsu Province. When asked if banks could access tax-related information about enterprises through the tax authorities, the official stated, "Banks can obtain some tax-related information about enterprises. For example, in our system integration with Bank A, the tax authorities provided the bank with information about the enterprise's export tax refund amount. The bank can use this information to understand the enterprise's operational status and assess its loan requirements, thereby enhancing the bank's credit resource allocation efficiency." Thus, it is evident that after the implementation of big data tax administration, tax authorities can bilaterally open up information channels with banks and other third parties, providing them with certain tax-related information to help enhance the efficiency of credit resource allocation by banks.

Big data tax administration drives banks to establish more convenient platforms for information communication and transmission, enabling them to obtain more comprehensive and accurate corporate information than before. For instance, according to a report by China UnionPay on Hubei Bank, in 2019, Hubei Bank launched a "Tax Easy Loan Platform" based on big data tax administration. This platform uses open application programming interface (API) technology and digital technology to improve data collection mechanisms and obtain more comprehensive external data about enterprises, including tax, business registration and credit information. By the end of 2021, the "Tax Easy Loan Platform" had issued more than 22,000 loans, totaling 2.798 billion yuan. This demonstrates that in the context of big data tax administration, banks actively participate in the construction of big data platforms to better integrate their systems with the tax authorities' systems.

In summary, based on the theoretical analysis and practical evidence of improved information disclosure quality, we contend that the quality of corporate information disclosure is enhanced in the context of big data tax administration. Furthermore, the tax authorities' systems in regions implementing big data tax administration become integrated with banking systems, achieving a bilateral information flow. Consequently, banks can access high-quality corporate information, which ultimately enhances the efficiency of banks' credit resource allocation and promotes greater access to bank credit financing for enterprises.

When a big data tax administration system is implemented, enterprises' need for and motivations to obtain funds may rise, leading them to seek more bank credit. Allingham and Sandmo (1972) develop an A–S deterrence model, which demonstrates that the optimal tax evasion choices of enterprises are related to the probability of being penalized and risk aversion preferences. Therefore, the more stringent the monitoring of corporate tax evasion and tax avoidance behaviors, the lower the motivations for tax evasion and the higher the tax compliance. Studies find that in an environment of big data tax administration, enterprises will increase their tax compliance (Sun and Shi, 2022). Furthermore, as tax avoidance behaviors decrease, tax expenses correspondingly increase, reducing the enterprises' operating cash flow and increasing their debt pressures. Thus, with reduced free cash flow and increased debt pressure, enterprises motivations to obtain funding rise, prompting them to seek more credit financing from banks, which is ultimately reflected in an increase in the scale of bank credit obtained by enterprises.

Potentially, however, there may be opposing effects arising from this mechanism that increase enterprises' need for funds. As noted, when enterprises reduce tax evasion due to the implementation of big data tax administration, their debt pressure increases. If banks are strongly regulated and identify the decrease in the enterprises' debt repayment capacity, they may reduce the credit limits of such enterprises, which ultimately weakens the enterprises' ability to obtain bank loans (Ivanov and Wang, 2023). Based on the above analysis, we propose our hypothesis in a competing form:

H1a: Following implementation of big data tax administration, the bank credit resources obtained by enterprises significantly increase.
H1b: Following implementation of big data tax administration, the bank credit resources obtained by enterprises significantly decrease.

3. Research design

3.1. Sample and data sources

We obtain data from China's A-share listed public firms during the period of 2014 to 2021. We adopt the approach of Sun and Shi (2022), conducting information retrieval through search engines such as Baidu and Bing and using web crawlers to capture and identify news content. This enables us to identify the earliest year in which the various provinces implement tax administration using big data. This process enables us to create a big data tax administration variable, *Bigdata*. The related financial indices and governance variables that we use in the study are sourced from the China Stock Market and Accounting Research database. After excluding observations with missing relevant indices, we obtain 23,007 firm-year observations. We winsorize all of the continuous variables at the 1 % and 99 % levels.

3.2. Variable definitions and regression model

The dependent variable in our study is the enterprises' bank credit, *Loan_all*, calculated as the new loans acquired by the enterprise in the current year divided by the total assets at the beginning of the year. The core explanatory variable is big data tax administration. We confirm the earliest year of implementation of big data tax administration for each region through a textual analysis of online news. Following the approach of Sun and Shi (2022), we conduct identification matching on network news with three sets of vocabulary. The first set includes terms relating to data-carrying platforms, such as "internet" and "database." The second set comprises specific technical method terms, such as "big data" and "crawler." The third set includes terms related to tax administration, such as "tax administration" and "tax collection." When news from a region contains terms from all three groups, this indicates that big data tax administration has been implemented in that region. Thereby, we define the dummy variable *Bigdata*, which equals 1 when big data tax administration

Table 1
Variable definitions.

Name	Definitions
Dependent Variable	
Loan_all	Incremental bank loans scaled by total assets
Independent Variable	
Bigdata	Dummy variable that equals 1 if big data tax administration is implemented in the province in which the enterprise is located in the current year or thereafter, and 0 otherwise
Control Variables	
Size	Natural logarithm of total assets
Roa	Earnings scaled by total assets
Lev	Total liabilities scaled by total assets
Rdfee	R&D expenditure scaled by operating income
Top1	The largest shareholder's shareholding percentage
Dir	Natural logarithm of the number of board directors + 1
Indir	Independent directors scaled by board directors
Dual	Dummy variable that equals 1 if the chair also serves as the general manager, and 0 otherwise
GT_Phase	Dummy variable that equals 1 if 'Golden Tax Phase III' is implemented in the province in which the enterprise is located

is implemented in an enterprise's location, and 0 otherwise. The definitions of the other variables are provided in Table 1.

Model (1) is used to test our Hypotheses 1a and 1b. The dependent variable, *Loan_all,* is a proxy for bank credit, as previously described. We use *Bigdata* as the core explanatory variable in our primary tests. It is assigned a value of 1 when big data tax administration is implemented in the province where the enterprise is registered, and 0 when it is not yet implemented. The model controls for firm size (*Size*), return on assets (*Roa*), leverage (*Lev*), the largest shareholder's holdings (*Top1*), board size (*Dir*), the proportion of independent directors (*Indir*) and combined chairperson and general manager roles (*Dual*). To avoid interference from other major policies that might affect the intensity of taxation, our model also controls for the implementation of the "Golden Tax Phase III" program (*GT_Phase*). Furthermore, Model (1) controls for year and firm fixed effects.

$$Loan\_all = \alpha + \beta_1 Bigdata + \beta_2 \sum Controls + \sum Firm + \sum year + \mu \tag{1}$$

4. Empirical results

4.1. Descriptive statistics

The descriptive statistics of the main variables are presented in Panel A of Table 2. The average ratios of total loans (*Loan_all*), short-term loans (*Loan_st*) and long-term loans (*Loan_lt*) are 16.9 %, 10.4 % and 4.9 %, respectively. The mean of *Bigdata* is 0.398, indicating that 39.8 % of the observations in the sample are influenced by big data tax administration. The average company size (*Size*) is 22.419. The means of the return on assets (*Roa*) for the leverage ratio (*Lev*) and the largest shareholder's holding (*Top1*) are 0.026, 0.468 and 33.4 %, respectively. The means of board size (*Dir*), the proportion of independent directors (*Indir*) and the

Table 2
Descriptive statistics for the main variables.

Panel A: Descriptive statistics for the full sample

Variables	*Mean*	*Std.Dev.*	*Min*	*P50*	*Max*
Loan_all	0.169	0.136	0.001	0.142	0.619
Bigdata	0.398	0.489	0.000	0.000	1.000
Size	22.419	1.350	19.863	22.221	26.501
Roa	0.026	0.078	–0.383	0.033	0.184
Lev	0.468	0.200	0.093	0.457	0.979
Top1	0.334	0.148	0.086	0.310	0.750
Dir	2.234	0.178	1.792	2.303	2.773
Indir	0.377	0.054	0.333	0.364	0.571
Dual	0.696	0.460	0.000	1.000	1.000
GT_Phase	0.692	0.462	0.000	1.000	1.000

Panel B: Univariate difference analysis

Variables	***Bigdata*** = 0 *Mean*	***Bigdata*** = 1 *Mean*	*DIFF*
Loan_all	0.162	0.179	–0.017***
Size	22.244	22.684	–0.440***
Roa	0.030	0.018	0.012***
Lev	0.450	0.496	–0.046***
Top1	0.339	0.327	0.013***
Dir	2.235	2.234	0.001
Indir	0.376	0.379	–0.003***
Dual	0.683	0.715	–0.032***
GT_Phase	0.568	0.879	–0.311***

Note: In Panel B, ***, ** and * in the group differences column indicate significance at the 1%, 5% and 10% levels, respectively.

incidence of dual chairperson–general manager roles (*Dual*) are 2.234, 37.7 % and 69.6 %, respectively. The proportion of observations that have implemented "Golden Tax Phase III" in the sample is 69.2 %.

Panel B of Table 2 reports the univariate analysis of differences for *Bigdata*. As theorized, big data tax administration is expected to promote corporate bank credit activities. The sample is divided into subsamples based on whether firms have been impacted by big data tax administration. The results show that observations impacted by big data tax administration have larger bank loans (*Loan_all*) compared with those not affected by it. Therefore, the inter-group differences in results generally align with the expectations set out in the theoretical analysis. Furthermore, firms in the subsample that have been affected by big data tax administration tend to have a larger company size (*Size*), higher leverage ratio (*Lev*) and a lower proportion of shares held by the largest shareholder (*Top1*) than firms not impacted.

4.2. Main results

The baseline regression results are shown in Table 3. Columns (1) and (2) report the regression results for the impact of big data tax administration on bank credit, with and without control variables, respectively. In both columns, the coefficients for *Bigdata* are positive and significant, indicating that big data tax administration significantly enhances the ability of enterprises to acquire bank loans. Our results support Hypothesis H1a, which states that big data tax administration can promote enterprise bank credit activities, enabling enterprises to obtain more bank loans than without big data tax administration.

Table 3
Baseline regression results.

Variables	(1)	(2)
	Loan_all	
Bigdata	0.020**	0.017**
	(2.528)	(2.219)
Size		–0.032***
		(–4.714)
Roa		–0.239***
		(–5.832)
Lev		0.494***
		(18.354)
Top1		–0.054
		(–1.161)
Dir		–0.022
		(–0.630)
Indir		–0.059
		(–0.645)
Dual		–0.004
		(–0.442)
GT_Phase		–0.021*
		(–1.729)
Constant	0.177***	0.749***
	(24.190)	(4.376)
Firm	YES	YES
Year	YES	YES
N	23,007	23,007
Within R^2	0.002	0.032

Note: In this table and all tables below, ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Values shown in parentheses are *t* values.

5. Robustness tests

5.1. Alternative measures of the independent variable

Based on the theoretical analysis and mechanism tests of our paper, the implementation of big data tax administration can break down data barriers between tax authorities and enterprises, enabling a more efficient transmission of more comprehensive tax-related data to the tax authorities than a traditional tax administration system. Simultaneously, the information barriers between tax authorities and banks break down, allowing for a bidirectional flow of information between the banks and tax authorities. Ultimately, this enhances the quality of corporate information disclosure, which improves information capture by banks and thus optimizes the efficiency of banks' credit resource allocation to enterprises.

Following this specific theoretical logic, in the robustness tests, we redefine the independent variable based on identifying and textually analyzing news articles on big data tax administration. First, we expand the three groups of vocabulary used to identify the original explanatory variable *Bigdata* by adding a fourth group that describes the specific tax administration methods used by government agencies or third parties to facilitate tax-related information channels; we identify vocabulary such as "data integration," "breaking down barriers" and "system integration." Local regions in which the local news articles match the criteria for the four groups of vocabulary criteria are defined as having implemented big data tax administration. Second, for each local region, the year in which such news articles are published is used to define the year of implementation of big data tax administration in that region. For local enterprises, this variable takes a value of 1 for that year and subsequent years, and 0 otherwise, resulting in a new alternative variable for big data tax administration, *Bigdata_alternative*.

The results after incorporating *Bigdata_alternative* into the main regression model and re-running the regression are shown in Table 4. It is evident that *Bigdata_alternative* is positive and significant at the 5 % level, and thus our main conclusions hold.

Table 4
Alternative measures for the independent variable.

Variables	(1) ***Loan all***
Bigdata_alternative	0.020**
	(2.383)
Size	–0.031***
	(–4.673)
Roa	–0.238***
	(–5.813)
Lev	0.494***
	(18.374)
Top1	–0.054
	(–1.161)
Dir	–0.023
	(–0.669)
Indir	–0.061
	(–0.658)
Dual	–0.003
	(–0.406)
GT_Phase	–0.028**
	(–2.091)
Constant	0.747***
	(4.366)
Firm	YES
Year	YES
N	23,007
Within R^2	0.032

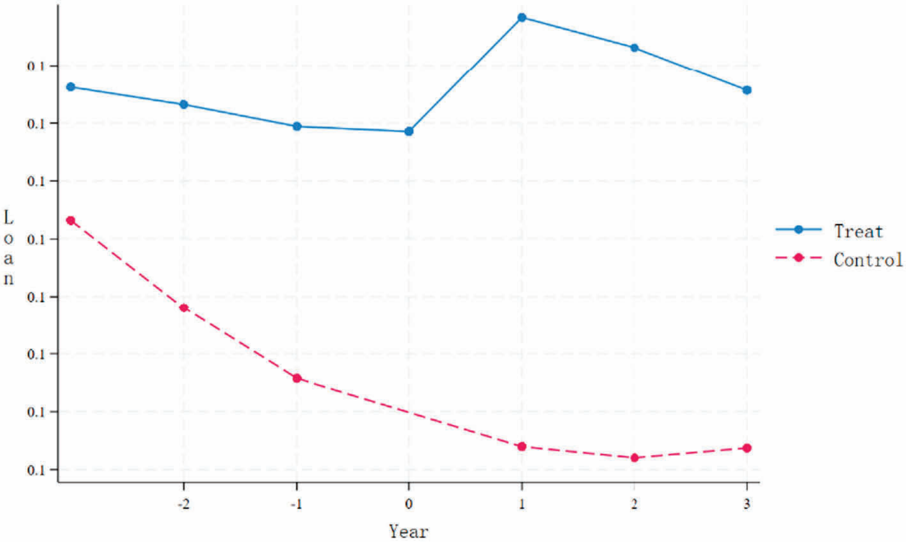

Fig. 1. Parallel trend test.

5.2. Parallel trends test

In this section, we test whether the treatment and control groups exhibit the same temporal trends before the implementation of big data tax administration. Following the approach of Jacobson et al. (1993) and Wang and Ge (2022), we aggregate and statistically analyze observations from 2 years before to 3 years after the shock, comparing the mean differences between the treatment and control groups relative to year –2 to year 0 around the shock year.[4] We focus on the differences between the treatment and control groups before the start of the shock to test whether there are significant time-related effects on corporate credit before the impact commenced. Fig. 1 reports the test results; the blue solid (red dashed) line represents the mean values of observations in the treatment (control) group before and after the shock. The results indicate that in the years before the implementation of big data tax administration, the corporate credit conditions of the treatment and control groups present broadly parallel trends, suggesting that the baseline results meet the assumption of parallel trends over time.

5.3. Adding city fixed effects

During the sample period, there are few instances of enterprises changing their operating locations. However, considering that regional factors are of strong importance to our analysis, changes in the location of enterprises could potentially affect the validity of our baseline results. Furthermore, it is possible that relevant tax administration policies other than other big data tax administration are introduced in an enterprise's location during the sample period (Hu et al., 2022). To eliminate this potential factor, we rerun the baseline regression, controlling for city fixed effects. Table 5 presents the results. After including city fixed effects, the coefficient on *Bigdata* remains positive and significant, indicating that the conclusions of the baseline tests are robust.

[4] There are few observations outside the period 2 years before or 3 years after the shock. Therefore, for simplicity and conciseness, we aggregate the data beyond the second year before the shock with the data for the second year before the shock. Similarly, data from beyond the third year after the shock are aggregated with the data for the third year after the shock.

Table 5
Adding city fixed effects.

Variables	(1)	(2)
	Loan_all	
Bigdata	0.046***	0.014**
	(7.727)	(2.320)
Size		–0.011***
		(–4.749)
Roa		–0.335***
		(–9.711)
Lev		0.484***
		(31.738)
Top1		0.019
		(1.119)
Dir		0.012
		(0.695)
Indir		–0.001
		(–0.015)
Dual		–0.000
		(–0.038)
GT_Phase		–0.010
		(–0.979)
Constant	0.216***	0.201***
	(9.907)	(3.098)
City	YES	YES
Year	YES	YES
N	23,007	23,007
Adj R^2	0.0242	0.0929

5.4. Propensity score matching (PSM)

The results of the baseline tests may be influenced by differences in control variables between groups. To eliminate interference from related factors, we employ the counterfactual inference method of propensity score matching (PSM). After performing a 1:1 matching without replacement, we obtain 6,535 observations in the treatment group (*Bigdata* = 1) and 6,535 observations in the control group (*Bigdata* = 0). Panel A of Table 6 shows the effects of the PSM matching. It can be observed that PSM effectively reduces inter-group differences in the sample compared with the univariate difference analysis results in Table 2. Panel B of Table 6 presents the regression results after using PSM. The coefficients on *Bigdata* remain positive and significant in columns (1) and (2), indicating that the conclusions of the baseline tests remain robust after PSM.

5.5. Placebo test

In the baseline regression results, it is possible that the impact of *Loan_all* on *Bigdata* is driven by random factors that we have overlooked. To dispel such concerns, we conduct a placebo test using the following basic method. The original *Bigdata* variable values are shuffled and randomly assigned to each firm-year observation to create a new dummy variable, *Bigdata_random*. Next, we rerun the regression to determine the coefficient of *Loan_all* on *Bigdata_random*, repeating this process 50, 100 and 200 times. The results are shown in Table 7. The coefficients of *Loan_all* on *Bigdata_random* are –0.003, 0.000 and –0.002 for the 50, 100 and 200 repetitions, respectively. The probabilities of this coefficient being significant and positive or negative are both small and roughly equal. The above analysis indicates that the random variable *Bigdata_random* does not have an effect on bank credit, thus confirming the robustness of the main results.

Table 6
Propensity score matching.

Panel A: Inter-group differences after PSM

Variables	***Bigdata*** = 0 (N = 6,535) *Mean*	***Bigdata*** = 1 (N = 6,535) *Mean*	*DIFF*
Size	22.403	22.424	–0.021
Roa	0.024	0.025	–0.001
Lev	0.468	0.468	0.000
Top1	0.328	0.331	–0.003
Dir	2.230	2.233	–0.003
Indir	0.378	0.377	0.000
Dual	0.704	0.694	0.010
GT_Phase	0.841	0.841	0.000

Panel B: Regression results after PSM

Variables	(1)	(2)
	Loan_all	
Bigdata	0.036**	0.039**
	(2.290)	(2.504)
Size		–0.060***
		(–4.134)
Roa		–0.236***
		(–3.029)
Lev		0.463***
		(8.420)
Top1		–0.092
		(–0.947)
Dir		0.025
		(0.346)
Indir		–0.069
		(–0.367)
Dual		–0.006
		(–0.381)
GT_Phase		–0.005
		(–0.204)
Constant	0.177***	1.283***
	(8.833)	(3.500)
Firm	YES	YES
Year	YES	YES
N	13,070	13,070
Within R^2	0.001	0.016

6. Further analysis

6.1. Mechanism analysis

The theoretical analysis of our paper suggests that big data tax administration improves the quality of corporate information, increasing banks' trust in corporate information and thereby promoting bank lending to corporations. In the logical framework and regression results of the previous sections, the improvement in corporate information quality plays a dominant role in increasing the ability of firms to obtain bank loans. To further verify the importance of the mechanism of enhanced information disclosure quality over the capital demand mechanism, in this section, we validate the mediating mechanism of corporate information disclosure quality.

The quality of corporate information disclosure is measured using the level of detail in the disclosures (*DQ*) and the information disclosure evaluation ratings (*DE*) provided by the Shenzhen and Shanghai Stock

Table 7
Placebo test.

Variables	*Bigdata_random*
50 repetitions	
The mean coefficient β on *Bigdata_random*	–0.000
[%β > 0 & α ≤ 5 %; %β < 0 & α ≤ 5 %]	[0.0 %; 0.0 %]
[%β > 0 & α ≤ 1 %; %β < 0 & α ≤ 1 %]	[0.0 %; 0.0 %]
100 repetitions	
The mean coefficient β on *Bigdata_random*	0.000
[%β > 0 & α ≤ 5 %; %β < 0 & α ≤ 5 %]	[2.0 %; 2.0 %]
[%β > 0 & α ≤ 1 %; %β < 0 & α ≤ 1 %]	[0.0 %; 0.0 %]
200 repetitions	
The mean coefficient β on *Bigdata_random*	–0.000
[%β > 0 & α ≤ 5 %; %β < 0 & α ≤ 5 %]	[0.0 %; 0.5 %]
[%β > 0 & α ≤ 1 %; %β < 0 & α ≤ 1 %]	[0.0 %; 0.0 %]

Exchanges for listed companies. Following Chen et al. (2015), we divide the accounts in China's financial statements (k) into five categories: current assets, non-current assets, current liabilities, non-current liabilities and equity. Variable *DQ* is calculated using Eq. (2), where Non-Missing Items represents the number of accounts that are not missing, Total Items represents the total number of accounts in category k, Assets_k refers to the total amount of non-missing account items in category k and Total Assets represents the total assets of the enterprise. Following Quan and Wu (2010), we utilize the quality rating for information disclosure determined by the Shenzhen and Shanghai Stock Exchanges. We assign a value of 1 to enterprises that achieve a rating of qualified or above in a given year, and 0 to enterprises rated as unqualified, resulting in the variable *DE*.

Table 8
Mechanism tests.

Variables	(1) ***DQ***	(2) ***DE***
Bigdata	0.004*	0.019***
	(1.869)	(2.732)
Size	0.005***	0.028***
	(2.599)	(4.705)
Roa	0.024**	0.497***
	(2.015)	(13.606)
Lev	–0.025***	–0.440***
	(–3.190)	(–18.355)
Top1	0.014	0.223***
	(1.020)	(5.331)
Dir	0.016	0.027
	(1.601)	(0.867)
Indir	0.050*	0.051
	(1.858)	(0.618)
Dual	–0.000	–0.024***
	(–0.010)	(–3.340)
GT_Phase	–0.512***	0.387***
	(–141.682)	(35.424)
Constant	0.696***	0.019***
	(13.790)	(2.732)
Firm	YES	YES
Year	YES	YES
N	23,007	23,007
Within R^2	0.850	0.315

$$\mathrm{DQ} = \sum_{k=1}^{5}\left\{\left(\frac{\#\mathrm{Non-Missing\ Items}}{\#\mathrm{Total\ Items}}\right)_{k} \times \frac{\mathrm{Assets_k}}{\mathrm{Total\ Assets}}\right\}\tilde{A} \cdot 2 \tag{2}$$

We use Model (2) for the mechanism tests, incorporating *DQ* and *DE* as dependent variables for the regression analysis. The results are shown in Table 8. Both *DQ* and *DE* have positive and significant regression coefficients on *Bigdata*, indicating that big data tax administration significantly improves the quality of corporate information disclosure, which in turn promotes enterprises' access to bank credit. This finding is consistent with our theoretical analysis.

6.2. Test to exclude alternative hypotheses

According to the theoretical analysis, after the implementation of big data tax administration, enterprises might improve the quality of information disclosure and banks could obtain more comprehensive tax information, reducing information asymmetry and thereby enabling enterprises to secure more credit financing. Conversely, however, the intensification of tax collection efforts reduces the possibilities for tax evasion and avoidance, thus increasing corporate tax expenditure and decreasing the disposable cash flow of enterprises. Facing cash flow pressures, enterprises might seek more credit financing based on funding needs. We posit that if enterprises seek more credit financing based on funding needs, those with weaker financial constraints will obtain more credit to meet needs for free cash flow. We use two methods to confirm the information disclosure mechanism and exclude this alternative hypothesis.

We use the Kaplan and Zingales (KZ) index, the nature of property rights and the political connections of enterprises to characterize the level of financial constraints faced by enterprises. First, a higher KZ index indicates stronger financial constraints (Kaplan and Zingales, 1997); we use the median industry-year KZ index to classify the sample into two subsamples above and below the industry-year median. The subsample above (be-

Table 9
Heterogeneity analysis of financial constraints.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Loan all					
	Higher KZ index	Lower KZ index	Non-SOEs	SOEs	Not politically connections	Politically connected
Bigdata	0.034**	–0.000	0.005***	0.035*	0.027**	0.001
	(2.146)	(–0.268)	(2.624)	(1.709)	(2.475)	(0.184)
Size	–0.051***	0.005***	–0.003	–0.080***	–0.032***	–0.028***
	(–4.254)	(2.769)	(–1.575)	(–4.327)	(–3.321)	(–9.824)
Roa	–0.271***	–0.100***	–0.098***	–0.671***	–0.108*	–0.120***
	(–3.954)	(–6.891)	(–9.753)	(–5.197)	(–1.915)	(–7.480)
Lev	0.485***	0.451***	0.448***	0.590***	0.472***	0.553***
	(9.527)	(57.943)	(63.666)	(7.605)	(12.489)	(49.650)
Top1	–0.081	0.001	–0.010	–0.115	–0.102	–0.039**
	(–0.902)	(0.113)	(–0.722)	(–0.966)	(–1.451)	(–2.245)
Dir	–0.033	–0.020***	–0.018*	0.001	–0.002	0.002
	(–0.477)	(–2.621)	(–1.871)	(0.015)	(–0.039)	(0.180)
Indir	–0.093	–0.005	–0.042	–0.080	–0.118	–0.046
	(–0.514)	(–0.254)	(–1.620)	(–0.360)	(–0.922)	(–1.261)
Dual	–0.009	0.003	–0.002	–0.003	–0.008	–0.001
	(–0.577)	(1.555)	(–1.095)	(–0.141)	(–0.722)	(–0.172)
GT_Phase	–0.033	–0.024***	–0.027***	–0.002	–0.028	–0.006
	(–1.378)	(–8.219)	(–7.491)	(–0.078)	(–1.586)	(–1.367)
Constant	1.244***	–0.117**	0.099**	1.803***	0.750***	0.560***
	(3.880)	(–2.508)	(2.122)	(3.968)	(3.093)	(7.775)
Diff	0.034**(p = 0.022)		0.029**(p = 0.042)		0.027**(p = 0.012)	
Firm	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	12,870	10,137	14,345	8,307	14,968	7,914
Within R^2	0.023	0.383	0.349	0.025	0.021	0.381

low) the median faces stronger (weaker) financial constraints. Second, state-owned enterprises (SOEs) have more stable channels for obtaining loans and face less uncertainty than non-SOEs. Consequently, in general, they face weaker financial constraints than non-SOEs (Almeida et al., 2004; Fang, 2007). We classify non-SOEs as having strong financial constraints and SOEs as having weak constraints. Third, enterprises with political connections tend to have weaker financial constraints and are more likely to obtain bank credit than those lacking such connections (Claessens et al., 2008). Political connections can also play a governance role in enterprises, alleviating problems with information quality (Yu et al., 2012). Therefore, we classify enterprises without (with) political connections as having strong (weak) financial constraints.

The results of the group regression based on the strength of financial constraints are shown in Table 9. They indicate that big data tax administration significantly increases the ability of enterprises with stronger financial constraints, non-SOEs and enterprises without political connections to obtain bank credit. Conversely, enterprises with weak financial constraints, SOEs and those with political connections do not obtain more bank credit. Therefore, this confirms that the motivation for enterprises to obtain more bank credit after big data tax administration is not an increase in funding needs, thus mitigating the potential interference from the alternative hypothesis proposed in our research.

Second, to exclude the possibility that an increase in tax expenses due to big data tax administration leads to increased enterprise loan demand, we design alternative dependent variables to test this mechanism. We calculate *Loan_Adj* by subtracting the current year's income tax expense from the credit funds of the same year, then adding 1 and taking the logarithm. In addition, we standardize the credit funds by calculating (credit funds of the current year – income tax expense of the current year) / credit funds of the current year, resulting in the *Loan_Adj_Ratio*. *Loan_Adj* and *Loan_Adj_Ratio* as alternative dependent variables. After rerunning the main regression model with these variables, the results are reported in Table 10. They show that after excluding the tax expense factor, the coefficients on *Bigdata* remain positive and significant. These results reject the alternative hypothesis of funding needs driving the increase in the scale of bank credit.

Table 10
Excluding the impact of tax expenses.

Variables	(1) ***Loan_Adj***	(2) ***Loan_Adj_Ratio***
Bigdata	0.033**	0.231**
	(1.963)	(2.050)
Size	1.087***	–0.027
	(75.935)	(–0.277)
Roa	–0.325***	0.252
	(–3.738)	(0.422)
Lev	3.219***	0.278
	(55.665)	(0.708)
Top1	0.003	–0.650
	(0.035)	(–0.950)
Dir	–0.072	–0.039
	(–0.978)	(–0.078)
Indir	–0.081	0.107
	(–0.416)	(0.080)
Dual	0.020	0.000
	(1.161)	(0.002)
GT_Phase	–0.222***	–0.437**
	(–8.420)	(–2.439)
Constant	–5.414***	0.753
	(–14.814)	(0.301)
Firm	YES	YES
Year	YES	YES
N	23,007	23,007
Within R^2	0.457	0.001

6.3. Regional-level analysis

The baseline tests use data at the firm-year level to examine the impact of big data tax administration on bank credit. However, the effects of big data tax administration are regional in nature, affecting the information quality of all local enterprises and the credit approval processes of banks generally. Therefore, in this section, we use region-year observations to further analyze the impact of implementing big data tax administration on local bank credit issuance. We replace the dependent variable with the natural logarithm of the total amount of new loans issued in the region for that year, *Loan_local*, and rerun the regression. Columns (1) and (2) of Table 11 report the results with and without control variables, respectively; both include province and year fixed effects. In columns (1) and (2), the coefficients of *Loan_local* on *Bigdata* are positive and significant, confirming that the regional government's application of big data tax administration promotes local credit activities at the macro level.

7. Conclusions and implications

The widespread adoption and application of the Internet and big data have reduced the cost of information flow, and the multi-party storage and sharing of big data has gradually become a new form of social capital. The use of big data by tax authorities not only improves the capabilities and efficiency of tax collection but also promotes the rational allocation of financial capital at the national level and facilitates enterprise financing. We investigate the effects of big data tax administration on corporate credit and find that implementing big data tax administration (1) has a positive impact on corporate bank credit; (2) improves the quality of corporate information, thereby promoting corporate credit and (3) has a more pronounced effect on enterprises with stronger (vs. weaker) financial constraints. The conclusions of our study are beneficial because they enhance academic understanding of the economic consequences of big data tax administration, and also have practical significance for tax authorities actively seeking external forces to improve tax collection procedures. Based on our theoretical and empirical analyses, we put forward the following policy recommendations.

First, the government should enhance cooperation between tax authorities and third-party online platforms, synchronously strengthening tax administration under the "delegation, management and service" framework. We show that by enhancing information collecting capabilities, big data tax administration improves the quality of corporate information disclosure, thereby optimizing corporate financing efficiency. In the context of the digital transformation of enterprises and the increasing application of big data in society, tax inspection departments should make full use of the data at the societal level, engaging in cooperation with online platforms and online assessment agencies. By utilizing the correlation between multi-party data and the data provided by enterprises, tax inspection departments can strengthen their verification of corporate information. This will help eliminate the corporate practices of inflating projects and manipulating information disclosure, and encourage and guide firms to improve their information quality.

Second, it is crucial to enhance the promotion of tax information technology and increase enterprises' willingness to improve information disclosure. Enhanced promotional guidance for enterprises is required to take full advantage of the governance role of big data tax administration in improving the financing environment

Table 11
Regional-level analysis.

Variables	(1)	(2)
	Loan_local	
Bigdata	0.797***	0.136*
	(6.700)	(1.832)
Controls		YES
Province		YES
Year		YES
N	374	374
Within R^2	0.618	0.893

for enterprises and the efficiency of resource allocation in society. Tax authorities should enhance communications with enterprises, focusing on providing explanations of and guidance regarding tax policies and should emphasize that "tax administration with big data" is not merely equivalent to "strict tax administration," but has benefits for building the enterprises' own credit and reputation systems.

Faced with a rapidly changing business environment and a gradually improving information taxation system, the value orientations and proactive attitudes of corporate decision-makers will determine whether they can respond positively and seize the opportunities to optimize and adjust their operations. As big data tax administration identifies and blocks many non-standard information disclosure practices, promotion and guidance by government departments for enterprises, along with the implementation of relevant supporting policies, are crucial in assisting enterprises to progress and achieve a win–win situation for both government and enterprises.

Declaration of competing interest

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

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The impact of big data tax administration on corporate ESG—A quasi-natural experiment based on Golden Tax Project III

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ABSTRACT

Environmental, social and governance (ESG) practices are pivotal to global sustainability yet face challenges. Based on the implementation of Golden Tax Project III, we find that big data tax administration decreases corporate ESG performance. Mechanism tests indicate that Golden Tax Project III can reduce tax avoidance, cash flow and green innovation, thereby inhibiting ESG through the "taxation effect." Conversely, the project can reduce agency costs and improve information transparency, thus promoting ESG performance through the "governance effect." Overall, however, the project inhibits corporate ESG performance. According to further analysis, the negative effect on ESG performance mainly impacts the environmental responsibility (*E*) element. This paper provides insights relevant to advancing China's "dual carbon" policy and formulating a "Chinese approach" to global sustainable development.

1. Introduction

In the post-pandemic era, the investment environment has grown increasingly complex and uncertain. Embracing sustainability, reducing corporate environmental pollution, fulfilling corporate social responsibility (CSR) and enhancing corporate governance have emerged as a vigorously advocated direction across society (Qiu and Yin, 2019). By July 2023, more than 5,370 institutions worldwide had signed the United Nations' Principles for Responsible Investment, with approximately 140 of these institutions based in China. In practice, however, the fulfillment of environmental, social and governance (ESG) responsibilities faces numerous

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challenges. The motivation for companies to engage in ESG investments often stems from external "push" factors such as policies, investors and market forces. However, corporate ESG activities are characterized by high costs, substantial risks and long payback periods, which reduce motivation. For instance, the development of ESG capacity requires the integration of professional human and material resources, entailing high costs and uncertainties. Consequently, it is crucial to provide policy support and guidance to motivate firms to proactively assume ESG responsibilities.

Taxation serves as a significant external governance tool to influence corporate ESG behavior. For example, tax reduction policies can alleviate funding constraints, incentivize enterprises to invest (Mei et al., 2022), improve business conditions and prompt firms to increase innovation expenditures and undertake green transformations (Fan and Peng, 2017; Fan et al., 2018). In recent years, information technologies such as big data, cloud computing and blockchain have begun to be widely adopted in tax administration. According to the OECD's *Tax Administration 2021*, which surveyed 59 advanced countries, over 80 % of tax departments within this sample had employed big data analysis tools and techniques to aid tax administration (henceforth, "big data tax administration"). The advancement of tax administration technology enhances tax departments' ability to acquire and supervise tax-related information, boosting administrative efficiency and ensuring national revenue. Furthermore, it improves corporate governance and reduces information asymmetry, alleviating financing constraints for businesses. However, it also greatly reduces the tax evasion space, so that the actual tax burden increases, thus reducing the free cash flow available to firms. Despite the existence of numerous challenges to the development of corporate ESG, little research thoroughly and systematically examines the impact of advances in tax administration technology on corporate ESG behavior.

This paper utilizes data on Shanghai and Shenzhen A-share listed companies from 2011 to 2020 and constructs a multi-time-point difference-in-differences (DID) model using Golden Tax Project III ("the project") to investigate the impact of big data tax administration on corporate ESG. The findings reveal that the implementation of the project decreases corporate ESG. Mechanism tests indicate that the project can reduce tax avoidance, corporate cash flow and green innovation, thereby inhibiting ESG through the "taxation effect." Conversely, it can enhance corporate information transparency and reduce agency costs, exerting a "governance effect" and promoting ESG. Overall, however, the project suppresses ESG performance. Heterogeneity analysis shows that the negative impact on ESG performance is more significant in areas with lower tax enforcement intensity, weaker environmental regulations and faster marketization processes, and in companies with less media attention and analyst attention, higher management shareholding ratios and no political connections. Further analysis reveals that the implementation of the project has varying effects on different dimensions of ESG, primarily manifested in differences in the taxation effect. Moreover, it suppresses corporate greenwashing and ESG earnings management behaviors. Economic consequence tests indicate that the restraining effect of the project on corporate ESG has led to declines in both financial performance and market value, negatively impacting firms' production and expansion. This indirectly suggests that the taxation effect of the project may have certain negative impacts.

The potential contributions of this paper are as follows. First, this paper expands the literature on factors influencing enterprise ESG. Studies of the driving factors of enterprise ESG mainly focus on external factors such as regulations, government actions and market power or internal factors such as ownership structure and corporate governance (Crifo et al., 2019; Ahn, 2020; Wang et al., 2021; DasGupta, 2022; Shen et al., 2023). However, there is relatively little research on factors such as the intensity and efficiency of tax administration; thus, this paper bridges the gap between tax and ESG.

Second, the paper enriches the literature on the economic consequences of Golden Tax Project III. Prior literature mainly examines the direct impacts of Golden Tax Project III from the perspectives of corporate tax burden and tax avoidance (Li et al., 2020; Zhang et al., 2020; Sun et al., 2021), or discusses its indirect effects in terms of corporate financial reporting quality, corporate investment and financing behavior (Cai et al., 2021a, 2021b). This article, focusing on corporate ESG, expands the perspective of research on Golden Tax Project III.

Third, the paper enriches and expands research on the relationship between corporate tax decisions and ESG. Jin and Huang (2022) find that the implementation of Golden Tax Project III reduces corporate donations. The present article, however, analyzes the impact of corporate tax avoidance behavior on corporate

ESG activities. This paper complements Jin and Huang (2022), offering new theoretical and empirical insights into the relationship between corporate tax avoidance and ESG.

Fourth, exploring the impact of Golden Tax Project III on corporate ESG not only provides references and insights relevant to improving financial and tax systems and thus alleviating the negative effects of big data tax administration; it also assists government departments in formulating policy guidelines to incentivize enterprises to actively fulfill their ESG responsibilities, promoting the achievement of China's "dual carbon" goals and providing a "Chinese approach" to global sustainable development.

2. Institutional background and research hypotheses

2.1. Development of Golden Tax Project III

Golden Tax Project I began in 1994, effectively enhancing the supervision of value-added tax (VAT) special invoices. However, due to the system's reliance on data sourced from enterprises, which had inherently low credibility, coupled with the need for secondary manual input by the tax department, the error rate was high. Additionally, its coverage was narrow, leading to its discontinuation by the end of 1996. To address the problems of Golden Tax Project I, Golden Tax Project II was initiated in 1998. This project strengthened the supervision of tax sources and tax payment processes, effectively safeguarding VAT sources and combating VAT evasion (Zhang et al., 2020). Unfortunately, the system had limited coverage, being only able to verify VAT special invoices.

Although Project II essentially realized the digitalization of VAT administration, taxation digitalization still has a long way to go. Golden Tax Project III was piloted in 2013 and achieved nationwide coverage by the end of 2016. The overall goal of this tax management information system project can be summarized as "One Platform, Two-level Processing, Three Coverage, Four Systems."

"One Platform" refers to a unified technical foundation platform including network hardware and basic software, which relies on big data and cloud computing to trace the production, sales, investment, operation fund flows and invoice information of enterprises across regions and monitor data related to various tax-related processes of enterprises. "Two-level Processing" refers to the centralized processing of tax administration information data by both state and provincial taxation administrations, to mitigate the risk of collusion between enterprises and grassroots authorities as well as the possibility of leakage of tax-related information. "Three Coverage" refers to coverage of all tax categories, all work stages and all national and local tax bureaus and relevant departments. The "Four Systems" constitute a system architecture centered on tax management systems, with auxiliary administrative management, external information and decision support systems.

2.2. Theoretical analysis and hypothesis development

The advancement in tax administration technology has significantly narrowed the room for tax evasion by enterprises, resulting in an increase in their actual tax burden and a corresponding decrease in discretionary operating cash flows. However, it has also dramatically enhanced transparency and improved corporate governance, thereby facilitating the exercise of external regulatory powers and promoting the healthy development of enterprises. Based on these facts, this paper proposes a "taxation hypothesis" and a "governance hypothesis" to examine the impact of Golden Tax Project III on the ESG performance of enterprises.

2.2.1. Taxation hypothesis

According to neoclassical theory, investments by enterprises in environmental and social responsibility do not yield direct economic benefits but instead occupy a portion of the enterprises' funds (Qiu and Yin, 2019; Gao et al., 2021). Moreover, maintaining good ESG performance can increase operating costs for enterprises (Li and Xu, 2022). Pollution prevention and green technological innovations require substantial capital investment, impacting the future cash flow of enterprises (Cai et al., 2021a, 2021b). Enterprises are profit-oriented economic entities, and their financial condition directly affects their development plans. According to the pyramid model of CSR (Carroll, 1991), creating value for shareholders is the most fundamental responsibility of a company. Enterprises should first fulfill lower-level responsibilities before those at higher levels (Seifert et al., 2004). Thus, given the increasingly competitive and rigorously regulated market environment, a sound financial condition is a prerequisite for assuming ESG responsibilities. Only with sufficient cash reserves can a company effectively balance its social responsibilities with its ongoing operations (Zhou, 2005) by meeting the sustained financial investment requirements of environmentally friendly hardware, technology and human resources.

Tax is the compulsory allocation of corporate earnings by the state, constituting a significant operating cost and expenditure for a company. Under imperfect financial market conditions, small and medium-sized enterprises often face difficulties accessing external financing. In such circumstances, tax avoidance not only serves as an effective means to increase retained earnings and cash flow, facilitating internal financing, but also helps enterprises better cope with external risks (Liu and Ye, 2014). However, the implementation of Golden Tax Project III has suppressed corporate ESG behavior by increasing the difficulty of and decreasing the motivation for tax avoidance.

From the perspective of the difficulty of corporate tax avoidance, Golden Tax Project III significantly enhances the audit capability of tax authorities, strongly deterring companies from engaging in illegal activities such as underreporting tax bases and issuing false invoices (Tang and Zhang, 2019). Companies that still intend to engage in tax avoidance would need to manipulate the complete information chain of their upstream and downstream companies, greatly increasing the difficulty of tax evasion. Moreover, by utilizing big data for analysis, the project offers a considerable ability to identify abnormal data and increase efficiency of tax administration. Even if there is falsification and tampering of information across the entire chain, if any one indicator shows an abnormality, the tax authorities can identify it and issue warnings (Wang, 2017). Enterprises' decisions regarding tax avoidance are generally based on an assessment of its benefits and costs. Following the implementation of Golden Tax Project III, companies face a dual challenge. On the one hand, they must dedicate more time and effort to designing tax avoidance schemes, raising the associated costs. On the other hand, such activities are relatively easily detected, and if discovered, companies may have to pay back taxes and face other penalties, directly leading to cash outflows. Moreover, detection can tarnish a firm's reputation, indirectly impacting its stock price negatively (Austin, 2017). It may also lead to closer scrutiny from other regulatory agencies, significantly increasing the political costs for enterprises of engaging in tax avoidance (Hanlon and Slemrod, 2009). Consequently, considering the balance between benefits and costs, enterprises are now more likely to reduce their tax avoidance behavior, which will increase their tax expenditure, thereby exerting a restraining effect on their operations and internal financing capability.

Meanwhile, from the perspective of the motivations for corporate tax avoidance, firms can assist governments in shouldering societal welfare tasks and environmental pressures, thereby cultivating favorable government–enterprise relations. Such companies can thereby acquire other scarce resources and potentially receive relatively lenient tax supervision. Given the high costs of tax auditing and the diverse and well-concealed tax avoidance methods employed by enterprises, the government may find it advantageous to relax tax supervision in exchange for other forms of revenue, thereby enhancing government fiscal revenue overall. Therefore, the government has a strong incentive to utilize its discretionary power in tax enforcement to facilitate mutual agreements with enterprises. However, the utilization of big data in Golden Tax Project III not only enhances tax administration capabilities and reduces associated costs but also contributes to establishing a sound governmental information disclosure mechanism, thereby increasing governmental information transparency (Zhao et al., 2019). This reduces the arbitrariness of tax officials' work, improves the standardization and transparency of the enforcement process, significantly curtails the government's discretionary power in tax enforcement and disrupts the implicit agreements between the government and enterprises. Consequently, it weakens the incentive for enterprises to fulfill their ESG responsibilities in exchange for lenient tax supervision and thereby reduces corporate ESG behavior.

Furthermore, Golden Tax Project III may affect various aspects of enterprises, including labor income shares (Yang and Lai, 2023), corporate donations (Jin and Huang, 2022), total factor productivity (Li and Wang, 2022), corporate innovation (Ji and Wang, 2019) and audit fees (Li and Zhu, 2022). It is highly feasible that the project's negative impact on these aspects will distract management's attention from enterprises' core business operations. This may lower the operational efficiency of enterprises and in turn negatively affect corporate profits (Zhang et al., 2020). The multiple calls on managerial attention may also divert some operating cash, leaving enterprises with fewer resources for ESG investments.

In summary, the implementation of Golden Tax Project III exerts a taxation effect, enhancing tax administration capacity and suppressing corporate tax avoidance while concurrently increasing corporate tax burdens. Additionally, the dispersion of managerial attention due to the pursuit of multiple objectives may reduce corporate cash flows, which would be detrimental to green innovation and consequently hamper corporate ESG performance.

2.2.2. Governance hypothesis

The separation of ownership and management has led to a series of principal–agent relationships, with a divergence in interests and objectives between company owners and managers, resulting in losses known as agency costs (Jensen and Meckling, 1976). Managers, influenced by factors such as performance, stock prices, public opinion and risks, will focus more on current company performance and tend to choose suboptimal short-term investment projects, thus forsaking long-term projects with higher risks (He and Tian, 2013; Fang et al., 2014). Green transformation represents a long-term investment for the sake of a company's sustainable development, and it may increase governance and operational management costs in the short term. The high costs and risks and long return cycles associated with ESG practices also contribute to a lack of internal incentives for company managers.

Due to the significant information asymmetry between companies and stakeholders, companies engage in "greenwashing" behaviors (Marquis et al., 2016), deliberately lowering the quality of information disclosure (Luo et al., 2017) and disclosing environmental information selectively. Some even exploit investors' limited cognitive abilities and leverage asymmetric information, using misleading language in their disclosures to guide and obtain investor endorsement, essentially pretending to undertake social responsibility to deceive stakeholders for their own benefit (Xiao et al., 2013). This phenomenon is especially prevalent in the absence of standardized ESG disclosure guidelines.

Tax administration, as an external regulatory tool, can effectively alleviate agency problems and enhance transparency, thereby exerting a governance effect. First, tax authorities can exert a governance effect directly. Although issues such as fund externalization, ultimate controllers and embezzlement are widespread in corporate governance, they inevitably leave abnormal signals in financial and tax information. Golden Tax Project III integrates vast amounts of data from multiple channels, and these data complement and corroborate each other, deterring the opportunistic enterprise behavior of providing different data to different departments. This greatly increases the probability of detecting tax evasion activities and fraudulent transactions, thus to some extent curbing the concealment of agency behavior such as embezzlement by management under complex transaction activities. The project also enhances tax analysis capabilities. By providing analysis and comparison of the key financial indicators of enterprises, the project overcomes the limitations imposed by the professional qualifications of individual tax personnel and enables suspicious enterprises to be efficiently identified, significantly increasing the potential costs of opportunistic managerial behavior during the agency process.

Second, tax authorities exert a governance effect indirectly through signal transmission. The tax department can periodically disclose the results of tax inspections and investigations in the form of "blacklists" and "whitelists" to the public. For instance, the State Administration of Taxation regularly releases a list of companies with an A-level tax credit rating, which strengthens societal attention to corporate tax credit and its association with corporate image, reducing information asymmetry between firms and market participants. During tax credit rating assessments, tax authorities can inspect a company's accounts, verifying its debtors' repayment ability and reducing creditors' recourse costs (Pan et al., 2013). Moreover, an A-level tax credit rating issued by the State Administration of Taxation conveys a powerful "good news" signal about a company's financial status (Sun et al., 2019). Conversely, a non-A rating implies that the company may have issues regarding its subjective attitude toward tax, its compliance capabilities, its actual tax expenditure and the extent of its dishonesty. The implementation of Golden Tax Project III can indirectly exert a "governance effect" by transmitting signals through the public disclosure of tax inspection results.

In summary, many stakeholders take an interest in corporate ESG, including but not limited to government departments, institutional investors and the media. Tax authorities directly inhibit corporate agency behavior through tax inspections, thereby enhancing corporate ESG. Other stakeholders concerned about ESG, although unable to directly access Golden Tax Project III data, can gain insight into the governance and operational status of companies through information publicly released by tax agencies, thereby indirectly exerting a governance effect. Therefore, companies facing stricter regulation and a more transparent information environment will devote more effort to maintaining a positive image. Consequently, this will enhance corporate ESG.

Based on the analysis above, Golden Tax Project III exerts both positive and negative impacts on firms' ESG performance. On one hand, it exerts a taxation effect, dampening ESG performance, while on the other hand, it exerts a governance effect, enhancing ESG performance. The overall logical framework of this analysis is depicted in Fig. 1. The net influence of the project on a firm's ESG performance depends on the relative strength of the taxation and governance effects. Therefore, we propose the following hypotheses:

H1: The implementation of Golden Tax Project III inhibits corporate ESG performance.

H2: The implementation of Golden Tax Project III enhances corporate ESG performance.

3. Research design

3.1. Sample and data

Golden Tax Project III was launched in the provinces of Chongqing, Shandong (except Qingdao) and Shanxi in 2013. In 2014, it was introduced in Guangdong (except Shenzhen), Henan and Inner Mongolia, marking the completion of the first phase. By 2015, it had been extended to 14 provinces or autonomous regions, including Ningxia, Hebei, Guizhou and Jilin. In 2016, it was expanded to 13 provinces and cities such as Liaoning, Jiangxi, Shanghai, Qingdao and Shenzhen, achieving nationwide coverage. To ensure that the research sample includes a period both before and after policy implementation, we select A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2011 to 2020. We exclude financial companies, ST-, *ST- or PT-listed companies and companies with missing key variables. Finally, 1,136 companies with a total of 9,951 observations are obtained. To eliminate the impact of outliers, we winsorize all continuous variables at the 1 % level. The main financial data in this study are sourced from the CSMAR database.

3.2. Empirical model and variable definitions

This study exploits the temporal and regional differences in the pilot implementation of Golden Tax Project III to construct a multi-time-point DID model. The specific empirical model is as follows:

$$ESG_{ijct} = \alpha_0 + \alpha_1 Treat_{ct} + \alpha_2 Controls_{ijct} + \varphi_t + \theta_j + \delta_i + \varepsilon_{it} \tag{1}$$

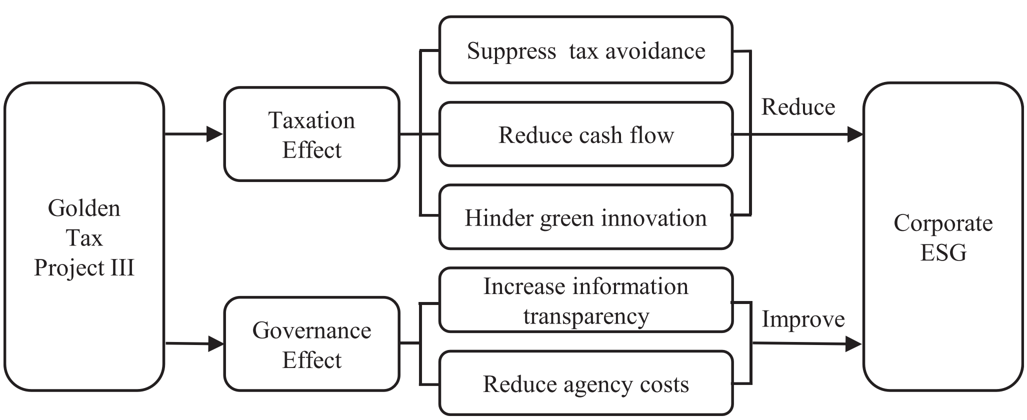

Fig. 1. The mechanism of the impact of "Golden Tax Project III" on corporate ESG performance.

In this study, the dependent variable *ESG* represents the ESG performance of enterprises. Drawing on the work of Wang et al. (2021), the ESG scores are obtained from the Bloomberg database. The ESG scoring system developed by Bloomberg LP is based on publicly available documents such as annual reports and sustainability reports. It is specifically designed to assess the level of ESG disclosure by global listed companies, thereby guiding investment decisions more effectively. The Bloomberg ESG disclosure score encompasses all three dimensions—*E*, *S* and *G*—and ranges from 0 to 100, with higher scores indicating superior ESG performance. This indicator is widely used in academia (Nie et al., 2023).

The independent variable *Treat* measures the implementation of Golden Tax Project III, following Liu et al. (2022) and Zhang et al. (2020). When the project is implemented in the region in which an enterprise is located in the current year, *Treat* equals 1; otherwise, it equals 0. As the implementation timings of the project in Qingdao and Shenzhen differ from those in their respective provinces, the *Treat* values for enterprises in these two cities are determined separately.

The controls comprise a series of enterprise characteristic variables and regional characteristic variables, following Jin and Huang (2022) and Zhang et al. (2020), such as enterprise size (*Size*), leverage ratio (*Lev*), revenue growth rate (*Growth*), ownership nature (*SOE*), regional gross domestic product (*lnGDP*) and per capita regional gross domestic product (*lnaveGDP*). Additionally, industry (θ_j), year (φ_t) and enterprise fixed effects (δ_i) are controlled for. The specific variable definitions are provided in Table 1.

4. Empirical results

4.1. Descriptive statistics

Figs. 2 to 5 depict the annual trends in overall ESG performance and the scores of the individual ESG dimensions for the sample enterprises. From 2011 to 2020, the ESG ratings exhibit an overall upward trend, indicating a gradual strengthening of the enterprises' emphasis on ESG. The annual trends of the scores in the three dimensions are generally consistent with the overall ESG performance. However, there are also differences in certain years. Specifically, the governance responsibility scores fluctuate slightly overall, whereas the environmental and social responsibility scores fluctuate before 2015 but continually rise after 2015. This change after 2015 may be due to the proposal of the Five Major Development Concepts during the Fifth Plenary Session of the Eighteenth Central Committee of the Communist Party of China in that year. Subsequently, legislative work in various areas, such as China's emission trading reform and environmental

Table 1
Variable definitions.

Variables	Definitions
ESG	The natural logarithm of ESG score from the Bloomberg
Treat	1 if a company has implemented the "Golden Tax Project III", and 0 otherwise
Size	The natural logarithm of total assets
Lev	Total debts divided by total assets
ROA	Net profit divided by total assets
ATO	operational revenue divided by total assets
Cashflow	net cash flow from operating activities divided by total assets
Growth	Growth rate of operational revenue
Top5	Shareholding ratio of the top five shareholder
Balance	Shareholding ratio of the second to fifth largest shareholders divided by shareholding ratio of the top one shareholder
ListAge	The natural logarithm of the number of years a company has been listed, incremented by one
Soe	1 if the company is state-owned enterprise, and 0 otherwise
Big4	1 if the company's auditor ranks in the "Big Four" accounting firms
FIXED	net fixed assets divided by total assets
lnGDP	The natural logarithm of regional gross domestic product
lnaveGDP	The natural logarithm of per capita regional gross domestic product
Indstruc	Output value of the tertiary industry divided by output value of the secondary industry

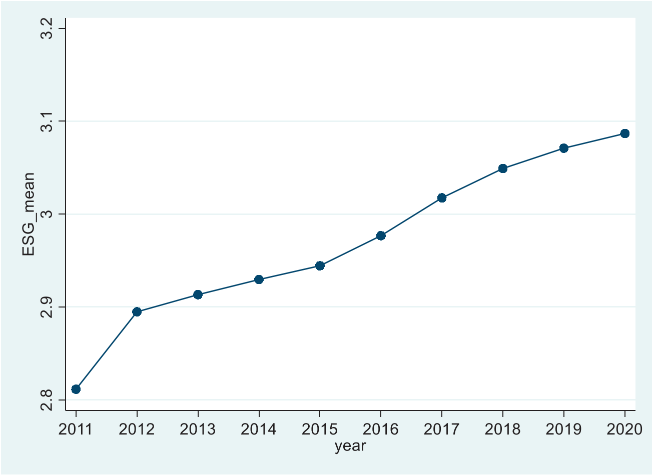

Fig. 2. Annual trend of enterprise ESG performance.

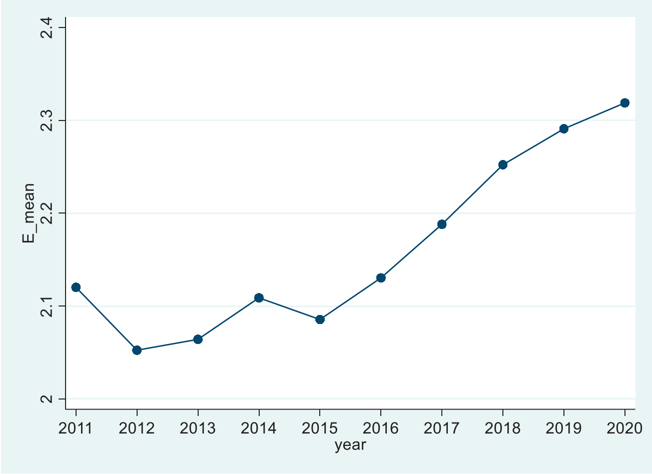

Fig. 3. Annual trend of enterprise E performance.

protection tax, progressed smoothly in 2016, and ecological environmental protection was incorporated into the Thirteenth Five-Year Plan. These developments solidified green and sustainable development.

We further statistically analyze the sample companies by industry and year, with the results presented in Appendix Table A1. Among the industries analyzed, Mining (B), Electricity, Heating, Gas and Water Production and Supply (D) and Transportation, Warehousing, and Postal Services (G) exhibit the highest mean ESG scores. This may be due to the combination of external regulatory pressure and their inherent need for sustainable development, which drives these enterprises to engage in more ESG disclosures, thus resulting in higher ESG scores. For example, China Petrochemical Corporation (Sinopec) has vigorously developed new energy-related businesses and has consistently disclosed its ESG reports for the past 16 years. Moreover, it hired the Chinese Corporate Social Responsibility Report Expert Rating Committee and KPMG to evaluate its reports (Mao et al., 2023). Meanwhile, industries with lower ESG scores include Information Transmission, Software and Information Technology Services (I) and Leasing and Business Services (L). This could be because companies in the service industry place limited emphasis on ESG.

Table 2 provides descriptive statistics for key variables. The mean of *ESG* is 2.979, with a minimum value of 0.215 and a maximum value of 4.161, indicating significant differences in ESG performance among companies.

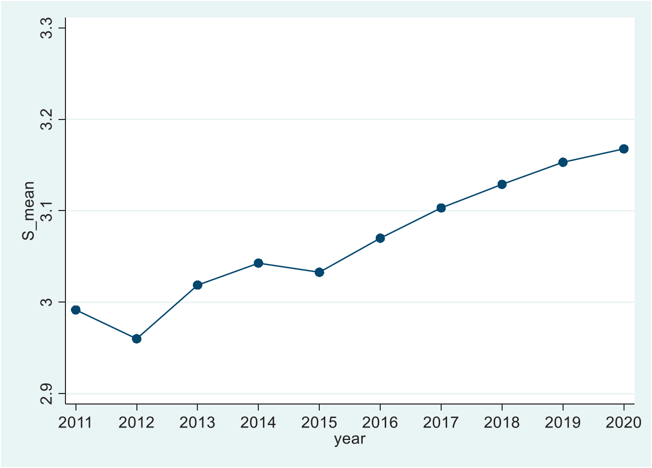

Fig. 4. Annual trend of enterprise S performance.

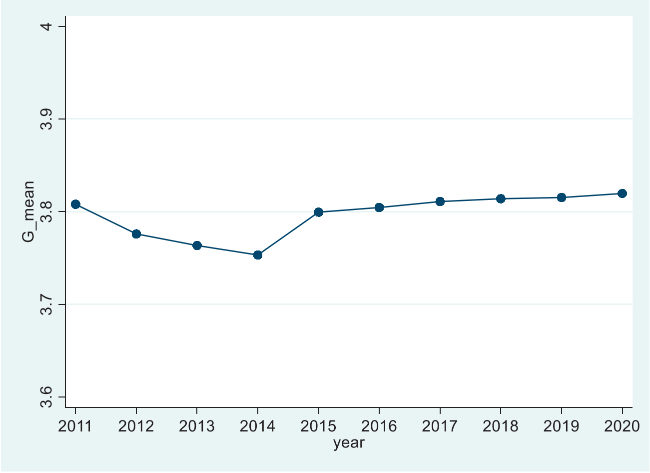

Fig. 5. Annual trend of enterprise G performance.

The mean of *Treat* is 0.618, indicating that from 2011 to 2020, approximately 61.8 % of the firm-year observations are affected by Golden Tax Project III, forming relatively balanced treatment and control groups. The standard deviation of enterprise size (*Size*) is 1.333, indicating relatively large differences in the size of companies within the sample. The leverage ratio (*Lev*) ranges from a minimum of 0.044 to a maximum of 0.907, with a mean of 0.476, indicating significant differences in the financial conditions of companies.

4.2. Regression analysis

Table 3 presents the regression results for the impact of the project on corporate ESG performance. Column (1) controls for year, industry and firm fixed effects; Column (2) adds a series of corporate characteristics and governance variables that affect ESG performance; and Column (3) further controls for characteristic variables relating to regional economic development. The coefficients of *Treat* are negative in all three columns and significant at the 1 % level, indicating that the implementation of the project decreases corporate ESG performance, thus supporting Hypothesis 1.

Table 2
Descriptive statistics.

variable	N	Mean	sd	min	p50	max
ESG	9,951	2.979	0.318	0.215	2.987	4.161
Treat	9,951	0.618	0.486	0	1	1
Size	9,951	23.108	1.333	20.109	22.986	27.511
Lev	9,951	0.476	0.200	0.044	0.487	0.907
ROA	9,951	0.047	0.062	−0.308	0.039	0.246
ATO	9,951	0.666	0.464	0.062	0.558	2.982
Cashflow	9,951	0.056	0.068	−0.203	0.054	0.267
Growth	9,951	0.161	0.427	−0.607	0.100	5.615
Top5	9,951	0.549	0.161	0.179	0.547	0.915
Balance2	9,951	0.659	0.586	0.014	0.469	2.807
ListAge	9,951	2.471	0.643	0.000	2.639	3.367
SOE	9,951	0.503	0.500	0	1	1
Big4	9,951	0.115	0.319	0	0	1
FIXED	9,951	0.229	0.179	0.001	0.185	0.760
lnGDP	9,951	10.375	0.730	7.421	10.383	11.615
Indstruc	9,951	1.538	1.072	0.518	1.153	5.297
lnaveGDP	9,951	11.129	0.453	9.706	11.139	12.013

4.3. Robustness tests

4.3.1. Parallel trend test

To test whether the models in this paper satisfy the parallel trend assumption, we first employ counterfactual analysis to modify the implementation timing of Golden Tax Project III across provinces or regions, uniformly advancing it by one to three years, respectively denoted as *Treat_1*, *Treat_2* and *Treat_3*. The regression results are shown in Column (1) of Table 4, where the coefficients of *Treat_1*, *Treat_2* and *Treat_3* are all nonsignificant, indicating that the ESG performance ratings of the treated and control companies satisfy the parallel trend assumption before the implementation of the project.

Next, we use event study analysis, setting up seven dummy variables: *Pre3*, *Pre2*, *Pre1*, *Current*, *Post1*, *Post2* and *Post3*. For data points three or more years before the implementation of Golden Tax Project III, *Pre3* equals 1; in the two years preceding implementation, *Pre2* equals 1; in the year immediately prior to implementation, *Pre1* equals 1; in the year of implementation itself, *Current* equals 1; and so forth. Using *Pre1* as the baseline group, as can be seen from Column (2) of Table 4, the coefficients of *Pre3* and *Pre2* are both nonsignificant. This indicates that before the implementation of the project, the ESG performance of both the treatment and control groups follows parallel time trends. However, after the implementation of the project, the coefficients of *Current*, *Post1* and *Post2* are negative and significant at the 5 % level or the 1 % level, indicating that the project causes the parallel trends to diverge by reducing the ESG performance of treated companies, and this effect persists within the two years following implementation. Fig. 6 presents the results of the parallel trend test visually.

4.3.2. Placebo test

The conclusions of this study may be influenced by other unobserved, time-varying omitted variables. To address this concern, a placebo test is conducted. Drawing from Wei et al. (2022), the placebo test employs two specific methods: randomly generating implementation times for Golden Tax Project III across regions and randomly selecting areas to serve as pilot zones for the project. Each randomization process is conducted for 500 replicates.

Fig. 7 and Fig. 8 show kernel density maps. Fig. 7 shows the results for the randomly selected pilot areas, while Fig. 8 presents the results for the randomly assigned implementation times. In both figures, it is evident that the estimated coefficients for *Treat* cluster closely around zero, indicating that the constructed virtual events have no significant impact on corporate ESG performance. This suggests that the baseline regression results are not due to other omitted variables, but rather the effects of the implementation of the project.

Table 3
The Impact of "Golden Tax Project III" on Corporate ESG.

	(1)	(2)	(3)
	ESG	*ESG*	*ESG*
Treat	−0.026***	−0.025***	−0.025***
	(−3.078)	(−3.032)	(−3.043)
Size		0.072***	0.073***
		(11.717)	(11.846)
Lev		−0.068***	−0.068***
		(−2.636)	(−2.613)
ROA		0.109**	0.112**
		(2.478)	(2.544)
ATO		−0.003	−0.002
		(−0.254)	(−0.197)
Cashflow		−0.010	−0.008
		(−0.279)	(−0.223)
Growth		−0.014***	−0.014***
		(−3.055)	(−3.128)
Top5		0.056*	0.053
		(1.695)	(1.605)
Balance2		−0.016**	−0.017**
		(−2.249)	(−2.392)
ListAge		0.022	0.023
		(1.492)	(1.532)
SOE		0.020	0.020
		(1.365)	(1.382)
Big4		0.051***	0.051***
		(2.920)	(2.920)
FIXED		0.061**	0.065**
		(2.150)	(2.288)
lnGDP			0.000
			(0.004)
Indstruc			0.023***
			(2.643)
lnaveGDP			−0.050*
			(−1.656)
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Constant	2.897***	1.242***	1.733***
	(64.650)	(8.903)	(6.637)
N	9951	9951	9951
r2_within	0.282	0.302	0.303

Note: t-statistics in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

4.3.3. Negative weights in DID

The essence of multi-time-period DID lies in the weighted average of multiple different treatment effects, where some weights may be negative. In cases where the weights are negative, the average treatment effect obtained by the weighted average of different treatment effects may be opposite in direction to the true average treatment effect. Goodman-Bacon (2021) posits that when treatment timing varies across treatment units, the two-way fixed effects DID estimator is the weighted average of all possible 2×2 DID estimators, which compare time groups with each other. In other words, the two-way fixed effects DID estimator is the sum of the products of all DID estimators and their comparison weights. Table 5 presents the results of Bacon decomposition.

As Golden Tax Project III was expanded nationwide in 2016, there are no untreated units in our sample. Therefore, in conducting Bacon decomposition, the only contrast group likely to introduce bias into the treatment effect estimator is the late-treatment vs. early-treatment group. When weighting the treatment effect of

Table 4
Parallel trend test.

	(1)	(2)
	ESG	*ESG*
Treat_3	−0.002	
	(−0.155)	
Treat_2	−0.004	
	(−0.391)	
Treat_1	−0.014	
	(−1.558)	
Pre3		0.018
		(1.407)
Pre2		0.007
		(0.769)
Current		−0.021**
		(−2.351)
Post1		−0.032***
		(−2.790)
Post2		−0.029**
		(−2.123)
Post3		−0.027
		(−1.536)
Controls	Yes	Yes
Year	Yes	Yes
Ind	Yes	Yes
Firm	Yes	Yes
Constant	1.724***	1.690***
	(6.603)	(6.612)
N	9951	9951
r2_within	0.302	0.303

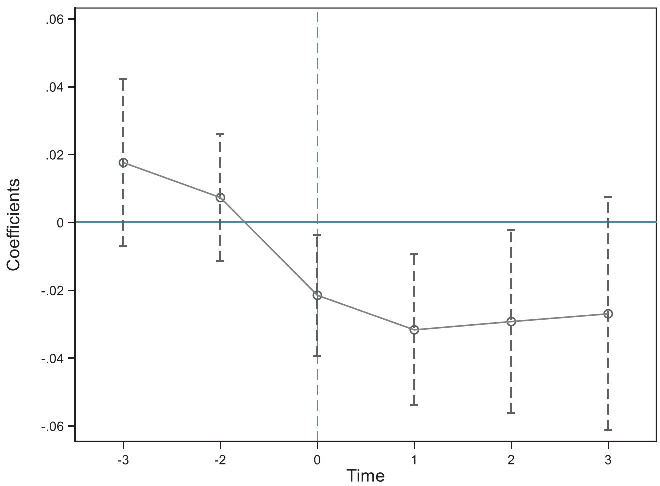

Fig. 6. Parallel trend test.

both the early-treatment vs. late-treatment and late-treatment vs. early-treatment groups, the weighted treatment effects are −0.0140 and −0.0061, respectively. From these results, it can be concluded that the impact of the late-treatment vs. early-treatment group on the treatment effect is not particularly great. The treatment effect is negative, consistent with the sign of the treatment effect of the early-treatment vs. late-treatment group, so it does not fundamentally alter the results. Thus, the core research conclusion remains unchanged even after accounting for negative weights.

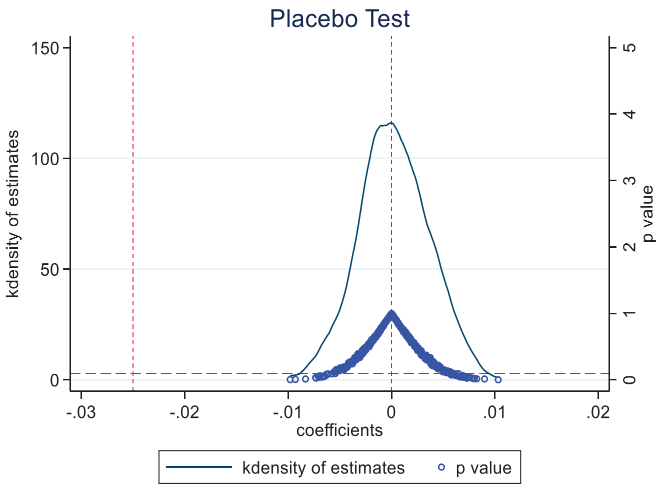

Fig. 7. Random selection of pilot areas.

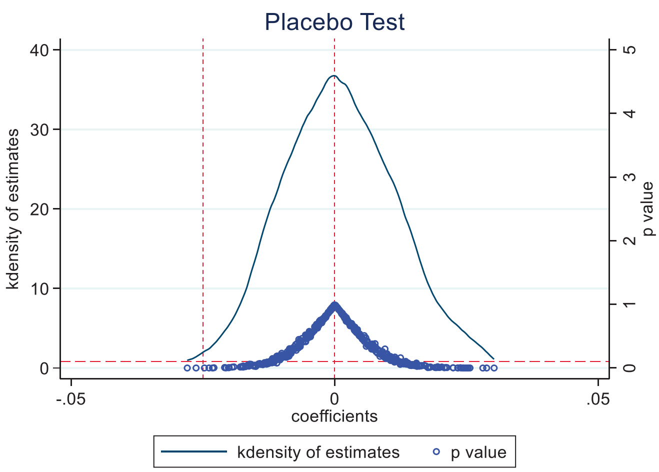

Fig. 8. Random selection of pilot time.

Table 5
The result of Bacon Decomposition.

	Beta	*TotalWeight*
Early_v_Late	0.024	0.010
Late_v_Early	−0.010	0.036
Early_v_Late	0.014	0.036
Late_v_Early	−0.030	0.109
Early_v_Late	−0.019	0.035
Late_v_Early	−0.035	0.071
Early_v_Late	−0.020	0.702

4.3.4. Excluding the influence of concurrent policy interference

The time points of the implementation of Golden Tax Project III coincided with a crucial period of China's economic transformation. The occurrence of numerous policies and shocks during the same period could influence the ESG performance of enterprises, thereby disrupting the robustness of our empirical results. Policies such as the VAT reform (known as "replacing business tax with VAT," or *ying-gai-zeng* in Chinese) and tax and fee reduction could affect corporate tax behavior, thereby influencing corporate ESG performance.

To exclude the influence of the VAT reform, we use the following two methods. First, following Zheng and Sun (2021), we use data from the Manufacturing Industry (C) and Wholesale & Retail Trade Industry (F), as these industries are less impacted than others by the VAT reform. The regression results are shown in Column (1) of Table 6. Second, referencing Zhang et al. (2020), based on the benchmark regression, we further control for the overall tax burden (*VBT*) (equaling the sum of business tax and VAT divided by operating income) to better distinguish the impact of the VAT reform. The results are shown in Column (2) of Table 6. It is evident that the coefficients of *Treat* in the above two tests remain negative and significant.

To further eliminate the influence of concurrent tax and fee reduction, following Liu et al. (2022), we control for the effective tax rate (*ETR*) of enterprises, calculated as the difference between taxes paid and tax refunds received, divided by operating revenue. The results are shown in Column (3) of Table 6, where the sign and significance of the *Treat* coefficient remain unchanged. In summary, the results in Columns (1) to (3) indicate that after controlling for the effects of the VAT reform and tax and fee reduction, the implementation of Golden Tax Project III still leads to a reduction in corporate ESG performance, thus confirming the main conclusion.

4.3.5. Other robustness tests

(1) Controlling for high-order fixed effects. We further control for industry-year combined fixed effects. The results are shown in Column (1) of Table 7, where the coefficient of *Treat* is negative and significant, indicating that policy changes relating to industries do not affect the reliability of the conclusion.

(2) The impact of the launch time of Golden Tax Project III. First, Guangdong Province, Henan Province and the Inner Mongolia Autonomous Region implemented the project toward the end of 2014, making it difficult to attribute the effects to any specific year. Therefore, enterprises from these provinces are excluded and the regression is conducted again, with the results presented in Column (2) of Table 7. The coefficient of *Treat* remains negative.

Second, the launch time of the project in some provinces (Guangdong Province (escept Shenzhen City), Henan Province and the Inner Mongolia Autonomous Region) occurred in the second half of the year, and its impact in the launch year might have been limited. Therefore, in such cases, we consider the reform to have been implemented in the following year, creating a new variable called *NewTreat*. The results are shown in Column (3) of Table 7, where the coefficient of *NewTreat* is negative, indicating that the implementation of Golden Tax Project III indeed lowered corporate ESG performance.

Table 6
Excluding the influence of concurrent policy interference.

	(1)	(2)	(3)
	ESG	*ESG*	*ESG*
Treat	−0.033***	−0.024***	−0.029***
	(−3.133)	(−2.648)	(−3.313)
VBT		0.216	
		(0.689)	
ETR			0.086
			(1.136)
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Constant	1.269***	2.009***	1.905***
	(3.636)	(6.914)	(6.779)
N	6404	8752	8720
r2_within	0.317	0.283	0.302

Table 7
Other robustness tests.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ESG	*ESG*	*ESG*	*ESG*	*ESG*	*ESG*	*ESG2*
Treat	−0.022***	−0.018**		−0.024**	−0.024**	−0.015*	−0.056*
	(−2.602)	(−2.150)		(−2.009)	(−2.302)	(−1.764)	(−1.730)
NewTreat			−0.014*				
			(−1.717)				
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	No
Ind*Year	Yes	No	No	No	No	No	No
Constant	1.579***	1.696***	1.752***	1.745***	2.052***	2.050***	0.572**
	(5.897)	(6.284)	(6.709)	(6.338)	(6.081)	(7.732)	(2.321)
N	9951	8843	9951	8875	7010	8753	9728
r2_within	0.320	0.313	0.302	0.320	0.315	0.259	0.395

(3) The stock market crash in 2015 created strong negative sentiments in the capital market, which could have had a detrimental impact on the operational conditions of companies, consequently lowering their ESG performance. Therefore, we exclude the data from 2015 and re-conduct the regression. The results presented in Column (4) of Table 7 reveal that the coefficient of *Treat* is negative and significant at the 5 % level.

(4) To ensure that each company has observations both before and after the implementation of the project, thus facilitating a more comprehensive assessment of its impact on corporate ESG behavior, we transform the original sample into a balanced panel and re-conduct the regression. The results in Column (5) of Table 7 show that the coefficient of *Treat* is negative and significant at the 5 % level.

(5) Lagged independent variables. We take the ESG performance in period $t + 1$ and the independent variables in period t. The regression results in Column (6) of Table 7 show that the coefficient of *Treat* is negative, indicating that the implementation of the project suppresses the ESG performance of enterprises in the following year, consistent with the main regression.

(6) Alternative ESG rating. Following Lei et al. (2023), the widely recognized and academically utilized CSR total score from Hexun.com is adopted in place of Bloomberg's ESG score as an ESG indicator. The Hexun.com rating encompasses five dimensions: environmental responsibility; shareholder responsibility; employee responsibility; supplier, customer and consumer rights responsibility; and social contribution responsibility. We take the logarithm of the rating and denote it as *ESG2*. The regression results are presented in Column (7) of Table 7, which again reveals that the implementation of the project negatively impacts firms' ESG performance.

4.4. Channel analysis

4.4.1. Taxation effect

The implementation of Golden Tax Project III has enhanced tax administration capabilities and restrained corporate tax avoidance. Following Ye and Liu (2014), we construct four indicators, namely *RATE_diff*, *LRATE_diff*, *BTD* and *DDBTD*, to measure the extent of corporate tax avoidance. *RATE_diff* represents the difference between a firm's nominal income tax rate and its actual income tax rate. A greater difference indicates a greater degree of tax avoidance. *LRATE_diff* is the five-year average difference between nominal and actual tax rates, calculated as the mean of *RATE_diff* values from years t–4 to the current year. *BTD* represents the accounting-tax difference, calculated as the difference between pre-tax accounting profit and taxable income, divided by period-end total assets. Here, taxable income equals the current income tax expense divided by the nominal income tax rate.

DDBTD represents the tax difference after deducting the impact of accrual profit, indicating the portion of *BTD* that cannot be explained by accrual profit. It is computed from models (2) and (3). Here, *TACC* is calculated as the difference between net profit and net cash flow from operating activities, divided by total assets. μ_i represents the average residual of company i over the sample period, while ε_{it} represents the deviation of residual in year t from the company's average residual μ_i.

$$BTD_{it} = \alpha TACC_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

$$DDBTD = \mu_i + \varepsilon_{it} \tag{3}$$

We employ interaction terms between the tax avoidance indicators and participation in Golden Tax Project III to investigate the mechanism through which the project influences corporate ESG. The regression results are presented in Table 8. In Columns (1) to (3), the coefficients of the interaction terms are all positive and significant, suggesting that the higher the level of tax avoidance by a firm, the better its ESG performance. However, the implementation of the project suppresses corporate tax avoidance, and thus increases the tax burden, thereby limiting the resources available for implementing ESG initiatives, consequently reducing corporate ESG performance. Generally, when a company's tax burden increases, its available cash flow decreases. We measure enterprises' corporate cash flow condition (*Cashflow*) using the ratio of operating cash flow to total assets. In Column (5), the coefficient of *Cashflow*Treat* is positive and significant, indicating that the implementation of the project reduces cash flow. Consequently, the decrease in operational cash flow will reduce enterprises' ESG performance.

Golden Tax Project III increases the corporate tax burden and reduces the resources available for companies, potentially lowering their level of green innovation. Following Song et al. (2022), we use the ratio of total green patent applications to total patent applications to measure corporate green innovation levels (*Patent*). The regression results in Column (5) of Table 8 show that the coefficient of *Patent*Treat* is positive and significant at the 1 % level. This suggests that the implementation of the project exacerbates the corporate tax burden, significantly reducing potential innovation investment by companies. Consequently, the decrease in corporate green innovation levels significantly hampers companies' ESG performance.

4.4.2. Governance effect

The implementation of Golden Tax Project III has significantly enhanced the collection and analysis of tax data, thus improving the authenticity of corporate disclosures and reducing information asymmetry between stakeholders and companies. With increased attention from regulatory agencies, media, investors and other stakeholders, companies are more likely to proactively fulfill their ESG responsibilities and increase ESG investments to meet their requirements, such as actively engaging in energy conservation and emissions reduction efforts. Moreover, the increase in information transparency lowers agency costs for companies, suppresses managerial self-serving behaviors such as on-the-job consumption and thus improves corporate ESG performance.

We use the management expense ratio (*Mfee*) to measure corporate agency costs. Additionally, following the approach of Xin et al. (2014), accounting information transparency (*Trans*) is used to further gauge information transparency. The regression results in Table 9 show that the coefficient of *Mfee*Treat* is negative, indicating that the governance function of the project significantly reduces corporate management expenses, thereby suppressing agency costs and improving corporate ESG performance. The coefficient of *Trans*Treat* is positive, suggesting that higher information transparency in companies correlates with better ESG performance. In summary, Golden Tax Project III reduces agency costs and enhances information transparency, which is beneficial for corporate ESG performance.

4.5. Heterogeneity analysis

We start by analyzing the heterogeneity of external governance characteristics to examine whether the implementation of the project has different effects on corporate ESG in different contexts. We primarily analyze this from macro-policy and market perspectives, then from the perspective of internal micro-enterprise characteristics.

Table 8
Channel analysis: Taxation effect.

	(1)	(2)	(3)	(4)	(5)	(6)
	ESG	*ESG*	*ESG*	*ESG*	*ESG*	*ESG*
Treat	−0.028***	−0.026***	−0.029***	−0.029***	−0.025***	−0.020**
	(−2.868)	(−2.590)	(−2.908)	(−2.932)	(−3.007)	(−2.430)
RATE_diff	−0.026					
	(−0.732)					
*RATE_diff*Treat*	0.013***					
	(2.885)					
LRATE_diff		−0.120*				
		(−1.909)				
*LRATE_diff*Treat*		0.014***				
		(3.255)				
BTD			−0.156			
			(−0.998)			
BTDxTreat			0.008*			
			(1.827)			
DDBTD				−0.155		
				(−1.003)		
*DDBTD*Treat*				0.006		
				(1.376)		
*Cashflow*Treat*					0.009**	
					(2.159)	
Patent						−0.028
						(−1.381)
*Patent*Treat*						0.011***
						(2.809)
Size	0.077***	0.076***	0.079***	0.080***	0.073***	0.067***
	(10.447)	(9.858)	(10.721)	(10.781)	(11.863)	(9.745)
Lev	−0.056*	−0.053*	−0.060*	−0.061*	−0.065**	−0.081***
	(−1.749)	(−1.657)	(−1.913)	(−1.932)	(−2.494)	(−2.798)
ROA	0.069	0.187**	0.092	0.104	0.106**	0.105*
	(0.832)	(2.243)	(1.042)	(1.214)	(2.409)	(1.892)
ATO	−0.007	−0.009	−0.007	−0.008	−0.003	0.004
	(−0.537)	(−0.683)	(−0.557)	(−0.587)	(−0.229)	(0.279)
Cashflow	−0.019	−0.036	−0.021	−0.021	−0.076	−0.015
	(−0.483)	(−0.914)	(−0.510)	(−0.531)	(−1.475)	(−0.388)
Growth	−0.014***	−0.015***	−0.014***	−0.014***	−0.014***	−0.013***
	(−2.761)	(−2.837)	(−2.805)	(−2.813)	(−3.111)	(−2.927)
Top5	0.075**	0.024	0.075**	0.074*	0.052	0.047
	(1.979)	(0.626)	(1.974)	(1.945)	(1.585)	(1.319)
Balance2	−0.020**	−0.016**	−0.021***	−0.020**	−0.016**	−0.014*
	(−2.569)	(−2.029)	(−2.585)	(−2.559)	(−2.300)	(−1.838)
ListAge	0.030*	−0.034*	0.031*	0.031*	0.023	0.029*
	(1.798)	(−1.757)	(1.860)	(1.857)	(1.506)	(1.762)
SOE	0.012	0.012	0.014	0.014	0.020	0.030*
	(0.687)	(0.649)	(0.776)	(0.783)	(1.362)	(1.799)
Big4	0.055***	0.058***	0.053***	0.053***	0.049***	0.051***
	(2.741)	(2.850)	(2.659)	(2.660)	(2.839)	(2.700)
FIXED	0.059*	0.079**	0.058*	0.058*	0.065**	0.072**
	(1.768)	(2.390)	(1.722)	(1.740)	(2.293)	(2.352)
lnGDP	0.005	0.019	0.006	0.006	0.001	−0.021
	(0.167)	(0.556)	(0.193)	(0.183)	(0.029)	(−0.649)
Indstruc	0.025**	0.028***	0.025**	0.025**	0.024***	0.022**
	(2.521)	(2.729)	(2.543)	(2.556)	(2.702)	(2.095)
lnaveGDP	−0.056	−0.055	−0.053	−0.053	−0.052*	−0.046
	(−1.492)	(−1.347)	(−1.437)	(−1.421)	(−1.709)	(−1.163)

(*continued on next page*)

Table 8 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)
	ESG	*ESG*	*ESG*	*ESG*	*ESG*	*ESG*
Year	Yes	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.686***	1.721***	1.600***	1.589***	1.743***	2.042***
	(5.534)	(5.499)	(5.289)	(5.258)	(6.680)	(6.264)
N	8607	8157	8607	8607	9951	8674
r2_within	0.306	0.297	0.305	0.305	0.303	0.302

Table 9
Channel analysis: Governance effect.

	(1)	(2)
	ESG	*ESG*
Treat	−0.024***	−0.021**
	(−2.912)	(−2.508)
Mfee	0.006	
	(0.086)	
*Mfee*Treat*	−0.008*	
	(−1.956)	
Trans		−0.049**
		(−2.211)
*Trans*Treat*		0.031***
		(8.164)
Controls	Yes	Yes
Year	Yes	Yes
Ind	Yes	Yes
Firm	Yes	Yes
Constant	1.742***	1.995***
	(6.631)	(7.660)
N	9951	9951
r2_within	0.303	0.309

4.5.1. Tax administration intensity

The higher the tax enforcement intensity in the region where a company is located, the higher the probability of tax evasion detection. In a scenario where the benefits of tax evasion remain constant, an increase in the opportunity cost of tax evasion will suppress companies' tax evasion activities (Jiang, 2013). In regions that already have high tax enforcement intensity, companies tend to have lower levels of tax evasion. Therefore, the taxation effect exerted by Golden Tax Project III is relatively limited. Consequently, it is expected that in regions with lower tax enforcement intensity, the project will more significantly enhance tax enforcement capabilities due to advancements in tax enforcement technology, thereby suppressing corporate tax evasion activities, reducing operational net cash flows and consequently lowering corporate ESG performance.

Following Jiang (2013), we construct a tax enforcement intensity indicator. Based on the annual average of tax enforcement intensity, the sample is divided into two groups: high tax enforcement intensity and low tax enforcement intensity. Regression analyses are then conducted separately for each group using Model (1). The results are presented in Column (1) and Column (2) of Table 10, showing that in the group with low tax enforcement intensity, the implementation of the project reduces corporate ESG performance more significantly.

Table 10
Policy-level heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
	High tax enforcement intensity	Low tax enforcement intensity	High environmental regulation intensity	Low environmental regulation intensity	Fast marketization process	Low marketization process
	ESG	*ESG*	*ESG*	*ESG*	*ESG*	*ESG*
Treat	−0.013	−0.028**	0.007	−0.049***	−0.038***	−0.003
	(−1.077)	(−2.321)	(0.498)	(−4.184)	(−3.676)	(−0.127)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.163***	0.896*	0.941**	1.892***	2.120***	−0.532
	(4.137)	(1.872)	(2.005)	(4.716)	(5.244)	(−0.799)
N	5233	4718	3480	6471	8086	1865
r2_within	0.297	0.276	0.302	0.308	0.303	0.342

4.5.2. Environmental regulation intensity

Environmental regulation is an effective administrative measure that governments use to constrain corporate production behavior and reduce pollutant emissions. It is thus an important tool for addressing environmental pollution issues and enhancing the quality of economic development. Drawing from Liu and He (2021), we adopt the ratio of investment in industrial-pollution minimization to the added value of the secondary industry to measure the intensity of environmental regulation in a region. A higher ratio indicates higher pollution-control expenditures by businesses and thus a greater intensity of environmental regulation.

Furthermore, the sample companies are divided into two groups based on the annual median of environmental regulation intensity for regression analysis. The results are shown in Column (3) and Column (4) of Table 10. In regions with high environmental regulation intensity, the implementation of Golden Tax Project III does not significantly affect corporate ESG performance. However, in regions with low environmental regulation intensity, the implementation of the project significantly reduces corporate ESG performance. This may be because in regions with high environmental regulation intensity, companies face significant regulatory pressure to maintain good ESG performance. Additionally, they may have invested more in energy-saving and emission-reduction equipment in the past and possess higher green innovation capabilities. Therefore, the increase in the tax burden does not immediately impact their ESG performance.

4.5.3. Regional marketization process

We obtain the regional level of marketization progress from the "China Provincial Marketization Index Report" (2018) compiled by Fan et al. (2019). Based on the median annual value of this index, the sample is divided into two groups representing fast and slow marketization processes. The results are shown in Column (5) and Column (6) of Table 10. In regions with a fast marketization process, the inhibitory effect of the project on corporate ESG performance is stronger, while in regions with a slow marketization process, the effect is not significant.

This could be because in regions with a fast marketization process, legal regulations are more comprehensive, exerting greater constraint on corporate behavior. If tax evasion by a company in such a region is detected, the penalties and potential damage to its reputation are more severe. Therefore, in regions with a fast marketization process, the cost of tax evasion for companies is higher, making it more likely that they will reduce their tax evasion activities. However, in regions with a slow marketization process, regulatory oversight may be more relaxed. Thus, the deterrent effect of penalties or other negative impacts may be limited. Consequently, the impact of the project on corporate ESG performance is smaller. This finding is consistent with the finding of Liu et al. (2022), who discover that the negative influence of Golden Tax Project III on related-party transactions is more pronounced in regions with higher levels of institutionalization. This further confirms that in areas with lower levels of marketization, the implementation of the project exerts a weaker impact on corporate ESG performance.

4.5.4. Media attention

With increasing social concern over environmental issues, fulfilling ESG responsibilities has become a crucial aspect of corporate legitimacy. To establish a positive image, companies engage in ESG activities to influence public perception of their image and meet investors' demands. We use the natural logarithm of the sum of one plus the number of times a company appears in the titles and content of online news articles from the CNRDS database to measure media attention. We divide the enterprises into two groups based on the industry annual median of this value.

The results of the grouped regressions are shown in Columns (1) and (2) of Table 11. In the high media attention group, the impact of the project on corporate ESG performance is not significant; however, in the low media attention group, the project significantly suppresses corporate ESG performance. This may be attributable to the fact that companies with lower media attention are often struggling or smaller in scale. The implementation of the project results in a lack of additional cash flow for ESG investments, resulting in poorer ESG performance.

4.5.5. Analyst coverage

From the perspective of the "information supervision hypothesis," analysts possess professional knowledge and high professional ethics, enabling them to uncover various aspects of company information and conduct analysis, thereby exposing self-serving behaviors of companies such as failure to fulfill social responsibilities and environmentally damaging practices. Meanwhile, from the perspective of the "performance pressure hypothesis," to meet analysts' performance expectations, management may engage in impression management by actively fulfilling ESG responsibilities to enhance investors' market evaluation of the company. Conversely, however, when management anticipates not meeting analysts' forecasted targets, then from the same perspective they may use impression management, in the form of ESG information disclosure, for self-protection, thus deflecting public attention and concealing their own faults. Therefore, among firms with higher analyst attention, the negative impact of Golden Tax Project III on corporate ESG is expected to be relatively nonsignificant.

We employ the natural logarithm of the sum of one plus the number of analysts tracking a firm to measure analyst attention, subsequently dividing the sample into two groups based on whether the firm's analyst attention level is above or below the industry's annual median for this value. The regression results are presented in Table 11, Columns (3) and (4). In the group with high analyst attention, the effect of Golden Tax Project III on ESG is not statistically significant. This might be because in the low analyst attention group, many companies

Table 11
Market-level heterogeneity analysis.

	(1)	(2)	(3)	(4)
	High media attention *ESG*	Low media attention *ESG*	High analyst attention *ESG*	Low analyst attention *ESG*
Treat	−0.013	−0.025**	−0.016	−0.035***
	(−1.062)	(−2.168)	(−1.364)	(−3.121)
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Constant	1.355***	1.961***	1.974***	2.130***
	(3.283)	(4.898)	(4.224)	(5.893)
N	5031	4920	5220	4731
r2_within	0.377	0.229	0.355	0.248

have poor financial performance or are small in scale, and the implementation of the project restricts their cash flows available for engaging in ESG activities, thereby significantly suppressing corporate ESG performance.

4.5.6. Management ownership ratio

Management ownership can alleviate agency problems and mitigate conflicts of interest between managers and the company, which may reduce the extent of corporate tax avoidance. However, management ownership also implies that executives possess residual claim rights to corporate capital, aligning their tax avoidance tendencies with those of shareholders and thereby enhancing the company's ability and willingness to engage in tax planning. We divide the sample into two groups based on the industry annual median of the management ownership ratio. The results, shown in Columns (1) and (2) of Table 12, indicate that in the high management shareholding ratio group, Golden Tax Project III has a significant negative effect on corporate ESG performance. Conversely, in the group with a low management ownership ratio, the effect of the project is not significant.

As mentioned earlier, on the one hand, companies in the high management shareholding ratio group may undergo a greater degree of tax avoidance, making them more susceptible to the regulatory effects of Golden Tax Project III. On the other hand, even within the low shareholding ratio group, managers' inclination toward tax avoidance may be stronger, but it is often conducted for personal gain rather than improving corporate ESG. After the implementation of the project, although the project suppresses managers' tax avoidance tendencies, it also increases transparency and limits managerial pursuit of personal interests. This may be why it does not have a significant impact on corporate ESG in the low shareholding ratio group.

4.5.7. Political connections

Political connections enable enterprises to obtain resources controlled by the government, such as tax incentives and government subsidies, providing direct financial support to companies. Additionally, political connections can reduce information asymmetry, assisting companies in obtaining loans and investments, thus alleviating their financing constraints. Finally, political connections can help companies quickly acquire information about government policy regarding taxation, environmental protection and other issues, enabling them to make response plans earlier (Yu et al., 2012; Li et al., 2016; Tian and Fan, 2018). Therefore, in enterprises with political connections, the impact of Golden Tax Project III on corporate ESG can be expected to be less significant than in those without such connections.

Following Zhang et al. (2013), if the chairman or CEO of a company has served, either currently or in the past, in central or local governments, courts or procuratorates, or held a position as a representative of the National People's Congress or member of the Chinese People's Political Consultative Conference, then the company is considered politically connected and takes a value of 1; otherwise, it takes a value of 0. The regression results in Columns (3) and (4) of Table 12 show that in politically connected groups, the ESG perfor-

Table 12
Firm-level heterogeneity analysis.

	(1)	(2)	(3)	(4)
	High management ownership ratio *ESG*	Low management ownership ratio *ESG*	With political connections *ESG*	Without political connections *ESG*
Treat	−0.035***	−0.011	−0.006	−0.030**
	(−2.951)	(−0.978)	(−0.461)	(−2.568)
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Constant	1.743***	1.186***	1.373**	1.783***
	(4.290)	(3.559)	(2.495)	(4.954)
N	5457	4494	3535	6416
r2_within	0.268	0.341	0.263	0.302

mance is not significantly affected by Golden Tax Project III, whereas in the group without political connections, the project significantly reduces corporate ESG performance. The reason for this is that companies without political connections have higher levels of financing constraints, and the implementation of the project exacerbates their already tight cash flow, leading to poorer ESG performance.

4.6. Further analysis

4.6.1. The impact of Golden Tax Project III on different dimensions of ESG

The previous analysis verifies the impact of Golden Tax Project III on companies' overall ESG performance. However, the effects may differ across the dimensions of Environment (*E*), Social (*S*) and Governance (*G*). As presented in Panel a of Table 13, the results indicate that the project has a negative and significant influence on *E*, while the impacts on the *S* and *G* dimensions, although also negative, are not statistically significant. This suggests that the influence of the project on corporate ESG is mainly reflected in environmentally responsible behaviors, with minimal impact observed on governance and social dimensions. This may be because fulfilling environmental responsibilities requires substantial investment in updating production equipment and green facilities, so that the project results in a greater negative impact on the environmental dimension. Conversely, corporate social performance and corporate governance are related to various factors such as long-established company culture and internal systems, which are influenced by a multitude of factors, not just economic pressure. Hence, the impact of the project on the social and governance dimension is nonsignificant.

To further explore whether the taxation effect of Golden Tax Project III differs across the ESG dimensions, we incorporate corporate tax avoidance (*RATE_diff*) and participation in the project (*Treat*) into a single model, along with their interaction term (*RATE_diff*Treat*). As shown in Panel b of Table 13, in the *E* and *S* dimensions, the interaction term is positive and significant, while it is not significant in the *G* dimension. This indicates that the taxation effect primarily affects the environmental and social responsibility dimensions. The project strengthens tax enforcement and reduces the cash flow available for environmental protection and social responsibility investments, leading to direct negative impacts on environmental and social performance. However, corporate governance is associated with long-established company culture and internal systems, which are not solely caused by cash pressures. Starks (2023) finds that due to differences in motivations for ESG (value or values), there are distinct differences in managers' attitude toward the E and S aspects compared with the G aspect. This is consistent with the significant differences in the impact of the project on the *E*, *S* and *G* dimensions.

The results of examining the governance effect across different dimensions are presented in Panel c of Table 13. First, we use *Mfee* as an indicator of corporate governance. In Column (1), the coefficient of the interaction term (*Mfee*Treat*) is negative and significant in the *E* and *G* dimensions, which suggests that the higher a company's agency costs, the poorer its ESG performance. Golden Tax Project III has effectively curbed managerial self-serving behaviors, leading to a significant decrease in management expense ratios. Simultaneously, executives, motivated by reputational concerns, redirect funds previously used for themselves toward ESG, thereby enhancing corporate ESG performance. Nevertheless, in terms of CSR, activities such as donations could serve as channels for managers to pursue self-interest and engage in opportunistic behavior when there is separation of ownership and control. For instance, managers may use donation activities to increase their compensation levels, burnish their personal social reputation or directly exploit economic rents (Zhai and Gu, 2014). Therefore, while the project reduces agency costs and potentially decreases corporate donations, it might concurrently stimulate the fulfillment of other CSR activities, thus resulting in a nonsignificant impact on the social responsibility dimension. Second, we use corporate transparency (*Trans*) to measure the quality of corporate governance. The results in Column (2) show that the coefficient of the interaction term (*Trans*Treat*) is positive across all three dimensions. The implementation of the project increases corporate transparency, compelling companies to enhance their ESG investments in all three dimensions to meet societal demands, thus improving overall ESG performance. In summary, for the governance effect, the impact of Golden Tax Project III on corporate ESG appears to be relatively consistent across dimensions.

Summing up the above results, it can be concluded that the impact of the project on the *E* dimension is negative and significant, while its effects on the *S* and *G* dimensions, although negative, are not significant.

Table 13
The differences in the impact on different dimensions of ESG.

Panel a:The differences in the impact of "Golden Tax Project III" on the three dimensions of corporate ESG

	(1) *E*	(2) *S*	(3) *G*
Treat	−0.043**	−0.017	−0.002
	(−2.104)	(−1.488)	(−0.824)
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Constant	0.303	1.218***	3.953***
	(0.427)	(3.352)	(43.237)
N	8438	9716	9951
r2_within	0.166	0.181	0.227

Panel b:The differences of "taxation effect" on the three dimensions of corporate ESG

	(1) *E*	(2) *S*	(3) *G*
Treat	−0.041*	−0.017	−0.002
	(−1.776)	(−1.275)	(−0.698)
RATE_diff	−0.138*	−0.062	0.019
	(−1.729)	(−1.282)	(1.434)
*RATE_diff*Treat*	0.027***	0.018***	−0.001
	(2.766)	(3.143)	(−0.869)
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Constant	0.223	1.022**	3.876***
	(0.290)	(2.292)	(36.545)
N	7359	8398	8607
r2_within	0.175	0.181	0.229

Panel c:The differences of "governance effect" on the three dimensions of corporate ESG

	(1) *E*	(2) *S*	(3) *G*	(4) *E*	(5) *S*	(6) *G*
Treat	−0.040*	−0.018	−0.002	−0.034	−0.014	−0.002
	(−1.952)	(−1.521)	(−0.677)	(−1.627)	(−1.223)	(−0.515)
Mfee	0.349**	−0.114	0.016			
	(2.115)	(−1.006)	(0.601)			
*Mfee*Treat*	−0.036***	0.001	−0.003*			
	(−3.749)	(0.228)	(−1.870)			
Trans				−0.143***	−0.025	−0.018**
				(−2.679)	(−0.770)	(−2.052)
*Trans*Treat*				0.078***	0.020***	0.007***
				(8.266)	(3.641)	(4.474)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.264	1.259***	3.951***	0.963	1.394***	4.004***
	(0.393)	(3.226)	(41.865)	(1.436)	(3.557)	(42.320)
N	8438	9716	9951	8438	9716	9951
r2_within	0.167	0.181	0.227	0.175	0.183	0.229

Further distinguishing between taxation and governance effects across the three dimensions, it is found that the taxation effect primarily influences the *E* and *S* dimensions. Meanwhile, the governance effect exists across all three dimensions. It can be inferred that due to the simultaneous presence of both effects, the differences in the impact of the project on the *E*, *S* and *G* dimensions are mainly influenced by the taxation effect. It is precisely due to the dominance of the taxation effect that the project overall suppresses corporate ESG performance.

4.6.2. Impact of Golden Tax Project III on the corporate tax burden

Referencing Li and Zhu (2022), we measure the overall tax burden of enterprises (*Tax_all*) as the ratio of total corporate taxes to total profits. The results, as shown in Table 14, indicate that the coefficient of *Treat* is positive, suggesting that the implementation of Golden Tax Project III increases the corporate tax burden. This further validates this study's taxation hypothesis.

4.6.3. Impact of Golden Tax Project III on financing constraints

Cai et al. (2021a, 2021b) find that Golden Tax Project III suppresses tax avoidance-based financing, thus exerting the taxation effect. However, it can also alleviate information asymmetry through the "bridge effect" and suppress management agency costs through the governance effect, thus promoting external financing. This implies that the impact of the project on corporate financing operates in opposing directions simultaneously, thus preventing a clear prediction. Therefore, we conduct tests of the impact of the project on corporate financing capabilities.

We construct a financing constraint (*FC*) index to measure the degree of corporate financing constraints, referring to Fee et al. (2009), Zhang et al. (2017) and Chen and Zheng (2020). The larger the *FC* index, the stronger the financing constraints faced by a company. The *FC* index is constructed as follows. First, we sort the listed companies in ascending order based on company size, age and cash dividend payout ratio, and then use the upper and lower tertiles as the boundary points for financing constraints. Companies above the 66th percentile are defined as the low financing constraint group, denoted as $FC = 0$, while companies below the 33rd percentile are defined as the high financing constraint group, denoted as $FC = 1$. Second, we conduct logit regression on Model (4) to obtain the *FC* index for each company in each year. In Model (4), *Size* is calculated as the natural logarithm of total assets; *Lev* is the asset–liability ratio, calculated as total liabilities divided by total assets; *CashDiv* is the cash dividends distributed by a company in the current year; *MB* is the market-to-book ratio of a company, calculated as market value divided by book value; *NWC* is the net working capital, calculated as operating working capital minus cash and short-term investments; *EBIT* is the earnings before interest and taxes; and *TA* represents total assets.

We further measure companies' debt financing cost (*DFC*) using the ratio of financial expenses to total liabilities and regress it as the dependent variable. The regression results are shown in Columns (1) and (2) of Table 15. The regression coefficients of *Treat* with the *FC* index and *DFC* are both nonsignificant. This indicates that Golden Tax Project III may either exacerbate or reduce companies' financing constraints. Although

Table 14
Impact of "Golden Tax Project III" on corporate tax burden.

	(1) *Tax_all*
Treat	0.071**
	(2.463)
Controls	Yes
Year	Yes
Ind	Yes
Firm	Yes
Constant	2.034*
	(1.920)
N	9951
r2_within	0.197

the effect cannot be statistically supported, it suggests that the impact on financing constraints and debt financing costs is not significant.

$$P(FC = 1or0|Z_{i,t}) = \frac{e^{Z_{i,t}}}{1+e^{Z_{i,t}}} \ where : \\ Z_{i,t} = \alpha_0 + \alpha_1 \text{ Size }_{i,t} + \alpha_2 Lev_{i,t} + \alpha_3\left(\frac{\text{CashDiv}}{\text{TA}}\right)_{i,t} + \alpha_4 MB_{i,t} + \alpha_5\left(\frac{NWC}{\text{TA}}\right)_{i,t} + \alpha_6\left(\frac{EBIT}{\text{TA}}\right)_{i,t} \tag{4}$$

Research generally finds a negative correlation between corporate tax avoidance and debt financing. The "cash flow effect" theory suggests that a decrease in corporate tax avoidance activities will lead to an increase in external financing to compensate for the decrease in tax cash flows (Dyreng et al., 2008; Edwards et al., 2016; Liu et al., 2017). Therefore, given that Golden Tax Project III suppresses corporate tax avoidance activities, companies can be expected to supplement their cash flows through external financing. Referring to Cai et al. (2021a, 2021b), the ratio of accounts payable to total assets is used as a proxy variable for credit financing (*Credit*). The results are shown in Column (3) of Table 15. It is evident that the impact of the project on corporate credit financing (*Credit*) is not significant. A potential explanation is that the cash flow pressure brought by the project also poses liquidity challenges for supply chain enterprises. To ensure they can quickly collect payments within a certain period, they may be less inclined to extend necessary commercial credit to their business counterparts. Furthermore, following Liu et al. (2017), we examine the impact of the project on corporate loan financing (*Loan*). We measure the corporate loan financing condition (*Loan*) as the ratio of long-term liabilities to total assets. In Column (4) of Table 15, the regression coefficient of *Treat* is positive and significant. The underlying reason is that the project improves the quality of corporate information disclosure, which may reduce creditors' concerns about default, thereby enhancing the availability and level of corporate debt financing. This indicates that the project increases corporate loan financing to some extent.

Furthermore, Golden Tax Project III has been found to decrease the total factor productivity of enterprises (Li and Wang, 2022), hinder innovation in enterprises (Ji and Wang, 2019), lower the profitability of listed companies (Zhang et al., 2020) and increase audit fees for listed companies (Li and Wang, 2022), among other negative impacts. These findings indicate that the strengthening of tax administration by the project has a widespread negative impact on enterprises. As the pyramid of CSR theory suggests, enterprises should first fulfill their lower-level responsibilities before considering higher-level responsibilities (Carroll, 1991). Moreover, a company's sound future operational condition is a prerequisite for its ability to repay its debts. Thus, resources obtained from external debt financing should initially be directed toward production and operation to create value for shareholders, and only then should higher-level responsibilities such as ESG investments be considered. Consequently, the project has a more significant negative impact on enterprises' ESG investments than on their routine operations.

4.6.4. The impact of Golden Tax Project III on ESG greenwashing by companies

With reference to Hu et al. (2023) and Zhang (2023), we construct an ESG greenwashing indicator. Bloomberg ESG ratings are used to represent disclosed scores, while Huazheng ESG ratings represent actual perfor-

Table 15
Impact of "Golden Tax Project III" on financing constraints.

	(1)	(2)	(3)	(3)
	FC	*DFC*	*Credit*	*Loan*
Treat	0.006	−0.001	−0.001	0.008***
	(1.224)	(−1.253)	(−0.402)	(3.217)
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Constant	3.734***	−0.052**	−0.085	−0.431***
	(23.052)	(−2.151)	(−1.616)	(−4.472)
N	9673	9864	9951	9951
r2_within	0.485	0.246	0.183	0.246

mance scores. $ESG_{Disclosure\ i,t} - \overline{ESG_{Disclosure\ i,t}}$ and $ESG_{Rating\ i,t} - \overline{ESG_{Rating\ i,t}}$ represent a company's relative position in ESG disclosure or ESG performance, respectively, compared with peers, and are standardized. $\frac{ESG_{Ratingi,t} - \overline{ESG_{Ratingi,t}}}{\sigma ESG_{Ratingi,t}}$ is subtracted from $\frac{ESG_{Disclosurei,t} - \overline{ESG_{Disclosurei,t}}}{\sigma ESG_{Disclosurei,t}}$ to obtain the level of ESG greenwashing (GW). The regression results are shown in Table 16, where the coefficient of *Treat* is negative. This indicates that the implementation of Golden Tax Project III reduces ESG greenwashing in companies, partially supporting the viewpoint that the project has a significant governance effect.

$$Greenwashing_{i,t} = \left[\frac{ESG_{Disclosurei,t} - \overline{ESG_{Disclosurei,t}}}{\sigma ESG_{Disclosurei,t}}\right] - \left[\frac{ESG_{Ratingi,t} - \overline{ESG_{Ratingi,t}}}{\sigma ESG_{Ratingi,t}}\right] \tag{5}$$

4.6.5. The impact of Golden Tax Project III on ESG earnings management by companies

We divide the sample into two groups based on the implementation time of Golden Tax Project III: before and after implementation. We then explore the impact of corporate ESG earnings management motivations on ESG behavior during these two periods. Table 17 presents the results of the analysis.

The financing constraint (*absSA*) is the absolute value of the SA index (Ju and Lu, 2013), where a higher value indicates greater financing constraints. The regression results in Table 17 show that before the implementation of the project, the coefficient of *absSA* is positive and significant. This indicates that under greater financing constraints, companies are more likely to engage in ESG practices to access financing opportunities if the tax administration environment is relatively relaxed. This suggests that before the implementation of the project, there were indeed ESG earnings management behavior of enterprises, which would lead to an increase in ESG activities to enhance their corporate image and potentially gain financing opportunities.

However, after the implementation of the project, the coefficient of *absSA* is negative and significant. This means that under greater financing constraints, companies' ESG levels decrease. Although the pressure to engage in tax avoidance may increase at this time, ESG earnings management behavior is constrained, making it difficult to access financing by engaging in more ESG practices. Consequently, this ultimately reduces ESG performance. This also indirectly confirms the governance effect of Golden Tax Project III, which it exerts through improving information quality and reducing ESG earnings management behavior.

4.7. Economic consequences test

We use return on equity (*ROE*) to measure the financial performance of companies, use Tobin's Q to measure their market value and employ the LP and OP methods (Lu and Lian, 2012) to estimate total factor productivity (*TFP_LP* and *TFP_OP*). From Table 18, it is evident that Golden Tax Project III does indeed reduce company performance and market value, but its impact on total factor productivity is not significant. Furthermore, the results in Columns 2 and 4 of Table 18 show that higher levels of ESG are associated with higher company performance and market value. Therefore, the implementation of the policy reduces corporate ESG,

Table 16
Impact of "Golden Tax Project III" on "ESG greenwashing".

	(1) *GW*
Treat	−0.115***
	(−2.690)
Controls	Yes
Year	Yes
Ind	Yes
Firm	Yes
Constant	3.626***
	(2.820)
N	9874
r2_within	0.027

Table 17
Impact of "Golden Tax Project III" on ESG "earnings management".

	(1)	(2)
	Treat = 0 *ESG*	*Treat* = 1 *ESG*
absSA	0.174*	−0.498***
	(1.705)	(−7.836)
Controls	Yes	Yes
Year	Yes	Yes
Ind	Yes	Yes
Firm	Yes	Yes
Constant	2.140**	3.492***
	(2.107)	(8.011)
N	3803	6148
r2_within	0.194	0.227

subsequently decreasing company performance and market value. This indirectly indicates that the taxation effect of the project has a negative impact.

5 Conclusions and limitations.

The application of big data technology has enhanced tax administration and gradually become a crucial aspect of China's tax security and its enhanced tax governance capabilities. Against the background of insufficient ESG incentives for Chinese enterprises, the following question arises: does the implementation of Golden Tax Project III primarily exert a taxation effect, a governance effect or a combination of both effects on corporate ESG performance?

Using data from Chinese A-share listed companies from 2011 to 2020, we examine the impact of the project on ESG performance and its underlying mechanisms. The findings indicate that the project has reduced corporate ESG performance. Mechanism analysis reveals that the project exerts a taxation effect with a negative impact on corporate ESG performance, while also exerting a governance effect with a positive impact on corporate ESG performance. Overall, however, the project has decreased corporate ESG performance.

Heterogeneity analysis shows that the negative impact on ESG performance is more significant in companies in areas with lower tax collection pressure, weaker environmental regulations and faster marketization processes, and in companies with less media attention and analyst attention, higher management shareholding ratios and no political connections. According to further analysis, the inhibitory effect of the project on ESG performance is mainly reflected in the *E* element, and the project indeed increases the overall tax burden of enterprises, further validating the taxation effect. However, its impact on financing constraints is not pronounced and it curbs corporate greenwashing and ESG earnings management behaviors. The economic con-

Table 18
Economic consequences test.

	(1)	(2)	(3)	(4)	(5)	(6)
	ROE	*ROE*	*Tobin Q*	*Tobin Q*	*TFP_LP*	*TFP_OP*
Treat	−0.017***		−0.140***		−0.006	−0.014
	(−3.546)		(−2.740)		(−0.645)	(−1.285)
ESG		0.016***		0.309***		
		(2.929)		(5.081)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−1.002***	−1.017***	4.862***	4.429***	−4.866***	−2.784***
	(−5.827)	(−5.894)	(3.532)	(3.210)	(−12.737)	(−6.588)
N	9951	9951	9951	9951	9315	9315
r2_within	0.273	0.272	0.178	0.180	0.783	0.668

sequence test reveals that the restraining effect of the project on corporate ESG leads to declines in both financial performance and market value, which is detrimental to the production and expansion of enterprises.

The conclusions presented in this research provide actionable guidance for advancing the realization of both tax and fee reduction and the dual carbon goal. First, even under tax reduction and fee reduction policies, the tax burden on enterprises may not necessarily decrease, because of advancements in information regulatory technology. Therefore, the government needs to further deepen tax and fee reduction and improve fiscal and taxation policies to support enterprise development.

Second, relevant departments could actively provide support and guidance to enterprises in enhancing their ESG performance. The guidelines and standards for ESG disclosure could be actively improved to encourage enterprises to disclose ESG information in a standardized manner and proactively fulfill their ESG responsibilities, thereby attracting investors focused on sustainability. At the same time, measures should be taken to alleviate financing constraints faced by businesses, such as by increasing environmental subsidies and developing green finance, to compensate for potential income reductions resulting from improving ESG performance.

Third, considering the potential financial pressures and compression of profit resulting from enhanced tax administration, enterprises should consciously comply with tax regulations and other requirements to reduce the legal risks of tax evasion, as well as internal and external information asymmetry. This will help alleviate financing constraints and enhance the self-reliance and external financing capabilities of enterprises. Additionally, enterprises should actively leverage the governance effect of tax management to improve their ESG performance and sustainable development capabilities.

Declaration of competing interest

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

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Appendix.

Table A1

Industry Annual Characteristics of Corporate ESG Performance.

Code	N	Mean	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
A	141	2.915	2.749	2.896	2.809	2.811	2.894	2.894	2.969	3.007	3.023	3.026
B	437	3.098	2.934	2.996	3.003	3.049	3.078	3.078	3.155	3.192	3.217	3.22
C1	734	2.920	2.755	2.856	2.857	2.872	2.881	2.881	2.961	3.015	3.01	3.024
C2	1714	2.998	2.773	2.889	2.911	2.929	2.966	2.966	3.067	3.1	3.103	3.117
C3	3251	3.006	2.844	2.921	2.953	2.959	2.951	2.951	3.037	3.071	3.105	3.121
C4	115	2.932	2.647	2.928	2.914	2.917	2.934	2.934	2.961	3.019	3.014	3.006
D	492	3.044	2.858	2.916	2.976	2.99	3.032	3.032	3.081	3.125	3.154	3.166
E	315	3.038	2.775	2.936	2.964	3.035	3.014	3.014	3.088	3.166	3.113	3.188
F	590	2.932	2.799	2.875	2.861	2.878	2.927	2.927	2.962	2.98	3.017	3.036
G	454	3.094	2.953	2.971	2.997	3.035	3.074	3.074	3.156	3.169	3.2	3.198
H	27	2.908	2.554	2.804	2.804	2.74	2.875	2.875	2.983	3.036	3.052	3.052
I	583	2.826	2.732	2.768	2.774	2.788	2.793	2.793	2.81	2.843	2.896	2.924
K	550	2.922	2.773	2.844	2.881	2.879	2.926	2.926	2.962	2.97	2.999	3.009
L	121	2.843	2.732	2.952	2.852	2.844	2.83	2.83	2.818	2.854	2.853	2.891

Table A1 (*continued*)

Code	N	Mean	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
M	43	2.851	2.941	2.643	2.628	2.527	2.773	2.773	2.842	2.906	2.934	3.001
N	73	3.042	2.92	2.871	2.934	3.066	3.018	3.018	3.177	3.137	3.112	3.06
O	2	2.621	2.621	0	0	0	0	0	0	0	0	0
Q	39	2.919	2.877	2.754	2.738	2.766	2.705	2.705	2.972	2.938	3.036	3.116
R	176	2.759	2.534	2.639	2.636	2.638	2.75	2.75	2.835	2.82	2.839	2.849
S	94	2.846	2.795	2.754	2.766	2.818	2.859	2.859	2.923	2.958	2.903	2.844
Total	9951	2.979	2.811	2.895	2.913	2.93	2.944	2.944	3.017	3.049	3.071	3.087

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Is audit materiality informative? Evidence from China

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ABSTRACT

To improve the usefulness of audit opinions, on 23 March 2021, the China Securities Regulatory Commission mandated that auditors disclose overall quantitative materiality of consolidated financial statements in special explanations of modified audit opinions. This paper selects Chinese A-share companies issued with modified audit opinions for the period of 2020–2022 as the research sample and analyzes the assessment of materiality in audit practice and the informativeness of audit materiality. Our findings are as follows. (1) The most commonly used bases for materiality by auditors are profit and income, with considerable differences in the percentages applied to the different bases and variations even within the same base. (2) The higher the materiality amount, the poorer the audit quality. This negative correlation is mainly observed in scenarios where the audited companies engage in downward earnings management and where the competency of audit firms or auditors is relatively low. (3) Companies that disclose quantitative materiality in the special explanations of modified audit opinions have a lower earnings response coefficient than companies that do not disclose audit materiality. This research sheds light on the "black box" of the audit process and verifies the information value of audit materiality. The conclusions are of significant value to auditing standard-setters, investors and regulators.

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Contents

1. Introduction . . . 2
2. Institutional background and literature review . . . 3
   2.1. Materiality-related auditing standards . . . 3
   2.2. Institutional background of materiality disclosure . . . 4
   2.3. Empirical research on audit materiality . . . 5
3. Research design and hypothesis development . . . 5
   3.1. Descriptive statistics of audit materiality . . . 6
   3.2. Relationship between materiality and audit quality. . . . 6
   3.3. The impact of materiality disclosure on investors' decision-making . . . 7
   3.4. Sample selection and data sources . . . 8
4. Empirical results and discussion . . . 9
   4.1. Descriptive statistics of audit materiality . . . 9
   4.2. Relationship between materiality and audit quality. . . . 12
   4.3. Impact of materiality disclosure on investor decision-making . . . 15
5. Conclusions and implications . . . 17
   Declaration of competing interest . . . 17
   Acknowledgements . . . 17
   References. . . . 17

1. Introduction

Materiality is the magnitude of the impact of audit errors on the audit client's decision making, which is one of the fundamental concepts of auditing and is utilized throughout the audit process (Christensen et al., 2020). In planning and performing an audit, an auditor is required to make judgments about materiality to provide a basis for assessing the risks of material misstatement and preparing for further audit procedures. They must also apply materiality when evaluating the impacts of identified audit misstatements and uncorrected misstatements on financial statements. Therefore, materiality directly determines the quality of the audit. However, due to data limitations, how auditors in China establish materiality has remained a "black box."

On 9 March 2021, the China Securities Regulatory Commission (CSRC) issued its "Guidelines for the Application of Supervisory Rules—Audit Category No. 1," explicitly mandating that "an auditor should disclose the overall quantitative materiality of consolidated financial statements in special explanations of modified audit opinions, including materiality bases and percentages, calculation results (the amount) and the basis for selection." This guideline took effect on 23 March 2021, following which auditors began to disclose the overall materiality of consolidated financial statements in special explanations of modified audit opinions.[1]

This regulatory policy provides an opportunity to enhance understanding of the selection of materiality bases and percentages in audit practice. We select Chinese A-share companies issued with modified audit opinions for the period of 2020–2022 as our research sample and examine three issues. First, we provide descriptive evidence on the disclosure of audit materiality as well as the selection of bases and percentages. Second, we explore the relationship between audit materiality and audit quality. Third, we examine whether the disclosure of quantitative materiality affects investor decision-making. By collating the disclosures of quantitative materiality, we find that the Big 10 audit firms are more likely to disclose audit materiality than other audit firms. In addition, profit and income are the bases most used by auditors and there is a certain connection between the percentage and the base, although, for the same base, the percentage chosen by auditors varies. Furthermore,

[1] For example, BDO Lixin Audit Firm mentions in its "Special Explanation on Modified Audit Opinion for Innovative Medical Management Co., Ltd.'s 2022 Financial Statements" that: "The materiality related to the 2022 consolidated financial statements used in our audit is as follows: the selected base is income, the percentage used is 1%, and the basis for selection is that the company is a listed company mainly aimed at making a profit, with profitability being the financial indicator most concerned by investors. However, due to the pre-tax loss and significant fluctuations this period, 1% of operating income was used as the materiality, resulting in a calculation of RMB 7.097 million.".

the empirical results show that materiality is informative, with lower materiality indicating higher audit quality, especially in the case of companies with negative earnings management, companies audited by non-Big 10 audit firms and companies audited by auditors without industry expertise. In addition, companies that disclose audit materiality have a lower earnings response coefficient than companies that do not disclose materiality.

The key contributions of this paper are as follows. First, based on Chinese audit materiality data, this paper opens the "black box" of audit materiality in China to some extent by revealing the bases and percentages selected for materiality in audit practice. Previous studies infer audit materiality from the critical values for identifying major deficiencies in internal controls (Zheng and Xu, 2020; Zhou et al., 2021) or accounting firms' internal audit guidelines (Blokdijk et al., 2003; Wang and Xu, 2009; Eilifsen and Messier, 2015). Although this approach is reasonable, it is subject to certain measurement errors. The few studies based on direct and observable materiality data tend to be empirical studies of developed countries, such as the UK and the US (Choudhary et al., 2019; Wang and Liu, 2019). This paper describes the bases and percentages of materiality actually used by Chinese auditors based on the latest data disclosed in special explanations of modified audit opinions.

Second, this study contributes to elucidating the global issue of whether to disclose materiality in audit reports. Currently, only the UK and the Netherlands require the disclosure of materiality in audit reports, whereas the International Auditing and Assurance Standards Board (IAASB) and the US's Public Company Accounting Oversight Board (PCAOB) do not yet require the disclosure of materiality in audit reports. China's aim is for its audit standards to converge continuously and comprehensively with international audit standards. Before March 2021, there was no requirement to disclose the level of audit materiality in China. In deciding to mandate the disclosure of materiality in special explanations of modified audit opinions, the CSRC combined securities markets' audit practices and drew on international best practices for audits. Our research shows that companies that disclose materiality in special explanations of modified audit opinions have a lower earnings response coefficient (ERC) than other companies, indicating that the disclosure of audit materiality has a significant impact on the informativeness of earnings and investor decision-making.

Third, this paper verifies the relationship between materiality and audit quality, expanding empirical research on the audit process. DeFond and Zhang (2014) encourage researchers to find creative research scenarios and designs for empirical research on the audit process, especially regarding audit risk assessment and the determinants of audit procedures. Materiality is applicable throughout the audit process and is the basis for determining risk assessment and audit procedures. Therefore, this study enriches empirical research on the audit process from the perspective of audit materiality. Lastly, the findings of this paper are of value to investors, analysts and regulators. This study finds that higher audit materiality indicates lower audit quality. Investors, analysts and regulators can use materiality to judge audit quality, thereby making targeted investments, analyses or regulations.

The remainder of this paper is organized as follows. Part 2 describes the institutional background and reviews the literature; Part 3 explains the research questions and research design; Part 4 presents the empirical analysis and results; and Part 5 provides conclusions and implications.

2. Institutional background and literature review

2.1. Materiality-related auditing standards

China's auditing standards relating to materiality are shown in Table 1. They include Standards No. 1221 (Materiality in Planning and Performing the Audit) and No. 1251 (Evaluating Misstatements Identified during the Audit). The former stipulates the determinant, execution, modification and documentation of materiality during the audit planning and execution phases, whereas the latter focuses on the application of the concept of materiality when evaluating the effect of identified misstatements on the audit and the effect of uncorrected misstatements on financial statements. In addition, there are various application guides relating to these standards as shown in Table 1 that provide detailed guidance for Chinese certified public accountants (CPAs) on applying the relevant audit standards. These guides and questions and answers provide detailed guidance for CPAs to apply the relevant audit standards in establishing materiality, evaluating the impact of uncorrected

Table 1
Materiality-related auditing standards, application guidance and Q&A.

Auditing standards	Auditing Standards for Chinese Certified Public Accountants No. 1221—Materiality in Planning and Performing an Audit
	Auditing Standards for Chinese Certified Public Accountants No. 1251—Evaluating Misstatements Identified during the Audit
Application guidance	Application Guidance on Auditing Standard No. 1221
	Application Guidance on Auditing Standard No. 1251
Q&A	Chinese Certified Public Accountants Auditing Standards Questions and Answers No. 8— Materiality and Evaluation of Misstatements
	Chinese Certified Public Accountants Auditing Standards Questions and Answers No. 16— Qualified Opinions in Audit Reports

misstatements on financial statements and issuing modified opinions. According to the provisions of the Chinese Institute of CPAs, auditors should master and implement audit standards, application guidelines and question answering when performing audit services.

Establishing materiality requires auditors to use their professional judgment. Generally, auditors first select a base and then multiply it by a certain percentage to determine the overall materiality for financial statements. The Chinese Auditing Standard No. 1221 "Materiality in Planning and Performing an Audit" and its Application Guide outline the factors that CPAs need to consider when choosing a base and the relationship between the percentage and the base. The Answers to Questions on Auditing Standard No. 8 "Materiality and Evaluation of Misstatements" provides some examples commonly used in practice for selecting materiality bases and percentages. However, it also emphasizes that the bases and percentages contained in the Answers to Questions are illustrative rather than prescriptive, and that auditors need to make appropriate choices and adjustments based on the specific circumstances of the audited entity and the audit engagement. Overall, Chinese auditing standards are qualitative in nature with respect to materiality and the assessment of materiality is based mainly on the auditor's professional judgment. Therefore, to understand the materiality assessments in audit practice, it is necessary to systematically collate and analyze materiality based on the consolidated financial statements disclosed in special explanations of modified audit opinions.

2.2. Institutional background of materiality disclosure

In recent years, there has been a heated debate among regulators around the world about whether materiality should be disclosed in audit reports. Proponents state that disclosure of materiality can assist investors' decision-making, whereas opponents argue that materiality disclosure may lead auditors to disclose quantitative materiality while ignoring qualitative descriptions of materiality (PCAOB, 2017), and that materiality disclosures are not comparable, resulting in inconsistent communications. In addition, they argue that because there are three materiality criteria—overall financial statement materiality, actual implementation materiality and thresholds for apparently minor misstatements—it is difficult to determine which materiality to disclose (PCAOB, 2011). Although the UK and the Netherlands require materiality disclosure in audit reports (FRC, 2013; NBA, 2014), neither the IAASB nor the PCAOB currently require materiality disclosure in audit reports (IAASB, 2015a, 2015b; PCAOB, 2017). Because China aims to aligns its auditing standards with the international auditing standards, before 2021, there was no requirement to disclose audit materiality in audit reports in China.

However, to standardize the issuance of appropriate audit opinions on financial statements by auditors and to further enhance the usefulness of audit opinions, in 2021, the CSRC issued Audit Category No. 1, which clearly requires the auditor to disclose the overall materiality of the consolidated financial statements in a special note on modified audit opinions, including the basis and percentage of materiality, the calculation results and the basis of selection. If there is a change in materiality between the current and previous periods, the reasons for the change must be disclosed. The guideline has been effective from 23 March 2021; as noted above, it was adopted by China in line with closely integrating audit market practices with the best practice of international audit markets. Two questions remain unanswered following the introduction of this policy. First, do China's listed companies disclose audit materiality as required? Second, what are the economic consequences of materiality disclosure?

2.3. Empirical research on audit materiality

Materiality is one of the basic concepts of auditing and related studies are relatively abundant. However, due to a lack of observable data, the empirical research on audit materiality is limited. Some researchers measure audit materiality using critical values for the criteria for identifying significant deficiencies in internal control to explore the determinants of the materiality (Zheng and Xu, 2020) and the consequences (Zhou et al., 2021). By obtaining data from accounting firms' audit manuals or guides through questionnaires, some studies introduce the assessment of materiality (Eilifsen and Messier, 2015) and examine the determinants of materiality (Blokdijk et al., 2003) or the relationship between materiality and audit opinions (Wang and Xu, 2009). Based on the PCAOB's proprietary data, Choudhary et al. (2019) provide a brief introduction to the determinants of audit materiality and explore the relationship between materiality and financial statement reliability. Wang and Liu (2019) analyze the bases and percentages of the overall materiality of financial statements based on audit reports in the UK. In addition, scholars use experimental studies to examine the impact of audit materiality disclosure on the investment decisions of professional and non-professional investors (Christensen et al., 2020; Eilifsen et al., 2021; Zhang et al., 2021a, 2021b; Zhang et al., 2023) and the impact of materiality assessment methodologies on auditors' decision-making (Nelson et al., 2005).

In summary, although some progress has been made in empirical research on audit materiality, due to data limitations, most studies measure materiality in an indirect manner.[2] A small number of studies conduct research based on direct materiality data, but these studies present empirical evidence from developed countries. Furthermore, there are no archival studies focusing on the economic consequences of materiality disclosures. This gap in the literature provides research opportunities that we aim to address in this study. Based on the materiality data of consolidated financial statements disclosed in the special notes on modified audit opinions since 2021, we reveal the assessment of materiality in China's auditing practice and explore the relationship between materiality and audit quality, as well as the impact of materiality disclosure on the informativeness of earnings and investors' decision-making. In doing so, we address the abovementioned research gaps.

3. Research design and hypothesis development

With the implementation of the CSRC's Audit Category No. 1, CPAs began to disclose the materiality of the consolidated financial statements in special notes on modified audit opinions. For example, PAN-CHINA disclosed in its "Special Note on the Modified Audit Opinion on the 2022 Financial Statements of Zhejiang Furun Company"[3] that "in performing the audit of the 2022 financial statements of Zhejiang Furun Company, we set the materiality amount of the consolidated financial statements at RMB 24.65 million. Zhejiang Furun is a profit-oriented enterprise and the auditors took the absolute value of its profit before tax from recurring operations of RMB 492.93 million (the absolute value of profit before tax excluding non-recurring gains and losses) as the base and multiplied it by 5 %, thus calculating the total materiality amount of the consolidated financial statements as RMB 24.65 million." This method of calculating materiality for the current period is consistent with that of the previous period. In another example, in its Special Note on Modified Audit Opinion of Innovative Medical Management Corporation,[4] BDO explains the overall materiality of the 2022 consolidated financial statements used in its audit as follows: "the materiality base is operating revenue and the percentage applied to this base is 1 %. The main purpose of a listed company is to make a profit and profitability is the financial indicator that investors are most interested in. However, the pre-tax

[2] The literature measures materiality by extrapolating from accounting firms' internal audit manuals or the criteria for identifying significant deficiencies in internal control, rather than determining the level of materiality used by auditors in practice.

[3] http://static.cninfo.com.cn/finalpage/2023–04-28/1216661080.PDF.

[4] http://static.cninfo.com.cn/finalpage/2023–04-28/1216660089.PDF.

profit for the period was loss-making and fluctuated widely. Therefore, 1 % of operating income was used as the materiality for the period and the calculation result was RMB 0.71 million."

Based on the materiality data disclosed in the special note on modified audit opinions, this paper mainly addresses the following three research questions (RQs): RQ1: what are the appropriate descriptive statistics for audit materiality?; RQ2: what is the relationship between materiality and audit quality?; and RQ3: what is the impact of materiality disclosure on investor decision-making? RQ1 involves basic descriptive analysis of the data, RQ2 examines the degree of informativeness embodied in materiality and RQ3 tests the economic consequences of disclosing this information about materiality.

3.1. Descriptive statistics of audit materiality

A systematic overview of materiality helps to understand the auditor's professional judgment on materiality in audit practice. Although the "Guidance on Application of Regulatory Rules—Audit Category No. 1" requires the disclosure of the overall materiality of the financial statements in special explanatory notes to modified audit opinions, not all auditors comply with this requirement in practice. Therefore, we first provide descriptive statistics on materiality by year and by audit firms, before proceeding to analyze the bases selected by auditors and the percentages applied to these bases.

3.2. Relationship between materiality and audit quality

Materiality is a critical piece of information in an audit and the CSRC's issuance of "Audit Category No. 1" aims to further enhance the usefulness of audit opinions. This raises the following questions: what information does materiality encompass? What is the relationship between audit materiality and audit quality?

According to "Chinese Auditing Standard No. 1221—Materiality in Planning and Performing an Audit," materiality refers to misstatements (including omissions) that, whether individually or cumulatively, are expected to influence the economic decisions of financial statement users. In planning and performing an audit, the auditor is required to make subjective judgments about materiality, which provides a basis for assessing the risks of material misstatement and determining further audit procedures. A higher level of materiality implies a higher threshold for acceptable misstatements or omissions by the auditor, resulting in a smaller scope of risk assessment procedures and further audit procedures (Choudhary et al., 2019; Christensen et al., 2020), which may ultimately lead to lower audit quality. Therefore, from the perspective of audit inputs, there is a negative correlation between materiality and audit quality. Conversely, however, materiality could be positively correlated with audit quality because a higher level of materiality means that auditors can focus on analyzing, testing and addressing the most significant risks of the audited entity rather than covering everything, which could help to improve audit quality.

In addition, the choice of materiality is endogenous. "Chinese Certified Public Accountants Auditing Standards Question and Answer No. 8—Materiality and Evaluation of Misstatements" states that auditors should consider materiality from the perspective of financial statement users, taking into account factors such as the nature of the audited entity, its life-cycle stage, industry and economic environment. Auditors should use appropriate bases such as assets, liabilities, equity, revenue, profit or expenses, or items of particular interest to users of the financial statements. The relationship between the percentage and the chosen base is somewhat interdependent; regardless of whether the percentage is higher or lower, as long as it fits the specific situation, it can be appropriate. Therefore, the choice of materiality depends on the auditor's subjective judgment after a comprehensive consideration of the audited entity's situation and the needs of financial statement users. According to the risk-oriented audit standard, for audited entities with high audit risk, auditors usually choose a lower level of materiality to reduce the audit risk to an acceptable level. For example, auditors usually select a lower level of materiality for new clients, whereas for more familiar, long-term clients, they tend to choose a more lenient materiality percentage. Therefore, there may not be any relationship between audit materiality and audit quality. Based on this, we propose the following hypothesis:

H1: Materiality is not significantly related to audit quality.

To test H1, we construct model (1) as follows:

Table 2
Variable Definitions.

Variable	Definition
absDA	The absolute value of the residual calculated by the modified Jones model (Dechow et al., 1995).
Materiality	Materiality amount divided by total assets.
Size	The natural logarithm of total assets at year end.
Lev	Total liabilities divided by total assets.
Lop	Takes a value of 1 if the previous year's audit opinion is a qualified audit opinion, and 0 otherwise.
SOE	Takes a value of 1 for state-owned enterprises, and 0 otherwise.
Age	The natural logarithm of the number of years the company has been listed.
Big10	Takes a value of 1 if the audit firm is in the top 10 of the Annual Comprehensive Evaluation of 100 Accounting Firms Ranking Information issued by the China Annotations Association, and 0 otherwise.
ROA	Operating profit divided by total assets.
Loss	Takes a value of 1 if the net profit of the company in the current year is less than 0, and 0 otherwise.
ST	Takes a value of 1 if the listed company is issued a risk warning by the stock exchange in the current year, and 0 otherwise.

$$\begin{aligned} absDA_{i,t} = {} & \beta_0 + \beta_1 Materiality_{i,t} + \beta_2 Size_{i,t} + \beta_3 Lev_{i,t} + \beta_4 Lop_{i,t} + \beta_5 SOE_{i,t} \\ & + \beta_6 Age_{i,t} + \beta_7 Big10_{i,t} + \beta_8 ROA_{i,t} + \beta_9 Loss_{i,t} + \beta_{10} ST_{i,t} + Year + Industry + \varepsilon \end{aligned} \tag{1}$$

where the dependent variable (*absDA*) is the absolute value of discretionary accruals, calculated as the absolute value of the residuals from the modified Jones model (Dechow et al., 1995).[5] Our independent variable, *Materiality*, is defined as the overall materiality amount of financial statements divided by total assets.[6] Following the literature, we include some common control variables. According to Dechow et al. (2010), the financial characteristics of the firm (such as operating performance, leverage and size) affect the quality of earnings. In addition, the earnings management level of listed companies in China is influenced by the age of listing (Chen et al., 2001) and the type of ownership (Chan et al., 2006; Wang et al., 2008). Therefore, we control for company size (*Size*), the debt-to-asset ratio (*Lev*), state-owned enterprise status (*SOE*), years listed (*Age*), profitability (*ROA*), whether the company is operating at a loss (*Loss*) and whether it is subject to a risk warning from the stock exchange (*ST*), following the literature (Chen et al., 2001; Chan et al., 2006; Wang et al., 2008; Choi et al., 2012; Gul et al., 2013). We also control for auditor-related characteristics, including the size of the audit firm (*Big10*) and the audit opinion in the previous period (*Lop*) (Gong et al., 2016). The specific definitions are shown in Table 2. In addition, we control for industry and year fixed effects and cluster standard errors at the company level. If materiality is not related to audit quality, $\beta 1$ should be statistically nonsignificant, which would indicate that H1 is valid.

3.3. The impact of materiality disclosure on investors' decision-making

Whether the disclosure of materiality can improve the usefulness of audit opinion and thus investor decision-making is an important question, worthy of study.

The auditor's overall objective in performing financial statement audit work is to express an opinion on whether the financial statements are prepared, in all material respects, in accordance with the applicable financial reporting framework and to provide reasonable assurance that the financial statements are free from material misstatement, whether due to fraud or error. The definitions of "material misstatement" and "material respects" reflect the auditor's professional judgment and represent the "accuracy" of the audit. Rational investors can use audit materiality to understand the scope of audit risk assessment procedures and the threshold for the impact of uncorrected misstatements on the financial statements to assess audit quality and financial reporting quality (Christensen et al., 2020). Therefore, disclosure of audit materiality enhances the informative value of the audit opinion and should assist investors in their decision-making.

[5] Our sample consists of listed companies that have been issued a modified audit opinion by their auditors and we focus on the period of 2020–2022. Because it takes time to issue financial restatements, it is not feasible to measure audit quality by either audit opinions or financial restatements in this paper.

[6] Materiality is calculated by multiplying the base by a percentage.

Nevertheless, auditors' materiality assessment depends on their professional judgment and is influenced by their understanding of the needs of financial statement users. According to "The Chinese Certified Public Accountants Auditing Standard No. 1221," it is reasonable for auditors to make the following assumptions about financial statement users: (1) They have appropriate knowledge of business, economic activities and accounting and are willing to carefully study the information in financial statements; (2) They understand that financial statements are prepared, presented and audited on the basis of materiality; (3) They recognize that accounting measurements have inherent uncertainties based on the application of estimates and judgments as well as the consideration of future events; and (4) They make reasonable economic decisions based on the information in financial statements. However, in the Chinese capital market, there are many retail investors, most of whom lack professional knowledge (Liu and Liu, 2014) and are irrational in their behavior (Wang and Sun, 2004; Lin and Yu, 2010; Hu and Chi, 2013). Therefore, investors may not be able to understand the concept of audit materiality and the relationship between materiality and audit quality. Only after the disclosure of audit materiality in special explanatory notes to modified audit opinions may such investors realize fully that the audit opinion provides a reasonable assurance that the financial statements are prepared, in all material respects, in accordance with the applicable financial reporting framework, rather than an absolute assurance (Zhang et al., 2021a, 2021b). Therefore, disclosure of materiality can negatively influence investor decisions.

In addition, in contrast with the UK and the Netherlands, which directly disclose materiality in audit reports, China requires the disclosure of the overall materiality of the consolidated financial statements in the special explanation of the modified audit opinion. According to information processing theory, individuals have limited cognitive ability, which manifests in limited attention and processing capacity (Libby et al., 2002; Hirshleifer and Teoh, 2003). The consequences of different disclosure locations and methods may vary significantly (Zhao and Chen, 2011; Zhang et al., 2021a, 2021b). Compared with the audit report, the special explanatory notes of the modified audit opinion are less visible to investors, and thus the disclosure of materiality in the special explanatory notes of the modified audit opinion may not have a significant impact on investor decision-making. Based on this, we propose the following hypothesis:

H2: The disclosure of audit materiality is not related to investor decisions.

To test H2, using ERC to measure investor response, we construct model (2) as follows:

$$\begin{aligned} CAR_{i,t} = \beta_0 + \beta_1 Disclose_{i,t} + \beta_2 UE_{i,t} + \beta_3 UE * Disclose_{i,t} + \beta_4 Size_{i,t} + \beta_5 Lev_{i,t} \\ + \beta_6 SOE_{i,t} + \beta_7 Age_{i,t} + \beta_8 Big10_{i,t} + \beta_9 ROA_{i,t} + \beta_{10} Loss_{i,t} + \beta_{11} ST_{i,t} + Year + Industry + \varepsilon \end{aligned} \tag{2}$$

where the dependent variable (CAR) is the cumulative abnormal return over the five trading days before and after audit materiality disclosure.[7] *Disclose* indicates whether materiality is disclosed; it takes a value of 1 if the listed company discloses materiality in a special note on the modified audit opinion, and 0 otherwise. *UE* is the unexpected earnings, which is the difference between the current year's net income and the previous year's net income divided by the current year's market value of equity. The specific definitions of the remaining variables are presented in Table 2. In addition, we control for industry and year fixed effects and cluster standard errors at the firm level. The interaction term *UE*Disclosure* measures the difference in *ERC* due to the disclosure of materiality. If the disclosure of materiality is not significantly related to investor decisions, then β3 should be nonsignificant.

3.4. Sample selection and data sources

The CSRC's "Provisional Application Guidelines for Regulatory Rules—Audit No. 1" state that, starting from 23 March 2021, auditors should disclose the overall materiality of the consolidated financial statements in the specific explanations of modified audit opinions. This disclosure includes the materiality base, percentage, amount and selection justification. As the date that the disclosure requirements commenced coincides with the period when listed companies disclosed their annual audit reports for 2020, our sample period is 2020–2022.

[7] We use 150 days to 30 days before the event date as the estimation period.

Our research sample consists of Chinese A-share listed companies that received modified audit opinions during the period of 2020–2022. We exclude samples that disclosed special explanations for modified audit opinions before 23 March 2021. For RQ3, we delete samples with missing control variables, resulting in a final sample of 716 observations. For RQ1, we further delete samples that did not effectively disclose the basis and percentage used for materiality in the special note on the modified audit opinion according to the regulations. This results in a final sample of 396 observations for RQ1. For RQ2, we remove samples that did not effectively disclose the audit materiality amount in the special note on the modified audit opinion, as well as financial companies and samples with missing control variables, which results in a final sample of 338 observations.

To eliminate the influence of outliers, all continuous variables are winsorized at the top and bottom 1 %. Following Petersen (2009), all regression results employ company-level clustering to correct the standard errors of the coefficient estimates. The audit materiality data used in this paper are manually compiled from the special notes on the modified audit opinions of listed companies. The remaining data are all obtained from the China Stock Market & Accounting Research database.

4. Empirical results and discussion

4.1. Descriptive statistics of audit materiality

Despite the CSRC's mandate that auditors disclose the overall materiality of the consolidated financial statements after 23 March 2021, not all auditors have made the required disclosures in practice. Table 3 provides a detailed list of materiality disclosures. Panel A shows the materiality disclosures by year. It is evident that from 2020 to 2022, 396 firms (54.8 % of the sample) disclosed audit materiality as required, with the remainder (45.2 %) not disclosing materiality.[8] Only 32.38 % of the sample made the required disclosure in 2020, although this proportion increased to 62.00 % in 2021 and 70.7 % in 2022, indicating that increasing numbers of audit firms are gradually adhering to the new regulations. Panel B shows materiality disclosures by type of audit firm (Big 10 and non-Big 10). As many as 70.72 % of companies audited by the Big 10 disclosed materiality, whereas the proportion for non-Big 10 clients is only 47.70 %, indicating that the Big 10 are more likely to conform with the disclosure requirements than the non-Big 10 auditors. Panel C shows the disclosure of materiality by audit firms. The audit firms with 100 % disclosure of materiality include Xigema, PwC, Shenzhen Jiu'An, Shenzhen Zhongxin International and Shenzhen Yongxin Ruihe, whereas 15 audit firms, including EY and Deloitte, did not disclose materiality in the special statements on modified audit opinions at all. The disclosure percentages of the remaining 33 audit firms range from 0 % to 100 %.

Table 4 shows the bases and percentages of overall materiality used by auditors for the consolidated financial statements. Panel A presents the descriptive statistics for the materiality bases. It can be observed that the most commonly used bases for materiality are profit (44.70 %) and income (42.17 %). In this regard, one auditor commented that "for profit-oriented enterprises, revenue and profit are the financial indicators that most users of financial statements pay most attention to."[9] This aligns with the statement in the Application Guide of the Chinese Auditing Standard No. 1221, which states that "for profit-oriented entities, profit before tax from recurring operations is generally used as the base. If profit before tax from recurring operations is volatile, other bases may be more appropriate, such as gross profit or income." In addition to profit and income, auditors also selected assets (6.31 %), equity (5.05 %), gross profit (1.26 %) and expenses (0.25 %) as bases.

Panel B presents the descriptive statistics for the percentages applied to the materiality bases. When profit is used as the base, the average percentage selected by the auditors is around 5.35 %, whereas when the base is income, the average percentage is about 0.80 %. It can be seen that there are large differences in the percentages applied to different bases. This conforms with the sentiments of the "Chinese Auditing Standards QA No. 8—Misstatement of Materiality and Evaluation," which states that "there is a certain link between the percentage and the selected base. For example, the percentage applied to the pre-tax profit base is usually higher than that applied to the income base. For a profit-oriented manufacturing entity, the CPA may consider 5 % of pre-tax profit to be appropriate; whereas for non-profit organizations, the CPA may consider 1 % of

[8] Although the special note on a modified audit opinion is issued by the listed company, it is provided by the relevant audit firm.
[9] http://static.cninfo.com.cn/finalpage/2021–04-20/1209723051.PDF.

Table 3
Audit materiality disclosure.

Panel A: Audit materiality disclosure by year			
Year	**Non-disclosures**	**Disclosures**	**Disclosure ratio**
2020	165	79	32.38 %
2021	95	155	62.00 %
2022	67	162	70.74 %
Total	327	396	54.77 %
Panel B: Audit materiality disclosure by type of audit firm			
CPA Firm type	**Non-disclosures**	**Disclosures**	**Disclosure ratio**
Big10	65	157	70.72 %
Non-Big10	262	239	47.70 %
Total	327	396	54.77 %
Panel C: Audit materiality disclosure by audit firms			
CPA Firms	**Non-disclosures**	**Disclosures**	**Disclosure ratio**
XIGEMA	0	6	100.00 %
PwC	0	6	100.00 %
SHENZHEN JIUAN	0	2	100.00 %
SHENZHEN ZHONGXIN INTERNATIONAL	0	1	100.00 %
SHENZHEN YONGXIN RUIHE	0	1	100.00 %
BDO	4	50	92.59 %
PAN-CHINA	5	51	91.07 %
GONGZHENG TIANYE	1	6	85.71 %
HEXIN	2	11	84.62 %
CHINA AUDIT ASIA PACIFIC	5	21	80.77 %
RSM	3	7	70.00 %
SUYA JINCHENG	4	9	69.23 %
GRANT THORNTON	5	8	61.54 %
PENGSHENG	2	3	60.00 %
ZHONGGUANGCAI GUANGHUA	33	49	59.76 %
ZHONGHUA	4	5	55.56 %
ZHONGHUI	4	5	55.56 %
ZHONGSHENZHONGHUAN	19	20	51.28 %
CHONGQING KANGHUA	1	1	50.00 %
LIXINZHONGLIAN	5	5	50.00 %
ZHONGZHENG TIANTONG	1	1	50.00 %
BEIJING XINGCHANGHUA	1	1	50.00 %
UNITAX ZHENQING	2	2	50.00 %
SHENZHEN XUTAI	1	1	50.00 %
DAHUA	33	32	49.23 %
ASIAN PACIFIC (GROUP)	23	21	47.73 %
SHINEWING	13	11	45.83 %
BAKERLITY	6	5	45.45 %
WUYIGE	16	11	40.74 %
ZHONGXINGHUA	29	17	36.96 %
ZHONGXI	9	5	35.71 %
YONGTUO	11	6	35.29 %
HUAXIN	8	4	33.33 %
TALENT	7	3	30.00 %
BEIJINGXINGHUA	8	3	27.27 %
SCPA	7	2	22.22 %
REANDA	12	3	20.00 %
PEKING	5	1	16.67 %
ZHONGZHUN	5	0	0.00 %
JONTEN	5	0	0.00 %
CAC	5	0	0.00 %
BEIJING ZHONGTIANHUAMAO	2	0	0.00 %
HUAXING	7	0	0.00 %

Table 3 (*continued*)

Panel A: Audit materiality disclosure by year			
Year	**Non-disclosures**	**Disclosures**	**Disclosure ratio**
EY	3	0	0.00 %
SINONG	1	0	0.00 %
DELOITTE	1	0	0.00 %
ZHEJIANG TIANPING	1	0	0.00 %
TTCPA	1	0	0.00 %
SHENZHEN GUANGSHEN	2	0	0.00 %
HUNANRONGXIN	2	0	0.00 %
SHANDONG SHUNTIANXINCHENG	1	0	0.00 %
HENGAN	1	0	0.00 %
SHENZHEN ZHENGYI	1	0	0.00 %
Total	327	396	54.77 %

Note: Disclosure ratio = Number of disclosures/(number non-disclosures + number of disclosures)*100 %.

Table 4
Descriptive statistics of materiality bases and percentages.

Panel A: Descriptive statistics of materiality bases		
Base	**Observations**	**Percentages**
Profit	177	44.70 %
Income	167	42.17 %
Assets	25	6.31 %
Equity	20	5.05 %
Gross profit	5	1.26 %
Expenses	1	0.25 %
Profit, equity and income	1	0.25 %
Total	396	100 %

Panel B: Descriptive statistics of materiality percentages					
Base	**Mean**	**SD**	**Min**	**Median**	**Max**
Profit	5.35	1.40	1	5	10
Income	0.80	0.73	0.10	0.50	7
Assets	0.51	0.27	0.03	0.50	1
Equity	1.77	1.47	0.10	1.10	5
Gross profit	2.56	1.57	0.80	2	5
Expenses	1	–	1	1	1
Profit, equity and income	2.50	–	2.50	2.50	2.50

Note: For profit, the bases used include profit before tax, total profit, net profit, adjusted profit before tax (deduction, average of recent years, etc.), adjusted total profit and adjusted net profit. The bases for income include a sample of the operating income and the average operating income of recent years. The equity bases consist of equity, average equity in recent years and equity attributable to the parent company. The bases for assets include the total assets, the average value of total assets in recent years and the total amount of unaudited assets. In the special explanation of the modified audit report issued by Sichuan Blu-ray Development Co., Ltd. in 2022, ShineWing selected the absolute value of consolidated profit, equity and income as the base for the materiality. Because this is the only case of such a base, no standard deviation is presented. Similarly, there is no standard deviation presented for the base using expenses because there is only one such observation.

revenue or expenses to be appropriate." In addition, there is some variation in the percentages applied to the same benchmark, e.g., when profit is the base, the percentages used range from 1 % to 10 %; when income is the base, they range from 0.10 % to 7 %.

4.2. Relationship between materiality and audit quality

Table 5 reports the descriptive statistics of the main variables, with Panel A providing the descriptive statistics of the full sample and Panel B providing those for the subsamples and the results of the difference test. It can be observed from Panel A that the mean value of *absDA* is 0.102. The mean value of *Materiality* is 0.005, which means that, on average, the audit materiality is 0.5 % of total assets. The descriptive statistics show that compared with peer companies, the sample companies have a higher proportion of modified audit opinions issued in the previous period, are less likely to be SOEs, have a lower return on assets and a higher probability of incurring losses this year and are subject to risk warnings. The remaining variables are consistent with the literature.

Panel B shows the results of the univariate tests. We divide the full sample into lower and higher materiality subsamples and compare the dependent variables and control variables between these two subsamples. The comparison shows that the absolute value of discretionary accruals is higher in the higher materiality subsample, in terms of both the mean and the median, and that the difference is significant. In addition, compared with samples with lower materiality, companies with higher materiality are smaller, have a shorter listing age, are more likely to incur losses and are subject to risk warnings.

Table 6 reports the results of testing Hypothesis 1. Columns (1) and (2) show the regression results of model (1) without and with control variables, respectively. The coefficients of *Materiality* (4.013 and 2.865) are positive and significant at the 1 % level, indicating that the higher the materiality, the higher is the level of discretionary accruals and, therefore, the lower is the audit quality. This result shows that overall, auditors fail to select the appropriate materiality considering the situation of the audited entity and the needs of the users of the financial statements. Economically, according to the results of column (2), for every 1 % increase in the

Table 5
Descriptive statistics for testing H1.

Panel A: Full sample descriptive statistics

Variables	**Observations**	**Mean**	**SD**	**Min**	**Median**	**Max**
absDA	338	0.102	0.088	0.000	0.078	0.308
Materiality	338	0.005	0.006	0.000	0.003	0.048
Size	338	21.919	1.195	20.006	21.854	24.857
Lev	338	0.594	0.234	0.105	0.654	0.829
Lop	338	0.666	0.473	0	1	1
SOE	338	0.124	0.330	0	0	1
Age	338	2.814	0.439	1.609	2.890	3.434
Big10	338	0.396	0.490	0	0	1
ROA	338	–0.038	0.061	–0.086	–0.078	0.137
Loss	338	0.725	0.447	0	1	1
ST	338	0.379	0.486	0	0	1

Panel B: Subsample descriptive statistics and difference test

Variables	Mean			Median		
	Low materiality	High materiality	T-value	Low materiality	High materiality	Z value
	N = 169	N = 169		N = 169	N = 169	
absDA	0.089	0.115	-2.75^{***}	0.072	0.090	-2.37^{**}
Size	22.155	21.683	3.69^{***}	22.151	21.570	4.57^{***}
Lev	0.583	0.606	–0.92	0.626	0.711	–1.09
Lop	0.627	0.704	–1.50	1	1	–1.50
SOE	0.148	0.101	1.32	0	0	1.32
Age	2.865	2.763	2.15^{**}	3.045	2.773	2.15^{**}
Big10	0.373	0.420	–0.89	0	0	–0.89
ROA	–0.033	–0.044	1.61	–0.045	–0.086	3.28^{***}
Loss	0.663	0.787	-2.57^{**}	1	1	-2.55^{**}
ST	0.331	0.426	–1.80*	0	0	–1.79*

Note: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6
Audit materiality and audit quality.

	(1)	(2)	(3)	(4)
Variable	*absDA*	*absDA*	*absDA* $DA > 0$	*absDA* $DA < 0$
Materiality	4.013***	2.865***	–1.211	2.162**
	(3.90)	(3.11)	(–0.42)	(2.12)
Size		–0.011**	–0.021**	–0.009*
		(–2.34)	(–2.12)	(–1.81)
Lev		0.079***	0.027	0.089***
		(3.56)	(0.67)	(3.32)
Lop		0.013	–0.002	0.006
		(1.45)	(–0.10)	(0.55)
SOE		0.015	0.022	0.007
		(0.92)	(0.75)	(0.41)
Age		–0.018	–0.007	–0.022
		(–1.46)	(–0.35)	(–1.35)
Big10		–0.023**	–0.027*	–0.017
		(–2.25)	(–1.74)	(–1.37)
ROA		0.033	0.720***	–0.761***
		(0.21)	(3.03)	(–3.64)
Loss		0.017	0.021	–0.032
		(0.98)	(0.78)	(–1.46)
ST		0.016	0.037	0.008
		(1.30)	(1.65)	(0.66)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Constant	0.060**	0.259**	0.472*	0.246**
	(2.24)	(2.41)	(1.97)	(2.19)
Observations	338	338	92	246
R-squared	0.162	0.28	0.444	0.355

Note: *t* values are shown in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

standard deviation of the audit materiality, the absolute value of the discretionary accrual increases by 16.9 % relative to the sample average, indicating that the impact of audit materiality on audit quality is economically significant.

In addition, we divide the sample into two groups, $DA > 0$ and $DA < 0$, to test the relationship between the audit materiality and earnings management in different directions, that is, upward and downward earnings management, respectively. From the results in columns (3) and (4), when $DA > 0$, the coefficient of *Materiality* is –1.211, but it is not significant. However, for the DA < 0 subsample, the coefficient of *Materiality* is 2.162, which is significant at the 5 % level, indicating that the negative correlation between audit materiality and audit quality occurs mainly in firms with downward earnings management. This may be because upward earnings management leads to greater audit risk than downward earnings management, and hence auditors are more motivated to inhibit upward (vs. downward) earnings management by expanding the scope of testing and increasing audit procedures (Caramanis and Lennox, 2008; Ke et al., 2014). However, auditors have weaker incentives to suppress downward earnings management and are less likely to increase audit effort, such that the negative correlation between materiality and audit quality occurs mainly in firms with downward earnings management.

Next, we perform a series of robustness tests, including replacing the measures of the independent and dependent variables. Specifically, considering that profit and income are the most commonly used materiality bases for auditors, we re-measure the explanatory variables by dividing the materiality amounts by net profit (*Materiality2*) and income (*Materiality3*). From the regression results shown in columns (1) and (2), respectively, of Table 7, it is evident that the coefficients of *Materiality2* and *Materiality3* remain positive and significant. In addition, considering that the materiality bases of different samples are inconsistent, we rank each

Table 7
Robustness tests.

Variable	(1)	(2)	(3)	(4)
	absDA	*absDA*	*absDA*	*absDA2*
Materiality2	0.002*			
	(1.79)			
Materiality3		0.347**		
		(2.05)		
Materiality4			0.046***	
			(9.17)	
Materiality				3.938***
				(4.52)
Size	–0.012**	–0.011**	–0.005	–0.010**
	(–2.57)	(–2.36)	(–1.19)	(–2.14)
Lev	0.088***	0.091***	0.090***	0.082***
	(3.99)	(4.22)	(4.59)	(3.74)
Lop	0.014	0.011	0.014*	0.020**
	(1.55)	(1.18)	(1.67)	(2.11)
SOE	0.012	0.016	0.020	0.007
	(0.80)	(1.02)	(1.37)	(0.43)
Age	–0.025*	–0.024*	–0.022*	0.002
	(–1.82)	(–1.91)	(–1.90)	(0.16)
Big10	–0.019*	–0.019*	–0.023***	–0.024**
	(–1.84)	(–1.86)	(–2.67)	(–2.42)
ROA	0.048	0.060	0.016	–0.042
	(0.29)	(0.39)	(0.12)	(–0.29)
Loss	0.025	0.021	0.011	0.034**
	(1.35)	(1.21)	(0.72)	(2.10)
ST	0.018	0.019	0.012	0.012
	(1.46)	(1.50)	(1.15)	(1.04)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Constant	0.303***	0.268**	0.048	0.148
	(2.74)	(2.48)	(0.51)	(1.44)
Observations	338	338	333	338
R-squared	0.252	0.274	0.404	0.361

Note: *Materiality2* is equal to the materiality amount divided by net profit; *Materiality3* is equal to the materiality amount divided by operating income; *Materiality4* is ranked according to the caliper of the materiality of each type from low to high and the percentage of each group is divided into three groups from lowest to highest values. The lowest group of *Materiality4* takes a value of 1, the middle group of *Materiality4* takes a value of 2 and the highest group of *Materiality4* takes a value of 3. *absDA2* is the absolute value of discretionary accruals estimated using the nonlinear model of Ball and Shivakumar (2006). In calculating *Materiality4*, we divide each materiality base into three groups based on the caliber of the base, and we retain only the observations corresponding to bases with sample sizes greater than 10.

type of base to control the problem of base selection. *Materiality4* is sorted according to the materiality base of each type from low to high and the percentages of each group are divided into three parts from low to high, with the lowest group of *Materiality4* taking a value of 1, the middle group of *Materiality4* taking a value of 2 and the highest group of *Materiality4* taking a value of 3. The regression results are shown in column (3) of Table 7 and it can be observed that the coefficient of *Materiality4* is positive and significant, indicating that our conclusions are robust. Finally, we use the absolute value of manipulable accruals (*absDA2*), estimated using the nonlinear model of Ball and Shivakumar (2006), to measure audit quality, with the regression results shown in column (4) of Table 7. The coefficient on *Materiality* remains positive and significant.

We further examine the impact of competence at the audit firm and individual auditor levels. The greater the auditor's expertise, the better the auditor will be able to select appropriate bases and percentages that consider factors such as the nature of the client's business, the stage of its life cycle and the industry and economic environment in which it operates. For companies with a higher audit risk, auditors with higher professional competence will choose a lower level of materiality and vice versa to ensure consistency in audit quality. Therefore, we expect the negative correlation between materiality and audit quality to occur mainly in the

Table 8
The impact of industry expertise.

Variable	(1)	(2)	(3)	(4)
	absDA	*absDA*	*absDA*	*absDA*
	Big 10	Non-Big 10	Auditor with industry expertise	Auditor without industry expertise
Materiality	0.968	4.002***	–0.15	4.601***
	(0.66)	(3.70)	(–0.11)	(4.85)
Size	–0.001	–0.013**	–0.013**	–0.009
	(–0.17)	(–2.20)	(–2.21)	(–1.15)
Lev	0.073*	0.063*	0.107***	0.055
	(1.91)	(1.94)	(3.50)	(1.62)
Lop	0.017	0.017	0.018	0.002
	(1.19)	(1.30)	(1.37)	(0.13)
SOE	0.021	0.024	0.014	0.010
	(0.94)	(1.08)	(0.77)	(0.30)
Age	–0.028	–0.017	–0.019	–0.025
	(–1.41)	(–0.94)	(–1.11)	(–1.42)
Big10			–0.001	–0.048***
			(–0.06)	(–3.59)
ROA	0.025	0.024	0.033	–0.038
	(0.12)	(0.10)	(0.12)	(–0.18)
Loss	0.031	0.002	0.006	0.020
	(1.28)	(0.08)	(0.22)	(0.67)
ST	0.004	0.029*	0.022	0.017
	(0.20)	(1.71)	(1.39)	(0.96)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Constant	0.066	0.317**	0.223*	0.255
	(0.39)	(2.17)	(1.69)	(1.44)
Observations	134	204	169	169
R-squared	0.329	0.308	0.278	0.376

Note: *t* values are shown in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

lower competence group. Following DeFond and Zhang (2014), we use audit firm size (Big 10 or non-Big 10) to measure audit firm competence, whereas auditor competence is measured by the auditor's industry expertise.[10]

Table 8 reports the regression results. The coefficient of *Materiality* is positive but nonsignificant when the firm is audited by a Big 10 audit firm, whereas the coefficient of *Materiality* in the non-Big 10 group is positive and significant at the 1 % level. These results suggest that the negative correlation between materiality and audit quality is more pronounced for non-Big 10 audit firms than for Big 10 audit firms. The results in columns (3) and (4) show that the coefficient of *Materiality* is nonsignificant in the group of auditors with industry expertise, whereas in the group of auditors without industry expertise, the coefficient of *Materiality* is positive and significant at the 1 % level. The above results show that the negative correlation between materiality and audit quality is mainly evident for companies audited by auditors with no industry expertise.

4.3. Impact of materiality disclosure on investor decision-making

Table 9 reports the descriptive statistics for the main variables used to test Hypothesis 2. The mean value of *CAR* is –0.126, indicating that on average, the stock price falls after the disclosure of modified audit opinions. The mean value of *Disclose* is 0.520, indicating that 52 % of the observations disclose audit materiality, which is close to the value of 54.77 % for the full sample in Table 3. These firms have a higher percentage of modified audit opinions in the previous period, are less likely to be state-owned, have a lower return on assets, are more likely to incur a loss in the current year and are more likely to be subject to a risk warning than peer firms.

[10] Auditor industry expertise is calculated using the industry portfolio share method based on the square root of the total assets of audited listed firms for the industry expertise of certified public accountants, with specific data from the CNRDS database.

Table 9
Descriptive statistics for testing H2.

Variable	Observations	Mean	SD	Min	Median	Max
CAR	716	–0.126	0.276	–1.410	–0.053	0.749
UE	716	0.000	0.345	–3.812	–0.007	2.283
Disclose	716	0.520	0.500	0	1	1
Size	716	21.820	1.356	18.910	21.750	26.920
Lev	716	0.644	0.280	0.051	0.661	1.015
Lop	716	0.634	0.482	0	1	1
SOE	716	0.123	0.329	0	0	1
Age	716	2.662	0.558	0.693	2.639	3.434
Big10	716	0.309	0.462	0	0	1
ROA	716	–0.105	0.142	–0.356	–0.081	0.223
Loss	716	0.732	0.443	0	1	1
ST	716	0.355	0.479	0	0	1

Table 10
The impact of audit materiality disclosures on investors' decisions.

	(1)	(2)
Variable	*CAR*	*CAR*
Disclose	0.046**	0.024
	(1.98)	(1.04)
UE	0.010	0.011
	(0.20)	(0.22)
*UE*Disclose*	–0.207**	–0.191**
	(–2.58)	(–2.57)
Size		0.021**
		(2.38)
Lev		–0.145***
		(–2.94)
SOE		–0.001
		(–0.06)
Age		0.039**
		(2.19)
Big10		0.039*
		(1.89)
ROA		–0.035
		(–0.28)
Loss		–0.046*
		(–1.65)
ST		0.059***
		(2.77)
Year	Yes	Yes
Industry	Yes	Yes
Constant	–0.047	–0.477***
	(–1.56)	(–2.60)
Observations	716	716
R-squared	0.149	0.197

Note: *t* values are shown in parentheses; ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 10 reports the test results for Hypothesis 2. Columns (1) and (2) show the regression results of model (2) without and with control variables, respectively. The coefficients of *UE*Disclose* are negative and significant, indicating that the disclosure of audit materiality significantly reduces firms' ERC response.[11] A possible reason is that after the disclosure of audit materiality in the modified audit opinion report, investors

[11] The explanatory variable *CARi,t* is the cumulative abnormal return of 5 trading days before and after the disclosure of audit materiality. In addition, we use the cumulative abnormal returns of 1, 3 or 7 trading days before and after the disclosure for the robustness test, and the conclusion remains qualitatively similar. Results are available upon request by contacting the authors.

become fully aware that the audit opinion provides reasonable rather absolute assurance that the financial statements are prepared in accordance with the applicable financial reporting basis in all material aspects, leading to a further reduction in the perceived reliability of the financial statements by investors.

5. Conclusions and implications

We take Chinese A-share listed companies issued with modified audit opinions during the period from 2020 to 2022 as a research sample to analyze materiality assessments in auditing practice, the relationship between materiality and audit quality and the impact of materiality disclosure on investor decision-making. We present four key results. First, the Big 10 audit firms are more likely to disclose audit materiality than peers. Second, the most common bases for materiality used by auditors are profit and income, the percentages applied to the different bases vary greatly and, even for the same base, the percentages vary to some extent. Third, the higher the materiality, the poorer is the quality of the audit. This negative correlation occurs mainly when the client firms engage in downward earnings management and among audit firms and auditors of lower competence than peers, indicating that materiality predicts the audit quality and has a certain level of informativeness. Fourth, disclosing audit materiality reduces investors' perceptions of the reliability of financial reports.

The research in this paper assists in understanding how auditors establish materiality in auditing practice, thus opening the "black box" of the auditing process to an extent. In addition, our findings have important implications. First, for the auditing standard-setters, although the relevant rules emphasize that the bases and percentages contained in the questions and answers are examples, not regulations, auditors rely heavily on the examples in auditing standards, application guides and questions and answers in practice. Therefore, standard-setters should pay attention to this phenomenon and treat the examples provided with caution. Second, materiality itself is informative, and this enables investors, analysts and regulators to judge the quality of audits or audited financial statements based on materiality and make better investment decisions or enhance the efficiency of regulation.

The conclusions of this study are based on the sample companies that disclose materiality during our period of analysis. However, there may be an element of self-selection in whether materiality is disclosed; thus, the research conclusions may be affected by an endogeneity problem. In addition, the research samples for this study are listed companies that have been issued with modified audit opinions, which may limit the generalizability of the research conclusions.

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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Spillover effect of digital transformation along the supply chain: From the perspective of suppliers' audit fees

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ABSTRACT

This research contributes to understanding the spillover effect of customer digital transformation along the supply chain. We take a supply chain relationship perspective to explore the influence of customers' digital transformation on suppliers' audit fees and find a significant reduction in such fees when customers undergo digital transformation. An economic mechanism analysis reveals that this transformation reduces audit fees by lowering the risks and costs encountered by auditors. This is achieved by mitigating suppliers' business risks and improving earnings quality. Heterogeneity analysis reveals that the impact of customers' digital transformation on suppliers' audit fees is more pronounced when the supply chain is geographically distant, suppliers with more specific investments and with high levels of market competition.

1. Introduction

Digital transformation involves shifting from a traditional "industrialized" management model to a digital management model (Verhoef et al., 2021). This transition goes beyond simply applying digital technologies to technical aspects of a business and involves a complete restructuring of business models and operational management. Research on the economic consequences of digital transformation emphasizes its potential influence on the quality of corporate disclosures and business risks. For example, digital technologies can improve operational management, promote networked and flattened organizational structures (Nambisan et al., 2019),

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increase corporate disclosure transparency and the quality of accounting information and enhance communication, production and operational efficiency (Wu et al., 2021; Chen et al., 2022a). By digitally collecting and analyzing data, firms can effectively visualize information, enhance interdepartmental coordination, refine risk control processes, mitigate operational risks and reduce management fraud and decision-making errors that lead to losses, thereby enhancing their market reputation (Manita et al., 2020; Zhou and Li, 2023). Most studies focus on the direct effects of digital transformation on firms' risk responses and information transfer capabilities, while its broader effects on the supply chain have not been sufficiently investigated (Guo et al., 2023).

The production operations of suppliers and their financial decisions are influenced and informed by their customers, who therefore play a vital role in the supply chain (Ak and Patatoukas, 2016). Investing in supply chain relationships promotes the economic interdependence of suppliers and customers. The value of such investment depends on customers' growth prospects, and ensuring the stability of their businesses can lead to higher expected returns from supply chain collaboration. Conversely, if customers face business challenges or go bankrupt, they can jeopardize the value of the assets allocated by suppliers (Raman and Shahrur, 2008). This increases suppliers' cash flow and operational risk (Itzkowitz, 2013). Thus, suppliers are highly sensitive to the operations and activities of their customers. The risks and information associated with customers can generate a spillover effect in the supply chain, which can then trigger cascading changes in suppliers' operational risks and influence their investments and financial decisions (Hertzel et al., 2008; Jacobson and von Schedvin, 2015; Chiu et al., 2019). By gaining access to more transparent customer information, suppliers can better forecast customer demand, reduce transaction costs, alleviate shortages and losses and enhance production efficiency and inventory management (Yang et al., 2020). Digital transformation can have positive effects on business risks and disclosure quality, in addition to the supply chain, but does the digital transformation of customer businesses also lead to additional spillover effects on suppliers?

The volume of literature examining audit fees has increased substantially in recent years, with a particular focus on the supply chain. Establishing stable relationships within a supply chain promotes integration (Krishnan et al., 2019), and some customers of an audited firm can help to reduce its audit fees, for example, if they are associated with the government, as this will have a positive influence on its market signals and credibility (Dou et al., 2019). Supply chain information spillover occurs when customers disclose non-compliance, and the resulting external transmission of negative information can exacerbate supply chain risk (Zhang and Smith, 2023), which in turn can increase suppliers' audit risks and costs. This suggests that suppliers and audit firms should carefully consider the risk contained in information provided by customers. We therefore investigate the role of customers' digital transformation in the impact of supply chain risk and information spillover on suppliers' audit fees.

We assess how the audit fees of A-share listed companies in Shanghai and Shenzhen from 2007 to 2020 are affected by their customers' digital transformation. We analyze publicly disclosed information about these suppliers' top five customers and find that digital transformation plays a significant role in reducing their audit fees. We confirm the validity of our findings through robustness tests and endogeneity treatments and propose an economic mechanism through which customers' digital transformation can mitigate suppliers' operational risk and earnings management via a supply chain spillover effect, leading to a decrease in audit risks and costs for suppliers. A heterogeneity analysis further demonstrates that the influence of digital transformation is more pronounced when there is a greater geographic distance between suppliers and customers, higher specific investment in supply chain relationships and more intense supplier market competition than in other situations. These findings provide additional evidence that digital transformation can mitigate business risks, enhance information sharing and optimize supply chain efficiency through the spillover effect.

This study contributes to several key research areas. First, previous studies mainly focus on the direct effects of digital transformation, such as improving firms' data processing capabilities, enhancing the efficiency of information transfer and reducing business risks (Chen et al., 2020; Zhou and Li, 2023). However, we examine the spillover effect of customers' digital transformation on suppliers' financial behavior, and thus its indirect influence on stakeholders. As customer–supplier relationships such as effective supply chain collaboration are economically important and can help to ensure that firms are competitive, this study provides valuable insights into the economic consequences of digital transformation by examining supply chain dynamics.

Second, we take a novel approach to examining the factors that influence audit fees. Previous studies indicate that the application of digital technologies can enhance corporate information transparency and decision-making accuracy and reduce business risks, which leads to lower audit fees (Zhang et al., 2021). Our study spans corporate boundaries and investigates how the digital transformation of downstream customers affects upstream suppliers' audit fees in supply chain relationships. This offers a new perspective on the factors that influence audit fees.

Third, this study makes a valuable contribution to the literature on supply chain spillovers. Previous research mainly focuses on the link between disclosure behavior, such as customer earnings announcements and annual reports, and suppliers. Studies of the spillover effects of digital transformation mainly examine supplier incentives and research and development (R&D) innovations (Guo et al., 2023). However, we take a different approach and investigate the relationship between suppliers' audit fees and their customers' digital transformation. We therefore further reveal the economic outcomes of supply chain spillovers resulting from digital transformation, and we confirm the positive impact of such transformation on supply chain synergy by considering audit fees.

The remainder of this paper is organized as follows. In Section 2, we review the related literature and provide the theoretical hypotheses. Section 3 describes the study's data, samples and research design. Section 4 provides the empirical results. Section 5 presents our further analyses. Finally, Section 6 concludes the study.

2. Literature review and hypothesis development

2.1. Literature review

2.1.1. Digital transformation and audit fees

An audit fee is the price for audit services agreed between the auditor and a business entity. It includes a premium to compensate for risks (Simunic, 1980). When a business entity faces a higher level of risk, its accounting earnings include more uncertainty, resulting in an increased risk of misrepresentation in its financial statements. The business risk of the audited entity is an important source of audit risk (Simunic, 1980). Digital transformation involves applying technologies such as artificial intelligence, blockchain technology, cloud computing and big data to collect information, analyze data and support decision-making. This leads to changes in organizational management styles, production management models and business strategies (Verhoef et al., 2021), along with extensive improvements in manufacturing, sales logistics and product innovation (Goldfarb and Tucker, 2019). Studies of digital transformation typically consider its impact on audit costs and audit risks.

Digital transformation has various benefits that can lead to reduced audit costs. Eliminating data silos across departments can help organizations identify potential opportunities and risks in dynamic environments. They can then draw on the more integrated data to inform risk assessment and operational decision-making (Tian et al., 2022). This can also enhance the level of collaboration in and the resilience of the supply chain (Guo et al., 2023) and mitigate operational risks (Zhang et al., 2021; Zhou and Li, 2023), which can result in lower audit fees. Through digital technologies, large amounts of unstructured and non-standardized data can be structured and standardized, which helps to reduce information asymmetry and enhances the quality of information disclosure, which also lowers audit risks and costs (Wu et al., 2021; Zhang et al., 2021; Wen et al., 2023) and thus audit fees.

However, digital transformation can also increase audit costs. The uncertainty associated with the transformation process, along with rapid product and technology updates, can intensify market competition and elevate operational risks for firms (Matt et al., 2015; Nambisan et al., 2019). If management and employees lack sufficient digital knowledge and skills or make biased predictions about market trends, operational risks can further increase. Digital transformation also has the potential to make firms' financial systems more complex, which may increase the likelihood of financial manipulation tactics such as earnings management. The firms' auditors must then extend the scope of their audits and must conduct additional procedures, leading to delays and decreased efficiency (Leng and Zhang, 2024).

2.1.2. Supply chain spillover effect

Effective corporate production and business operations require smooth coordination and cooperation throughout the supply chain. To gain a competitive advantage in the market, leveraging the strengths of each participant in the supply chain will enhance its resilience. Suppliers rely heavily on orders from their major customers as their primary source of sales revenue and cash flow, and thus these customers have a major impact on their operations and overall development (Ak and Patatoukas, 2016). Customers and suppliers are interdependent and make substantial relationship-specific investments (Raman and Shahrur, 2008). This interdependence affects both customers and suppliers, leading to the phenomenon of "prosperity for all, loss for all."

The presence of operational risks associated with customers in the supply chain has major implications, as customers serve as vital economic resources for suppliers. They influence various aspects of supplier operations such as performance and product pricing (Ak and Patatoukas, 2016) and play a role in suppliers' financial decisions, including those regarding capital structure (Itzkowitz, 2013). Any risks they encounter can also spill over to suppliers. For instance, if a customer faces financial difficulties or goes bankrupt due to poor operational performance, this risk can propagate throughout the supply chain and affect upstream suppliers who may encounter delays in collecting accounts receivable, which can have adverse effects on their cash flow and borrowing capacity (Battiston et al., 2007; Campello and Gao, 2017). Thus, suppliers may face financial distress (Hertzel et al., 2008). Peng and Wang (2018) further emphasize that a decline in customers' stock prices can also have repercussions for suppliers, especially when they are not adequately resilient to such risk.

Customers also transmit information to suppliers, which can result in information spillovers. If their customers publicly disclose high-quality information, suppliers can forecast demand more accurately, minimize the shortages or losses brought by slow-selling products and make optimal decisions regarding production and inventory. This helps to reduce the "bullwhip effect" and to optimize suppliers' investment efficiency and operational performance (Chiu et al., 2019; Yang et al., 2020; Chen et al., 2022a). If customers exceed expectations when announcing earnings, suppliers will increase their levels of disclosure to divert the attention of external investors away from any potential operational risks (Cho et al., 2020). If customers disclose negative information, the suppliers may increase their cash holdings (Di et al., 2020) or reduce their R&D activities (Chen et al., 2022b) to mitigate the potential negative effects. Such disclosure can increase the operational risks of supplier firms, which then results in higher audit fees (Zhang and Smith, 2023).

2.2. Hypothesis development

Customers play a vital role in the supply chain and represent key stakeholders for suppliers. They possess valuable insights into market demand and future development prospects (Lee et al., 1997), and in addition to being important sources of revenue for suppliers, they dictate production and sales strategies. Suppliers strategically align their production with customer demand and rely on it to sustain their business operations. They aim to establish stable and beneficial collaborations by investing in relationship-specific assets that enable the creation of unique or customized goods and services (Raman and Shahrur, 2008). The disruption of these supply chain relationships can lead to substantial switching costs and economic losses (Dou et al., 2013), and thus the risks associated with customers can affect the overall efficiency of the entire supply chain (Hertzel et al., 2008; Xuan and Xiongyuan, 2018). Information related to customer risk is therefore valuable and influences suppliers' economic interests and decision-making processes (Chiu et al., 2019) and is extremely important for auditors when evaluating these suppliers (Zhang and Smith, 2023). Customer information can also spill over into the supply chain, and its effective disclosure can enhance the accuracy of suppliers' demand forecasts and mitigate the supply–demand discrepancies, thereby improving decision-making efficiency and overall business performance (Yang et al., 2020). We propose that the spillover effect of customers' digital transformation influences suppliers' audit risks and audit costs, and thus their audit fees.

First, customers' digital transformation has the potential to alleviate suppliers' audit risks. In terms of supply chain risk spillovers, customers facing higher levels of risk will have reduced purchasing power, which can result in financial liquidity constraints. In turn, this can have a detrimental impact on suppliers' sales performance, leading to inventory backlogs and extended payment terms. Consequently, the suppliers' overall business risk will increase (Gosman et al., 2004). If customers face bankruptcy due to mismanagement, suppliers will be burdened with sunk costs such as bad receivables and disrupted supply chain connections, thereby exacerbating operational problems (Battiston et al., 2007). Digital transformation can help to enhance the efficiency of information feedback and market responsiveness (Verhoef et al., 2021). This allows for enhanced market sensitivity and the timely identification of opportunities and risks, thus facilitating rational resource allocation (Loebbecke and Picot, 2015). Thus, customers' digital transformation strengthens information coordination and market perception capabilities, increases resilience to business risks, optimizes decision-making efficiency and reduces the likelihood of fluctuations in customer performance. The risk of bankruptcy or liquidation is thus mitigated, reducing suppliers' exposure to customer-related business risks.

Digital transformation can also facilitate effective information-sharing and enhance the efficiency of supply chain collaboration (Goldfarb and Tucker, 2019). Through the resulting information spillover, they can communicate information more accurately to suppliers (Guo et al., 2023). Through this information, suppliers may gain access to actual customer sales data and business strategies, which can enable them to make accurate market demand predictions and swiftly adjust their own strategies (Ngo et al., 2023). Information collaboration within the supply chain reduces the revenue volatility caused by suppliers' biased demand forecasts and decision-making errors (Yang et al., 2020) and ensures smooth turnover of working capital (Gu et al., 2022), which then alleviates the pressure on suppliers' management teams to manipulate earnings in response to performance demands.

To summarize, customers' digital transformation can effectively lead to supply chain information spillovers, which in turn reduces the business risks faced by supplier firms and discourages their earnings manipulation. Some scholars argue that the operational risks and earnings manipulation behavior of audited entities significantly affect their overall audit risk (Simunic, 1980; Defond and Lennox, 2011). The digital transformation of customers can thus help to mitigate audit risk for supplier firms by decreasing auditors' perceptions of risk, ultimately resulting in lower audit fees.

The digital transformation of customer firms also improves their own production, operational efficiency and risk response capabilities. This can help to reduce the uncertainty caused by the impact of any potential customer risks on suppliers and enhance the risk coordination ability of the entire supply chain. Therefore, the positive effect of supply chain integration enables suppliers' funds to circulate normally and maintain good liquidity (Gu et al., 2022). Their operational performance and market value are then guaranteed, which serves to reduce the opportunistic behavior of their management in terms of manipulating financial statements due to performance assessment and reputational pressure, and thus enhances financial information transparency. Improvements in financial statement quality make it easier for auditors to collect relevant evidence and thus make audit judgments (Zhang et al., 2021), thereby reducing the costs for their services and thus the audit fees paid by suppliers.

From the above analysis, we propose the following hypothesis:

Hypothesis H1a: Customers' digital transformation reduces suppliers' audit fees.

However, customer digital transformation may also increase suppliers' audit fees. First, an increase in supply chain risks, and specifically operational risks, can result from customer digitalization, as they may need to find new avenues for growth, make long-term investments and engage in activities that involve trial-and-error (Goldfarb and Tucker, 2019). These endeavors can result in short-term financial setbacks and an increase in operational risks, which then impact suppliers. Second, customers' digital transformation can lead suppliers to incur higher operational expenses due to the spillover of information within the supply chain. The changes in resources and information structure that customers seek in their pursuit of collaborative relationships may not necessarily result in more efficient data use. The lack of compatibility or inadequate interpretive ability between customer and supplier information systems can impede communication, leading to increased operational risks and costs for suppliers. Auditors must then conduct more comprehensive testing and auditing, thus leading to greater audit risk (Dou et al., 2019). Consequently, auditors may charge suppliers additional fees due to the operational risks and increased workload caused by customers' digital transformation. Thus, the financial implications for suppliers may be extensive.

Based on the arguments above, we propose the following hypothesis:

Hypothesis H1b: Customers' digital transformation increases suppliers' audit fees.

3. Data, sample and research design

3.1. Data and sample

The China Securities Regulatory Commission (CSRC) does not require listed companies to disclose customer information. However, since 2007, most listed companies disclose information about their major customers. In this study, we focused on Shanghai and Shenzhen A-share listed supplier companies from 2007 to 2020. We selected sample observations based on full disclosure of the names and sales figures of the top five customers. We followed Di et al. (2020) and included observations from suppliers with listed customers by applying the following exclusion criteria: (1) those listed for less than one year; (2) those classified as financial companies; (3) those designated as Special Treatment (ST) and Starred Special Treatment (*ST); and (4) those with missing variables. After the screening process, we obtained a final sample of 1,419 firm-year observations from A-share listed companies in Shanghai and Shenzhen. Supply chain, corporate financial- and corporate governance-related data were obtained from the CSMAR database. We winsorized all continuous variables at the 1st and 99th percentiles to mitigate the impact of extreme values.

3.2. Measures of customer digital transformation

We followed Di et al. (2020) and Wu et al. (2021) to develop an indicator of customer digital transformation. We examined the frequency of terms related to digital transformation in the annual reports of the listed customer companies disclosed by suppliers. The frequencies of these terms were first calculated using the digital transformation thesaurus developed by Wu et al. (2021), who we also followed to calculate the corporate digital transformation indicator. This involved dividing the total occurrence of digital transformation words in the annual reports by the total word count, multiplying by 100 and taking the natural logarithm of the resulting figure. We then computed customer digital transformation indicators, as outlined by Di et al. (2020), with adjustments based on the sales share of the top five customers as disclosed by the suppliers. This process involved three steps: (1) identifying and collecting data on the top five customers mentioned in a supplier's annual report, and we retained the sample if listed firms were included; (2) we calculated weights for customers identified as listed firms based on the proportion of sales to them relative to the total sales of the top five customers; and (3) we computed the digital transformation metrics for each customer using these weights, resulting in weighted sums that represented our customer digital transformation variables (*CusDigit*1 and *CusDigit*2).

3.3. Research design

We constructed the following model to examine the relationship between customer digital transformation and supplier audit fees:

$$Lnfee_{i,t} = \beta_0 + \beta_1 CusDigit_{i,t} + \sum Controls_{i,t} + \sum Firm_i + \sum year_t + \varepsilon_{i,t} \tag{1}$$

where the dependent variable *Lnfee* is the natural logarithm of the audit fees disclosed in the supplier's annual report. The independent variable *CusDigit* represents the customer digital transformation variables (*CusDigit*1 and *CusDigit*2). We also controlled for the following variables: a supplier's asset size (*Size*), leverage (*Lev*), cash flow (*CF*), current ratio (*Current*), return on total assets (*ROA*), percentage of accounts receivable (*Receiv*), whether the supplier is in a loss position (*Loss*), the supplier's age of establishment (*Age*), business segment (*BusSeg*), digital transformation (*Digit*), board size (*Board*), percentage of independent directors (*Indrt*), ownership nature (*SOE*), customer concentration (*CC*), customer stock market return (*CusRet*), customer sales revenue volatility (*stdCusGro*), whether the supplier changes its accounting firm (*Change*), whether the supplier is audited by an international Big4 firm (*Big*4), whether the customer and supplier share the same auditor (*ComAud*) and marketization degree (*MKT*). Table 1 provides more details on each variable. We also controlled for firm fixed effects (*Firm*) and year fixed effects (*Year*) and cluster-adjusted the standard errors of the regression results at the firm level.

Table 1
Variable definitions.

Variables	Definition
Panel A: Independent and dependent variables	
Lnfee	Natural logarithm of supplier audit costs
*CusDigit*1	Weighted average of customer sales share (number of digital transformation-related terms in the annual report/total number of terms in the annual report × 100)
*CusDigit*2	Weighted average of the logarithm of the number of digital transformation-related terms in the annual report calculated as a percentage of customer sales
Panel B: Control variables	
Size	Natural logarithm of suppliers' total assets
Lev	Ratio of suppliers' total liabilities to total assets
CF	Ratio of suppliers' cash flow from operating activities to total assets
Current	Ratio of suppliers' current assets to current liabilities
ROA	Ratio of suppliers' net profit to total assets
Receiv	Ratio of suppliers' net accounts receivable to total assets
Loss	If the supplier's net profit for the year is less than 0, it takes the value of 1 and 0 otherwise
Age	Suppliers' year of establishment divided by 100
BusSeg	Suppliers' number of business segments
Digit	A supplier's share of digital transformation words, i.e., (number of digital transformation-related terms in the supplier's annual report/total number of terms in the supplier's annual report) × 100
Board	Natural logarithm of the number of directors of the supplier company
Indrt	Ratio of the number of suppliers' independent directors to the total number of directors
Sep	Proportion of control of the listed company owned by the beneficial owner of the supplier company minus proportion of ownership of the listed company owned by the beneficial owner of the supplier company
SOE	The nature of the supplier's property rights, which takes the value of 1 if it is a state-owned enterprise and 0 otherwise
CC	Sum of squared ratios of sales to total sales from the top five customers
CusRet	Equity return on customers weighted by customers' share of sales
stdCusGro	Volatility of sales revenue from customers weighted by their share of sales
Change	If there is a change in the supplier's accounting firm, it takes the value of 1 and 0 otherwise
*Big*4	If the supplier is audited by a Big 4 accounting firm, it takes the value of 1 and 0 otherwise
ComAud	If there is a common auditor between the customer and the supplier, it takes the value of 1 and 0 otherwise
MKT	If the marketization index is greater than the sample period average, it takes the value of 1 and 0 otherwise

4. Empirical results

4.1. Descriptive statistics

Table 2 presents the descriptive statistics of the main variables. The means of *CusDigit*1 and *CusDigit*2 are 0.013 and 0.713, respectively, with standard deviations of 0.029 and 1.146. The dependent variable, audit fees, has a mean of 13.574 and a standard deviation of 0.685. These statistics suggest significant variations in both customer digitization transformation and audit fees across different supplier firms, consistent with previous research (Di et al., 2020). The remaining control variables also align with those in other studies (Di et al., 2020; Zhang et al., 2021).

4.2. Baseline results

Table 3 presents the regression results for the effect of customer digital transformation on supplier audit fees. The estimated regression coefficients for *CusDigit* when controlling for *Firm* and *Year* are –1.132 and –0.030, respectively, and are both statistically significant at the 1 % level. These results suggest that customers' digital transformation significantly reduces suppliers' audit fees, thus preliminarily confirming H1a. This finding has economic significance: for every standard deviation increase in *CusDigit* (0.029 and 1.146), the standard deviation of supplier audit fees (0.685) will decrease by 4.79 % and 5.02 %, respectively.[1]

[1] Taking the coefficients on *CusDigit*1 from column (1) of Table 3 as an example, a one standard deviation increase in *CusDigit*1 (0.029), relative to the standard deviation of *Lnfee* (0.685), results in a decrease in *Lnfee* of 4.79%, calculated as 1.132 × 0.029/0.685.

Table 2
Descriptive statistic.

Variable	N	Mean	SD	P25	Median	P75	Max
Lnfee	1,419	13.574	0.685	13.122	13.459	13.955	15.956
*CusDigit*1	1,419	0.013	0.029	0.000	0.000	0.010	0.170
*CusDigit*2	1,419	0.713	1.146	0.000	0.000	1.147	4.248
Size	1,419	21.920	1.223	20.987	21.759	22.690	25.114
Lev	1,419	0.421	0.213	0.254	0.410	0.585	0.902
CF	1,419	0.040	0.065	0.003	0.039	0.076	0.214
Current	1,419	2.668	3.243	1.086	1.657	2.839	23.189
ROA	1,419	0.038	0.065	0.014	0.037	0.068	0.203
Receiv	1,419	0.137	0.112	0.046	0.116	0.201	0.528
Loss	1,419	0.102	0.303	0.000	0.000	0.000	1.000
Age	1,419	0.153	0.058	0.110	0.150	0.190	0.310
BusSeg	1,419	0.702	1.558	0.000	0.000	0.000	7.000
Digit	1,419	0.024	0.060	0.000	0.000	0.013	0.326
Board	1,419	2.178	0.175	2.079	2.197	2.197	2.708
Indrt	1,419	0.368	0.050	0.333	0.333	0.400	0.556
Sep	1,419	5.657	8.080	0.000	0.000	10.659	29.936
SOE	1,419	0.414	0.493	0.000	0.000	1.000	1.000
CC	1,419	5.624	9.829	0.540	1.679	5.826	52.604
CusRet	1,419	0.096	0.405	–0.105	0.000	0.188	1.667
stdCusGro	1,419	0.075	0.099	0.000	0.044	0.105	0.471
Change	1,419	0.129	0.335	0.000	0.000	0.000	1.000
*Big*4	1,419	0.044	0.204	0.000	0.000	0.000	1.000
ComAud	1,419	0.014	0.118	0.000	0.000	0.000	1.000
MKT	1,419	0.550	0.498	0.000	1.000	1.000	1.000

4.3. Robustness tests

4.3.1. Alternative measures of customer digital transformation

To enhance the robustness of our findings, we took two approaches to recalibrate customer digital transformation. First, following Yuan et al. (2021), we divided the total number of occurrences of digital transformation terms in the management discussion and analysis (MD&A) sections of the top five listed customers disclosed by the suppliers by the total MD&A word count and multiplied by 100. The resulting number of digital transformation terms in the MD&A sections was then transformed using the natural logarithm and weighted by the customer's sales share, to compute the customer's level of digital transformation (*CusDigit*3 and *CusDigit*4). Second, following the methodology proposed by Di et al. (2020), equal weights were assigned to calculate the proportion of digitized vocabulary in annual customer reports (*CusDT*1) and the logarithm of the number of occurrences of digitized vocabulary in annual customer reports (*CusDT*2). The robustness regression results presented in Table 4 demonstrate that regardless of the approach used to compute customer digital transformation, the coefficient on *Lnfee* consistently and significantly shows a negative relationship, significant at least at the 5 % level. These findings support H1a, indicating that customers' digital transformation has a diminishing effect on suppliers' audit fees.

4.3.2. Alternative measure of supplier audit fees

To account for the effects on audit fees of variations in auditor workload attributed to supplier size, we used suppliers' audit fees adjusted for operating revenue as the explanatory variable (*AuditFee*) in our robustness test. Columns (1) and (2) of Table 5 present the results of this robustness test with the alternative measure of supplier audit fees. The coefficient of *CusDigit* on *AuditFee* remains statistically significant, at least at the 5 % level.

Table 3
Customer digital transformation and supplier audit fees.

Variable	(1) *Lnfee*	(2) *Lnfee*
*CusDigit*1	–1.132***	
	(–2.77)	
*CusDigit*2		–0.030***
		(–2.68)
Size	0.342***	0.343***
	(7.63)	(7.63)
Lev	–0.098	–0.100
	(–0.60)	(–0.61)
CF	0.366**	0.355**
	(2.51)	(2.42)
Current	–0.008*	–0.008*
	(–1.89)	(–1.88)
ROA	0.022	0.019
	(0.08)	(0.07)
Receiv	0.313	0.320
	(1.13)	(1.14)
Loss	0.080*	0.078*
	(1.92)	(1.85)
Age	6.752***	6.745***
	(4.18)	(4.09)
BusSeg	–0.006	–0.006
	(–0.63)	(–0.66)
Digit	–0.098	–0.091
	(–0.39)	(–0.36)
Board	0.189	0.181
	(1.55)	(1.48)
Indrt	0.301	0.283
	(0.87)	(0.83)
Sep	–0.000	–0.000
	(–0.09)	(–0.14)
SOE	0.221*	0.216*
	(1.89)	(1.81)
CC	–0.004**	–0.004**
	(–2.56)	(–2.58)
CusRet	–0.023	–0.023
	(–1.18)	(–1.18)
stdCusGro	0.129	0.128
	(1.36)	(1.36)
Change	–0.032	–0.030
	(–1.38)	(–1.29)
*Big*4	0.300***	0.304***
	(3.01)	(3.09)
ComAud	0.138	0.137
	(1.51)	(1.47)
MKT	0.135***	0.132***
	(3.07)	(2.97)
Constant	4.375***	4.391***
	(4.02)	(4.04)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	1,419	1,419
Adj. R^2	0.240	0.239

Notes: Standard errors are clustered at the firm level. *statistically significant at the 10%, **statistically significant at the 5% and ***statistically significant at the 1% level. The t-statistics are provided in parentheses, and the same notation is used throughout the text.

Table 4
Robustness test: Alternative measurement of independent variables.

Variable	(1) *Lnfee*	(2) *Lnfee*	(3) *Lnfee*	(4) *Lnfee*
*CusDigit*3	–0.177**			
	(–2.19)			
*CusDigit*4		–0.036***		
		(–3.09)		
*CusDT*1			–1.125***	
			(–2.66)	
*CusDT*2				–0.031***
				(–2.71)
Size	0.340***	0.340***	0.343***	0.344***
	(7.54)	(7.60)	(7.64)	(7.67)
Lev	–0.099	–0.103	–0.098	–0.101
	(–0.60)	(–0.63)	(–0.60)	(–0.61)
CF	0.366**	0.359**	0.364**	0.357**
	(2.51)	(2.46)	(2.50)	(2.44)
Current	–0.008*	–0.008*	–0.008*	–0.008*
	(–1.88)	(–1.90)	(–1.90)	(–1.90)
ROA	0.010	0.027	0.021	0.017
	(0.04)	(0.10)	(0.07)	(0.06)
Receiv	0.324	0.337	0.311	0.317
	(1.17)	(1.22)	(1.12)	(1.14)
Loss	0.078*	0.079*	0.081*	0.078*
	(1.87)	(1.88)	(1.93)	(1.86)
Age	6.709***	6.726***	6.753***	6.750***
	(4.19)	(4.13)	(4.19)	(4.11)
BusSeg	–0.006	–0.007	–0.006	–0.006
	(–0.65)	(–0.74)	(–0.65)	(–0.67)
Digit	–0.157	–0.150	–0.102	–0.093
	(–0.60)	(–0.58)	(–0.40)	(–0.37)
Board	0.187	0.177	0.190	0.182
	(1.52)	(1.45)	(1.56)	(1.48)
Indrt	0.273	0.248	0.298	0.282
	(0.79)	(0.73)	(0.86)	(0.82)
Sep	–0.000	–0.000	–0.000	–0.000
	(–0.11)	(–0.14)	(–0.09)	(–0.14)
SOE	0.215*	0.212*	0.221*	0.216*
	(1.86)	(1.82)	(1.89)	(1.81)
CC	–0.004**	–0.004**	–0.004**	–0.004**
	(–2.45)	(–2.51)	(–2.53)	(–2.57)
CusRet	–0.025	–0.027	–0.023	–0.023
	(–1.27)	(–1.37)	(–1.18)	(–1.17)
stdCusGro	0.130	0.135	0.129	0.128
	(1.37)	(1.43)	(1.35)	(1.36)
Change	–0.031	–0.032	–0.032	–0.030
	(–1.35)	(–1.38)	(–1.39)	(–1.32)
*Big*4	0.305***	0.310***	0.301***	0.303***
	(3.10)	(3.09)	(3.01)	(3.08)
ComAud	0.138	0.132	0.138	0.138
	(1.57)	(1.45)	(1.52)	(1.48)
MKT	0.137***	0.140***	0.135***	0.132***
	(3.11)	(3.15)	(3.06)	(2.97)
Constant	4.448***	4.474***	4.371***	4.373***
	(4.11)	(4.15)	(4.02)	(4.04)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,419	1,419	1,419	1,419
Adj. R^2	0.237	0.241	0.239	0.240

Table 5
Robustness tests: Alternative measure of the dependent variable and excluding the 2019 and 2020 samples.

Variable	(1) *AuditFee*	(2) *AuditFee*	(3) *Lnfee*	(4) *Lnfee*
*CusDigit*1	–0.302**		–1.048**	
	(–2.38)		(–2.19)	
*CusDigit*2		–0.008***		–0.033***
		(–2.59)		(–2.85)
Size	–0.060***	–0.060***	0.349***	0.350***
	(–3.79)	(–3.79)	(7.62)	(7.75)
Lev	0.099**	0.099*	–0.076	–0.081
	(1.97)	(1.96)	(–0.45)	(–0.47)
CF	0.047	0.044	0.346**	0.334**
	(0.69)	(0.65)	(2.19)	(2.10)
Current	0.003	0.003*	–0.004	–0.004
	(1.62)	(1.66)	(–0.93)	(–0.92)
ROA	–0.436***	–0.436***	0.220	0.218
	(–3.82)	(–3.84)	(0.72)	(0.71)
Receiv	–0.178	–0.176	0.265	0.264
	(–1.56)	(–1.54)	(0.94)	(0.93)
Loss	0.005	0.004	0.061*	0.059
	(0.42)	(0.37)	(1.65)	(1.60)
Age	1.009	1.010	6.177***	6.372***
	(1.53)	(1.49)	(3.45)	(3.45)
BusSeg	–0.000	–0.000	–0.006	–0.007
	(–0.10)	(–0.14)	(–0.72)	(–0.79)
Digit	0.001	0.004	–0.032	–0.010
	(0.02)	(0.06)	(–0.12)	(–0.04)
Board	0.018	0.016	0.172	0.167
	(0.53)	(0.47)	(1.29)	(1.25)
Indrt	0.012	0.008	0.167	0.165
	(0.12)	(0.08)	(0.43)	(0.43)
Sep	–0.000	–0.000	–0.003	–0.003
	(–0.19)	(–0.24)	(–0.81)	(–0.84)
SOE	–0.042	–0.043	0.258	0.260
	(–1.12)	(–1.12)	(1.27)	(1.26)
CC	–0.002*	–0.002*	–0.004*	–0.004**
	(–1.77)	(–1.79)	(–1.91)	(–1.97)
CusRet	–0.013**	–0.013**	–0.020	–0.020
	(–2.01)	(–2.01)	(–0.97)	(–1.01)
stdCusGro	–0.003	–0.003	0.113	0.116
	(−0.13)	(−0.14)	(1.14)	(1.19)
Change	–0.003	–0.003	–0.042*	–0.041*
	(–0.82)	(–0.68)	(–1.77)	(–1.74)
*Big*4	–0.003	–0.002	0.228*	0.229**
	(–0.15)	(–0.11)	(1.96)	(2.00)
ComAud	–0.012	–0.012	–0.001	–0.008
	(–0.95)	(–1.01)	(–0.01)	(–0.09)
MKT	0.019	0.018	0.094**	0.090**
	(1.22)	(1.15)	(2.26)	(2.16)
Constant	1.221***	1.222***	4.437***	4.402***
	(3.27)	(3.29)	(3.92)	(3.94)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,419	1,419	1,269	1,269
Adj. R^2	0.271	0.272	0.257	0.260

4.3.3. Excluding samples from 2019 and 2020

The COVID-19 outbreak may have had a negative impact on firms' production, business conditions and auditing. Thus, we excluded the 2019 and 2020 samples to test robustness. The regression results in Columns (3) and (4) of Table 5 show that the coefficients of *CusDigit* on *Lnfee* remain negative and significant, at least at the 5 % level, further confirming the robustness of our findings.

4.3.4. Controlling the impact of sticky audit fees

As audit fees are sticky, we used two methods to control for their possible impact on the findings. First, the previous year's audit fee ($Lnfee_{t-1}$) was added to the control variables for robustness testing. Second, Using the one-period lead of the dependent variable as the dependent variable ($Lnfee_{t+1}$). The regression results in Table 6 indicate that when controlling for $Lnfee_{t-1}$ in Columns (1) and (2), the coefficients of *CusDigit* on *Lnfee* remain negative and significant, at least at the 5 % level. Columns (3) and (4) show that the coefficients of *CusDigit* on $Lnfee_{t+1}$ remain negative and significant, at least at the 5 % level.

4.4. Endogeneity

4.4.1. Instrumental variable regression

Potential reverse causation between customer digital transformation and supplier audit fees is a concern. Lower audit fees may indicate a decrease in a supplier's operational risk and an improvement in financial statement quality. This could potentially attract customers with higher levels of digitization. To address this concern, we used the two-stage least squares (2SLS) statistical method to mitigate endogeneity issues. To proxy for customer digital transformation (*CusDigit*), two instrumental variables were selected based on previous studies (Di et al., 2020; Zhao et al., 2022). The first instrumental variable, *Dige*, combines the number of post offices per 10,000 people and the number of Internet users in the country in 1984 for each city. The second instrumental variable, *CusDigit_Peer*, represents the mean customer digital transformation of other suppliers in the same region and year. These instrumental variables were chosen because post offices have historically served as the primary communication infrastructure in China, influencing regional communication capacity and digitalization. In addition, the role of traditional postal communication has declined as technology has developed, reducing its impact on supplier audit costs and thus meeting the exclusivity requirement of instrumental variables. Additionally, customers within the same region share similar market environments, making their digital transformation decisions relevant, whereas the digitization level of other customers does not directly affect suppliers' audit fees.

The findings in Table 7 regarding the first-stage regression of the instrumental variables indicate a positive relationship between *Dige*/*CusDigit_Peer* and*CusDigit* significant at the 1 % level. This suggests a satisfactory correlation between the variables. Table 7 presents the results of the second-stage regression of the instrumental variables. The results of the weak instrument test are greater than 10 and the Hansen J statistic does not pass the significance test, which indicates that the instrumental variables we selected are appropriate. Consequently, the second-stage regression results show a negative relationship between *CusDigit* and the instrumental variables significant at the 1 % level. These findings suggest that reverse causality has a minimal effect on the influence of customers' digital transformation on suppliers' audit fees.

4.4.2. Entropy balancing method

Multiple linear regression enables the identification of causal effects by controlling for observable confounding variables. However, the functional form must be correctly specified to avoid capturing residual terms and introducing endogeneity issues. To mitigate this concern, we used the entropy balancing (EB) method suggested by Hainmueller (2012) to address potential endogeneity problems arising from misspecifications in the regression model. EB adjusts the observed values of the control group by assigning optimal weights, thus enhancing the similarity in covariates between the control and treatment groups.

The EB method also minimizes the higher-order moment gaps of all control variables, based primarily on the level of customer digital transformation (grouped according to the annual median of *CusDigit*).The descriptive statistics after EB are presented in Table 8. By applying EB weights, we minimized the differences between the treatment (*CusDigit_Dum* = 1) and control (*CusDigit_Dum* = 0) groups in terms of first-, second-

Table 6
Robustness test: Controlling for the impact of sticky audit fees.

Variable	(1) *Lnfee*	(2) *Lnfee*	(3) $Lnfee_{t+1}$	(4) $Lnfee_{t+1}$
*CusDigit*1	–0.948**		–1.877**	
	(–2.54)		(–2.32)	
*CusDigit*2		–0.022**		–0.034**
		(–2.03)		(–1.97)
$Lnfee_{t-1}$	0.255***	0.254***		
	(5.77)	(5.74)		
Size	0.256***	0.255***	0.460***	0.459***
	(6.56)	(6.49)	(3.18)	(3.19)
Lev	0.019	0.017	–0.265	–0.271
	(0.14)	(0.12)	(–0.60)	(–0.61)
CF	0.239*	0.227*	–0.351	–0.373
	(1.94)	(1.84)	(–0.67)	(–0.71)
Current	–0.012***	–0.012***	–0.009	–0.008
	(–2.92)	(–2.90)	(–1.14)	(–1.12)
ROA	0.071	0.066	0.407	0.394
	(0.28)	(0.26)	(0.68)	(0.66)
Receiv	0.176	0.178	0.053	0.056
	(0.72)	(0.72)	(0.07)	(0.08)
Loss	0.059	0.057	0.077	0.074
	(1.44)	(1.39)	(1.28)	(1.22)
Age	7.682***	7.631***	–6.687	–6.790
	(5.46)	(5.29)	(–0.36)	(–0.36)
BusSeg	–0.002	–0.002	–0.004	–0.004
	(–0.19)	(–0.19)	(–0.37)	(–0.37)
Digit	0.005	0.001	–0.475	–0.488
	(0.02)	(0.00)	(–1.18)	(–1.20)
Board	0.200*	0.193*	0.080	0.063
	(1.75)	(1.68)	(0.38)	(0.30)
Indrt	0.094	0.076	1.660	1.612
	(0.29)	(0.24)	(1.26)	(1.23)
Sep	–0.001	–0.001	0.001	0.001
	(–0.36)	(–0.40)	(0.19)	(0.14)
SOE	0.158	0.152	–0.039	–0.051
	(1.57)	(1.46)	(–0.31)	(–0.40)
CC	–0.003*	–0.003*	0.000	0.000
	(–1.94)	(–1.84)	(0.12)	(0.18)
CusRet	–0.008	–0.009	–0.098	–0.100
	(–0.45)	(–0.47)	(–1.06)	(–1.08)
stdCusGro	0.116	0.111	–0.198	–0.211
	(1.22)	(1.18)	(–0.83)	(–0.87)
Change	–0.038	–0.037	–0.013	–0.010
	(–1.63)	(–1.56)	(–0.13)	(–0.10)
*Big*4	0.285***	0.287***	0.253	0.258*
	(3.08)	(3.15)	(1.60)	(1.65)
ComAud	0.101	0.101	0.022	0.022
	(1.42)	(1.40)	(0.16)	(0.16)
MKT	0.113***	0.111***	–0.055	–0.057
	(2.67)	(2.61)	(–0.51)	(–0.53)
Constant	2.747**	2.816***	3.993	4.106
	(2.57)	(2.63)	(1.02)	(1.05)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,347	1,347	1,419	1,419
Adj. R^2	0.293	0.291	0.016	0.015

Table 7
Endogeneity: Instrumental variable analysis.

Variable	(1) *CusDigit*1	(2) *CusDigit*2	(3) *Lnfee*	(4) *Lnfee*
Dige	0.001***	0.034***		
	(2.88)	(3.59)		
CusDigit_Peer	0.005***	0.211***		
	(3.09)	(3.22)		
*CusDigit*1			–9.273***	
			(–2.97)	
*CusDigit*2				–0.213***
				(–3.30)
Size	0.004	0.201**	0.379***	0.381***
	(1.27)	(2.03)	(7.21)	(7.98)
Lev	0.005	0.129	–0.058	–0.081
	(0.61)	(0.40)	(–0.33)	(–0.45)
CF	0.016	0.251	0.498***	0.400**
	(1.18)	(0.53)	(2.69)	(2.33)
Current	–0.000	–0.004	–0.010*	–0.009*
	(–0.42)	(–0.23)	(–1.68)	(–1.71)
ROA	0.014	0.423	0.173	0.132
	(0.67)	(0.62)	(0.57)	(0.44)
Receiv	0.004	0.350	0.373	0.411
	(0.14)	(0.40)	(1.05)	(1.33)
Loss	–0.000	–0.106	0.082*	0.063
	(−0.13)	(−1.05)	(1.65)	(1.33)
Age	0.311	12.219	8.065***	7.817***
	(1.35)	(1.41)	(4.18)	(3.83)
BusSeg	–0.000	–0.020	–0.011	–0.012
	(–0.53)	(–0.87)	(–1.00)	(–1.18)
Digit	0.031	1.393	0.213	0.219
	(1.00)	(1.52)	(0.60)	(0.76)
Board	0.009	0.053	0.288*	0.216
	(0.97)	(0.17)	(1.95)	(1.53)
Indrt	0.048	1.210	0.693	0.510
	(1.34)	(0.93)	(1.39)	(1.17)
Sep	0.000	–0.004	0.000	–0.001
	(0.16)	(–0.51)	(0.08)	(–0.25)
SOE	0.010	0.228	0.313**	0.265**
	(0.87)	(0.66)	(2.53)	(2.22)
CC	–0.000*	–0.018**	–0.008***	–0.007***
	(–1.87)	(–2.40)	(–3.08)	(–3.60)
CusRet	0.003*	0.128*	–0.000	–0.003
	(1.75)	(1.73)	(–0.01)	(–0.12)
stdCusGro	0.011	0.326	0.287*	0.254*
	(0.85)	(0.67)	(1.82)	(1.85)
Change	–0.001	0.012	–0.041	–0.025
	(–0.86)	(0.18)	(–1.54)	(–0.98)
*Big*4	0.002	0.217	0.283**	0.311***
	(0.27)	(0.66)	(2.23)	(2.74)
ComAud	–0.000	–0.013	0.130	0.127
	(–0.01)	(–0.03)	(0.96)	(0.86)
MKT	–0.002	–0.196	0.118*	0.096
	(–0.46)	(–1.23)	(1.87)	(1.60)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 7 (*continued*)

Variable	(1) *CusDigit*1	(2) *CusDigit*2	(3) *Lnfee*	(4) *Lnfee*
N	1,419	1,419	1,419	1,419
Kleibergen–Paap rk Wald F			16.569	15.175
Hansen–J P value			0.486	0.436

Notes: Standard errors are clustered at the firm level. *statistically significant at the 10%, **statistically significant at the 5% and ***statistically significant at the 1% level. Z-statistics are given in parentheses.

and third-order moments. This reduction in the dependence on the functional form setting enabled our subsequent analysis. Table 9 displays the regression results based on entropy balanced samples, with regression weights calculated from all control variables presented in Columns (1) and (2). The regression results indicate negative coefficients for *CusDigit* significant at least at the 5 % level across all weight variations. This finding suggests that the endogeneity problem resulting from biased functional form specifications is minimal.

4.4.3. Excluding the effect of strategic disclosure

We took three approaches to address concerns about the accuracy of textual information disclosure when evaluating customer digital transformation. First, we used a financial indicator, the ratio of digitization-related intangible assets to total intangible assets in customers' financial statements, as proposed by Zhang et al. (2021), as an endogeneity test for customer digital transformation (referred to as *CusDigit_Intan*). Second, we followed the methodology of Li et al. (2022) and excluded customer firms with poor disclosure quality, including those penalized by regulatory bodies such as the U.S. Securities and Exchange Commission (SEC) or stock exchanges for disclosure-related issues. Finally, we omitted customer firms operating in the digitization industry from the sample.

Table 8
Endogeneity: EB descriptive statistics.

Variable	*CusDigit_Dum* = 1			*CusDigit_Dum* = 0		
	Mean_Tr	*Var_Tr*	*Skew_Tr*	*Mean_Co_Post*	*Var_Co_Post*	*Skew_Co_Post*
Size	21.78890	1.308296	0.562143	21.78613	1.308151	0.569496
Lev	0.401146	0.044788	0.219762	0.401096	0.044783	0.220499
CF	0.039810	0.004114	0.086055	0.039805	0.004114	0.086306
Current	2.972146	12.46674	3.549138	2.971747	12.46506	3.549703
ROA	0.042792	0.004424	–1.336220	0.042786	0.004423	–1.336040
Receiv	0.158129	0.014073	0.955495	0.158108	0.014071	0.956069
Loss	0.095528	0.086579	2.752036	0.095580	0.086538	2.751026
Age	0.163232	0.003298	0.223656	0.163211	0.003298	0.224762
BusSeg	0.894309	2.664978	2.017626	0.894191	2.664640	2.017977
Digit	0.045841	0.006354	2.226320	0.045834	0.006353	2.226701
Board	2.156997	0.033773	–0.44095	2.156723	0.033769	–0.436470
Indrt	0.370739	0.002474	1.466918	0.370692	0.002474	1.469896
Sep	5.033947	59.31967	1.341298	5.033343	59.31253	1.341623
SOE	0.363821	0.231927	0.566117	0.364068	0.231773	0.565008
CC	5.016167	65.66496	3.062957	5.015568	65.65821	3.063388
CusRet	0.138168	0.167075	1.326649	0.138151	0.167054	1.326868
stdCusGro	0.078922	0.008491	2.056275	0.078912	0.008490	2.056727
Change	0.130081	0.113391	2.199326	0.130243	0.113402	2.197206
*Big*4	0.012195	0.012071	8.888889	0.012212	0.012076	8.882332
ComAud	0.03252	0.031527	5.271016	0.032540	0.031515	5.269221
MKT	0.593496	0.241750	–0.380700	0.593295	0.241557	–0.379850

Table 9
Endogeneity: EB method.

Variable	(1) *Lnfee*	(2) *Lnfee*
*CusDigit*1	–1.111***	
	(–2.61)	
*CusDigit*2		–0.026**
		(–2.26)
Size	0.313***	0.331***
	(6.64)	(6.45)
Lev	–0.031	–0.076
	(–0.18)	(–0.41)
CF	0.380**	0.437**
	(2.50)	(2.53)
Current	–0.007	–0.008*
	(–1.42)	(–1.71)
ROA	0.075	0.275
	(0.29)	(0.94)
Receiv	0.339	0.353
	(1.18)	(1.20)
Loss	0.065	0.086*
	(1.42)	(1.70)
Age	6.083	3.664
	(1.34)	(0.82)
BusSeg	–0.008	–0.010
	(–1.00)	(–1.33)
Digit	0.034	–0.031
	(0.12)	(–0.11)
Board	0.167	0.152
	(1.33)	(1.22)
Indrt	0.009	0.017
	(0.02)	(0.05)
Sep	0.001	–0.000
	(0.17)	(–0.15)
SOE	0.227**	0.201*
	(2.06)	(1.76)
CC	–0.004*	–0.004*
	(–1.87)	(–1.83)
CusRet	–0.014	–0.016
	(–0.75)	(–0.79)
stdCusGro	0.196*	0.170
	(1.68)	(1.40)
Change	–0.030	–0.026
	(–1.09)	(–0.88)
*Big*4	0.281***	0.291***
	(3.03)	(4.13)
ComAud	0.103**	0.122**
	(1.98)	(2.02)
MKT	0.143***	0.132**
	(2.61)	(2.34)
Constant	5.196***	5.265***
	(4.17)	(4.01)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	1,419	1,419
Adj. R^2	0.254	0.276

Table 10
Endogeneity: Excluding the effect of strategic disclosure.

Variable	(1) *Lnfee*	(2) *Lnfee*	(3) *Lnfee*	(4) *Lnfee*	(5) *Lnfee*
CusDigit_Intan	–0.053**				
	(–2.01)				
*CusDigit*1		–1.487***		–1.222***	
		(–2.85)		(–2.96)	
*CusDigit*2			–0.046***		–0.032***
			(–3.54)		(–2.63)
Size	0.341***	0.342***	0.347***	0.371***	0.373***
	(7.50)	(7.38)	(7.43)	(8.20)	(8.21)
Lev	–0.101	–0.206	–0.210	–0.188	–0.189
	(–0.62)	(–1.22)	(–1.23)	(–1.10)	(–1.09)
CF	0.327**	0.327**	0.327**	0.382***	0.363**
	(2.24)	(2.10)	(2.07)	(2.66)	(2.55)
Current	–0.009*	–0.008*	–0.008*	–0.006	–0.006
	(–1.87)	(–1.74)	(–1.68)	(–1.45)	(–1.45)
ROA	0.009	0.360	0.365	–0.005	0.000
	(0.03)	(1.23)	(1.21)	(–0.02)	(0.00)
Receiv	0.309	0.117	0.150	0.631**	0.640**
	(1.10)	(0.40)	(0.51)	(2.06)	(2.08)
Loss	0.077*	0.079**	0.077**	0.075*	0.073*
	(1.84)	(2.12)	(2.09)	(1.72)	(1.67)
Age	6.392***	2.190	2.205	11.143***	11.111***
	(4.00)	(1.48)	(1.45)	(3.44)	(3.46)
BusSeg	–0.006	–0.009	–0.010	–0.005	–0.005
	(–0.63)	(–1.02)	(–1.12)	(–0.52)	(–0.54)
Digit	–0.119	0.110	0.158	–0.140	–0.144
	(–0.45)	(0.40)	(0.58)	(–0.51)	(–0.51)
Board	0.170	0.334***	0.329***	0.121	0.114
	(1.41)	(2.75)	(2.69)	(1.01)	(0.95)
Indrt	0.220	0.633*	0.608*	–0.018	–0.003
	(0.65)	(1.91)	(1.90)	(–0.05)	(–0.01)
Sep	–0.000	–0.000	–0.000	0.001	0.001
	(–0.10)	(–0.03)	(–0.12)	(0.21)	(0.20)
SOE	0.199*	0.320***	0.319***	0.272**	0.271**
	(1.66)	(2.80)	(2.78)	(2.49)	(2.45)
CC	–0.004**	–0.003**	–0.003**	–0.005***	–0.005***
	(–2.31)	(–2.04)	(–2.18)	(–2.67)	(–2.64)
CusRet	–0.028	–0.022	–0.020	–0.035	–0.034
	(–1.38)	(–1.15)	(–1.10)	(–1.60)	(–1.55)
stdCusGro	0.112	0.168*	0.167*	0.194**	0.185*
	(1.17)	(1.70)	(1.73)	(2.04)	(1.95)
Change	–0.031	–0.044**	–0.042*	–0.040	–0.037
	(–1.34)	(–1.96)	(–1.90)	(–1.58)	(–1.48)
*Big*4	0.304***	0.296***	0.301***	0.304***	0.310***
	(3.08)	(3.02)	(3.23)	(3.34)	(3.43)
ComAud	0.146	0.019	0.014	0.139	0.135
	(1.60)	(0.20)	(0.14)	(1.12)	(1.04)
MKT	0.138***	0.115**	0.107**	0.108***	0.105***
	(3.10)	(2.49)	(2.28)	(2.76)	(2.65)
Constant	4.531***	4.631***	4.572***	3.310***	3.286***
	(4.16)	(4.34)	(4.26)	(3.50)	(3.49)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	1,419	1,166	1,166	1,266	1,266
Adj. R^2	0.236	0.266	0.271	0.266	0.266

The results in Column (1) of Table 10 indicate that *CusDigit_Intan* has a statistically significant impact on reducing suppliers' audit fees at the 5 % level. To further validate these findings, we excluded samples with disclosure violations and find negative regression coefficients for *CusDigit*1 and *CusDigit*2 on suppliers' audit fees in Columns (2) and (3), significant at the 1 % level. Likewise, in Columns (4) and (5), we exclude digitization-related industries and find negative regression coefficients for *CusDigit*1 and *CusDigit*2 on suppliers' audit fees, significant at the 1 % level. These results address concerns about potential noise in the disclosure of customer digital transformation, thereby reinforcing the reliability of our conclusions.

4.4.4. Heckman two-stage test

We identified two potential issues related to self-selection. First, lower audit fees may indicate suppliers with more reliable financial statements and lower business risk. Such suppliers may deliberately choose to collaborate with customers that have higher growth prospects and invest more in digital transformation. This selection process may introduce bias into our study. The second issue relates to the costs associated with disclosing important customer information. The CSRC only encourages listed companies to disclose details about their top five customers, rather than making it mandatory. Suppliers' disclosure of customer information is thus voluntary, which introduces another self-selection issue into the sample. We addressed these concerns using the Heckman two-stage test.

To address the first type of self-selection problem, we used a two-stage regression approach. In the first stage, we conducted a logit regression, in which the dependent variable (*CusDigit_Dum*) was regressed on the control and instrumental variables (*Dige*).[2] The Inverse Mills Ratio (*IMR*1) was estimated using the regression. In the second stage, the estimated *IMR*1 was incorporated into Model (1) for further regression analysis. The regression results in Columns (2) and (3) of Table 11 demonstrate a statistically significant negative relationship between *CusDigit* and *Lnfee*.

We used a logit regression in the first stage to address the second type of self-selection issue (Di et al., 2020). The dependent variable in this regression was whether the supplier discloses customer information in the current year (*DiscloCus*) and the instrumental variable was the mean disclosure status of other suppliers in the same region and year (*mean_DiscloCus*). In the second stage, we incorporated the estimated *IMR*2 into regression Model (1). Columns (2) and (3) of Table 12 reveal a significant negative relationship between *CusDigit* and *Lnfee*. The findings in Tables 11 and 12 indicate that the results remain robust when considering self-selection issues.

5. Additional tests

5.1. Mechanisms analysis

5.1.1. Audit risk

Operational risk and earnings management can potentially increase audit risks and audit fees (Shimnitsch, 1980; Defond and Lennox, 2011). We propose that customers' digital transformation helps to reduce suppliers' audit costs by reducing their audit risks. Digital transformation can enhance customers' information transparency and decrease their operational risks (Zhang et al., 2021), thus alleviating the operational risks that can spill over to suppliers through the supply chain. This digital transformation also reduces suppliers' incentives to manipulate earnings, as it empowers customers to respond better to risks, encourages information transparency and facilitates efficient collaboration throughout the supply chain. This reduces the volatility of supplier performance and the motivation of management to manipulate earnings and financial statements, ultimately enhancing the quality of these firms' accounting information. Customers' digital transformation therefore mitigates suppliers' operational risks and earnings manipulation, leading to a reduction in auditors' perceptions of risk and thus suppliers' audit fees.

[2] *Dige* represents the number of post offices per 10,000 people and the number of Internet users in the country in 1984 for each city.

Table 11
Endogeneity: Heckman two-stage test- The self-selection problem for customer digital transformation.

Variable	(1) *CusDigit1_Dum*	(2) *Lnfee*	(3) *Lnfee*
Dige	0.136***		
	(2.96)		
*CusDigit*1		–1.048**	
		(–2.58)	
*CusDigit*2			–0.027**
			(–2.44)
*IMR*1		–0.001	–0.001
		(–1.02)	(–0.86)
Size	0.967*	0.345***	0.345***
	(1.81)	(7.64)	(7.62)
Lev	1.670	–0.101	–0.103
	(0.95)	(–0.62)	(–0.63)
CF	1.919	0.360**	0.350**
	(0.73)	(2.45)	(2.39)
Current	–0.045	–0.009**	–0.009**
	(–0.41)	(–1.99)	(–1.97)
ROA	3.429	0.038	0.032
	(0.82)	(0.14)	(0.12)
Receiv	3.756	0.319	0.324
	(1.11)	(1.15)	(1.16)
Loss	–0.724	0.079*	0.077*
	(–1.05)	(1.89)	(1.83)
Age	–3.818	6.109***	6.196***
	(–0.03)	(3.52)	(3.53)
BusSeg	–0.296**	–0.006	–0.006
	(–2.38)	(–0.65)	(–0.67)
Digit	1.209	–0.101	–0.095
	(0.26)	(–0.40)	(–0.37)
Board	–0.233	0.187	0.180
	(–0.11)	(1.54)	(1.47)
Indrt	–1.883	0.300	0.283
	(–0.32)	(0.87)	(0.83)
Sep	0.028	–0.000	–0.000
	(0.47)	(–0.09)	(–0.13)
SOE	1.669	0.226*	0.221*
	(1.19)	(1.93)	(1.85)
CC	–0.060*	–0.005***	–0.005***
	(–1.91)	(–2.63)	(–2.63)
CusRet	0.439	–0.021	–0.022
	(1.15)	(–1.08)	(–1.10)
stdCusGro	1.633	0.132	0.130
	(1.01)	(1.39)	(1.38)
Change	0.966***	–0.030	–0.028
	(2.58)	(–1.28)	(–1.21)
*Big*4	–0.503	0.295***	0.299***
	(–0.35)	(3.01)	(3.09)
ComAud	–1.119	0.138	0.137
	(–0.84)	(1.51)	(1.47)
MKT	–2.615**	0.126***	0.124***
	(–2.38)	(2.87)	(2.81)
Constant		4.420***	4.432***
		(4.04)	(4.07)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

(*continued on next page*)

Table 11 (*continued*)

Variable	(1) *CusDigit1_Dum*	(2) *Lnfee*	(3) *Lnfee*
N	466	1,419	1,419
Adj. R^2	0.249	0.240	0.239

Notes: To ensure consistency in the full text model, xtlogit, which controls for firm-level fixed effects, is chosen for the first-stage regression, resulting in a sample size that differs from the benchmark regression (1,419), but this does not affect the results of the second-stage regression.

We tested this mechanism by measuring supplier firms' business risk (*Risk*) by the volatility of return on assets and used the modified Jones model to assess earnings management (*AbsDA*) (Dechow et al., 1995; Dou et al., 2019). Table 13 presents the mechanism analysis, indicating that the coefficients of *CusDigit* on *Risk* and *AbsDA* are statistically significant, with a negative value of at least 10 %. This suggests that digital transformation can mitigate suppliers' audit risks.

5.1.2. Audit cost

Auditors tasked with high-risk audit projects must implement more procedures and incur higher costs to maintain acceptable levels of audit risk (Zhang et al., 2021). The digital transformation of customers mitigates the operational risks faced by suppliers and discourages earnings management behavior, thereby ensuring the accuracy and reliability of suppliers' financial information and subsequently reducing their audit risks. This reduces the workload of auditors, leading to decreased audit costs and fees. To evaluate this mechanism, we followed previous research (Ashton et al., 1989) and used the audit reporting time lag (*AudLag*) as a proxy for audit input. *AudLag* represents the number of calendar days between the balance sheet date and the date on which a certified public accountant (CPA) signed the audit report. Table 14 shows a negative regression coefficient of *CusDigit* on *AudLag* significant at least at the 5 % level. This indicates that customers' digital transformation has a positive spillover effect on the supply chain, resulting in reduced audit costs.

5.2. Heterogeneity analysis

5.2.1. Supply chain geographic distance

The proximity between stakeholders can lead to reduced information-gathering costs, address information asymmetry and enhance monitoring efficiency (Chu et al., 2019). Digital transformation can also overcome spatial barriers and facilitate swift data exchange and collaboration (Li et al., 2022). As customers undergo digital transformation, they encourage information collaboration within the supply chain, thereby alleviating information asymmetry and the communication challenges caused by significant geographic distance. Thus, we argue that a greater geographic distance within the supply chain leads to a more evident spillover effect from customer-driven digital transformation on suppliers. This effect enables suppliers to promptly acquire and comprehend customer information, leading to the more rational management of production and operational activities, improved operational efficiency and enhanced information quality in financial statements. Ultimately, these outcomes reduce audit costs. In this study, we define supply chain geographic distance (*Distance*) as the distance between each customer's location and that of the supplier company (in terms of latitude and longitude), weighted by the percentage of customer sales. We performed a heterogeneity analysis by cross-multiplying the independent variables by supply chain geographic distance (*CusDigit* × *Distance*). Table 15 shows that the regression coefficient of this cross-multiplication term is negative and significant at the 1 % level. This finding suggests that customers' digital transformation compensates for the challenges associated with accessing information arising from geographic distance, thus enabling suppliers to make timely adjustments to their business decisions and mitigate operational volatility. This consequently reduces the audit risk premium and costs.

Table 12
Endogeneity: Heckman two-stage test- The self-selection problem in corporate disclosure of customer information.

Variable	(1) *DiscloCus*	(2) *Lnfee*	(3) *Lnfee*
mean_DiscloCus	2.745***		
	(5.57)		
*CusDigit*1		–1.142***	
		(–2.78)	
*CusDigit*2			–0.030***
			(–2.71)
*IMR*2		0.021	0.024
		(0.43)	(0.48)
Size	–0.557***	0.332***	0.331***
	(–6.54)	(7.36)	(7.28)
Lev	0.368	–0.093	–0.095
	(1.06)	(–0.57)	(–0.57)
CF	–1.116**	0.339**	0.325**
	(–2.21)	(2.37)	(2.26)
Current	0.005	–0.008*	–0.008*
	(0.27)	(–1.89)	(–1.88)
ROA	0.023	0.018	0.015
	(0.03)	(0.07)	(0.06)
Receiv	–1.513***	0.282	0.285
	(–2.59)	(0.99)	(0.99)
Loss	–0.188	0.076*	0.073*
	(–1.45)	(1.84)	(1.75)
Age	0.380*	7.577***	7.665***
	(1.78)	(2.98)	(2.99)
BusSeg	–0.025	–0.006	–0.007
	(–1.09)	(–0.70)	(–0.74)
Digit	–4.873***	–0.219	–0.225
	(–4.57)	(–0.54)	(–0.55)
Board	0.062	0.188	0.180
	(0.17)	(1.56)	(1.48)
Indrt	–1.558	0.257	0.235
	(–1.46)	(0.75)	(0.70)
Sep	0.001	–0.000	–0.000
	(0.16)	(–0.09)	(–0.13)
SOE	0.053	0.222*	0.217*
	(0.21)	(1.90)	(1.82)
CC	0.026***	–0.004*	–0.004*
	(5.36)	(–1.80)	(–1.78)
Change	–0.194**	–0.036	–0.034
	(–2.21)	(–1.47)	(–1.41)
*Big*4	0.019	0.303***	0.307***
	(0.06)	(3.05)	(3.14)
ComAud	16.125	0.486	0.525
	(0.01)	(0.59)	(0.63)
MKT	0.468***	0.143***	0.140***
	(3.51)	(3.09)	(3.02)
CusRet		–0.024	–0.024
		(–1.21)	(–1.22)
stdCusGro		0.130	0.128
		(1.35)	(1.35)
Constant		3.991**	3.962**
		(2.51)	(2.51)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

(*continued on next page*)

Table 12 (*continued*)

Variable	(1) *DiscloCus*	(2) *Lnfee*	(3) *Lnfee*
N	10,420	1,419	1,419
Adj. R^2	0.369	0.239	0.239

Notes: The second type of self-selection problem considers the fact that listed firms in China selectively disclose customer information, which can lead to a restricted research sample in this paper that does not fully observe the customers of listed firms. To address this type of self-selection problem, the *DiscloCus* variable in the first stage measures whether or not all A-share listed firms in China disclose their customers, and this is used to estimate the inverse Mills ratio. This results in a difference between the first stage regression sample and the benchmark regression.

5.2.2. Specialization investment intensity

Supply chain-specific investments are irreversible, and thus their value is closely tied to customers' survival cycles and growth prospects. Stable relationships with customers lead to a higher likelihood of achieving a higher return on investment. However, if these relationships are severed, suppliers may incur significant costs when attempting to find replacements (Raman and Shahrur, 2008). Suppliers who make substantial investments that are specific to the supply chain are susceptible to a major risk known as "lock-in." Customers demand lower prices or extended credit terms, which affect firms' profits (Gosman et al., 2004). Suppliers then feel compelled to increase their accounts receivable and inventory levels, which in turn increases their operational and financial risks. This escalation also leads to higher audit costs and risks for auditors. We argue that as customers undergo digital transformation, the mitigating effect on suppliers' operational risks becomes more pronounced with higher levels of supply chain-specific investments. This in turn influences suppliers' audit costs.

To support our argument, we followed Raman and Shahrur (2008) and defined supply chain specialization investment as the ratio of suppliers' R&D investments to their total assets in the preceding year. We then established a dummy variable, supply chain-specific investment intensity (*SpeInv*), based on the median value of annual supply chain specialization investment. We assigned *SpeInv* a value of 1 for supply chain specialization investment that exceeds the annual median value and 0 otherwise. Table 16 shows that the regression coefficient of the interaction term (*CusDigit* × *SpeInv*) is negative and significant at least at the 5 % level. This implies that as suppliers increase their supply chain-specific investments, their economic relationship with their customers strengthens, enhancing the effect of customer risk mitigation on the value of the supply chain relationship. The reduction in supplier audit costs resulting from customer digital transformation is thus greater when suppliers invest more in supply chain-specific relationships.

5.2.3. Supplier market competition

A firm's bargaining power can help to shape and influence the dynamics of its relationships in the supply chain (Dhaliwal et al., 2016). When faced with intense market competition, customers often gain power, enabling them to switch to suppliers who offer lower prices and more favorable credit terms. However, the severing of ties can impose significant costs on suppliers and potential loss of revenue, forcing them to choose between compromising on profits or investing more in maintaining stable relationships (Gosman et al., 2004). This vulnerability exposes suppliers to economic pressure from key customers and to disruption in competitive markets, thereby increasing their business risks. We argue that the digital transformation of their customers can alleviate their business risks through the spillover effect, particularly in highly competitive markets. Consequently, the impact on suppliers' audit fees of their customers' digital transformation is magnified in competitive market environments.

We addressed this using the Herfindahl index to assess suppliers' bargaining power, by examining their market share of sales revenue within the industry for the same year. We established a binary variable representing supplier market competition (*HHI*) based on the annual median of the Herfindahl index. *HHI* was assigned a value of 1 when the Herfindahl index is less than or equal to the annual median and 0 otherwise. A lower Herfindahl index indicates a higher level of market competition among suppliers. The regression results in Table 17 demonstrate a negative coefficient for the cross-multiplier term of customer digital trans-

Table 13
Mechanisms analysis: Audit risk.

Variable	(1) *Risk*	(2) *Risk*	(3) *AbsDA*	(4) *AbsDA*
*CusDigit*1	–0.478**		–0.170*	
	(–2.13)		(–1.86)	
*CusDigit*2		–0.013**		–0.004*
		(–2.18)		(–1.68)
Size	–0.003	–0.003	0.002	0.002
	(–0.19)	(–0.16)	(0.33)	(0.35)
Lev	0.004	0.003	–0.022	–0.023
	(0.10)	(0.07)	(–0.87)	(–0.88)
CF	0.012	0.007	–0.283***	–0.285***
	(0.16)	(0.10)	(–5.73)	(–5.77)
Current	–0.001	–0.001	–0.002	–0.002
	(–0.54)	(–0.52)	(–1.44)	(–1.43)
ROA	0.054	0.052	0.034	0.034
	(0.65)	(0.63)	(0.45)	(0.45)
Receiv	–0.150	–0.148	0.065	0.066
	(–1.36)	(–1.34)	(0.97)	(0.98)
Loss	0.032***	0.031***	0.009	0.008
	(2.89)	(2.81)	(1.12)	(1.06)
Age	0.323	0.319	1.789***	1.787***
	(0.58)	(0.57)	(5.35)	(5.40)
BusSeg	–0.004	–0.004	–0.001	–0.001
	(–1.54)	(–1.57)	(–0.33)	(–0.35)
Digit	0.039	0.042	–0.008	–0.007
	(0.20)	(0.22)	(–0.13)	(–0.12)
Board	–0.068	–0.072	0.020	0.019
	(–1.13)	(–1.19)	(0.79)	(0.74)
Indrt	0.040	0.032	–0.007	–0.010
	(0.26)	(0.22)	(–0.09)	(–0.12)
Sep	–0.000	–0.000	–0.000	–0.001
	(–0.27)	(–0.40)	(–1.00)	(–1.05)
SOE	–0.002	–0.004	–0.010	–0.011
	(–0.11)	(–0.23)	(–0.57)	(–0.61)
CC	–0.001	–0.001	–0.000	–0.000
	(–0.80)	(–0.81)	(–0.84)	(–0.84)
CusRet	–0.003	–0.003	–0.004	–0.004
	(–0.33)	(–0.33)	(–0.63)	(–0.63)
stdCusGro	0.040	0.039	–0.012	–0.012
	(0.60)	(0.59)	(–0.48)	(–0.49)
Change	0.002	0.003	0.012**	0.012**
	(0.20)	(0.29)	(2.02)	(2.08)
*Big*4	0.044	0.046	–0.009	–0.008
	(0.78)	(0.80)	(–0.38)	(–0.36)
ComAud	0.089	0.089	–0.005	–0.005
	(1.08)	(1.08)	(–0.54)	(–0.56)
MKT	0.023	0.021	0.004	0.003
	(1.54)	(1.43)	(0.33)	(0.28)
Constant	0.207	0.214	–0.275	–0.273
	(0.64)	(0.67)	(–1.52)	(–1.50)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,419	1,419	1,419	1,419
Adj. R^2	0.019	0.018	0.090	0.089

Table 14
Mechanisms analysis: Audit cost.

Variable	(1) *AudLag*	(2) *AudLag*
*CusDigit*1	–1.122***	
	(–3.41)	
*CusDigit*2		–0.022**
		(–2.39)
Size	0.036	0.035
	(1.17)	(1.15)
Lev	0.011	0.008
	(0.12)	(0.08)
CF	–0.227	–0.239
	(–1.56)	(–1.64)
Current	–0.004	–0.004
	(–1.22)	(–1.18)
ROA	–0.157	–0.164
	(–0.76)	(–0.79)
Receiv	–0.095	–0.092
	(–0.52)	(–0.50)
Loss	0.042	0.040
	(1.28)	(1.21)
Age	6.122***	6.070***
	(2.98)	(2.89)
BusSeg	–0.000	–0.000
	(–0.03)	(–0.03)
Digit	–0.000	–0.006
	(–0.00)	(–0.03)
Board	–0.046	–0.055
	(–0.50)	(–0.60)
Indrt	0.091	0.064
	(0.28)	(0.20)
Sep	–0.001	–0.002
	(–0.68)	(–0.74)
SOE	0.036	0.029
	(0.61)	(0.47)
CC	–0.003**	–0.003**
	(–2.06)	(–2.04)
CusRet	0.014	0.014
	(0.75)	(0.71)
stdCusGro	0.110	0.103
	(1.16)	(1.09)
Change	0.023	0.025
	(1.17)	(1.26)
*Big*4	0.140	0.143
	(1.25)	(1.28)
ComAud	–0.118*	–0.118*
	(–1.80)	(–1.77)
MKT	0.005	0.003
	(0.12)	(0.07)
Constant	–0.844	–0.785
	(–0.96)	(–0.89)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	1,419	1,419
Adj. R^2	0.026	0.020

Table 15
Heterogeneity analysis: Supply chain geographic distance.

Variable	(1) *Lnfee*	(2) *Lnfee*
*CusDigit*1	–0.910**	
	(–2.33)	
*CusDigit*1 × *Distance*	–0.563***	
	(–3.36)	
*CusDigit*2		–0.026**
		(–2.36)
*CusDigit*2 × *Distance*		–0.006***
		(–2.82)
Distance	0.003**	0.001
	(2.34)	(0.93)
Size	0.344***	0.344***
	(7.76)	(7.69)
Lev	–0.094	–0.098
	(–0.58)	(–0.59)
CF	0.368**	0.352**
	(2.53)	(2.42)
Current	–0.008*	–0.008*
	(–1.78)	(–1.79)
ROA	0.013	0.017
	(0.05)	(0.06)
Receiv	0.318	0.321
	(1.16)	(1.16)
Loss	0.079*	0.078*
	(1.89)	(1.85)
Age	6.779***	6.745***
	(4.24)	(4.11)
BusSeg	–0.007	–0.007
	(–0.75)	(–0.73)
Digit	–0.102	–0.091
	(–0.40)	(–0.36)
Board	0.187	0.179
	(1.53)	(1.46)
Indrt	0.281	0.272
	(0.81)	(0.79)
Sep	–0.000	–0.000
	(–0.10)	(–0.14)
SOE	0.219*	0.216*
	(1.85)	(1.80)
CC	–0.005***	–0.005***
	(–2.79)	(–2.75)
CusRet	–0.022	–0.023
	(–1.14)	(–1.17)
stdCusGro	0.125	0.125
	(1.31)	(1.32)
Change	–0.030	–0.028
	(–1.28)	(–1.21)
*Big*4	0.301***	0.302***
	(3.06)	(3.13)
ComAud	0.149*	0.155*
	(1.71)	(1.70)
MKT	0.133***	0.130***
	(3.07)	(2.95)
Constant	4.350***	4.390***
	(4.04)	(4.06)

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Table 15 (*continued*)

Variable	(1) *Lnfee*	(2) *Lnfee*
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	1,419	1,419
Adj. R^2	0.243	0.240

Table 16
Heterogeneity analysis: Suppliers' specialization investment intensity.

Variable	(1) *Lnfee*	(2) *Lnfee*
*CusDigit*1	–0.247	
	(–0.49)	
*CusDigit*1 × *SpeInv*	–1.545***	
	(–2.66)	
*CusDigit*2		–0.006
		(–0.43)
*CusDigit*2 × *SpeInv*		–0.050***
		(–3.25)
SpeInv	0.028	0.040
	(1.15)	(1.63)
Size	0.348***	0.351***
	(7.74)	(7.86)
Lev	–0.107	–0.116
	(–0.65)	(–0.70)
CF	0.367**	0.366**
	(2.51)	(2.50)
Current	–0.008*	–0.008*
	(–1.89)	(–1.79)
ROA	–0.024	–0.038
	(–0.09)	(–0.14)
Receiv	0.314	0.324
	(1.13)	(1.18)
Loss	0.077*	0.075*
	(1.84)	(1.81)
Age	7.482***	7.839***
	(4.50)	(4.66)
BusSeg	–0.006	–0.006
	(–0.69)	(–0.70)
Digit	–0.068	–0.061
	(–0.27)	(–0.24)
Board	0.194	0.181
	(1.59)	(1.48)
Indrt	0.276	0.254
	(0.80)	(0.74)
Sep	–0.000	–0.000
	(–0.05)	(–0.05)
SOE	0.205*	0.203*
	(1.70)	(1.70)
CC	–0.005***	–0.005***
	(–2.60)	(–2.63)
CusRet	–0.024	–0.025
	(–1.21)	(–1.26)

Table 16 (*continued*)

Variable	(1) *Lnfee*	(2) *Lnfee*
stdCusGro	0.122	0.125
	(1.27)	(1.33)
Change	–0.031	–0.029
	(–1.35)	(–1.26)
*Big*4	0.304***	0.305***
	(3.00)	(3.05)
ComAud	0.136	0.134
	(1.52)	(1.50)
MKT	0.130***	0.123***
	(2.96)	(2.80)
Constant	4.135***	4.070***
	(3.78)	(3.73)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	1,419	1,419
Adj. R^2	0.243	0.248

Table 17
Heterogeneity analysis: Supplier market competition.

Variable	(1) *Lnfee*	(2) *Lnfee*
*CusDigit*1	0.504	
	(0.65)	
*CusDigit*1 × *HHI*	–1.867**	
	(–2.24)	
*CusDigit*2		0.014
		(0.54)
*CusDigit*2 × *HHI*		–0.056**
		(–2.06)
HHI	0.046	0.062
	(1.06)	(1.43)
Size	0.343***	0.342***
	(7.74)	(7.84)
Lev	–0.089	–0.088
	(–0.55)	(–0.55)
CF	0.383***	0.378**
	(2.62)	(2.58)
Current	–0.008*	–0.008*
	(–1.79)	(–1.76)
ROA	0.039	0.068
	(0.14)	(0.25)
Receiv	0.324	0.333
	(1.17)	(1.20)
Loss	0.082*	0.082*
	(1.96)	(1.96)
Age	6.579***	6.460***
	(4.18)	(4.08)
BusSeg	–0.006	–0.006
	(–0.63)	(–0.68)
Digit	–0.071	–0.027
	(–0.28)	(–0.11)

(*continued on next page*)

Table 17 (*continued*)

Variable	(1) *Lnfee*	(2) *Lnfee*
Board	0.190	0.181
	(1.57)	(1.51)
Indrt	0.283	0.240
	(0.81)	(0.71)
Sep	–0.001	–0.001
	(–0.19)	(–0.26)
SOE	0.233**	0.226**
	(2.05)	(1.96)
CC	–0.005***	–0.005***
	(–2.65)	(–2.84)
CusRet	–0.023	–0.021
	(–1.14)	(–1.06)
stdCusGro	0.147	0.146
	(1.54)	(1.55)
Change	–0.032	–0.032
	(–1.39)	(–1.38)
*Big*4	0.280***	0.276***
	(2.70)	(2.68)
ComAud	0.137	0.134
	(1.56)	(1.54)
MKT	0.136***	0.136***
	(3.08)	(3.09)
Constant	4.345***	4.417***
	(4.03)	(4.16)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	1,419	1,419
Adj. R^2	0.242	0.245

formation and supplier market competitiveness dummy variables ($CusDigit \times HHI$) significant at the 5 % level. This implies that the ability of customers' digital transformation to reduce suppliers' audit fees is greater in markets characterized by intense supplier competition.

6. Conclusion and discussion

Amid increased economic uncertainty, businesses are increasingly turning to digital transformation to enhance their resilience and optimize their resource allocation. The supply chain is a critical component of business operations that integrates logistics, information flow and capital flow. Microenterprises aiming to gain a competitive advantage can enhance their collaborations within supply chains. We investigated the spillover effect of customer digital transformation on suppliers through assessing its impact on audit fees. This extends research on the economic consequences of digital transformation beyond the boundaries of supply chain relationships. Our empirical findings indicate that customers' digital transformation can reduce suppliers' audit fees. Our heterogeneity analysis shows that this effect is more evident when there is a greater geographic distance between suppliers and customers, higher levels of dedicated investment and increased competitiveness in the supplier market. Through the economic mechanism of mitigating supply chain risk and facilitating collaboration and information transfer in supply chains, customers' digital transformation reduces suppliers' audit risks and costs, thus leading to lower audit fees.

Based on previous research findings, we offer the following conclusions. First, the implementation of digital transformation by suppliers' customers can potentially cause a spillover effect across the supply chain, thereby affecting the economic interests and decisions of suppliers. Consequently, when faced with fierce market competition, firms should fully realize the beneficial effects of digital transformation on information transfer efficiency and collaboration within the supply chain. Such transformation should therefore be actively promoted, because through it firms can facilitate a seamless connection of resources, information and knowledge within the supply chain, thus fostering sustainable economic growth through enhanced coordination and cooperation.

Second, in the audit context, customer digital transformation can help to bridge geographic information gaps and enhance the exchange of information between customers and suppliers. It can also enhance the efficiency of suppliers' decision-making and risk management, thereby reducing uncertainties and income fluctuations and ultimately mitigating audit risks. Audit firms should recognize the spillover effect of digital technologies on the supply chain. They can then conduct comprehensive risk assessments involving all relevant stakeholders and develop and implement effective audit protocols to minimize audit risks and safeguard investors' legitimate rights and interests. Additionally, to align themselves with current technological developments, audit practices should focus on big data and a value-added approach and should consistently promote the digital transformation of audit processes. This is critical for the dynamic evaluation of corporate financial statement quality, which can then increase audit efficiency.

Third, in terms of policy regulation, the government should take a broad approach but also customize interventions based on the specific needs of firms and offer digital transformation initiatives. By closely monitoring and supporting supply chains, the government can encourage customers with significant power within the supply chain to embark on digital initiatives, while also assisting in the integration of digital technologies throughout the supply chain. This involves facilitating the transformation of procurement, R&D, production, transportation and other related processes to increase the efficiency of supply chain management as a whole. However, the government should also endeavor to remove obstacles to firms' digital transformation. This includes addressing difficulties and barriers, improving the training and recruitment of digital professionals and providing financial and policy support for the research, development, application and dissemination of advanced technologies throughout the supply chain.

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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Peer effect on climate risk information disclosure

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ABSTRACT

In this study, we examine the peer effect on climate risk information disclosure by analyzing A-share listed companies in China. We find that industry peers influence target firms' climate risk information disclosure through active (passive) imitation resulting from cost–benefit considerations (institutional pressures). Leader companies are more likely to be emulated by within-industry follower companies and target firms prefer to learn from similar within-industry firms. Executive overconfidence and performance pressure negatively affect target firms' willingness to emulate their peers. Finally, the peer effect of climate risk information disclosure demonstrates a regional aspect. Our findings have implications for reasonable climate risk information disclosure at the micro level and effective regulation to move toward achieving carbon peak/neutrality at the macro level.

1. Introduction

The frequency of natural disasters and extreme weather events worldwide has surged in recent years, surpassing initial expectations and significantly affecting human society. For instance, Hurricane Harvey and Hurricane Irma in 2017 were calamities that caused economic losses exceeding US$200 billion and affected millions of individuals. Climate change is expected to lead to a global gross domestic product loss of 3.3 % by 2060, which is expected to reach 10 % by 2100 (OECD, 2015). Climate risks are highly uncertain in nature and extensive in scope, and they include extreme weather phenomena, rising sea levels and ecosystem collapse. These risks profoundly affect the environment and pose potential threats to business operations and financial markets. Examples include asset depreciation, increased insurance costs, production interruptions and resource shortages (Nguyen et al., 2022). Consequently, effective climate risk management has become an imperative concern for financial institutions and enterprises aiming to enhance resilience and sustainability

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through long-term strategies. It is crucial for the international community to collaborate in developing comprehensive global climate risk mitigation strategies.

Building on prior researches (Luo, 2019; Velte, 2020; Flammer et al., 2021; Ding et al., 2023), the disclosure of corporate climate risk information is influenced by both environmental performance and internal governance. Such disclosure in turn affects stock prices, capital structures and the behavior and decision-making of institutional investors and other stakeholders (Faccini et al., 2023; Ginglinger and Moreau, 2023; Ilhan et al., 2023). Studies primarily focus on the motivation and economic consequences of climate risk information disclosure, leading to a gap in the understanding of the influence of mutual imitation learning among enterprises on climate risk information disclosure. Therefore, in this study, we aim to investigate the peer effect of corporate climate risk information disclosure and its underlying mechanisms using cost–benefit analysis and institutional pressure theory to elucidate how peer firms' climate risk information disclosure affects target firms.

Using a sample of A-share listed companies in China from 2007 to 2022, we construct an index for climate risk information disclosure based on textual data from annual reports and investigate the peer effect of such disclosure. Our findings reveal that climate risk information disclosure exhibits a peer effect within the industry, driven by active imitation under cost–benefit considerations and passive imitation due to institutional pressure. Heterogeneity analysis indicates that follower firms within the same industry are most willing to learn from leader firms. Furthermore, target firms tend to imitate similar peers within their industries. Additionally, executive overconfidence and performance pressure negatively affect target firms' inclination to imitate their peers. Further analysis demonstrates that both physical and transition risks also exhibit a peer effect and that climate risk information disclosure enhances text similarity in financial reports between firms and other peer enterprises. Finally, our findings indicate that a regional peer effect is associated with climate risk information disclosure.

This study is conducted in the Chinese context for two primary reasons. First, China is more vulnerable than many other countries to the impact of climate change, with a heating rate that is much higher than the global average.[1] Additionally, it ranks second worldwide in terms of losses caused by climate-related disasters (UNISDR and CRED, 2018[2]; Huang et al., 2018). Consequently, compared with their counterparts in other countries, Chinese firms are more vulnerable to economic losses stemming from climate risks and thus aim to mitigate potential risks by providing stakeholders valuable risk information through disclosure practices. Second, as China is an emerging market country, its corporate information disclosure standards are still less robust than those of developed countries in the West (Lennox and Wu, 2022). The physical and transition risks associated with climate change may result in the stranding or impairment of firm assets, often inadequately anticipated by capital market participants. This introduces significant ambiguity and risk to investors' decision-making processes and expected returns (Hickey et al., 2021; Ginglinger and Moreau, 2023), highlighting the urgent need for China to establish a comprehensive climate risk disclosure system. Simultaneously, in line with the promotion of carbon peak and carbon neutrality, Chinese firms face pressure to reduce carbon emissions and prioritize environmental protection (Wang et al., 2019; Li and Lu, 2020), which inevitably influences their decisions regarding climate risk information disclosure. Therefore, investigating the climate risk information disclosure behavior of listed companies within the Chinese context can offer guidance for policy formulation by the Chinese government and regulators and provide practical insights from China for other emerging market economies.

We make several significant contributions. First, we extend the research on peer effects at the micro level from the perspective of information disclosure—specifically, firms' voluntary disclosure of climate risk information. Previous studies mainly focus on peer effects in corporate investment and financing decisions, dividend policy and capital structure (Leaey and Roberts, 2014; Grennan, 2019; Bustamante and Fresard, 2021). Second, we enhance research on the peer effect of corporate information disclosure. The peer effect of firm information disclosure is addressed from two contrasting perspectives. For instance, some studies identify a negative relationship between peer firms and target firms (Baginski and Hinson, 2016; Capkun et al., 2023).

[1] https://www.cma.gov.cn/2011xwzx/2011xqxxw/2011xqxyw/202307/t20230708_5635282.html.

[2] https://www.unisdr.org/files/61119_credeconomiclosses.pdf.

In contrast, drawing on information mosaic theory, Seo (2021) posits that peer firms' information disclosure improves the accuracy of private information obtained by the management of target firms and stimulates the target firms' voluntary disclosure. Diverging from studies using other types of information, such as clinical trials in medical firms and management forecasts, we focus on non-financial climate risk information through an unbiased lens. Enterprise dissemination of such information can mitigate informational asymmetry between enterprises and external investors, alleviate enterprise liability for losses associated with climate risks, yet this information disclosure could also expose the possibility of climate damage to enterprises and disrupt their operations and financial decisions (Flammer et al., 2021). By examining the peer effect of disclosure through the lens of climate risk information, we can further deepen our understanding of corporate decisions on information disclosure. Third, we expand the scope of both cost–benefit theory and institutional pressure theory from the active and passive imitation perspectives. The literature identifies the peer effect of environmental, social and governance (ESG) information disclosure as being influenced by profit-seeking behavior among competitors, harm-avoiding behavior within co-groups and reference effects within industries (Li and Li, 2023). Using text analysis to directly construct an index for climate risk information disclosure, we demonstrate that active and passive imitation among enterprises are key drivers of the peer effect in climate risk information disclosure. We enhance the existing research framework on peer effects and enrich the applicability of cost–benefit theory and institutional pressure theory to decision-making regarding corporate information disclosure. Fourth, we enhance research on corporate climate risk information disclosure. Previous research on the factors influencing climate risk information disclosure primarily focuses on firms making independent decisions (Flammer et al., 2021; Ding et al., 2023), thereby neglecting the impact of interaction among firms on decision-making. We enhance understanding of the factors influencing climate risk information disclosure by examining the presence, mechanism and economic consequences of the peer effect in the context of corporate climate risk information disclosure. Fifth, we provide a significant reference point for the disclosure of and response to corporate climate risks and for the formulation of relevant government policies. Against the backdrop of China's macro objective of achieving carbon peak and carbon neutrality, the theoretical and empirical findings presented in this study offer valuable insights for enterprises seeking to enhance their climate risk information disclosure, elevate their level of climate risk governance, achieve green and sustainable development and further advance China's strategic objective of achieving carbon peak and carbon neutrality.

2. Hypothesis development

2.1. Presence of the peer effect of climate risk information disclosure

The peer effect is the phenomenon in which individuals make optimal decisions by considering the characteristics and behaviors of others in their group after rational analysis (Manski, 1993). Numerous studies explore the peer effect of firms in various respects, finding that it is widely present in production and operation activities such as IPO decisions (Aghamolla and Thakor, 2022), dividend policies (Grennan, 2019), investment and financing decisions (Bustamante and Fresard, 2021; Peng et al., 2021), capital structure (Leaey and Roberts, 2014), tax liabilities (Bird et al., 2018), irregularities (Parsons et al., 2018) and corporate social responsibility practices (Cao et al., 2019; Li and Wang, 2022). However, given the escalating threat of climate change to current business operations and production, disclosing climate risk information has emerged as a crucial means by which enterprises can enhance transparency, bolster their reputation and secure trust and resources from stakeholders. Nevertheless, few studies focus on corporate decision-making regarding climate risk disclosure from the perspective of peer effects. In this study, we posit that the peer effect plays a significant role when firms make choices concerning the disclosure of climate risk information. Specifically, when faced with uncertainty, target firms are substantially influenced by other firms behavior and may refer to peer firms when making decisions on climate risk information disclosure (Lieberman and Asaba, 2006). In addition, firms' disclosure of climate risk information can enhance their transparency, mitigate liability for losses incurred by relevant parties due to climate risks, enable informed decision-making among stakeholders, facilitate effective risk management practices and ultimately enhance their long-term value (Flammer et al., 2021). Therefore, we argue that the peer effect plays a role in climate risk information disclosure. Accordingly, we propose the following hypothesis.

H1. There is an industry peer effect in the disclosure of climate risk information, indicating a positive correlation between the information disclosed by peer firms and that of target firms.

2.2. Active imitation mechanism of the peer effect of climate risk information disclosure

Assuming that the peer effect of climate risk information disclosure is present, we further investigate the mechanism underlying this effect. Specifically, we examine how peer firms influence the climate risk information disclosure of target firms.

We posit that the peer effect of climate risk information disclosure operates through target enterprises' active motivation to imitate, taking into account the costs and benefits associated with disclosure. Considering the cost of climate risk information disclosure, enterprises can mitigate information acquisition and decision-making costs by referencing their peers' disclosures (Leaey and Roberts, 2014). In complex and volatile economic environments, enterprises' independent disclosure of climate risk information incurs high costs. It entails gathering relevant policy information and evaluating the climate risks associated with each subsidiary, thereby significantly increasing coordination and informational expenses related to enterprises' disclosure decisions. Consequently, when confronted with a highly uncertain climate environment, referencing the paradigm and style of climate risk information disclosure adopted by peer firms can effectively mitigate the costs associated with information disclosure.

Furthermore, from the perspective of the benefit of climate risk information disclosure, enterprises can enhance their information transparency and reduce both information asymmetry in the capital market and transaction costs for investors by observing the disclosure practices of their peer enterprises (Jouvenot and Krueger, 2019; Downar et al., 2021). Drawing on stakeholder theory and resource dependence theory, effective information disclosure empowers enterprises to strengthen their ability to acquire resources from supply chains, investors and creditors, thereby ensuring operational continuity and sustainable development (Lambert et al., 2007; Balvers et al., 2016). Based on the discussion above, we propose the following hypothesis.

H2. Driven by cost and benefit, the active imitation mechanism induces the peer effect of corporate climate risk information disclosure.

2.3. Passive imitation mechanism of the peer effect of climate risk information disclosure

Institutional pressure theory posits that an enterprise's organizational structure and behavioral patterns are predominantly shaped by its surrounding environment. That is, external factors influence the organizational behavior of enterprises, compelling them to adopt widely accepted organizational forms and associated behaviors while adapting their own decision-making processes. Additionally, the convergence of corporate behaviors under institutional pressure primarily stems from firms' concern for legitimacy rather than economic benefits, and such convergence may not necessarily enhance enterprises' operational performance (Powell and DiMaggio, 2012; Shen and Su, 2012). Studies categorize institutional pressure into three distinct types: imitation pressure, normative pressure and coercive pressure (DiMaggio and Powell, 1983; Carpenter and Feroz, 2001). Imitation pressure arises because organizations exist within social networks and tend to emulate the behaviors exhibited by other members of those networks. For instance, target firms establish their institutional structures by drawing inspiration from more reputable entities within their industry to navigate uncertainties prevalent in the business environment. Normative pressure refers to the constraints imposed on each firm's behavior by external stakeholders' norms, standards and expectations. Coercive pressure emanates from governmental laws and regulations, which necessitate enterprises' compliance to obtain legitimacy bestowed upon them by authorities.

We posit that peer firms influence target firms' imitation behavior through the three aforementioned types of institutional pressure. First, without a straightforward course of action, management tends to observe and reflexively implement behavioral decisions made by exemplary firms within the industry (Haunschild and Miner, 1997; Aerts et al., 2006). Such imitation pressure compels firms to adopt similar decisions regarding climate risk information disclosure, thus enhancing their ability to navigate uncertainties associated with climate risks. Second, as stakeholders represent a significant external governance group and source of normative pressure mechanisms, stakeholder attention reinforces firms' perception of potential resource loss. A threat to their legitimacy compels enterprises to closely monitor the decision-making patterns of their peers, drawing on climate risk information disclosure decisions made by peer enterprises as a benchmark and subsequently enhancing their standards for disclosing climate risk information (Ben-Amar et al., 2023; Ilhan et al., 2023). Furthermore, considering the coercive pressures exerted by government supervision and regulatory requirements, firms' decision-making motivation and the peer effect of climate risk information disclosure are both influenced. Since the 18th National Congress of the Communist Party of China (CPC), the State Council has issued a series of documents, including the 12th Five-Year Plan for Energy Conservation and Emission Reduction, implementing a national strategy to actively respond to climate and environmental change while accelerating green and low-carbon transformation in the economy and society (Wang, 2017). Consequently, firms have become more attentive to climate change and more susceptible to the impact of their peers' disclosure of climate risk information. Based on the above discussion, we propose the following hypothesis.

H3. Driven by institutional pressures, the passive imitation mechanism facilitates the peer effect of corporate climate risk information disclosure.

However, firms may refrain from emulating the climate risk information disclosure behavior of peer firms for several reasons (Flammer et al., 2021). First, disclosing climate risks can expose firms' vulnerabilities and may increase their borrowing costs. Second, climate risk disclosure enhances firms' relevant human capital. Third, disclosing climate risks can increase the likelihood of stakeholders' abandoning high-risk firms. For instance, once informed, stakeholders may opt to invest in firms less affected by climate change while abandoning more vulnerable ones. These factors may cause target firms to be more cautious in mimicking their peers' climate risk information disclosure behavior.

3. Data and research methodology

3.1. Sample selection and data sources

The initial sample for this study comprises A-share listed companies from 2007 to 2022 in China, with the following exclusions made: (1) observations from the financial and insurance industries, (2) observations classified as special treatment (i.e., ST and ST*), terminated listings or insolvent and (3) observations with missing data. To mitigate the impact of extreme values, all continuous variables involved are winsorized at the 1 % and 99 % quantiles. The final sample includes 33,878 valid observations, with the relevant financial data being sourced from the Wind and China Stock Market & Accounting Research databases.

3.2. Model setting and variable definition

To examine H1, we construct the following model:

$$Clirisk = \beta_0 + \beta_1 Peer\_Clirisk + Controls + YearFe + IndustryFe + RegionFe + FirmFe + \varepsilon \quad (1)$$

In Model (1), the dependent variable is the extent of climate risk information disclosure (*Clirisk*). Following Li et al. (2024) and Du et al. (2023), we implement a text analysis approach to construct the index of climate risk information disclosure (*Clirisk*) through a series of steps, including the establishment of a climate risk dictionary, the extraction of information from the text of annual reports, the identification of climate risk words and the construction of an index. The climate risk dictionary comprises 64 specific physical risk words, such as "disaster," "earthquake" and "typhoon," and 32 transition risk words related to "energy saving," "solar energy" and "wind power." For detailed information on these climate risk words, please refer to Appendix 1 and Appendix 2. The following model is utilized to calculate the level of climate risk information disclosure:

$$Clirisk = CliriskWords / Words \times 100 \quad (2)$$

In Model (2), *Clirisk* quantifies the extent of climate risk information disclosure in the current fiscal year. *CliriskWords* represents the count of climate risk-related words within a firm's annual report. *Words* denotes the total word count of the annual report. A higher value of *Clirisk* indicates a greater degree of climate risk information disclosure.

The explanatory variable in this study is the extent of climate risk information disclosure of peer firms (*Peer_Clirisk*). Drawing on the calculation methodology proposed by Manski (1993) and Seo (2021), we construct the following model to measure the explanatory variable:

$$Peer\_Clirisk = \frac{1}{N-1}\left(\sum_{i=1}^{N} Clirisk - Clirisk\right) \quad (3)$$

In Model (3), *Peer_Clirisk* evaluates the extent of climate risk information disclosure among firms within the same industry. *N* represents the total number of firms in that industry. This model calculates the average level of climate risk information disclosure of peer firms within an industry (excluding the target firm itself) in a given year.

In addition, we control for certain firm characteristics, including size (*Size*), leverage (*Lev*), return on total assets (*Roa*), growth ability (*Growth*), state ownership (*Soe*), the shareholding proportion of the largest shareholder (*Top1*), board size (*Board*), age (*Age*), the proportion of independent directors (*Inddir*), cash flow (*Cfo*) and Tobin's Q (*Tobinq*). Building on peer effect research and incorporating findings from Wang et al. (2023), we further consider the relevant characteristics of peer firms as well as year, industry, region and firm fixed effects (see Table 1).

Table 1
Variable definitions.

	Symbol	Definition
Dependent variables	*Clirisk*	The level of climate risk information disclosure of the target enterprise calculated according to Model (2)
Independent variables	*Peer_Clirisk*	The level of climate risk information disclosure of the peer enterprises calculated according to Model (3)
Control variables	*Size*	The natural logarithm of total assets
	Lev	Total liabilities/Total assets
	Roa	Net profit/Total assets
	Growth	The sales growth rate
	Soe	A dummy variable that equals 1 if the firm is a state-owned enterprise, and 0 otherwise
	Top1	Number of shares held by the top shareholder/Total share capital
	Board	The natural logarithm of the number of board members
	Age	The natural logarithm of the number of years listed
	Inddir	Number of independent directors/Number of board directors
	Cfo	Net cash flow from operating activities/Total assets
	Tobinq	Market value of assets/Book value of assets
	Peer_Size	The average size of peer firms calculated using an equal-weighting approach
	Peer_Lev	The average leverage of peer firms calculated using an equal-weighting approach
	Peer_Roa	The average return on assets of peer firms calculated using an equal-weighting approach
	Peer_Growth	The average growth ability of peer firms calculated using an equal-weighting approach
	Peer_Soe	The average state ownership of peer firms calculated using an equal-weighting approach
	Peer_Top1	The average shareholding proportion of the largest shareholder of peer firms calculated using an equal-weighting approach
	Peer_Board	The average board size of peer firms calculated using an equal-weighting approach
	Peer_Age	The average age of peer firms calculated using an equal-weighting approach
	Peer_Inddir	The average proportion of independent directors of peer firms calculated using an equal-weighting approach
	Peer_Cfo	The average cash flow of peer firms calculated using an equal-weighting approach
	Peer_Tobinq	The average Tobin's Q of peer firms calculated using an equal-weighting approach
	Year Fe	Year dummy control variable
	Industry Fe	Industry dummy control variable
	Region Fe	Region dummy control variable
	Firm Fe	Firm dummy control variable

4. Empirical results

4.1. Descriptive statistics

The descriptive statistics of the sample are presented in Table 2. The average level of climate risk information disclosure in China is 0.170, ranging from a minimum value of 0.013 to a maximum value of 0.769. These results indicate significant variation in climate risk information disclosure among firms. Further analysis reveals that most of the sampled firms cluster around the mean value, providing robust empirical support for this study. The descriptive statistics of the other control variables do not exhibit significant deviations from those reported in the literature (Li et al., 2023; Wang et al., 2023).

4.2. Correlation analysis

The correlation matrix of the main variables is presented in Table 3. The correlation coefficient between *Clirisk* and *Peer_Clirisk* is 0.506, which is positive and statistically significant at the 1 % level. This result provides initial support for H1, which suggests the presence of peer effects of climate risk information disclosure.

4.3. Main regression

The results of the main regression are presented in Table 4. The empirical analysis investigates the peer effects of climate risk information disclosure. The results of the regression that solely considers the characteristics of the target firms are presented in Column (1), and the results of the regression in which we account for both target and peer firm characteristics are presented in Column (2). Regardless of whether peer firm characteristics are controlled for, the coefficient of *Peer_Clirisk* is positive and statistically significant at the 1 % level. The results thus support H1. Furthermore, larger, less leveraged and more profitable firms exhibit a greater inclination to disclose climate risks.

Table 2
Descriptive statistics.

Variable	N	Mean	SD	Min.	p25	p50	p75	Max.
Clirisk	33,878	0.170	0.143	0.013	0.075	0.128	0.214	0.769
Peer_Clirisk	33,878	0.167	0.072	0.020	0.118	0.168	0.186	0.577
Size	33,878	22.200	1.332	18.970	21.270	22.020	22.950	26.740
Lev	33,878	0.438	0.205	0.054	0.276	0.434	0.591	0.998
Roa	33,878	0.037	0.066	–0.377	0.014	0.036	0.066	0.215
Growth	33,878	0.187	0.448	–0.570	–0.020	0.114	0.280	2.923
Soe	33,878	0.402	0.490	0.000	0.000	0.000	1.000	1.000
Top1	33,878	0.345	0.149	0.088	0.229	0.324	0.448	0.753
Board	33,878	2.246	0.179	1.792	2.079	2.303	2.303	2.773
Age	33,878	2.033	0.921	0.000	1.386	2.303	2.773	3.332
Inddir	33,878	0.375	0.054	0.300	0.333	0.357	0.429	0.571
Cfo	33,878	0.048	0.071	–0.173	0.009	0.047	0.089	0.256
Tobinq	33,878	2.067	1.340	0.854	1.241	1.634	2.358	8.469
Peer_Size	33,878	22.100	0.571	19.530	21.790	22.040	22.190	24.080
Peer_Lev	33,878	0.426	0.088	0.126	0.367	0.404	0.457	0.784
Peer_Roa	33,878	0.039	0.015	–0.083	0.031	0.040	0.049	0.165
Peer_Growth	33,878	0.173	0.094	–0.313	0.117	0.165	0.231	1.397
Peer_Soe	33,878	0.375	0.191	0.000	0.229	0.309	0.500	1.000
Peer_Top1	33,878	0.337	0.057	0.073	0.321	0.342	0.370	0.582
Peer_Board	33,878	2.243	0.046	1.792	2.210	2.232	2.269	2.543
Peer_Age	33,878	1.850	0.382	0.000	1.643	1.756	1.952	3.302
Peer_Inddir	33,878	0.374	0.008	0.333	0.369	0.375	0.379	0.571
Peer_Cfo	33,878	0.048	0.021	–0.046	0.035	0.046	0.062	0.243
Peer_Tobinq	33,878	1.953	0.462	1.097	1.584	1.937	2.257	8.469

Table 3
Correlation matrix of the main variables.

	Clirisk	*Peer_Clirisk*	*Size*	*Lev*	*Roa*	*Growth*	*Soe*	*Top1*	*Board*	*Age*	*Inddir*	*Cfo*	*Tobinq*
Clirisk	1.000												
Peer_Clirisk	0.506***	1.000											
Size	0.281***	0.195***	1.000										
Lev	0.123***	0.018***	0.442***	1.000									
Roa	–0.011*	–0.022***	0.034***	–0.322***	1.000								
Growth	–0.006	–0.011**	0.031***	0.050***	0.211***	1.000							
Soe	0.050***	0.008	0.301***	0.281***	–0.074***	–0.051***	1.000						
Top1	0.056***	0.011**	0.205***	0.063***	0.123***	0.018***	0.236***	1.000					
Board	0.075***	–0.002	0.253***	0.159***	0.015***	–0.012**	0.286***	0.042***	1.000				
Age	0.073***	0.067***	0.381***	0.350***	–0.171***	–0.054***	0.422***	–0.061***	0.134***	1.000			
Inddir	–0.030***	0.023***	0.011*	–0.028***	–0.013**	0.001	–0.079***	0.031***	–0.516***	–0.029***	1.000		
Cfo	0.044***	0.070***	0.068***	–0.160***	0.366***	0.028***	–0.005	0.080***	0.046***	–0.014**	–0.014***	1.000	
Tobinq	–0.157***	–0.076***	–0.401***	–0.266***	0.151***	0.054***	–0.155***	–0.128***	–0.133***	–0.052***	0.042***	0.096***	1.000

Note: ***, ** and * denote significance at the 0.01, 0.05 and 0.10 levels, respectively.

Table 4
Main regression.

	(1)	(2)
	Clirisk	*Clirisk*
Peer_Clirisk	0.579***	0.540***
	(8.64)	(8.08)
Size	0.017***	0.017***
	(7.07)	(7.21)
Lev	–0.017**	–0.016**
	(–2.19)	(–2.03)
Roa	0.031***	0.027***
	(3.12)	(2.71)
Growth	–0.000	–0.001
	(–0.24)	(–0.62)
Soe	–0.002	–0.002
	(–0.46)	(–0.54)
Top1	0.028**	0.029**
	(2.04)	(2.11)
Board	–0.004	–0.004
	(–0.50)	(–0.48)
Age	–0.001	–0.003
	(–0.66)	(–1.53)
Inddir	–0.016	–0.016
	(–0.78)	(–0.78)
Cfo	0.006	0.006
	(0.73)	(0.70)
Tobinq	–0.002**	–0.002**
	(–2.24)	(–2.22)
Peer_Size		–0.026***
		(–3.49)
Peer_Lev		–0.059
		(–1.28)
Peer_Roa		0.069
		(1.22)
Peer_Growth		0.010
		(1.34)
Peer_Soe		0.003
		(0.14)
Peer_Top1		0.004
		(0.07)
Peer_Board		–0.132***
		(–2.73)
Peer_Age		0.013
		(1.44)
Peer_Inddir		–0.134
		(–0.81)
Peer_Cfo		0.080
		(1.48)
Peer_Tobinq		0.003
		(1.23)
Constant	–0.376***	0.502**
	(–6.29)	(2.54)
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
Region Fe	Yes	Yes
Firm Fe	Yes	Yes
N	33,878	33,878
Number of firms	3,868	3,868
Adj. R^2	0.301	0.304

Note: t-statistics are in parentheses. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 levels, respectively.

Table 5
Robustness tests.

Panel A: Robustness test

	(1)	(2)	(3)	(4)
	Alternative measures of the explanatory variables		Future period	First difference method
	Clirisk_2	*Clirisk*	*FClirisk*	*Clirisk_chg*
Peer_Clirisk_2	0.528***			
	(7.74)			
Peer_Clirisk_res		0.237***		
		(3.44)		
Peer_Clirisk			0.341***	
			(4.92)	
Peer_Clirisk_chg				0.275***
				(7.11)
Constant	0.478**	0.960***	0.546***	0.029***
	(2.16)	(4.77)	(2.63)	(2.81)
Firm controls	Yes	Yes	Yes	No
Peer firm controls	Yes	Yes	Yes	No
Firm change controls	No	No	No	Yes
Peer firm change controls	No	No	No	Yes
Year Fe	Yes	Yes	Yes	Yes
Industry Fe	Yes	Yes	Yes	Yes
Region Fe	Yes	Yes	Yes	Yes
Firm Fe	Yes	Yes	Yes	Yes
N	33,878	33,878	31,043	27,716
Number of firms	3,868	3,868	3,780	3,432
Adj. R^2	0.286	0.295	0.258	0.059

Panel B: Endogeneity test

	(1)	(2)	(3)
	Instrumental variables		Heckman (second stage)
	Peer_Clirisk	*Clirisk*	*Clirisk*
Iv	0.008***		
	(6.19)		
Peer_Clirisk		0.856*	7.886***
		(1.70)	(5.95)
Imr			11.076***
			(5.58)
Constant	1.450***	0.116	0.510
	(17.58)	(0.14)	(0.63)
Firm controls	Yes	Yes	Yes
Peer firm controls	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes
Industry Fe	Yes	Yes	Yes
Region Fe	Yes	Yes	Yes
Firm Fe	Yes	Yes	Yes
N	32,278	32,278	32,278
Number of firms	3,831	3,831	3,831
Adj. R^2	0.874	0.272	0.278
Kleibergen-Paap rk LM		92.150***	
Cragg–Donald Wald F		81.815<16.38>	

Panel C: System GMM regression

	(1)	(2)
	One-step method	Two-step method
	Clirisk	*Clirisk*
Peer_Clirisk	0.878***	1.283***
	(2.84)	(3.46)
LClirisk	0.655***	0.606***
	(19.27)	(15.46)
Constant	–1.618	–2.596
	(–0.47)	(–0.71)
Firm controls	Yes	Yes
Peer firm controls	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	No	No
Region Fe	No	No
Firm Fe	Yes	Yes
N	33,711	33,711
AR(1)	–13.060	–12.350
(p-value)	0.000	0.000
AR(2)	–1.380	–0.690
(p-value)	0.168	0.492
Hansen	103.980	103.980
(p-value)	0.104	0.104

Panel D: Exclusion of other effects

	(1)	(2)
	Exclusion of the common trend effect	Exclusion of the agglomeration effect
	Clirisk	*Clirisk*
Peer_Clirisk	0.516***	
	(7.19)	
Common	0.019*	
	(1.85)	
LPeer_Clirisk_mean		0.128
		(0.84)
Constant	0.573***	–1.048
	(2.77)	(–1.31)
Firm controls	Yes	Yes
Peer firm controls	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
Region Fe	Yes	Yes
Firm Fe	Yes	No
N	32,878	2,622
Number of firms	3,868	2,622
Adj. R^2	0.282	0.292

Note: at-statistics are in parentheses. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 levels, respectively.

4.4. Robustness tests

4.4.1. Alternative measures of the explanatory variables

We introduce a modified measurement method for the explanatory variables, using the ratio of corporate climate risk words to the total number of words excluding English and numbers to indicate climate risk information disclosure (*Clirisk_2*). The regression results presented in Column (1) of Panel A in Table 5 demonstrate a positive and significant impact of peer enterprises' climate risk information disclosure on that of target enterprises, consistent with the main regression results.

To mitigate the influence of industry consensus, we apply the regression residual method to further examine the incremental information effect of peer influence. Specifically, we regress the climate risk information disclosure of the target enterprise in the current year on that of its peer firms and obtain the residual from this regression, which represents the additional information provided by peer enterprises' climate risk disclosures. This residual is then included in Model (1) for retesting purposes. The results reported in Column (2) of Panel A in Table 5 demonstrate that the coefficient estimate for the residual of climate risk information disclosure from peer enterprises (*Peer_Clirisk_res*) remains positive and statistically significant, thus confirming the robustness of the main results.

4.4.2. Future period

Given the potential influence of climate risk information disclosure by peer firms on target enterprises' decision regarding climate risk information disclosure in subsequent periods, we further substitute the dependent variable with the level of corporate climate risk information disclosure in period $t + 1$ (*FClirisk*). The regression results presented in Column (3) of Panel A in Table 5 demonstrate that the level of climate risk information disclosure by peer firms continues to have a positive impact on the target enterprises' climate risk information disclosure in the following period, thereby providing additional support for our findings.

4.4.3. First difference method

To address the endogeneity problem arising from the omission of relevant variables and to capture changes in corporate climate risk information disclosure, we use the first difference method for robustness testing. The regression results are presented in Column (4) of Panel A in Table 5. Notably, the impact of peer enterprises' change in climate risk information disclosure on target enterprises' change in climate risk information disclosure is positive and significant at the 1 % level, indicating the presence of the peer effect in corporate climate risk information disclosure.

4.4.4. Instrumental variables

Given that enterprises within the same industry typically encounter similar macro policies, economic environments and institutional backgrounds, similarity in their behaviors may be attributed to common factors rather than mutual influence among them. Following Leary and Roberts (2014), we address this endogeneity issue by using stock idiosyncratic return as an instrumental variable in a two-stage least squares (2SLS) regression. The advantage of using this instrumental variable lies in its sole association with the idiosyncratic factors specific to each enterprise. The detailed calculations are presented in Models (4) to (6):

$$r_{i,j,t} = \alpha_{i,j,t} + \beta^{M}_{i,j,t}(rm_t - rf_t) + \beta^{ind}_{i,j,t}\left(\bar{r}_{-i,j,t} - rf_t\right) + \sigma_{i,j,t} \tag{4}$$

$$\widehat{r}_{i,j,t} = \widehat{\alpha}_{i,j,t} + \widehat{\beta}^{M}_{i,j,t}(rm_t - rf_t) + \widehat{\beta}^{ind}_{i,j,t}\left(\bar{r}_{-i,j,t} - rf_t\right) + \sigma_{i,j,t} \tag{5}$$

$$\widehat{\sigma}_{i,j,t} = r_{i,j,t} - \widehat{r}_{i,j,t} \tag{6}$$

In the above models, $r_{i,j,t}$ represents the stock return rate of enterprise i in industry j in month t, rm_t represents the market return rate in month t, rf_t represents the risk-free return rate in month t and $\bar{r}_{-i,j,t}$ represents the stock return rate of peer firms. Regression Model (4) uses data from the initial 36 months, and the regressions involving less than 20 months are excluded to estimate each regression coefficient. Based on Model (5), we calculate the expected return $\widehat{r}_{i,j,t}$ using these estimated coefficients. Subsequently, we obtain the monthly idiosyncratic return $\widehat{\sigma}_{i,j,t}$ for enterprise i by subtracting this expected return $\widehat{r}_{i,j,t}$ from its corresponding stock return $r_{i,j,t}$ according to Model (6). Finally, compounding these idiosyncratic returns over each month yields the annual stock idiosyncratic return for enterprise i.

To further validate our hypothesis and mitigate potential issues related to reverse causality, we use the mean of the annual stock idiosyncratic return for peer firms in the t–1 period as an instrumental variable (*Iv*). The regression results are presented in Panel B of Table 5, with Column (1) displaying the results of the first stage. Notably, the coefficient of the instrumental variable (*Iv*) is positive and significant at the 1 % level, indicating its strong explanatory power. Column (2) presents the second-stage regression results. The coefficient of *Peer_Clirisk* is positive and significant. Furthermore, the Cragg–Donald Wald F statistic is greater than the critical value of 10 % bias under the Stock–Yogo weak instrumental variable test, indicating the absence of a weak instrumental variable problem. Additionally, in the unidentifiable test, the *p*-value of the LM statistic is less than 0.001, indicating that the insufficient identification of instrumental variables is of no concern. Consequently, these instrumentally estimated regression results effectively address endogeneity concerns and provide support for our findings.

4.4.5. Heckman's two-stage model

Whether an enterprise decides to imitate its peer enterprises in terms of climate risk information disclosure may be influenced by sample self-selection. To address the endogeneity problem caused by sample selection bias, we use Heckman's two-stage model to reexamine the peer effect of corporate climate risk information disclosure. In the first stage, a probit model is established for all listed companies to determine whether they disclose more climate risk information within the same industry and year, while controlling for relevant variables. In the second stage, Model (1) incorporates the inverse Mills ratio (*Imr*), calculated based on the first-stage regression results. Column (3) of Panel B in Table 5 presents the second-stage regression results of the Heckman two-stage model, demonstrating that even after overcoming the endogeneity issues arising from sample selection bias, a confirmed peer effect still exists in climate risk information disclosure.

4.4.6. System generalized method of moments (GMM) regression

To address endogeneity issues arising from unobservable factors and reverse causality, we apply the lagged term of the explained variable (*LClirisk*) as an instrumental variable and the system GMM method to further validate our findings. Columns (1) and (2) in Panel C of Table 5 present the regression results using the one-step and two-step system GMM methods. The *p*-value of AR(1) is less than 0.1, whereas the *p*-value of AR(2) is greater than 0.1. This aligns with the expectation that first-order disturbance terms exhibit autocorrelation but second-order disturbance terms do not. Additionally, Hansen's test yields a *p*-value of 0.104, indicating the validity and appropriateness of the instrumental variable used. The coefficients of both *LClirisk* and *Peer_Clirisk* are positive and significant at the 1 % level, thereby confirming the robustness of our main findings.

4.4.7. Exclusion of the common trend effect

Determining whether enterprises within the same industry adopt similar climate risk information disclosure decisions through imitation or due to industry-wide requirements and backgrounds poses a challenge. Building on the work of Khan and Tsoukala (2011), we incorporate the factor of industry-specific climate risk information disclosure into Model (1) to assess the collective trend of climate risk information disclosure among enterprises operating in the same industry, thereby yielding Model (7):

$$Common = \frac{Max(N_{Clirisk\_increase}, N_{Clirisk\_decrease})}{N_{Clirisk\_increase} + N_{Clirisk\_decrease}} \tag{7}$$

In Model (7), *Common* represents the collective trend of climate risk information disclosure among enterprises within the same industry. $N_{Clirisk\_increase}$ denotes the number of enterprises that have increased their climate risk information disclosure, whereas $N_{Clirisk\_decrease}$ denotes the number of enterprises that have reduced such disclosure. An increase or decrease in the number of firms disclosing climate risk information within an industry indicates a corresponding increase or decrease in the level of common disclosure in that industry.

Based on Column (1) of Panel D in Table 5, it is evident that even after incorporating the industry-wide common climate risk information disclosure trend factor, the regression coefficient of *Peer_Clirisk* remains positive and significant at the 1 % level. This finding indicates that the peer effect on climate risk information disclosure among listed companies persists despite controlling for the industry-wide common climate risk information disclosure trend.

4.4.8. Exclusion of the agglomeration effect

The industrial linkage effect of enterprise behavior may also arise from the agglomeration of similar enterprises rather than the peer effect. Suppose that newly listed companies select their listing registration location based on the climate risk of listed companies in the industry. This may lead to a significant correlation between the level of climate risk information disclosure of target enterprises and that of other companies in the industry. To mitigate the potential influence of the agglomeration effect on our findings, we focus on the newly listed companies in the sample within the specified time frame. The aim is to investigate the impact of the average climate risk information disclosure by industry-listed companies in the year preceding a newly listed firm's listing (*LPeer_Clirisk_mean*) on newly listed companies' climate risk information disclosure during their listing year. As shown in Column (2) of Panel D in Table 5, the regression coefficient of *LPeer_Clirisk_mean* is not statistically significant. This result indicates that the climate risk information disclosure of newly listed companies is not affected by the level of information disclosure of listed companies in the previous year of their registered location. These results partially alleviate concerns regarding the potential industrial agglomeration effects related to corporate climate risks and validate the robustness of our findings.

5. Mechanism analysis

5.1. Active imitation mechanism

In this section, we examine the active imitation mechanism of the peer effects of climate risk information disclosure from the cost and benefit perspectives based on cost–benefit theory.

5.1.1. Cost perspective

In this section, we examine the active imitation channel of peer effects on firm climate risk information disclosure from a cost perspective. Based on the aforementioned analysis, target firms' imitation of climate risk information disclosure can reduce coordination and information costs, thereby enhancing the accuracy, timeliness and comparability of firms' disclosures. Consequently, the peer effect of corporate climate risk information disclosure is expected to be more pronounced in firms with elevated coordination and information costs. Following Dyreng et al. (2020) and Li et al. (2023), we measure coordination cost (*Subs*) as the natural logarithm of a firm's subsidiary count and information cost (*Structural*) as the average structural hole among a firm's directors. A higher number of subsidiaries indicates more internal coordination costs, whereas a higher average structural hole among firm directors signifies increased informational advantage and reduced informational cost. Panel A of Table 6 presents the regression results regarding the peer effect of the active imitation channel of climate risk information disclosure from a cost perspective. The results provide support for H2 (i.e., that peer firms can influence target firms' active imitation behavior by influencing their consideration of the costs associated with climate risk information disclosure).

5.1.2. Benefit perspective

Simultaneously, to examine the peer effect of the active imitation channel of climate risk information disclosure from a benefit perspective, we explore information transparency and resource limitation separately. Following Chen et al. (2023), we use firms' information disclosure ratings on the Shenzhen Stock Exchange as a measure of information transparency (*Rate*). When rated as unqualified or qualified, firms are considered to have low information transparency ($Rate = 1$); when rated as good or excellent, firms are regarded as having high information transparency ($Rate = 0$). Drawing on the studies of Kaplan and Zingales (1997) and Li et al. (2023), we utilize the *Fc* index to gauge the firms' resource limitation, with higher values indicating greater degrees of limitation. Panel B of Table 6 presents the regression results regarding the peer effect of the active imitation channel of climate risk information disclosure from a benefit perspective. The results provide further support for H2 (i.e., that peer firms can influence target firms' active imitation behavior by influencing their consideration of the benefits associated with climate risk information disclosure).

5.2. Passive imitation mechanism

To comprehensively investigate the passive imitation mechanism of the peer effect of climate risk information disclosure, we examine three types of institutional pressure: imitation pressure, normative pressure and coercive pressure.

Table 6
Mechanism test: Active imitation mechanism.

Panel A: Cost perspective

	(1)	(2)
	Coordination cost	Information cost
	Clirisk	*Clirisk*
Peer_Clirisk	0.197**	0.542***
	(2.10)	(8.09)
Subs × *Peer_Clirisk*	0.087***	
	(3.44)	
Structural × *Peer_Clirisk*		–0.204**
		(–2.08)
Subs	–0.007	
	(–1.51)	
Structural		0.041***
		(2.68)
Constant	0.499**	0.429**
	(2.52)	(2.17)
Firm controls	Yes	Yes
Peer firm controls	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
Region Fe	Yes	Yes
Firm Fe	Yes	Yes
N	32,897	33,878
Number of firms	3,844	3,868
Adj. R^2	0.309	0.305

Panel B: Benefit perspective

	(1)	(2)
	Information transparency	Resource limitation
	Clirisk	*Clirisk*
Peer_Clirisk	0.532***	0.615***
	(6.45)	(8.48)
Rate×*Peer_Clirisk*	0.133***	
	(3.92)	
Fc×*Peer_Clirisk*		0.409***
		(4.64)
Rate	–0.021***	
	(–3.61)	
Fc		–0.056***
		(–4.16)
Constant	0.434*	0.389*
	(1.86)	(1.95)
Firm controls	Yes	Yes
Peer firm controls	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
Region Fe	Yes	Yes
Firm Fe	Yes	Yes
N	24,383	33,878
Number of firms	3,589	3,868
Adj. R^2	0.288	0.308

Note: t-statistics are in parentheses. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 levels, respectively.

Table 7
Mechanism test: Passive imitation mechanism.

Panel A: Imitation pressure

	(1)	(2)
	Huazheng ESG	Bloomberg ESG
	Clirisk	*Clirisk*
Peer_Clirisk	0.477***	0.436***
	(7.40)	(6.42)
ESG_1 × *Peer_Clirisk*	0.017***	
	(3.15)	
ESG_2 × *Peer_Clirisk*		0.004**
		(2.06)
ESG_1	0.001	
	(1.47)	
ESG_2		–0.000
		(–0.45)
Constant	0.522**	0.686***
	(2.55)	(2.85)
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
Region Fe	Yes	Yes
Firm Fe	Yes	Yes
N	31,745	27,152
Number of firms	3,864	3,791
Adj. R^2	0.279	0.270

Panel B: Normative pressure

	(1)	(2)
	Institutional investor shareholding	Analyst attention
	Clirisk	*Clirisk*
Peer_Clirisk	0.313***	0.500***
	(4.01)	(7.66)
Inst×*Peer_Clirisk*	0.384***	
	(3.73)	
Analyst×*Peer_Clirisk*		0.040**
		(2.48)
Inst	–0.042**	
	(–2.47)	
Analyst		–0.002
		(–0.78)
Constant	0.579***	0.566***
	(2.90)	(2.86)
Firm controls	Yes	Yes
Peer firm controls	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
Region Fe	Yes	Yes
Firm Fe	Yes	Yes
N	33,878	33,878
Number of firms	3,868	3,868
Adj. R^2	0.306	0.306

Panel C: Coercive pressure

	(1)	(2)
	Full sample	Samples from 2011 to 2015
	Clirisk	*Clirisk*
Peer_Clirisk	0.307***	0.080
	(4.43)	(0.76)
Post×Peer_Clirisk	0.163***	0.147***
	(2.72)	(3.00)
Post	0.054***	0.031**
	(2.60)	(2.39)
Constant	0.365*	0.580**
	(1.79)	(2.17)
Firm controls	Yes	Yes
Peer firm controls	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
Region Fe	Yes	Yes
Firm Fe	Yes	Yes
N	33,878	10,679
Number of firms	3,868	2,227
Adj. R^2	0.305	0.140

Note: t-statistics are in parentheses. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 levels, respectively.

5.2.1. Imitation pressure

Studies consistently demonstrate that firms with high ESG performance possess robust capabilities for sustainable development and green transformation (Li and Li, 2023), enabling them to effectively address climate change risks (Ginglinger and Moreau, 2023). Consequently, firms with high ESG performance in the same industry have a higher reference value for target firms and impose a certain level of imitation pressure upon them. Based on the theoretical analysis above, we posit that such imitation pressure further amplifies the peer effect of climate information disclosure. To test this hypothesis, we utilize the maximum ESG scores from the Huazheng ESG and Bloomberg ESG databases (*ESG_1* and *ESG_2*, respectively) among industry peers as indicators of imitation pressure. Panel A of Table 7 presents the regression results pertaining to the mechanism of imitation pressure. The coefficient of the interaction term between *ESG* and *Peer_Clirisk* is positive and significant at the 5 % level at least, highlighting the important influence of imitation pressure on the peer effect of climate risk information disclosure.

5.2.2. Normative pressure

To examine the channel role of normative pressure in the peer effect of climate risk information disclosure, we draw on the research of Ilhan et al. (2023) and Ben-Amar et al. (2023). Specifically, we use institutional investors' shareholding ratio (*Inst*) and analyst attention (*Analyst*) as measures of normative pressure. Institutional investors, as significant stakeholders in firms, can affect firms' disclosure decisions; analysts, acting as information intermediaries in the capital market, promptly acquire the information disclosed by firms to issue analyst reports for investor reference, thereby indirectly influencing corporate behavior. We measure institutional investors' shareholding ratio (*Inst*) using the ratio of their shares held to total shares in a firm. Analyst attention (*Analyst*) is measured by taking the natural logarithm of the number of analysts following a firm plus 1. The higher the values of both factors, the greater the normative pressure exerted on firms. Panel B of Table 7 presents the regression results, which illustrate that the coefficients of *Inst* × *Peer_Clirisk* and *Analyst* × *Peer_Clirisk* are positive and significant. These results indicate that normative pressure is an essential channel affecting the peer effect of climate risk information disclosure.

5.2.3. Coercive pressure

Since the 18th CPC National Congress in 2012 introduced the strategic decision to actively promote "ecological civilization construction," the State Council has issued a series of documents, including the 12th Five-Year Plan for Energy Conservation and Emission Reduction, that have significantly intensified external environmental regulations and increased firms' burden of environmental governance costs. This has prompted Chinese firms to pay greater attention to climate risks and adopt corresponding measures (Wang, 2017). Therefore, we argue that firms face heightened coercive pressure following the 18th CPC National Congress, leading target firms to be more inclined to imitate their peers' decisions to disclose climate risk information.

We designate 2013 as the event start year and construct a dummy variable (*Post*), which equals 1 for years after 2013 and onward and 0 otherwise. We also introduce an interaction term (*Post* × *Peer_Clirisk*) between the climate risk information disclosure index of peer firms and *Post* in Model (1). The regression results are presented in Panel C of Table 7. Column (1) reports the results based on the entire sample, and Column (2) reports the results of the sample from 2011 to 2015 (to address concerns regarding sample symmetry). Our findings reveal that the coefficient of *Post* × *Peer_Clirisk* is positive and significant at the 1 % level. This suggests that since the introduction of ecological civilization construction at the 18th CPC National Congress, firms have experienced changes in the coercive pressure they face, subsequently influencing their willingness and motivation to disclose climate risk information. Ultimately, our analysis highlights that industry peers play a significant role in shaping climate risk information disclosure practices, indicating that coercive pressure is one channel through which peer effects operate.

6. Heterogeneity analysis

To further support our main findings, we conduct a heterogeneity analysis from two perspectives: one examines which types of firms are more (less) susceptible to imitation and the other explores which types of firms are more (less) prone to imitation.

6.1. Which types of firms are more (less) susceptible to imitation?

6.1.1. Leader and follower enterprises

In analyzing heterogeneity, we initially explore which types of firms are more (less) susceptible to imitation. Without objective criteria, industry-leading firms serve as benchmarks in their respective fields, often possessing greater discourse power and advantages in information acquisition. Follower firms tend to learn from and refer to these leader firms in terms of behavioral decision-making (Leary and Roberts, 2014). By emulating leader firms, follower firms can effectively optimize decision-making costs and benefits. Consequently, peer effects are more likely to arise as follower firms imitate behavioral decisions.

Drawing on the work of Leary and Roberts (2014), we adopt the following methodologies to differentiate leader firms from follower firms. First, within each industry–year combination, sample firms are ranked based on their firm size or market value, with the top 30 % classified as leader firms and the bottom 30 % classified as follower firms. Compared with smaller-scale and lower-market-value companies, larger-scale and higher-market-value companies typically possess more robust information advantages and exhibit superior information collection and processing capabilities, making them more likely to serve as sources of learning and guidance for follower firms. The follower firm subsample is used to analyze industry followers' reactions to leader firms. Similarly, when calculating climate risk information disclosure among peer firms, only all industry leader firms are considered as peers and the peer index (*Peer_Clirisk_leader*) is recalibrated. Conversely, the leader firm subsample is utilized to examine industry leaders' responses to followers. To compute the explanatory variable on climate risk information disclosure among peer firms, only all follower firms in the industry are regarded as peers for recalculating the peer index (*Peer_Clirisk_follower*). Following these adjustments, a regression analysis is conducted based on Model (1), and the coefficients are compared to explore disparities in peer effects regarding climate risk information disclosure between leader and follower firms.

The regression results are presented in Panel A of Table 8. Columns (1) and (2) depict the responses of industry followers to their leaders, whereas Columns (3) and (4) illustrate the reactions of industry leaders to their followers. The findings indicate that at the industry level, irrespective of firm size or market value,

Table 8
Heterogeneity analysis: Which types of firms are more (less) susceptible to imitation?

Panel A: Leader and follower enterprises

	(1)	(2)	(3)	(4)
	Imitation of the leader by the follower		Imitation of the follower by the leader	
	Clirisk	*Clirisk*	*Clirisk*	*Clirisk*
Peer_Clirisk_leader_size	1.112***			
	(3.99)			
Peer_Clirisk_leader_mv		0.802***		
		(4.30)		
Peer_Clirisk_follower_size			0.682***	
			(2.62)	
Peer_Clirisk_follower_mv				0.626**
				(2.47)
Constant	0.469	0.503	1.110***	0.903***
	(1.36)	(1.40)	(3.29)	(2.62)
Firm controls	Yes	Yes	Yes	Yes
Peer firm controls	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
Industry Fe	Yes	Yes	Yes	Yes
Region Fe	Yes	Yes	Yes	Yes
Firm Fe	Yes	Yes	Yes	Yes
N	8,987	8,787	11,246	11,019
Number of firms	2,007	2,194	1,616	1,729
Adj. R^2	0.207	0.217	0.311	0.304

Panel B: Similar and dissimilar enterprises

	(1)	(2)	(3)	(4)
	Imitation of the similar by the target		Imitation of the dissimilar by the target	
	Clirisk	*Clirisk*	*Clirisk*	*Clirisk*
Peer_Clirisk_sim_size	0.534***			
	(9.20)			
Peer_Clirisk_sim_mv		0.491***		
		(8.73)		
Peer_Clirisk_unsim_size			0.213***	
			(4.37)	
Peer_Clirisk_unsim_mv				0.079***
				(2.59)
Constant	0.465**	0.551***	0.996***	1.168***
	(2.32)	(2.75)	(4.75)	(5.36)
Firm controls	Yes	Yes	Yes	Yes
Peer firm controls	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
Industry Fe	Yes	Yes	Yes	Yes
Region Fe	Yes	Yes	Yes	Yes
Firm Fe	Yes	Yes	Yes	Yes
N	32,405	32,405	32,405	32,405
Number of firms	3,788	3,788	3,788	3,788
Adj. R^2	0.303	0.302	0.293	0.291

Note: t-statistics are in parentheses. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 levels, respectively.

follower firms demonstrate a greater propensity than other firms to learn from leader firms and promptly acquire valuable information on climate risks to make disclosure decisions. However, owing to their informational advantages, leader firms in the industry exhibit a certain degree of disregard of their follower firms.

Table 9
Heterogeneity analysis: Which types of firms are more (less) prone to imitation?

	(1)	(2)
	Manager perspective	Enterprise perspective
	Clirisk	*Clirisk*
Peer_Clirisk	0.605***	0.542***
	(7.74)	(8.12)
Overconfidence × *Peer_Clirisk*	–0.377*	
	(–1.74)	
Pressure × *Peer_Clirisk*		–0.362**
		(–2.01)
Overconfidence	0.047	
	(1.32)	
Pressure		0.130***
		(3.68)
Constant	0.494**	0.531***
	(2.49)	(2.69)
Firm controls	Yes	Yes
Peer firm controls	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
Region Fe	Yes	Yes
Firm Fe	Yes	Yes
N	33,825	33,878
Number of firms	3,867	3,868
Adj. R^2	0.304	0.305

Note: t-statistics are in parentheses. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 levels, respectively.

6.1.2. Similar and dissimilar enterprises

We further examine the responses of target firms to the disclosure of climate risk information by firms that are either similar or dissimilar. Following Tuo et al. (2020), we determine the similarity of firms to the target firms as follows. First, we calculate the absolute percentage difference in size or market value between the target firm and other industry firms. Second, we compare this value with the average deviation between the size or market value of the target firm and all industry firms. A firm that is within the same industry as the target firm and demonstrates a difference that is smaller than this average deviation is classified as a similar peer (*Peer_sim*). Conversely, a firm that is within the same industry as the target firm and demonstrates a difference greater than this average deviation is categorized as a dissimilar peer (*Peer_unsim*).

The regression results for this section are presented in Panel B of Table 8. Columns (1) and (2) display the target firms' responses to similar firms within the industry, whereas Columns (3) and (4) illustrate their responses to dissimilar firms. The coefficients of *Peer_Clirisk_sim_size*, *Peer_Clirisk_sim_mv*, *Peer_Clirisk_unsim_size* and *Peer_Clirisk_unsim_mv* are all positive and significant at the 1 % level. This indicates that regardless of whether they are similar or dissimilar from a target firm, other firms in the industry serve as models for imitation; however, the imitation is more pronounced for similar firms.

6.2. Which types of firms are more (less) prone to imitation?

6.2.1. Manager perspective

Given the pivotal role that senior executives play in implementing firm decision-making, they possess significant discretion and authority regarding information disclosure. Drawing on Grennan (2019), we explore the psychological perspective of executives by examining the influence of overconfidence on target firms' imitation behavior. Overconfident executives tend to weigh their firm's disclosure irrationally, underestimating

Table 10
Further analysis: Distinguishing between types of climate risk disclosure.

	(1)	(2)
	Phyrisk	*Transrisk*
Peer_Phyrisk	0.471***	
	(5.40)	
Peer_Transrisk		0.531***
		(7.84)
Constant	0.005	0.505***
	(0.32)	(2.59)
Firm controls	Yes	Yes
Peer firm controls	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
Region Fe	Yes	Yes
Firm Fe	Yes	Yes
N	33,878	33,878
Number of firms	3,868	3,868
Adj. R2	0.090	0.306

Note: t-statistics are in parentheses. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 levels, respectively.

the likelihood of negative impacts from random events. Consequently, these overconfident executives are less inclined to imitate behavioral decisions made by peer firms. Following Hayward and Hambrick (1997), we utilize the ratio of total compensation for the top three executives to overall management compensation as a proxy variable for executive overconfidence. In Column (1) of Table 9, we present the impact of executive overconfidence on the peer effect regarding climate risk information disclosure. The results demonstrate that *Overconfidence* × *Peer_Clirisk* is negative and significant at the 10 % level, providing evidence that firms led by overconfident executives, compared with their counterparts not led by overconfident executives, are less likely to emulate their peers' decisions concerning climate risk information disclosure.

6.2.2. Enterprise perspective

From the firm's perspective, research demonstrates that performance benchmarks significantly influence subsequent organizational decision-making processes (Grinyer and McKiernan, 1990; Greve, 1998). We posit that when a firm faces heightened performance pressure, it tends to minimize the identification and disclosure of climate risks to mitigate potential adverse reactions by investors while maintaining stakeholders' existing perceptions of the firm. To empirically test this hypothesis, we draw on the study of Greve (2003) and use the expected performance gap as a measure of pressure on firm performance:

$$A_{i,t} = \alpha HA_{i,t} + (1 - \alpha)SA_{i,t} \tag{8}$$

In Model (8), *HA* represents a firm's historical expected performance, measured by its *Roa* in period $t - 1$. *SA* denotes the market' s expectation of the firm' s performance, calculated as the average *Roa* of other industry firms excluding itself in period t. The weight α is set to 0.5 based on prior studies (Greve, 2003). The expected performance (A) of the firm is derived using Model (8), and the anticipated performance gap (*Pressure*) is obtained by subtracting the actual *Roa* for the current year. Column (2) of Table 9 presents how firm performance pressure affects our findings. The coefficient of *Pressure* × *Peer_Clirisk* is negative and significant at the 5 % level, indicating that firm performance pressure adversely affects the peer effect of climate risk information disclosure, thus confirming our previous hypotheses.

Table 11
Further analysis: Economic consequences of the peer effect of climate risk information disclosure.

	(1)	(2)
	Similarity_1	*Similarity_2*
Peer_Clirisk × *Clirisk*	15.273*	13.621**
	(1.93)	(2.12)
Peer_Clirisk	–6.673**	–5.516**
	(–2.02)	(–2.00)
Clirisk	–0.011	–0.011
	(–1.14)	(–1.31)
Size	–0.001	–0.002
	(–0.48)	(–1.36)
Lev	–0.016**	–0.009
	(–2.33)	(–1.55)
Roa	–0.006	–0.010
	(–0.58)	(–1.18)
Growth	0.002*	0.001
	(1.78)	(1.02)
Soe	–0.004	–0.002
	(–0.72)	(–0.43)
Top1	0.007	0.004
	(0.55)	(0.39)
Board	–0.005	–0.001
	(–0.55)	(–0.19)
Age	0.004	–0.002
	(1.60)	(–0.91)
Inddir	–0.034	–0.021
	(–1.52)	(–1.20)
Cfo	–0.010	–0.003
	(–1.09)	(–0.42)
Tobinq	0.000	–0.000
	(0.14)	(–0.57)
Constant	0.855***	0.845***
	(18.33)	(21.71)
Year Fe	Yes	Yes
Firm Fe	Yes	Yes
N	29,802	29,802
Number of firms	3,406	3,406
Adj. R^2	0.479	0.556

Note: t-statistics are in parentheses. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 levels, respectively.

7. Further analysis

7.1. Distinguishing between types of climate risk disclosure

To provide a more comprehensive evidence base for our conclusions, we further differentiate between the types of climate risk information disclosure. Based on Li et al. (2024) and Giglio et al. (2021), we categorize climate risk into physical risk and transition risk. First, we divide the word set of climate risk into two subcategories: physical risk and transition risk (see Appendix 2 for detailed information). Second, we estimate the information disclosure indicators for physical risk (*Peer_Phyrisk*) and transition risk (*Peer_Transrisk*) using the same methodology as that used for climate risk indicators, while using Model (1) for the regression analysis to explore industry peer effects associated with different types of climate risk information disclosure. The regression results regarding the peer effect of physical and transition risks are presented in Table 10. The coefficients of both *Peer_Phyrisk* and *Peer_Transrisk* are positive and significant at the 1 % level, indicating the

Table 12
Further analysis: Regional peer effect of climate risk information disclosure.

	(1)	(2)	(3)
	Clirisk	*Clirisk*	*Clirisk*
Peer_Clirisk_reg	0.097***	0.086***	0.074**
	(3.20)	(2.90)	(2.57)
Peer_Clirisk			0.535***
			(8.05)
Size	0.016***	0.016***	0.017***
	(6.83)	(6.85)	(7.23)
Lev	–0.017**	–0.017**	–0.016**
	(–2.15)	(–2.12)	(–2.01)
Roa	0.035***	0.035***	0.027***
	(3.49)	(3.50)	(2.75)
Growth	–0.000	–0.000	–0.001
	(–0.17)	(–0.18)	(–0.61)
Soe	–0.000	–0.000	–0.002
	(–0.08)	(–0.03)	(–0.45)
Top1	0.030**	0.030**	0.030**
	(2.08)	(2.08)	(2.13)
Board	–0.007	–0.007	–0.004
	(–0.81)	(–0.80)	(–0.48)
Age	–0.003	–0.003	–0.003
	(–1.12)	(–1.16)	(–1.47)
Inddir	–0.021	–0.021	–0.015
	(–1.00)	(–1.02)	(–0.75)
Cfo	0.002	0.002	0.005
	(0.30)	(0.24)	(0.60)
Tobinq	–0.002**	–0.002***	–0.002**
	(–2.53)	(–2.58)	(–2.27)
Peer_Size_reg		0.004	0.002
		(0.85)	(0.58)
Peer_Lev_reg		–0.022	–0.011
		(–1.19)	(–0.59)
Peer_Roa_reg		0.009	0.002
		(0.28)	(0.05)
Peer_Growth_reg		0.001	0.002
		(0.33)	(0.58)
Peer_Soe_reg		0.003	0.004
		(0.33)	(0.35)
Peer_Top1_reg		0.013	0.011
		(0.55)	(0.48)
Peer_Board_reg		–0.008	–0.009
		(–0.48)	(–0.57)
Peer_Age_reg		0.004	0.001
		(1.03)	(0.23)
Peer_Inddir_reg		–0.028	–0.013
		(–0.55)	(–0.26)
Peer_Cfo_reg		0.052*	0.049*
		(1.89)	(1.81)
Peer_Tobinq_reg		–0.000	–0.000
		(–0.24)	(–0.19)
Peer_Size			–0.026***
			(–3.48)
Peer_Lev			–0.054
			(–1.17)

(*continued on next page*)

Table 12 (*continued*)

	(1)	(2)	(3)
	Clirisk	*Clirisk*	*Clirisk*
Peer_Roa			0.066
			(1.16)
Peer_Growth			0.009
			(1.24)
Peer_Soe			0.005
			(0.21)
Peer_Top1			0.002
			(0.03)
Peer_Board			–0.133***
			(–2.76)
Peer_Age			0.013
			(1.43)
Peer_Inddir			–0.135
			(–0.81)
Peer_Cfo			0.076
			(1.40)
Peer_Tobinq			0.003
			(1.24)
Constant	–0.340***	–0.398***	0.453**
	(–5.63)	(–3.52)	(2.08)
Year Fe	Yes	Yes	Yes
Industry Fe	Yes	Yes	Yes
Region Fe	Yes	Yes	Yes
Firm Fe	Yes	Yes	Yes
N	33,878	33,878	33,878
Number of firms	3,868	3,868	3,868
Adj. R^2	0.287	0.288	0.305

Note: t-statistics are in parentheses. ***, ** and * denote significance at the 0.01, 0.05 and 0.10 levels, respectively.

presence of industry peer effects in disclosing information related to physical and transition risks and thereby further validating the hypotheses.

7.2. Economic consequences of the peer effect of climate risk information disclosure

The results of this study reveal the presence of industry peer effects in climate risk information disclosure, driven by both active and passive imitation motives. Notably, regardless of the type of imitation, the peer effect helps to enhance the textual similarity of disclosed information among firms (Gaulin and Peng, 2021). To further validate the proposed mechanism, Model (9) is constructed to investigate the impact of the peer effect of climate risk information disclosure on text similarity:

$$Similarity = \beta_0 + \beta_1 Peer\_Clirisk \times Clirisk + \beta_2 Peer\_Clirisk + \beta_3 Clirisk + Controls + YearFe + FirmFe + \varepsilon \tag{9}$$

In Model (9), the dependent variable is the similarity of the annual report between the target firm and other firms within the same industry, measured by the median and mean similarity (*Similarity_1* and *Similarity_2*, respectively) between the current financial reports of target firms and all other firms within the same industry based on the Latent Dirichlet Allocation model. The data are sourced from the WinGo Text data platform.[3] The independent variable is an interaction term involving climate risk information disclosure for both the

[3] https://www.wingodata.cn/#/cn/pages/wenben?id=2&type=3&wenben=0.

target firm and its peer firms (*Peer_Clirisk* × *Clirisk*). The regression results are presented in Table 11. The coefficient of *Peer_Clirisk* × *Clirisk* is positive and significant at the 10 % level at least when examining its impact on *Similarity*. This finding suggests that climate risk information disclosure among peer firms can enhance text similarity within financial reports between these firms, thereby providing further support for our main findings.[4]

7.3. Regional peer effect of climate risk information disclosure

Research demonstrates that the actions of geographically adjacent peer firms can significantly influence the investment decisions and salary policies of target firms (Kedia and Rajgopal, 2009; Dougal et al., 2015). Furthermore, climate risks exhibit distinct regional and local characteristics, with firms in the same geographical area facing similar climate-related challenges (Giorgi and Mearns, 1991; Pierce et al., 2009). Consequently, companies operating within the same region may experience comparable climate pressures, leading to information disclosure homogeneity and highlighting the presence of a regional peer effect in disclosing climate risk information. To test these hypotheses empirically, we use Model (3) to calculate the level of climate risk information disclosure among regional peer firms (*Peer_Clirisk_reg*), while controlling for relevant firm characteristics to further investigate the existence of a regional peer effect in disclosing climate risk information. The regression results in Columns (1) and (2) of Table 12 demonstrate a positive relationship between *Peer_Clirisk_reg* and *Clirisk* that is significant at the 1 % level, indicating the existence of regional peer effects. Furthermore, when incorporating *Peer_Clirisk* into the model, the coefficient of *Peer_Clirisk* is significantly larger than that of *Peer_Clirisk_reg* (F-value = 42.67). This suggests that firms are more influenced by industry peers than regional peers, highlighting the more substantial impact of industry peer effects on climate risk information disclosure.

8. Conclusions

Climate risks not only directly threaten firms' production and operations but also jeopardize their economic benefits and profitability, potentially triggering disruptions in global supply chains that would profoundly affect the overall economic system. Therefore, enterprises must adopt proactive climate risk management strategies and enhance information disclosure to mitigate potential negative impacts and promote sustainable economic development. In this study, we utilize textual information from annual reports to investigate the peer effect of corporate climate risk disclosure. The findings confirm the presence of industry peer effects in corporate climate risk disclosure, with active imitation driven by cost–benefit considerations and passive imitation influenced by institutional pressure identified as the main mechanisms underlying this phenomenon. Heterogeneity analysis indicates that follower enterprises within the same industry are more inclined to learn from leader companies and that target enterprises demonstrate a greater willingness to emulate similar peers within their industry. Furthermore, enterprises with overconfident executives and high performance pressure are less inclined to emulate their peers' decisions regarding information disclosure. Our analysis also demonstrates that physical risk and transition risk disclosures exhibit industry peer effects. Additionally, disclosing climate risk information enhances financial report similarity between companies and their peers, and a regional peer effect of climate risk information disclosure is also observed.

The policy implications of this study are as follows. First, enterprises can gradually enhance their level of climate risk information disclosure through mutual imitation and learning. Simultaneously, at the critical juncture of China's high-quality economic development and the implementation of carbon peak and carbon neutrality, government departments can effectively leverage the enterprise peer effect imitation mechanism to

[4] We thank the reviewers for their suggestions.

bolster enterprises' awareness in responding to climate change. This would fully mobilize enterprises' enthusiasm for information disclosure and enhance the overall level of climate risk information disclosure. Enterprises can also promptly adapt to stakeholders' requirements for climate risk disclosure by emulating and learning from peer enterprises. This would enhance their information transparency and prepare them for more comprehensive climate risk management in the future.

Second, governments and regulators must enhance the disclosure system for climate risk information. For instance, governments should establish precise and standardized guidelines for disclosing climate risk information, develop a regulatory framework that mandates corporate disclosure of climate risks, augment transparency among investors and other stakeholders regarding corporate climate risk management practices and mitigate the adverse effects of such risks. Regulators should also actively guide enterprises in fulfilling their obligation to disclose climate risk information as dictated by regulations while implementing appropriate regulatory measures against violations. By establishing a robust information disclosure system, governments and regulators can effectively compel companies to accurately divulge their climate risks. In turn, this would allow for the establishment of a more dependable baseline from which to address the challenges posed by climate change at the societal level.

The limitations of this study suggest intriguing avenues for future research. First, the study delves into the factors influencing climate risk information disclosure among listed companies from a peer perspective. Further exploration of the impact of such peer effects on investment decisions, financing choices and other outcomes of target enterprises could be conducted. Second, the mechanism of imitation learning in risk information dissemination across firms is investigated with a focus on corporate climate risk information disclosure. Future research could explore the economic implications of other types of information disclosure. Third, we solely examine the tangible influence of climate risks on enterprises through corporate climate risk disclosure analysis. However, future work could also analyze how businesses identify and respond to climate risk pressures to formulate more effective response measures against the adverse impacts of climate change.

Declaration of Competing Interest

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

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Appendix. *Appendix 1. Climate risk word set*

Word type	Word set
Seed word	节能、电能、能源、清洁、燃料、生态、节水、环境、绿色、转型、太阳能、升级、改造、利用率、核电、风电、天然气、增效、燃油、效率、循环、再生、高效、光伏、减排、降耗、灾害、地震、台风、海啸、洪涝、旱涝、火灾、极端、暴雨、恶劣、内涝、大风、沙尘、冰雹、特殊、旱灾、飓风、霜冻、水灾、风暴、泥石流、滑坡、洪水、洪灾、干旱、暴雪、凌冻、雪灾、冰雪、气候、天气、自然、潮湿、水温、降温、寒冷、气温、降雨、温度、雨水、雨季、雨情、冰冻、降水、早霜、低温、高温、雨雪 Energy saving, electric energy, energy, clean, fuel, ecology, water saving, environment, green, transformation, solar energy, upgrading, transformation, utilization rate, nuclear power, natural gas, efficiency enhancement, fuel, efficiency, recycling, regeneration, high efficiency, photovoltaic, emission reduction, consumption reduction, disaster, earthquake, typhoon, tsunami, flood, drought, fire, extreme, rainstorm, destructive, waterlogging, wind, Dust, hail, exceptional, drought, hurricane, frost, flood, storm, debris flow, landslide, flood, flood, drought, blizzard, Lingfrost, snow disaster, ice and snow, climate, weather, nature, humidity, water temperature, cooling, cold, temperature, rainfall, temperature, rain, rainy season, rain, freezing, precipitation, early frost, low temperature, high temperature, rain and snow
Augmented word	节能、能源、清洁、生态、环境、转型、太阳能、升级、循环、利用率、核电、天然气、增效、燃油、效率、再生、减排、环保、绿色、低碳、降耗、燃料、节水、光伏、高效、改造、油耗、电耗、能耗、风电、光伏、效能、集约、灾害、地震、台风、海啸、旱涝、极端、恶劣、内涝、大风、沙尘、飓风、霜冻、水灾、风暴、泥石流、滑坡、凌冻、雪灾、旱灾、洪涝、暴雨、龙卷风、冰雹、洪灾、雨雪、冰冻、暴雪、冻害、干旱、旱情、强降雨、洪水、严寒、风沙、气候、天气、潮湿、水温、降温、寒冷、气温、降雨、温度、雨水、雨季、雨情、降水、阴雨、多雨、极寒、冬季、汛期、高湿、水情、水位、光照、缺水、高寒、寒潮、沉降、地下水、汛情、地表、蓄水 Energy saving, energy, clean, ecology, environment, transformation, solar energy, upgrading, recycling, utilization rate, nuclear power, natural gas, efficiency enhancement, fuel, efficiency, regeneration, emission reduction, environmental protection, green, low-carbon, consumption reduction, fuel, water saving, high efficiency, transformation, fuel consumption, power consumption, energy consumption, wind power, photovoltaic, efficiency, intensive, disaster, earthquake, typhoon, tsunami, drought and flood, Extreme, severe, waterlogging, wind, sand dust, hurricane, frost, flood, storm, debris flow, landslide, Ling frost, snow, drought, flood, storm, tornado, hail, flood, rain and snow, freezing, blizzard, freezing damage, drought, drought, heavy rainfall, flood, cold, sand, climate, weather, humidity, water temperature, cooling, cold, temperature, rainfall, temperature, rain, Rainy season, rain situation, precipitation, overrain, rainy, extremely cold, winter, flood season, high humidity, water situation, water level, light, water shortage, high cold, cold tide, settlement, groundwater, flood situation, surface, water storage

Appendix 2. Physical risk and transition risk word set

Risk type	Word set
Physical risk	灾害、地震、台风、海啸、旱涝、极端、恶劣、内涝、大风、沙尘、飓风、霜冻、水灾、风暴、泥石流、滑坡、凌冻、雪灾、旱灾、洪涝、暴雨、龙卷风、冰雹、洪灾、雨雪、冰冻、暴雪、冻害、干旱、旱情、强降雨、洪水、严寒、风沙、气候、天气、潮湿、水温、降温、寒冷、气温、降雨、温度、雨水、雨季、雨情、降水、阴雨、多雨、极寒、冬季、汛期、高湿、水情、水位、光照、缺水、高寒、寒潮、沉降、地下水、汛情、地表、蓄水 Disaster, earthquake, typhoon, tsunami, drought-flood, extreme, severe, waterlogging, wind, sand dust, hurricane, frost, flood, storm, debris flow, landslide, Ling frost, snow, drought, flood, rainstorm, tornado, hail, flood, rain and snow, freezing, blizzard, freezing damage, drought, drought, heavy rainfall, flood, cold, wind and sand, climate, weather, humidity, water temperature, cooling, cold, temperature, rainfall, temperature, rain, rainy season, rain, precipitation, overcast rain, rainy, extremely cold, winter, flood season, high humidity, water situation, water level, light, water shortage, high cold, cold wave, settlement, groundwater, flood situation, surface, water storage
Transition Risk	节能、能源、清洁、生态、环境、转型、太阳能、升级、循环、利用率、核电、风电、天然气、增效、燃油、效率、再生、减排、环保、绿色、低碳、降耗、燃料、节水、光伏、高效、改造、油耗、电耗、能耗、效能、集约 Energy saving, energy, clean, ecology, environment, transformation, solar energy, upgrading, recycling, utilization rate, nuclear power, wind power, natural gas, efficiency enhancement, fuel oil, efficiency, regeneration, emission reduction, environmental protection, green, low-carbon, consumption reduction, fuel, water saving, photovoltaic, high-efficiency, transformation, fuel consumption, electricity consumption, energy consumption, efficiency, intensive

Notes: Chinese near-synonyms and English-Chinese contextual differences are considered in the screening process.

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The spillover effect of customers' ESG performance on suppliers' green innovation quality

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ABSTRACT

This study investigates whether and how customer firms' environmental, social and governance (ESG) performance impacts suppliers' green innovation quality using a sample of Chinese A-share listed companies from 2009 to 2022. We find that customers' ESG performance facilitates suppliers' green innovation quality through green learning and corporate competition. Additional tests indicate that customers with stickier customer–supplier relationships and a more central position in the supply chain network than peers enhance suppliers' green innovation quality. After categorizing whether customers engage in greenwashing, we determine that those adherence to green principles, genuinely promote suppliers' green innovation quality. Finally, we find the above effect ultimately enhances suppliers' environmental performance. This study provides valuable insights for supply chain companies into collaboratively achieving sustainable development.

1. Introduction

In recent years, there has been a growing number of academic studies on how environmental, social and governance (ESG) performance influences firms' operations and performance. Studies find that good ESG performance not only can reduce a firm's financing costs (Eliwa et al., 2021) and systemic risk (Albuquerque et al., 2019) but also contributes to profit growth (Fatemi et al., 2015) and long-term performance (Velte, 2017) by exerting value-creation effects (Tran and Coqueret, 2023). Furthermore, external stakeholders pay attention to a firm's ESG performance and suppliers, as crucial partners are inclined to provide

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more trade credit to firms with good (vs. poor) ESG performance (Li and Feng, 2022), thereby enhancing these firms' influence in the supply chain (Li et al., 2023). The attentiveness of suppliers to their customers' ESG performance raises the question of whether the positive spillover effect of customers' good ESG performance effectively promotes and accelerates the green transformation of suppliers, thereby achieving the sustainable development of the entire supply chain. However, the literature does not explore whether suppliers follow the lead of their customer firms by imitating their good ESG performance, and there is a lack of attention to the positive spillover effects of good ESG performance.

In this study, we attempt to fill this gap in the literature. We primarily focus on China, the world's largest emerging market, for the following reasons. First, in recent years, China has been transitioning from high-speed growth to high-quality development. To achieve more sustainable and high-quality economic development, the Chinese government has established strategic goals of reaching a carbon peak by 2030 and carbon neutrality by 2060, emphasizing the shift toward a green, low-carbon path to actively address global climate change and promote development for all of humanity. In 2024, the Central Committee of the Communist Party of China proposed advancing the establishment of a "Beautiful China", transitioning China from a participant in global environmental governance to a leader, accelerating green and low-carbon development and advancing a harmonious coexistence between humans and nature in a modernized society. In this context, firms are gradually adjusting their business strategies and actively embracing ESG principles to achieve sustainable development and enhance their competitive advantage (Albuquerque et al., 2019). The active practice of ESG principles by Chinese firms not only contributes to the construction of a "Beautiful China" but also supports the realization of global sustainable development goals. Therefore, exploring the ESG practices of Chinese firms can provide valuable insights and references for other emerging market firms in terms of addressing environmental and societal challenges through green transformation. Second, as the main battleground for reducing carbon emissions, the supply chain plays a crucial role in achieving sustainable development goals. Chinese firms have a higher customer concentration than firms in other countries. Cao et al. (2023) find that from 2007 to 2019, the top five customers of Chinese companies collectively accounted for an average of 30.8 % of total sales revenue, whereas in the United States, the average proportion of sales from major customers was 9 % (Chiu et al., 2019). This concentration indicates the considerable reliance of Chinese companies on their major customers and implies that these major customers hold substantial bargaining power. In such circumstances, the influence of customers on suppliers becomes more pronounced than in circumstances where customer concentration is lower. Therefore, when customers signal their commitment to sustainable development, suppliers are more likely to respond to these demands by actively engaging in green transformation. Thus, our study focuses on Chinese supply chain enterprises and investigates whether customers' ESG performance can facilitate suppliers' green transformation, thus providing micro-level evidence on the achievement of green governance in the supply chain industry.

In this study, we investigate whether and how customers' ESG performance fosters the improvement of suppliers' green innovation quality through transmission across the supply chain based on the positive externalities stemming from customers' ESG performance. In addition, we inquire into whether different relationships between customers and suppliers exert differing moderating effects and whether suppliers discern divergence in client ESG ratings that are indicative of potential "greenwashing" practices. The insights from these heterogeneity analyses not only assist firms in proactively pursuing green transformation via transmission and beneficial spillovers throughout the supply chain, but also provide guidance and a reference for the implementation of China's "dual carbon" strategy.

Our study contributes to three strands of literature. First, we enrich the research on the economic implications of ESG performance from the perspective of suppliers. We demonstrate the positive spillover effect of customers' ESG performance on suppliers' green innovation quality, extending the boundaries of stakeholder theory. Studies focus mainly on the impact of ESG performance on firms' internal operational decisions and performance, with limited exploration of the spillover effects of ESG performance and its influence on external stakeholders' decisions and behaviors. This paper selects suppliers as the pivotal external stakeholders, uses Python to construct a dataset of paired customers and suppliers and demonstrates that customers' ESG performance fosters the improvement of green innovation quality by suppliers. Thus, we provide micro-level evidence on how suppliers can foster green cooperation with customers with good ESG performance.

Second, starting from the positive externalities of good ESG performance, our study broadens the research on factors influencing green innovation from a supply chain perspective. Studies explore firms' internal factors that shape green innovation, such as their willingness to innovate, but overlook pressures from other stakeholders and the impact of active learning and emulation on green innovation. The supply chain can link upstream suppliers and downstream customers, facilitating the transmission of green concepts to achieve collaborative green governance. Therefore, this paper focuses on the customer–supplier chain to explore whether and how customers' ESG performance drives suppliers' green innovation quality, enriching the research on the factors influencing green innovation and expanding and extending the research boundaries of social learning theory and resource-based theory in the context of the dual carbon strategy.

Third, focusing on the supply chain, we investigate how heterogeneity in various dimensions of customer–supplier relationships influences how customers' ESG performance impacts suppliers' green innovation quality. In addition, our study relaxes the implicit assumption of consistency between customers' ESG information disclosure and ESG practices. We use customers' ESG rating divergences to identify firms engaging in "greenwashing" practices and examine suppliers' reactions, with a particular focus on whether suppliers can identify customers engaging in greenwashing. By confirming that suppliers, as important partners of customers, can distinguish genuine green customers and greenwashing customers, our research provides empirical evidence on how supply chain firms can achieve effective collaborative green governance.

The remainder of our paper is organized as follows. In Section 2, we review the relevant literature. In Section 3, we present our theoretical analysis and hypotheses. The research design is explained in detail in Section 4. In Section 5, we present the empirical tests and results analysis. Further analysis is presented in Section 6. Finally, Section 7 provides conclusions and implications.

2. Literature review

2.1. Research on the economic consequences of corporate ESG performance

The concept of ESG performance was introduced by the United Nations in 2004, and a range of indicators have been refined to construct a set of ESG evaluation systems. ESG underscores a firm's sustainable advancement, advocating for the unity of economic and environmental benefits in the operating process. As a growing number of scholars are becoming aware of the significant impact of ESG performance on firms at the micro level, they are paying considerable attention to the effect of firms' ESG performance on their operations and performance, along with the effect of stakeholders evaluating firms' ESG performance.

For companies themselves, ESG performance not only reduces systemic risks and enhances corporate value (Albuquerque et al., 2019) but also mitigates operational risks and contributes to profit growth (Fatemi et al., 2015). Kuo et al. (2021) find that a firm's ESG performance can weaken its core business capabilities, leading to short-term performance reduction. However, from a long-term performance perspective, a firm's ESG performance exhibits a value-creation effect (Velte, 2017; Tran and Coqueret, 2023). For stakeholders, ESG performance enhances the relevance of a firm's earnings value, influencing investors' decision-making and behavioral responses (Wu et al., 2023). Similarly, good ESG performance by companies attracts attention from creditors. Lending institutions lower their debt financing costs after observing a firm's proactive efforts to implement ESG strategies and establish effective commitments (Eliwa et al., 2021). As crucial partners, suppliers devote considerable attention to the competitive advantages and risk resilience conveyed by a firm's ESG performance, leading to increased provision of trade credit financing (Li and Feng, 2022). Owing to these in-depth studies of ESG performance, its spillover effects are becoming increasingly apparent. However, there is limited research focusing on the positive externalities of ESG performance at the supply chain level.

2.2. Research on the factors influencing green innovation

Corporate green innovation refers to technological innovations related to green processes or products and encompasses innovations in energy conservation, pollution prevention, waste utilization and other aspects (Chen et al., 2006). As a crucial driver of national green transformation and high-quality economic development, green innovation is garnering significant attention from scholars. The literature primarily explores the factors influencing green innovation from two dimensions, namely motivation and resources, based on internal and external perspectives.

First, considering motivations for green innovation, external environmental regulation is a major factor inducing firms to engage in green innovation. Qi et al. (2018) focus on market-oriented environmental regulatory policies and find that the pilot emission trading policy stimulates green innovation in firms, significantly enhancing the quality of green innovation. Conversely, Tao et al. (2021) determine that command-type environmental regulatory policies promote an increase in the quantity of green innovation but lead to a decline in the quality of green innovation. Turning to the internal motivations of firms, as decision-makers regarding green innovation, executives' myopia can inhibit green innovation (Zhang et al., 2023). However, executives with green experience pay attention to sustainability issues, engage in corresponding environmental behaviors and promote active green innovation within their firm (Lu and Jiang, 2022). Considering external stakeholders, competitors' behavior and consumers' environmental awareness also influence firms' green innovation (Chen et al., 2006; Lin and Chen, 2017).

Considering the second dimension of green innovation resources, green knowledge-sharing contributes to improving the quality of green innovation by firms (Lin and Chen, 2017). Acquiring external knowledge is more beneficial than internal knowledge for green innovation (Martínez-ros and Kunapatarawong, 2019), and the ability to transform such external knowledge internally is crucial for enhancing green innovation (Ben et al., 2018). Chen (2008) determines that green relationship capital from business partners can facilitate firms' green innovation and enhance their competitive advantage. Furthermore, directors with green experience not only alleviate executive myopia and enhance executive environmental awareness but also aid firms to acquire resources to promote the quantity and quality of green innovation (Wang et al., 2023).

2.3. Research on the spillover effects of customer information disclosure on supplier behavior and decisions

A series of studies analyze the impact of customer information disclosure on supplier behavior and decisions, with a focus on how suppliers respond to negative information disclosed by customers. For instance, Hertzel et al. (2008) reveal that bankruptcy announcements by customers increase management costs and reduce stock prices for suppliers. Qian and Zhu (2017) indicate that financial restatements conveying negative corporate information draw the attention of suppliers to their customers' poor accounting information quality and result in reduced credit limits. Other studies into the spillover effects of customer information disclosure across the supply chain examine the influence of non-visible customer information disclosure on supplier behavior. Yin and Jia (2017) find that supplier behavior can be influenced by their customers' earnings management practices, resulting in a decrease in firms' investment efficiency. Similarly, Chen et al. (2019) note that suppliers reduce their investment efficiency if they perceive low-quality forward-looking information or risk-related information disclosures by customers (Chiu et al., 2019). Furthermore, Di et al. (2020) confirm that negative tones conveyed by customers in annual reports are perceived by suppliers and lead them to increase cash holdings. Fewer scholars focus on how suppliers react to positive (vs. negative) information disclosed by customers. Zhang (2021) discover that suppliers trust customers who receive an A-level rating for trustworthy taxation and, as a result, they can obtain more credit than their peers. Chen et al. (2021) find that suppliers obtain demand information from customers' high-quality earnings information, which thereby improves suppliers' investment efficiency. However, there is a lack of literature exploring the spillover effects of customers in the supply chain in the context of ESG performance and green governance.

2.4. Analysis of the literature

First, the majority of studies on the economic consequences of firms' ESG performance focus on aspects such as firms' operational decisions and performance. There is scant research on ESG performance from the perspective of external stakeholders, particularly on how a firm's ESG performance affects the behavior of partners, such as suppliers, and the underlying mechanisms. In this study, building on stakeholder theory, we specifically examine the impact of customer ESG performance on suppliers' decisions to explore the positive externalities generated by customer ESG performance.

Second, the literature on the determinants of firms' green innovation concentrates on the motivation and resource dimensions. However, to achieve "green environmental protection" practices and dual carbon goals, the participation of every entity involved in production and operational activities must be considered. Few studies integrate upstream and downstream supply chain partners into their research on green governance. Based on constructing "customer–supplier-year" samples, this paper investigates whether and how customer ESG performance can enhance the quality of suppliers' green innovation, providing micro-evidence on how supply chain businesses can achieve green co-governance through various pathways.

Finally, given that customers' ESG performance can generate positive spillover effects, a key question is whether the diverse relationships between customers and suppliers moderate the impact of customers' ESG performance on suppliers' green innovation quality. In this paper, we explore this question by considering the "stickiness" between customers and suppliers and their position in the supply chain network. In addition, we relax the implicit assumption of consistency between ESG information disclosure and ESG practices to examine how customers' ESG behavior, based on ESG rating divergence, influences suppliers' green innovation quality and thus provide empirical evidence on how supply chain firms can authentically achieve green cooperation.

3. Theoretical analysis and hypothesis development

Severe environmental issues have led firms to expand their focus beyond economic concerns and to consider the impact of their activities on society and the environment. As a core framework and evaluation system for sustainable development, improving ESG performance not only aligns with China's dual carbon goal but also empowers companies to facilitate their green transformation (Wu et al., 2023). Studies find that firms with ESG advantages can improve their risk management and alleviate financing constraints (Li and Feng, 2022), promote performance growth, achieve value creation (Fatemi et al., 2015; Velte, 2017; Tran and Coqueret, 2023) and gain favor from external stakeholders, such as banks and suppliers (Eliwa et al., 2021; Li et al., 2023). As the competitive advantages of ESG become increasingly evident, the importance and necessity of practicing ESG concepts are attracting attention.

Focusing on the supply chain, firms with better ESG performance place greater emphasis on the severe impact of environmental incidents on their financial condition and operational management, leading to a more cautious selection of supply chain partners. Customers with good ESG performance can influence their upstream suppliers and thus achieve green co-governance of the supply chain through the green learning of suppliers. Furthermore, they can exercise their power through the supplier selection process (Li et al., 2023), intensifying competition among suppliers and forcing them to enhance the quality of their green innovation to meet customer demands for green development. For example, in its 2022 ESG report, Midea Group (SZ.000333) highlights its "AA" rating in terms of the ESG Index constructed by the China Securities Index and issues a "Green Development Initiative" to encourage suppliers to actively engage in green practices, thus integrating sustainable development concepts into every aspect of its firms' production and operations. To reduce the energy consumption involved in production and enhance environmental friendliness, Midea Group actively collaborates with suppliers on innovative new materials and processes, jointly exploring energy-saving and emission-reducing pathways such as the application of environmentally friendly materials and optimizing materials delivery. For instance, in the field of recycled plastics, Midea developed PCR materials in cooperation with its supplier Ineos Benzene and applied them to its sustainable household appliance series. This collaborative effort not only enhances the supplier's green innovation capabilities but also contributes to the circular economy.[1] Hence, customers with good ESG performance can generate positive spillover effects in the supply chain, promoting the green transformation and development of their suppliers.

From the perspective of the green learning mechanism for suppliers, good ESG performance by customers can help suppliers access resources or technologies related to green innovation and enhance the suppliers' green awareness, thereby improving the quality of green innovation. Considering green resource acquisition,

[1] https://www.midea.com.cn/content/dam/mideacn-aem/investors/reports/2022%E7%BE%8E%E7%9A%84%E9%9B%86%E5%9B%A2ESG%E6%8A%A5%E5%91%8A.pdf.coredownload.inline.pdf.

customers aiming to enhance their ESG performance will adopt advanced and environmentally friendly production technologies and processes (Wu et al., 2023), strive to apply innovative eco-friendly technologies to reduce the environmental pollution from production and end-of-life waste and accelerate the creation of green production lines (Velte, 2017). In this process, customers will accumulate a wealth of green knowledge and innovative green technologies, completing their green resource reserves. Compared with general innovation, green innovation is more complex for firms because they not only need diverse knowledge and technological resources but must also gradually shift from internal acquisition to external absorption of green knowledge and technological resources (Martínez-ros and Kunapatarawong, 2019). Customers, as important trading partners, provide channels for suppliers to acquire green innovation knowledge and information (Albornoz et al., 2009). The acquisition of external green knowledge helps suppliers reshape their internal knowledge systems and overcome the challenges of achieving green innovation (Albort-Morant et al., 2016), significantly reduces the uncertainty of supplier green innovation (Ben et al., 2018) and promotes the improvement of the quality of supplier green innovation. Next, from the perspective of enhancing green awareness, customers integrate ESG concepts into various aspects such as raw material selection, product design and packaging during the supplier procurement process, thus sending environmental signals to suppliers (Li and Feng, 2022) and enhancing the suppliers' green awareness. Furthermore, customers with good ESG performance also reduce firms' systemic risks (Albuquerque et al., 2019), enhance profitability (Velte, 2017) and generate corporate value-creation opportunities (Fatemi et al., 2015; Tran and Coqueret, 2023). Social learning theory suggests that an entity can enhance its advantages by imitating the characteristics and behaviors of others, especially demonstrators (Bandura and Walters, 1977). After observing the ESG advantages obtained by customers, suppliers develop a strong imitation psychology and quickly adjust their green innovation strategies (Song et al., 2023) to align their green awareness with the customers' green development concepts. With the enhancement of managers' green awareness within the supplier firms, more resources and management support will be allocated to relevant green issues, thereby facilitating the acquisition and integration of green resources and ultimately improving the quality of green innovation.

From the perspective of the corporate competition mechanism, good ESG performance endows customers with the power to influence the supply chain (Li et al., 2023), making them sought-after partners for suppliers and intensifying competition among suppliers. Suppliers pioneering in green innovation can gain a first-mover advantage (Chen, 2008), prompting supplier firms to adjust their myopic behaviors and increase their R&D investment to build customer-specific assets and thus gain recognition and preference from customers. First, in terms of curbing managerial myopia, green innovation exhibits a "dual externality" relating to technology and the environment (Rennings, 2000) and tends to be characterized by high risk and long timeframes. Managers focusing their decisions and firm operations on short-term benefits will not pursue green innovation adequately, inducing shortsighted behaviors among the management (Zhang et al., 2023). However, customers with high ESG performance have strong demands for green, low-carbon production and create significant pressure within the supply chain, pushing suppliers to actively fulfill their commitments to produce green products (Dai et al., 2021). Therefore, compelled by customers' green development concepts, managers will reduce their myopic behaviors and implement green innovation strategies to meet the customers' demands for green products and processes, enabling the managers to gain a first-move advantage through improved green innovation quality. Furthermore, in terms of investment in relationship-specific assets, customers, as crucial partners of suppliers, have a decisive influence on suppliers' operations and strategies. The enhanced influence of customers with ESG advantages in the supply chain then leads suppliers to strengthen their productive cooperation with customers and increase their investment in proprietary assets (Di et al., 2020). Suppliers build relationship-specific assets by increasing R&D investment and other intangible assets (Ge et al., 2022), such as green innovation investment, enhancing trust from customers, facilitating more trade interactions and establishing stable cooperative relationships (Lui et al., 2009). Therefore, good ESG performance endows customers with a choice of supply chain partners and pushes suppliers to increase their green innovation R&D investment to construct and prevent the devaluation of relationship-specific assets to maintain cooperative relationships, thereby promoting the quality of green innovation.

Based on this discussion of how customers' ESG performance influences the quality of suppliers' green innovation, we propose the following hypothesis:

H1. Good ESG performance by customers promotes improvements in suppliers' green innovation quality.

4. Research design

4.1. Sample selection and data sources

Our sample consists of all Chinese-listed firms for the period from 2009 to 2022. We collect data on green innovation quality from the Chinese Research Data Service database, and we obtain supply chain and other variable data from the China Stock Market and Accounting Research database. Following the literature, we first select firms that are customers of listed firms. The top five customers disclosed by listed firms include both listed and non-listed firms. As financial data for non-listed companies are not available, we manually collect data on listed firms through the Tianyancha data platform,[2] obtaining a sample of 2,530 pairs of customers and suppliers belonging to listed companies. Second, we remove 33 samples of financial firms, 62 samples of special treatment (ST and *ST) firms and 306 samples with missing variables, resulting in 2,129 "customer–supplier-year" observations. To reduce the impact of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

4.2. Variable definition

4.2.1. Supplier green innovation quality

Compared with green utility patents, green invention patents yield higher value to firms (Qi et al., 2018). Therefore, following Kim et al. (2016) and Xu et al. (2019), we measure green innovation quality in terms of technological diversification (*Diver*) and innovation breakthroughs (*Break*), which are calculated based on the International Patent Classification (IPC) information of green invention patents. Based on the current IPC, invention patents are generally categorized into the following five hierarchical levels, from high to low: section, class, subclass, main group and subgroup. Each subsequent level is a subset of and inherits the class number from the preceding level. Taking A06Q30/04 as an example, the first character A represents a section, the first three characters A06 represent a class, the first four characters A06Q represent a subclass, the main group is A06Q30 before the "/" and the subgroup is the entire A06Q30/04. The current IPC classification includes eight sections; based on the subclass of the first four characters of the IPC classification of invention patents in China, there are a total of 650 subclasses. Therefore, the range of values for the subclass is [1, 650]. To calculate technological diversification, we employ Eqs. (1)–(3):

$$Diver = \sum_{k=1}^{650} \mathrm{PS}_{ikt} \ln \frac{1}{\mathrm{PS}_{ikt}} \tag{1}$$

$$PS_{ikt} = \frac{P_{ikt}}{P_{it}} \tag{2}$$

where PS_{ikt} represents the number of new green invention patent applications belonging to subclass k for firm i in year t as a proportion of the total number of new green invention patent applications, and P_{ikt} is the number of new green invention patent applications belonging to subclass k for firm i in year t. P_{it} is the total number of new green invention patent applications for the firm i in year t, that is:

$$P_{it} = \sum_{k=1}^{650} P_{ikt} \tag{3}$$

where technological diversification (*Diver*) is measured by the entropy value of patent quality. A larger entropy value reflects that a firm not only has a greater number of categories of invention patents, indicating a broader range of knowledge and technological breadth, but also has a more evenly distributed range of technological categories. Innovation breakthrough (*Break*) is calculated based on the subclass data of the first four

[2] https://www.tianyancha.com.

characters of the IPC classification of invention patents. We take the natural logarithm of the number of new IPC categories (subclasses) for the company in the current year plus 1, with a larger value indicating a higher quality of supplier green innovation.

4.2.2. Customer ESG performance

In both the main regression and the further analysis, the independent variable is customer ESG performance (*Cus_esg*), calculated with unequal weights. However, the economic importance of the top five customers to the supplier varies, and customers responsible for different proportions of supplier sales exert varying degrees of influence on suppliers' green innovation quality. Therefore, we recalculate customer ESG performance based on the sales revenue of each customer as a proportion of the total sales revenue of each supplier's top five customers. This recalculated variable is denoted as *Cus_avesg* and is used for supplementary testing in the main regression and robustness tests. Following the approach of Li et al. (2023), we utilize data from Huazheng ESG ratings to measure customer ESG performance. The Huazheng Index refers to mainstream international methods and practices, incorporates the essence of international ESG practices and combines characteristics of China's conditions and capital market to rate companies from C to AAA in three dimensions: environment, social responsibility and corporate governance. Compared with other rating systems, the wide coverage, high update frequency and large sample size of the Huazheng Index are conducive to the large-sample empirical research in this paper. The paper assigns values from 1 to 9 to the rating results from C to AAA in ascending order, with higher values indicating better ESG performance by the firm.

4.2.3. Control variables

Following Yang et al. (2022), we select control variables, including supplier company size (*Sup_size*), supplier company debt-to-equity ratio (*Sup_lev*), supplier company age (*Sup_age*), supplier company profitability (*Sup_roa*), supplier growth capability (*Sup_growth*), supplier R&D expenditure (*Sup_rd*), supplier net working capital (*Sup_nwc*), supplier ownership nature (*Sup_soe*), supplier ownership concentration (*Sup_top1*), supplier management shareholding ratio (*Sup_msh*), supplier board size (*Sup_board*), supplier city GDP (*Sup_gdp*), customer company size (*Cus_size*), customer company age (*Cus_age*), customer company profitability (*Cus_roa*), customer growth capability (*Cus_growth*) and customer sales revenue volatility (*Cus_vol*). In addition, we control for time, industry and individual fixed effects. Detailed variable definitions are provided in Table 1.

4.3. Model specification

Drawing on the research by Dai et al. (2021), we examine the effect of customers' ESG performance on suppliers' green innovation quality using Models (1) and (2) as follows:

$$Diver^{s}_{i,t} = \alpha_0 + \alpha_1 Cus\_esg^{c}_{i,t-1} + \alpha_2 \sum Controls_{i,t-1} + Year_i + Pair_i + Ind_i + \varepsilon_{i,t} \tag{1}$$

$$Break^{s}_{i,t} = \beta_0 + \beta_1 Cus\_esg^{c}_{i,t-1} + \beta_2 \sum Controls_{i,t-1} + Year_i + Pair_i + Ind_i + \varepsilon_{i,t} \tag{2}$$

where $Diver^{s}_{i,t}$ and $Break^{s}_{i,t}$ are the dependent variables, representing the green innovation quality of supplier firms in supply chain *i* in year *t*; $Cus\_esg^{c}_{i,t-1}$ represents the ESG performance of customer firms in supply chain *i* in period *t-1*; $Controls_{i,t-1}$ denotes a set of control variables, including control variables for customers and suppliers; and $\varepsilon_{i,t}$ is the error term. Because the impact of customer ESG performance on supplier green innovation quality may require time, we apply a lag of one period to the core independent variables. In addition, we control for individual (*Pair*), industry (*Ind*) and year (*Year*) fixed effects.

5. Empirical results

5.1. Summary statistics

Table 2 presents the summary statistics of our main variables in this paper. The mean of supplier green innovation diversification (*Diver*) is 0.486, with a minimum of 0 and a maximum of 4.116. The mean of sup-

Table 1
Variable definitions.

Variable	Description	Definition
Diver	Supplier's technological diversification in green innovation	See Formula 1 for details.
Break	Supplier's breakthroughs in green innovation	Natural logarithm of the number of new IPC subclassifications for green invention patent applications in the current year plus 1.
Cus_esg	Customer's ESG performance	Customer's ESG score derived from Huazheng ESG ratings, ranging from 1 to 9.
Sup_size	Supplier's firm size	Natural logarithm of total assets at the end of the period.
Sup_lev	Supplier asset–liability ratio	Total liabilities divided by total assets.
Sup_age	Supplier's age	Natural logarithm of the difference between the observation year and the supplier company's listing year.
Sup_roa	Supplier's profitability	The ratio of net profit to average total assets.
Sup_growth	Supplier's growth capability	Main revenue growth rate.
Sup_rd	Supplier's R&D expenditure	Research and development expenditure divided by operating income.
Sup_nwc	Supplier's net working capital	(Current assets − current liabilities − cash) divided by total assets.
Sup_soe	Supplier's ownership	Equals 1 for state-owned enterprise; otherwise equals 0.
Sup_top1	Supplier's ownership concentration	Percentage of shares held by the largest shareholder.
Sup_msh	Supplier's management ownership	Percentage of shares held by the management team.
Sup_board	Supplier's board size	Natural logarithm of the number of board members.
Sup_gdp	GDP of supplier's city	Natural logarithm of the GDP of the city where the supplier is located.
Cus_size	Customer's firm size	Natural logarithm of total assets at the end of the period.
Cus_age	Customer's age	Natural logarithm of the difference between the observation year and the customer company's listing year.
Cus_roa	Customer's growth capability	The ratio of net profit to average total assets.
Cus_growth	Customer's profitability	Main revenue growth rate.
Cus_vol	Customer's sales revenue volatility	Sales revenue volatility of the customer calculated weighted by their proportion of sales.
Year	Time fixed effects	Time dummy variable.
Ind	Industry fixed effects	Industry dummy variables obtained from the "Listed Company Industry Classification Guidelines."
Pair	Individual fixed effects	Customers and suppliers involved in establishing cooperative relationships in the supply chain are considered as entities.

plier green innovation breakthrough (*Break*) is 0.629, with a minimum of 0 and a maximum of 5.820, indicating that overall, supplier green innovation quality is relatively low, with significant variation across firms. The mean of customer ESG performance (*Cus_esg*) is 4.378, with a standard deviation of 1.160, suggesting that customer firms have a moderate level of general ESG performance and that there are noticeable differences in ESG performance across firms. At the control variable level, approximately 42.1 % of firms are state-owned supplier firms, the mean of firm growth (*Sup_growth*) is 15.1 %, the mean of return on assets (*Sup_roa*) is 3.9 % and the mean of the leverage ratio (*Sup_lev*) is 44 %; these values are not significantly different from those in the literature.

5.2. Main regression results

Table 3 presents the test results for the positive correlation between customers' ESG performance and suppliers' green innovation quality. The results in columns (1) and (2) show that when using customer ESG performance (*Cus_esg*) calculated with unequal weights, with *Diver* as the dependent variable, the parameter estimate for α_1 is 0.182, which is significant at the 1 % level. With *Break* as the dependent variable, the parameter estimate for β_1 is 0.219, which again is significant at the 1 % level. The estimates of α_1 and β_1 hold economic significance, indicating that for every one standard deviation increase in customer ESG performance (*Cus_esg*), supplier firms' green innovation diversification increases by 21.11 % (=0.182 × 1.160), explaining 43.44 % (=21.11 % / 48.6 %) of the variance over the sample mean of 48.6 %, whereas green innovation breakthrough increases by 25.4 % (=0.219 × 1.160), explaining 40.38 % (=25.4 % / 62.9 %) of the variance over the sample mean of 62.9 %. These results suggest that the good ESG performance of major customers can signif-

Table 2
Summary statistics of main variables.

Variables	Sample	Mean	SD	Minimum	Median	Maximum
Diver	2,129	0.486	0.939	0.000	0.000	4.116
Break	2,129	0.629	1.127	0.000	0.000	5.820
Cus_esg	2,129	4.378	1.160	1.000	4.000	6.000
Sup_size	2,129	22.486	1.678	19.914	22.184	28.504
Sup_age	2,129	2.124	0.814	0.000	2.303	3.258
Sup_lev	2,129	0.440	0.202	0.051	0.444	0.896
Sup_roa	2,129	0.039	0.057	–0.202	0.038	0.197
Sup_growth	2,129	0.151	0.279	–0.399	0.119	1.367
Sup_rd	2,129	0.045	0.057	0.000	0.034	0.365
Sup_nwc	2,129	0.212	0.265	–0.415	0.210	0.764
Sup_soe	2,129	0.421	0.494	0.000	0.000	1.000
Sup_top1	2,129	0.361	0.158	0.090	0.324	0.802
Sup_msh	2,129	0.124	0.194	0.000	0.002	0.660
Sup_board	2,129	2.372	0.270	0.000	2.398	3.219
Sup_gdp	2,129	10.409	0.720	6.408	10.408	11.731
Cus_size	2,129	23.865	2.571	18.847	23.240	31.191
Cus_age	2,129	2.359	0.709	0.000	2.565	3.332
Cus_roa	2,129	0.035	0.043	–0.118	0.031	0.161
Cus_growth	2,129	0.126	0.224	–0.405	0.110	0.987
Cus_vol	2,129	5.844	5.654	0.120	4.088	30.310

icantly boost the quality of green innovation among suppliers. Columns (3) and (4) use customer ESG performance (*Cus_avesg*) calculated with equal weights as an alternative independent variable, repeating the test for Hypothesis 1. The results show that the parameter estimates for *Diver* and *Break* are 0.210 and 0.263, respectively, and both are significant at the 5 % statistical level. These results support Hypothesis 1, indicating that good ESG performance by customers generates spillover effects along the supply chain, prompting suppliers to improve their green innovation quality in response to the green development concepts conveyed by customers.

5.3. Addressing endogeneity concerns

This paper employs the instrumental variable method to mitigate potential issues of reverse causality. The Heckman two-stage method is utilized to control for endogeneity arising from sample self-selection. In addition, we conduct a placebo test to exclude the possibility of random correlation in the research findings.

5.3.1. Instrumental variable regression

Drawing on Wu et al. (2023), we select the average ESG performance of other firms in the same industry and province in the same year as the customer as the instrumental variables, denoted by *IV1* and *IV2*, respectively. The two-stage least squares method (2SLS) is employed for the estimation. Because the external environmental characteristics are similar within the same industry or area, customer ESG performance can be influenced by other companies in the same industry or region. Thus, there is a correlation between the industry-wide or regional average and customers' ESG performance. Furthermore, the average ESG performance of other firms at the industry or regional level is a macro-regional characteristic and is unlikely to affect the green innovation quality of suppliers collaborating with customers at the micro level, thus meeting the exogeneity requirement. To examine the validity of the instrumental variables, tests for under-identification, weak instrument variables and overidentification are conducted. The results indicate that the Anderson LM test significantly rejects the null hypothesis, suggesting that under-identification is not a problem. The Cragg–Donald Wald F statistic of 74.84 exceeds the Stock–Yogo weak instrument test critical value of 19.93 at the 10 % level, significantly rejecting the null hypothesis of a weak instrument and thereby indicating that weak instruments are not a problem in the model. The *p* value of the Sargan test is greater than 0.1, indicating the suitability of the two instrumental variables selected. The regression results presented in Table 4, column (1) indicate that

Table 3
Customers' ESG performance and suppliers' green innovation quality: Main regression results.

Variable	Unequal Weight Calculation		Equal Weight Calculation	
	(1)	(2)	(3)	(4)
	Diver	*Break*	*Diver*	*Break*
Cus_esg	0.182***	0.219***		
	(3.73)	(3.63)		
Cus_avesg			0.210**	0.263**
			(2.18)	(2.17)
Sup_size	0.226*	0.231*	0.214*	0.217
	(1.92)	(1.66)	(1.81)	(1.54)
Sup_age	0.087	0.119	0.095	0.130
	(0.51)	(0.59)	(0.54)	(0.63)
Sup_lev	–0.299	–0.219	–0.284	–0.199
	(–0.65)	(–0.39)	(–0.62)	(–0.36)
Sup_roa	1.009*	1.718**	1.112*	1.842***
	(1.79)	(2.58)	(1.92)	(2.70)
Sup_growth	–0.127	–0.176*	–0.120	–0.167*
	(–1.58)	(–1.78)	(–1.51)	(–1.71)
Sup_rd	–0.762	0.252	–0.765	0.248
	(–0.67)	(0.16)	(–0.64)	(0.15)
Sup_nwc	0.051	0.078	0.025	0.046
	(0.14)	(0.17)	(0.07)	(0.10)
Sup_soe	0.084	0.063	0.089	0.073
	(0.16)	(0.10)	(0.16)	(0.11)
Sup_top1	–0.093	–0.153	–0.002	–0.046
	(–0.33)	(–0.46)	(–0.01)	(–0.14)
Sup_msh	–0.093	–0.128	–0.116	–0.156
	(–0.70)	(–0.80)	(–0.82)	(–0.93)
Sup_board	0.200	0.228	0.200	0.229
	(1.63)	(1.35)	(1.60)	(1.36)
Sup_gdp	–0.278	–0.302	–0.314	–0.345
	(–0.77)	(–0.75)	(–0.84)	(–0.82)
Cus_size	0.264**	0.331**	0.341**	0.422**
	(2.03)	(2.09)	(2.49)	(2.54)
Cus_age	–0.062	–0.132	–0.113	–0.193
	(–0.35)	(–0.64)	(–0.61)	(–0.91)
Cus_roa	0.350	0.271	0.655	0.636
	(0.47)	(0.31)	(0.89)	(0.72)
Cus_growth	–0.083	–0.063	–0.081	–0.061
	(–0.63)	(–0.42)	(–0.59)	(–0.39)
Cus_vol	0.004	0.005	0.005	0.006
	(0.82)	(0.81)	(0.97)	(0.96)
Year/Ind/Pair FE	Yes	Yes	Yes	Yes
	–8.431	–9.897	–8.781	–10.319
Constant	(–1.55)	(–1.58)	(–1.53)	(–1.58)
R^2	0.065	0.068	0.038	0.042
N	2,129	2,129	2,129	2,129

Note: Numbers in parentheses are *t* statistics based on robust standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. This note also applies to all of the following tables.

the coefficients of *IV1* and *IV2* are 0.551 and 0.464, respectively, and both are significant at the 1 % level. Columns (2) and (3) show that the coefficients of *Cus_esg* are 0.215 and 0.245, which are significant at the 1 % and 5 % levels, respectively, consistent with the findings of the literature.

Table 4
Endogeneity test: Instrumental variable regression and Heckman two-stage method.

Variable	(1)	(2)	(3)	(4)	(5)
	Cus_esg	*Diver*	*Break*	*Diver*	*Break*
IV1	0.551***				
	(7.33)				
IV2	0.464***				
	(8.81)				
Cus_esg		0.215***	0.245**	0.138***	0.150***
		(2.60)	(2.47)	(2.96)	(2.72)
Sup_size	–0.079	0.229***	0.234**	0.253*	0.235
	(–0.88)	(2.77)	(2.36)	(1.91)	(1.54)
Sup_age	0.157	0.087	0.118	–0.005	–0.057
	(0.93)	(0.59)	(0.67)	(–0.02)	(–0.21)
Sup_lev	0.165	–0.302	–0.224	–1.221*	–1.399*
	(0.41)	(–0.75)	(–0.46)	(–1.82)	(–1.71)
Sup_roa	0.775	0.988	1.703**	0.708	1.550**
	(1.25)	(1.61)	(2.32)	(1.12)	(2.14)
Sup_growth	–0.038	–0.127	–0.176	–0.079	–0.109
	(–0.41)	(–1.25)	(–1.44)	(–0.86)	(–0.99)
Sup_rd	–0.036	–0.765	0.249	–1.013	–0.719
	(–0.03)	(–0.46)	(0.13)	(–0.64)	(–0.40)
Sup_nwc	0.130	0.052	0.077	0.123	–0.049
	(0.40)	(0.16)	(0.20)	(0.23)	(–0.07)
Sup_soe	–0.030	0.203	0.230	0.169	–0.010
	(–0.38)	(0.88)	(0.83)	(0.29)	(–0.01)
Sup_top1	–0.533	0.092	0.066	–0.291	–0.346
	(–1.05)	(0.19)	(0.12)	(–0.98)	(–1.00)
Sup_msh	0.355	–0.121	–0.178	0.062	0.080
	(1.14)	(–0.40)	(–0.49)	(0.50)	(0.57)
Sup_board	–0.116	–0.079	–0.111	–0.448	–0.499
	(–0.93)	(–0.72)	(–0.84)	(–1.50)	(–1.39)
Sup_gdp	–0.183	–0.260	–0.280	–0.063	–0.036
	(–0.55)	(–0.84)	(–0.76)	(–0.13)	(–0.07)
Cus_size	0.445***	0.248**	0.317**	0.094	0.146
	(3.39)	(2.22)	(2.37)	(0.66)	(0.84)
Cus_age	–0.122	–0.052	–0.123	–0.146	–0.203
	(–0.51)	(–0.30)	(–0.59)	(–0.75)	(–0.94)
Cus_roa	1.815*	0.289	0.226	1.182	1.358
	(1.80)	(0.33)	(0.21)	(1.19)	(1.20)
Cus_growth	0.066	–0.086	–0.065	–0.257	–0.289
	(0.48)	(–0.72)	(–0.45)	(–1.48)	(–1.56)
Cus_vol	0.006	0.004	0.005	0.011	0.010
	(1.21)	(0.78)	(0.78)	(1.63)	(1.43)
Imr				–1.506***	–1.788***
				(–2.80)	(–2.96)
Year/Ind/Pair FE	Yes	Yes	Yes	Yes	Yes
Constant	–6.821	–8.831**	–10.329*	–4.716	–5.173
	(–1.34)	(–1.98)	(–1.93)	(–0.69)	(–0.66)
R^2	0.192	0.076	0.080	0.060	0.055
N	2,129	2,129	2,129	2,129	2,129

5.3.2. Heckman two-stage method

The China Securities Regulatory Commission encourages listed companies to disclose information such as the names and sales revenues of their top five customers, but the disclosure of primary customer information by listed companies is voluntary. This might lead to a sample self-selection bias issue in this paper. Therefore, following Di et al. (2020), we employ the Heckman two-stage regression model. In the first stage, using all listed firms from 2009 to 2022 as the research subjects, "whether the supplier discloses the customer's name" is taken as the dependent variable (*Disdum*), where a value of 1 indicates that the supplier discloses specific customer names, and 0 indicates that they do not. Considering that the disclosure of customer information by suppliers may be influenced by industry characteristics, company features and the personal characteristics of executives, a series of control variables are included as explanatory variables in the first stage. The probit model, Model (3), is used to estimate the probability of suppliers disclosing customer names and to obtain the inverse Mills ratio (*imr*). In the second stage, the inverse Mills ratio is included as a control variable in Models (1) and (2) of the regression. The regression results in columns (4) and (5) of Table 4 reveal that customer ESG performance (*Cus_esg*) is positive and significant, which is consistent with the baseline regression results, indicating the robustness of the study's conclusions. Next, we have:

$$Disdum_{i,t} = \varphi_0 + \varphi_1 Size_{i,t} + \varphi_2 Lev_{i,t} + \varphi_3 Roa_{i,t} + \varphi_4 Hhi_{i,t} + \varphi_5 Top1_{i,t} + \varphi_6 Soe_{i,t} + \varphi_7 Growth_{i,t} + \varepsilon_{i,t} \quad (3)$$

where supplier firm size (*Sup_size*) is measured by the natural logarithm of the total assets at the end of the period; the supplier asset–liability ratio (*Sup_lev*) is measured by the total liabilities divided by the total assets; the supplier return on assets (*Sup_roa*) is measured by the net profit of the firms in the current year divided by the average total assets; the supplier industry competition level (*Sup_hhi*) is measured by the Herfindahl–Hirschman Index; the percentage of shares held by the largest shareholder is denoted by *Sup_top1*; the nature of the firm is denoted by *Sup_soe*, where a value of 1 indicates state-owned firms and 0 indicates non-state-owned firms; and firm growth (*Sup_growth*) is measured by the growth rate of their main revenue.

5.3.3. Placebo test

To verify that the effect of customer ESG performance on supplier green innovation quality is not a random result, we follow Wang et al. (2023) and employ a placebo test to address potential measurement errors. The specific steps are as follows: (1) A high or low level of customer ESG performance is randomly assigned to each firm; (2) The randomly assigned customer ESG performance is regressed against supplier green innovation technological diversification (*Diver*) and green innovation breakthrough (*Break*); (3) Steps (1) and (2) are repeated 1,000 times. After randomization, the impact of customer ESG performance on supplier green innovation quality is no longer significant. Fig. 1 shows the distribution of regression coefficients between customer ESG performance (*Cus_esg*) and supplier green innovation technological diversification (*Diver*) after 1,000 randomizations, which is concentrated near 0 and significantly lower than the estimated value of 0.182. Fig. 2 displays the distribution of regression coefficients between customer ESG performance (*Cus_esg*) and supplier green innovation breakthrough (*Break*) after 1,000 randomizations, which is also concentrated near 0 and significantly lower than the estimated value of 0.219. This further confirms that customer ESG performance enhances supplier green innovation quality, indicating that the conclusions of this study are not randomly obtained and excluding the possibility of random correlation.

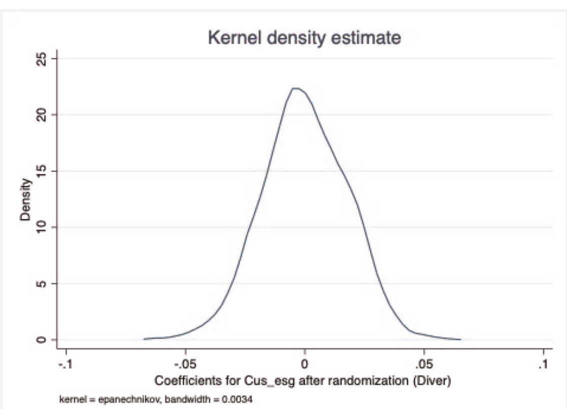

Fig. 1. Distribution of coefficients for *Cus_esg* after randomization (*Diver*).

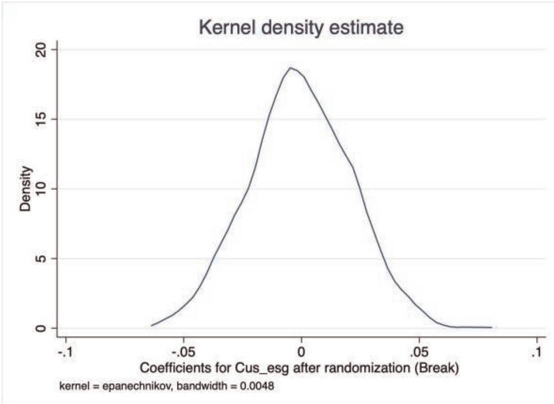

Fig. 2. Distribution of coefficients for *Cus_esg* after randomization (*Break*).

5.4. Robustness tests

5.4.1. Replacement of independent variable measurement methods

Following Li et al. (2023), we reconstruct the independent variable based on the Huazheng ESG ratings. When a company receives an ESG rating of A–AAA, B–BBB or C–CCC, it is assigned a value of 1, 2 or 3, respectively, resulting in the calculation of customer ESG performance with unequal weights (*Cus_esg1*) and customer ESG performance with equal weights (*Cus_avesg1*). Then, the regression Models (1) and (2) are re-estimated. Columns (1) and (2) in Table 5 present the regression results using customer ESG performance with unequal weights, with regression coefficients of 0.307 and 0.371 for *Cus_esg1*, which are both significant at the 1 % level. Columns (3) and (4) in Table 5 show the regression results using customer ESG performance with equal weights, with regression coefficients of 0.367 and 0.461 for *Cus_avesg1*, which are both significant at the 5 % level. These results indicate that customer ESG performance significantly promotes the improvement of supplier green innovation quality, which is consistent with the main regression test results and thus verifies the robustness of the conclusions of this paper.

5.4.2. Replacement of dependent variable measurement methods

First, this study replaces the IPC classification numbers of green invention patent applications used in the main regression with the IPC classification numbers of granted green invention patents to recalculate technology diversification (*Diverg*) and innovation breakthrough (*Breakg*) as the dependent variables. The regression results in columns (1) and (2) of Table 6 show that the regression coefficients for *Cus_esg* are 0.121 and 0.140, which are both significant at the 5 % level. Second, we replace the dependent variables in Models (1) and (2) with environmental investment (*Envinv*) and pollution fees (*Pwfee*) and re-conduct the regression. The regression results in columns (3) and (4) of Table 6 reveal that the regression coefficients for *Cus_esg* are 0.349 and –0.168, both of which are significant at the 10 % level. These results are consistent with the main test, further confirming the robustness of the study's conclusions.

5.4.3. Considering the lagged effect of green patent applications

Due to the lag in green innovation patent applications, this study regresses two future periods of green innovation technological diversification (*FDiver*) and green innovation breakthrough (*FBreak*) as the dependent variables in Models (1) and (2). The regression results in columns (5) and (6) of Table 6 show that the regression coefficients for *Cus_esg* are 0.114 and 0.128, which are both significant at the 5 % level. These results are consistent with the main regression test results, further confirming the robustness of the study's conclusions.

Table 5
Robustness tests: Replacement of independent variable measurement methods.

Variable	Unequal Weight Calculation		Equal Weight Calculation	
	(1)	(2)	(3)	(4)
	Diverg	*Breakg*	*Diverg*	*Breakg*
Cus_esg1	0.307***	0.371***		
	(3.70)	(3.64)		
Cus_avesg1			0.367**	0.461**
			(2.14)	(2.14)
Sup_size	0.231*	0.237*	0.212*	0.214
	(1.95)	(1.68)	(1.79)	(1.53)
Sup_age	0.057	0.083	0.083	0.115
	(0.34)	(0.41)	(0.48)	(0.56)
Sup_lev	–0.264	–0.176	–0.293	–0.210
	(–0.58)	(–0.32)	(–0.65)	(–0.38)
Sup_roa	0.944*	1.639**	1.092*	1.816***
	(1.68)	(2.47)	(1.88)	(2.66)
Sup_growth	–0.113	–0.159	–0.116	–0.161*
	(–1.42)	(–1.62)	(–1.46)	(–1.65)
Sup_rd	–0.649	0.389	–0.772	0.240
	(–0.56)	(0.24)	(–0.64)	(0.15)
Sup_nwc	0.026	0.048	0.018	0.039
	(0.07)	(0.10)	(0.05)	(0.08)
Sup_soe	–0.023	–0.066	0.067	0.046
	(–0.04)	(–0.10)	(0.12)	(0.07)
Sup_top1	–0.054	–0.107	–0.011	–0.058
	(–0.20)	(–0.33)	(–0.04)	(–0.18)
Sup_msh	–0.057	–0.083	–0.096	–0.132
	(–0.44)	(–0.54)	(–0.71)	(–0.81)
Sup_board	0.186	0.211	0.199	0.228
	(1.38)	(1.15)	(1.59)	(1.35)
Sup_gdp	–0.261	–0.278	–0.296	–0.320
	(–0.68)	(–0.65)	(–0.77)	(–0.75)
Cus_size	0.304**	0.378**	0.344**	0.426**
	(2.25)	(2.30)	(2.49)	(2.54)
Cus_age	–0.066	–0.136	–0.110	–0.189
	(–0.37)	(–0.67)	(–0.59)	(–0.90)
Cus_roa	0.405	0.337	0.631	0.607
	(0.54)	(0.38)	(0.86)	(0.69)
Cus_growth	–0.071	–0.048	–0.075	–0.054
	(–0.55)	(–0.33)	(–0.56)	(–0.35)
Cus_vol	0.005	0.006	0.005	0.006
	(0.95)	(0.95)	(0.94)	(0.94)
Year/Ind/Pair FE	Yes	Yes	Yes	Yes
Constant	–9.599*	–11.342*	–9.012	–10.638
	(–1.68)	(–1.73)	(–1.55)	(–1.61)
R^2	0.060	0.063	0.037	0.041
N	2,129	2,129	2,129	2,129

5.4.4. Subsample regression

To encourage firms to achieve low-carbon transformation and drive green and low-carbon development, the Chinese government implemented the Low-Carbon City Pilot Policy in 2010 and subsequently gradually expanded its scope. To an extent, the Low-Carbon City Pilot Policy has induced overall green innovation at the corporate level. Therefore, the driving influence of customer ESG performance on supplier green innovation quality may be attributed to the implementation of the Low-Carbon City Pilot Policy. To eliminate the impact of this policy on both customers and suppliers in the sample, we remove firms located in low-carbon

Table 6
Robustness tests: Replacement of dependent variables and consideration of green innovation lag.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Diverg	*Breakg*	*Envinv*	*Pwfee*	*FDiver*	*FBreak*
Cus_esg	0.121**	0.140**	0.349*	–0.168*	0.114**	0.128**
	(2.34)	(2.42)	(1.70)	(–1.71)	(2.57)	(2.43)
Sup_size	0.381***	0.453***	0.124	–0.957*	0.030	0.030
	(3.22)	(3.31)	(0.21)	(–1.92)	(0.37)	(0.31)
Sup_age	–0.411**	–0.480**	–0.665	0.631	0.166	0.206
	(–2.23)	(–2.31)	(–0.60)	(1.15)	(1.16)	(1.21)
Sup_lev	–0.931**	–1.052**	–0.863	–1.502	0.070	0.176
	(–2.28)	(–2.27)	(–0.22)	(–0.69)	(0.19)	(0.41)
Sup_roa	–0.288	–0.392	–1.354	1.215	0.852*	1.115*
	(–0.48)	(–0.58)	(–0.29)	(0.52)	(1.67)	(1.86)
Sup_growth	–0.135*	–0.163**	–0.284	0.305	–0.064	–0.084
	(–1.94)	(–1.98)	(–0.34)	(0.78)	(–0.81)	(–0.94)
Sup_rd	–0.189	–0.324	1.248	–0.055	–2.337*	–2.674*
	(–0.17)	(–0.25)	(0.88)	(–0.01)	(–1.86)	(–1.81)
Sup_nwc	–0.466	–0.526	0.947	–1.895	–0.311	–0.308
	(–1.32)	(–1.34)	(0.36)	(–1.30)	(–1.04)	(–0.87)
Sup_soe	–0.298	–0.591	0.390	0.229	–0.193	–0.127
	(–0.57)	(–0.99)	(0.76)	(0.91)	(–0.45)	(–0.25)
Sup_top1	–0.100	–0.120	–0.431*	–0.876	0.061	0.005
	(–0.47)	(–0.49)	(–1.89)	(–1.21)	(0.29)	(0.02)
Sup_msh	0.054	0.063	1.362	0.157	0.097	0.081
	(0.52)	(0.52)	(1.37)	(0.44)	(1.05)	(0.74)
Sup_board	0.203**	0.254**	1.537	–0.316	–0.022	–0.044
	(2.16)	(2.05)	(0.52)	(–0.58)	(–0.16)	(–0.27)
Sup_gdp	0.465	0.579	1.951	4.649**	–0.341	–0.400
	(1.47)	(1.61)	(0.83)	(2.01)	(–1.12)	(–1.13)
Cus_size	0.280**	0.327**	–0.435	0.503	0.286***	0.347***
	(2.25)	(2.29)	(–0.62)	(0.54)	(2.87)	(2.92)
Cus_age	0.144	0.180	1.414	1.258*	–0.193	–0.236
	(0.74)	(0.80)	(1.46)	(1.76)	(–1.41)	(–1.49)
Cus_roa	–0.141	–0.124	–0.460	0.603	0.357	0.173
	(–0.18)	(–0.14)	(–0.60)	(1.35)	(0.57)	(0.24)
Cus_growth	–0.099	–0.147	–0.196	0.255	–0.232*	–0.257*
	(–1.11)	(–1.38)	(–0.25)	(0.64)	(–1.90)	(–1.89)
Cus_vol	–0.003	–0.003	–0.021	–0.003	0.005	0.007
	(–0.45)	(–0.43)	(–0.65)	(–0.12)	(0.95)	(1.22)
Year/Ind/Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–18.879***	–22.495***	–16.266	–33.865	–3.941	–4.663
	(–3.42)	(–3.51)	(–0.50)	(–1.23)	(–1.00)	(–1.05)
R^2	0.066	0.070	0.032	0.069	0.116	0.120
N	2,129	2,129	2,129	2,129	2,129	2,129

cities and re-regress Models (1) and (2). As shown in columns (1) and (2) of Table 7, after excluding the interference of the Low-Carbon City Pilot Policy, the regression coefficients for customer ESG performance (*Cus_esg*) are 0.249 and 0.298, which are both significant at the 1 % level. In addition, firms in heavily polluting industries are more likely to be affected by environmental regulations (Qi et al., 2018), leading them to enhance their green innovation quality to achieve green transformation. To exclude the influence of heavily polluting firms on the regression results, customers and suppliers in these industries are removed from the sample, and Models (1) and (2) are regressed again. As shown in columns (3) and (4) of Table 7, the regression coefficients of customer ESG performance (*Cus_esg*) are 0.154 and 0.195, which are both significant at the 1 % level. These results confirm that the improvement in supplier green innovation quality is indeed driven by customer ESG performance, further validating the reliability of the study's conclusions.

Table 7
Robustness tests: Subsample regression.

Variable	(1)	(2)	(3)	(4)
	Diver	*Break*	*Diver*	*Break*
Cus_esg	0.249***	0.298***	0.154***	0.195***
	(3.35)	(3.16)	(2.87)	(2.92)
Sup_size	0.262*	0.238	0.148	0.148
	(1.78)	(1.35)	(1.18)	(0.98)
Sup_age	0.316*	0.421**	–0.013	0.014
	(1.84)	(2.02)	(–0.07)	(0.07)
Sup_lev	–0.508	–0.347	–0.203	–0.155
	(–0.97)	(–0.56)	(–0.38)	(–0.24)
Sup_roa	–0.060	0.440	1.355**	2.083***
	(–0.07)	(0.44)	(2.14)	(2.73)
Sup_growth	–0.015	–0.068	–0.203**	–0.264**
	(–0.16)	(–0.60)	(–2.23)	(–2.35)
Sup_rd	0.327	0.783	–1.008	–0.043
	(0.13)	(0.27)	(–0.90)	(–0.03)
Sup_nwc	0.290	0.425	–0.019	–0.024
	(0.73)	(0.91)	(–0.04)	(–0.04)
Sup_soe	0.599	0.765	–0.728	–0.995
	(1.16)	(1.19)	(–1.16)	(–1.30)
Sup_top1	–0.116	–0.115	–0.200	–0.250
	(–0.35)	(–0.28)	(–0.68)	(–0.71)
Sup_msh	–0.349**	–0.461**	0.035	0.025
	(–2.38)	(–2.53)	(0.24)	(0.14)
Sup_board	0.037	0.028	0.117	0.166
	(0.22)	(0.13)	(0.83)	(0.88)
Sup_gdp	–0.618	–0.631	–0.290	–0.208
	(–1.46)	(–1.33)	(–0.64)	(–0.41)
Cus_size	0.293*	0.382*	0.289*	0.357*
	(1.78)	(1.85)	(1.87)	(1.89)
Cus_age	–0.239	–0.368	–0.151	–0.212
	(–1.22)	(–1.63)	(–0.83)	(–1.02)
Cus_roa	0.604	0.630	–0.353	–0.672
	(0.65)	(0.56)	(–0.43)	(–0.67)
Cus_growth	–0.011	–0.017	–0.183	–0.157
	(–0.09)	(–0.11)	(–1.22)	(–0.91)
Cus_vol	–0.000	0.000	0.005	0.006
	(–0.06)	(0.02)	(0.84)	(0.81)
Year/Ind/Pair FE	Yes	Yes	Yes	Yes
Constant	–6.278	–7.679	–6.823	–9.192
	(–0.94)	(–0.98)	(–1.05)	(–1.24)
R^2	0.111	0.113	0.059	0.064
N	1,381	1,381	1,759	1,759

6. Further analysis

6.1. Mechanism testing of the impact of customer ESG performance on supplier green innovation quality

Building on theoretical analyses in the literature, we posit that the mechanism through which customers' good ESG performance generates spillover effects on supplier green innovation quality along the supply chain is reflected in green learning and corporate competition. Therefore, this section focuses on examining the spillover effects of customer ESG performance on suppliers from the perspectives of green learning and corporate competition. Drawing on Dai et al. (2021), we construct Model (4) by incorporating interaction terms based on Models (1) and (2) to investigate the impact mechanism of customer ESG performance on supplier green innovation quality:

$$Diver^{s}_{i,t} = \theta_0 + \theta_1 Cus\_esg^{c}_{i,t-1} + \theta_2 Z_{i,t-1} + \theta_3 Cus\_esg^{c}_{i,t-1} \times Z_{i,t-1} + \sum Controls_{i,t-1} + Year_i + Pair_i + Ind_i + \varepsilon_{i,t} \quad (4)$$

where the mechanism variable $Z_{i,t-1}$ includes green learning and corporate competition. Other variables are consistent with the settings in Models (1) and (2), which control for individual, industry and year fixed effects. If this mechanism is accurate, the coefficients in Model (4) should be statistically significant.

6.1.1. Green learning mechanism

Regarding the suppliers' green learning mechanism, customers' good ESG performance not only helps suppliers acquire resources or technologies related to green innovation but also enhances their green awareness, thereby promoting the improvement of suppliers' green innovation quality. Firms' citation of other firms' patents can be considered indicative of obtaining and absorbing knowledge and information resources from other firms. Hence, patent citations among firms are frequently used to represent the acquisition of knowledge and resources. Building on Yang et al. (2022), this study uses the citation of customer green patents by suppliers to measure the acquisition of green resources by suppliers (*Resource*). This variable takes a value of 1 if citations exist and 0 otherwise. As shown in columns (1) and (2) of Table 8, the coefficients of $Cus\_esg \times Resource$ are 0.096 and 0.123, respectively, which are both significant at the 10 % level. This indicates that suppliers obtain green innovation resources from customers committed to green development and invest them in their green innovation activities, thereby improving the quality of their green innovation.

To measure the level of green awareness of suppliers (*Aware*), we refer to the measurement methods developed by Duriau et al. (2007) and Wang et al. (2023) for management cognition. We conduct a textual analysis of the annual reports of supplier firms, using frequency statistics of relevant keywords (including energy conservation and emission reduction, environmental strategy, environmental philosophy, environmental training, environmental technology development, environmental audit, environmental protection supervision and environmental governance) to construct an indicator to measure the green environmental awareness of senior executives of listed firms. As shown in columns (3) and (4) of Table 8, the coefficients of $Cus\_esg \times Aware$ are 0.015 and 0.016, respectively, which are significant at the 5 % and 10 % levels, respectively. This indicates that customers with good ESG performance can prompt suppliers to respond to their green demands, enhancing the suppliers' green awareness and promoting the acquisition and integration of green resources, which in turn improves the suppliers' green innovation quality and leads to an increase in diversification and breakthroughs in green innovation technologies. In conclusion, along the supply chain, customers with good ESG performance induce suppliers to enhance their green awareness, acquire green innovation resources and improve green innovation quality, thus confirming the existence of the suppliers' green learning mechanism.

6.1.2. Corporate competition mechanism

From the perspective of the competition mechanism, high-quality customers are often the preferred partners for firms within the supply chain. Therefore, customers with good ESG performance intensify the level of competition among supplier companies, placing significant pressure on suppliers and compelling their management to adopt green innovation strategies to meet the green development demands of customers. Under pressure from customers' green development concepts, management will correct myopic behaviors and actively implement green innovation strategies to meet the demands for green products and processes. Moreover, to stand out in supplier competition, firms will actively invest in relationship-specific assets tailored to respond to their customers' green development demands, enhancing their green innovation quality to gain a first-mover advantage.

Drawing from Zhang et al. (2023), we use the management discussion and analysis (MD&A) sections of the annual reports of listed firms to depict managers' attitudes to the future development of the firm. We use a dictionary approach to quantify the number of words related to managerial shortsightedness and divide this frequency by the total word count in the MD&A section to measure managerial myopia (*Myopia*). For interpretability, this measure is multiplied by 100 and then inverted; the higher the value, the higher the degree to which managerial tendencies toward shortsightedness are suppressed in favor of green innovation quality. As

Table 8
Results of mechanism testing: Green learning mechanism.

Variable	(1)	(2)	(3)	(4)
	Acquisition of green resources		Enhancement of green awareness	
	Diver	*Break*	*Diver*	*Break*
Cus_esg	0.141***	0.168**	0.105*	0.133*
	(2.61)	(2.46)	(1.79)	(1.79)
Resource	–0.323	–0.436		
	(–1.41)	(–1.56)		
Cus_esg × *Resource*	0.096*	0.123*		
	(1.79)	(1.88)		
Aware			0.002	0.009
			(0.07)	(0.27)
Cus_esg × *Aware*			0.015**	0.016*
			(2.09)	(1.90)
Sup_size	0.219**	0.223*	0.168	0.162
	(1.96)	(1.69)	(1.51)	(1.23)
Sup_age	0.095	0.131	0.084	0.112
	(0.59)	(0.68)	(0.52)	(0.59)
Sup_lev	–0.310	–0.230	–0.260	–0.172
	(–0.69)	(–0.42)	(–0.63)	(–0.34)
Sup_roa	0.970*	0.167***	0.838	0.151**
	(1.77)	(2.60)	(1.59)	(2.44)
Sup_growth	–0.116	–0.162*	–0.715	–0.108
	(–1.47)	(–1.67)	(–0.95)	(–1.17)
Sup_rd	–0.377	0.713	–0.684	0.312
	(–0.34)	(0.48)	(–0.74)	(0.24)
Sup_nwc	–0.009	0.006	0.059	0.089
	(–0.02)	(0.01)	(0.17)	(0.21)
Sup_soe	0.196	0.223	0.265**	0.305**
	(1.46)	(1.21)	(2.51)	(2.05)
Sup_top1	0.166	0.165	0.0219	–0.0217
	(0.33)	(0.27)	(0.04)	(–0.03)
Sup_msh	–0.095	–0.159	–0.086	–0.151
	(–0.34)	(–0.47)	(–0.34)	(–0.50)
Sup_board	–0.066	–0.094	–0.091	–0.126
	(–0.51)	(–0.61)	(–0.69)	(–0.81)
Sup_gdp	–0.291	–0.321	–0.110	–0.090
	(–0.79)	(–0.78)	(–0.35)	(–0.26)
Cus_size	0.265**	0.332**	0.274**	0.341**
	(2.05)	(2.10)	(2.29)	(2.36)
Cus_age	–0.044	–0.107	–0.038	–0.101
	(–0.25)	(–0.53)	(–0.23)	(–0.54)
Cus_roa	0.377	0.298	0.427	0.353
	(0.50)	(0.33)	(0.62)	(0.43)
Cus_growth	–0.066	–0.045	–0.112	–0.097
	(–0.50)	(–0.30)	(–0.88)	(–0.68)
Cus_vol	0.004	0.004	0.003	0.003
	(0.71)	(0.70)	(0.49)	(0.48)
Year/Ind/Pair FE	Yes	Yes	Yes	Yes
Constant	–8.153	–9.540	–8.945*	–10.617*
	(–1.53)	(–1.56)	(–1.72)	(–1.79)
R^2	0.078	0.081	0.137	0.141
N	2,129	2,129	2,129	2,129

shown in columns (1) and (2) of Table 9, the coefficients of the interaction term *Cus_esg* × *Myopia* are 0.013 and 0.016, respectively, which are both significant at the 5 % level. This indicates that customers with good ESG performance intensify competition among supplier companies, prompting suppliers' management to

Table 9
Results of mechanism testing: Corporate competition mechanism.

Variable	(1)	(2)	(3)	(4)
	Inhibition of managerial shortsightedness		Investment in relationship-specific assets	
	Diver	*Break*	*Diver*	*Break*
Cus_esg	0.096**	0.113**	0.087	0.103
	(2.29)	(2.28)	(1.56)	(1.60)
Myopia	0.057**	0.069**		
	(2.38)	(2.25)		
Cus_esg × *Myopia*	0.013**	0.016**		
	(2.49)	(2.42)		
Rsa			0.340	0.471
			(0.53)	(0.66)
Cus_esg × *Rsa*			0.272*	0.331**
			(1.92)	(2.04)
Sup_size	0.210*	0.210	0.205*	0.204
	(1.80)	(1.52)	(1.69)	(1.41)
Sup_age	0.073	0.101	–0.009	–0.002
	(0.44)	(0.51)	(–0.06)	(–0.01)
Sup_lev	–0.329	–0.256	–0.217	–0.116
	(–0.72)	(–0.46)	(–0.47)	(–0.20)
Sup_roa	1.039*	1.759***	0.716	1.352**
	(1.85)	(2.66)	(1.38)	(2.23)
Sup_growth	–0.117	–0.163*	–0.084	–0.126
	(–1.47)	(–1.66)	(–1.12)	(–1.31)
Sup_rd	–0.830	0.179	–0.268	0.867
	(–0.71)	(0.11)	(–0.22)	(0.53)
Sup_nwc	0.006	0.018	0.265	0.346
	(0.02)	(0.04)	(0.70)	(0.74)
Sup_soe	–0.101	–0.172	0.084	0.061
	(–0.20)	(–0.28)	(0.15)	(0.09)
Sup_top1	–0.016	–0.058	–0.092	–0.155
	(–0.06)	(–0.17)	(–0.34)	(–0.48)
Sup_msh	–0.093	–0.127	–0.077	–0.108
	(–0.70)	(–0.80)	(–0.62)	(–0.73)
Sup_board	0.201	0.230	0.325**	0.384**
	(1.60)	(1.32)	(2.53)	(2.26)
Sup_gdp	–0.256	–0.274	–0.258	–0.275
	(–0.72)	(–0.70)	(–0.78)	(–0.74)
Cus_size	0.264**	0.329**	0.221*	0.277*
	(2.08)	(2.13)	(1.74)	(1.79)
Cus_age	–0.028	–0.091	–0.027	–0.089
	(–0.16)	(–0.47)	(–0.15)	(–0.45)
Cus_roa	0.535	0.493	0.160	0.326
	(0.71)	(0.55)	(0.22)	(0.04)
Cus_growth	–0.104	–0.091	–0.063	–0.037
	(–0.81)	(–0.62)	(–0.50)	(–0.26)
Cus_vol	0.004	0.005	0.005	0.006
	(0.78)	(0.76)	(1.01)	(1.02)
Year/Ind/Pair FE	Yes	Yes	Yes	Yes
Constant	–7.877	–9.203	–7.190	–8.398
	(–1.44)	(–1.47)	(–1.35)	(–1.36)
R^2	0.079	0.083	0.135	0.145
N	2,129	2,129	2,129	2,129

curb their short-sighted behaviors and actively enhance green innovation quality to align with customers' green development concepts.

Given the interchangeability of asset specificity in transaction cost economics and relationship-specific assets in the theory of relational resources (Lui et al., 2009), we follow Ge et al. (2022) and measure the investment of suppliers in relationship-specific assets for customers (*Rsa*) by the sum of year-end fixed assets, construction in progress, net intangible assets and long-term deferred expenses divided by total assets. As shown in columns (3) and (4) of Table 9, the coefficients of $Cus\_esg \times Rsa$ are 0.272 and 0.313, which are significant at the 10 % and 5 % levels, respectively. This demonstrates that customers with good ESG performance can intensify competition among supplier firms, prompting suppliers to make investments in relationship-specific assets to enhance the quality of green innovation and meet customers' demands for green development. In summary, along the supply chain, customers with good ESG performance drive suppliers to control managerial shortsightedness and increase investment in relationship-specific assets, thus promoting the improvement of green innovation quality through the business competition mechanism of supplier firms.

6.2. Heterogeneity analysis of customer–supplier relationships

The previous discussion highlights how customer ESG performance significantly enhances supplier green innovation quality. One mechanism at play is that the competitive advantage gained from customer ESG performance prompts suppliers to imitate and learn green development principles, enhance their green awareness and leverage the cooperative relationship to acquire green innovation resources from customers, thereby improving diversification and breakthroughs in green innovation technologies. Another mechanism involves customers with good ESG performance as high-quality partners in the supply chain, triggering competition among supplier firm and compelling suppliers' management to curb short-sighted behaviors and increase investment in relationship-specific assets for cooperative customers, thus actively enhancing green innovation quality to gain a competitive advantage. However, the impact of customer ESG performance on the quality of supplier green innovation is inevitably influenced by the characteristics of the relationship between the customer and supplier. To address this, we use customer–supplier stickiness and the customer's position within the supply chain network to measure the characteristics of customer–supplier relationships as a further analysis.

First, stickiness between suppliers and customers characterizes the quality of their trade relationship from a qualitative perspective. In the supply chain relationship, customers are vital resources for listed firms to survive and grow sustainably. A high level of stickiness with customers implies that customers have a high level of satisfaction with supplier firms, representing a high-quality cooperative relationship between both parties. High-quality cooperative relationships are more conducive to suppliers enhancing their green innovation quality through the learning mechanism than low-quality relationships. Suppliers are more likely to observe the competitive advantages that they will gain through customer ESG performance in the case of higher-quality relationships, leading to strong imitation and a learning mentality inclined to enhance their green awareness. Furthermore, a high-quality cooperative relationship facilitates the sharing of green knowledge, technologies and resources between customers and suppliers, thereby assisting suppliers to improve their green innovation quality. Therefore, we posit that the impact of customer ESG performance on supplier green innovation quality is more significant in groups with higher (vs. lower) customer–supplier stickiness. We use the frequency of cooperation between customers and suppliers during the sample period to measure the stickiness of customers for listed firms and conduct a test by groups based on the median of customer stickiness. As shown in columns (1) and (3) of Table 10, in groups with high customer–supplier stickiness, the coefficients of *Cus_esg* are 0.220 and 0.254, which are both significant at the 1 % level, indicating that the higher the stickiness between suppliers and customers, the more that suppliers benefit in terms of enhancing their green innovation quality through learning mechanisms.

Second, the position of a firm in the supply chain network characterizes the relationship between suppliers and customers from a status perspective. In socioeconomic activities, the actions of actors are both autonomous and embedded in interactive networks, and thus influenced by social networks. Network centrality is commonly used to evaluate the importance of individuals in a social network, measuring their superiority, privilege and social reputation. In the case of firms, the higher a firm's network centrality, the more it is posi-

Table 10
Heterogeneity analysis: Based on the perspective of customer–supplier relationship stickiness.

Variable	(1)	(2)	(3)	(4)
	High stickiness	Low stickiness	High stickiness	Low stickiness
	Diver	*Diver*	*Break*	*Break*
Cus_esg	0.220***	0.037	0.254***	0.086
	(3.59)	(0.47)	(3.33)	(0.99)
Sup_size	0.272**	–0.155	0.282*	–0.206
	(1.98)	(–0.53)	(1.70)	(–0.65)
Sup_age	0.191	–0.747	0.213	–0.960
	(1.02)	(–1.06)	(0.95)	(–1.24)
Sup_lev	–0.344	0.906	–0.229	1.377
	(–0.62)	(1.00)	(–0.34)	(1.33)
Sup_roa	0.797	1.341	1.623**	2.222
	(1.33)	(0.90)	(2.33)	(1.25)
Sup_growth	–0.059	–0.140	–0.107	–0.163
	(–0.57)	(–0.71)	(–0.80)	(–0.74)
Sup_rd	–0.529	4.040	1.265	4.338
	(–0.35)	(0.92)	(0.62)	(0.82)
Sup_nwc	0.018	0.292	0.024	0.456
	(0.04)	(0.46)	(0.04)	(0.62)
Sup_soe	0.128	–1.513	0.110	–1.664
	(0.22)	(–0.58)	(0.15)	(–0.58)
Sup_top1	0.0873	–0.242	0.572	–0.497
	(0.25)	(–0.32)	(0.01)	(–0.64)
Sup_msh	–0.140	–0.251	–0.145	–0.459
	(–0.86)	(–0.95)	(–0.75)	(–1.48)
Sup_board	0.159	–0.025	0.169	–0.047
	(0.97)	(–0.11)	(0.75)	(–0.17)
Sup_gdp	–0.078	–0.968	–0.069	–0.741
	(–0.20)	(–0.89)	(–0.16)	(–0.60)
Cus_size	0.409***	–0.705*	0.502***	–0.965**
	(2.65)	(–1.90)	(2.69)	(–2.35)
Cus_age	–0.076	–0.249	–0.166	–0.224
	(–0.42)	(–0.61)	(–0.79)	(–0.51)
Cus_roa	–0.602	0.696***	–0.717	0.834***
	(–0.78)	(3.80)	(–0.76)	(4.35)
Cus_growth	–0.804	–2.944	1.682	–2.607
	(–0.04)	(–1.22)	(0.08)	(–1.04)
Cus_vol	0.005	0.016	0.006	0.022
	(0.77)	(0.93)	(0.89)	(1.13)
Year/Ind/Pair FE	Yes	Yes	Yes	Yes
Constant	–14.944**	31.514*	–17.457***	36.681**
	(–2.57)	(1.92)	(–2.63)	(2.05)
R^2	0.101	0.148	0.105	0.180
N	1,314	815	1,314	815

tioned at the core of the network, granting it control and resource advantages. Firms with higher centrality have greater choices when selecting partners, whereas relatively peripheral partners tend to establish stable relationships with more central firms to access resources and information (Yu et al., 2022). This asymmetry in choice compels suppliers to enhance their green innovation quality to align with customers' ESG concepts. Therefore, this study posits that the impact of customer ESG performance on supplier green innovation quality is more significant in groups with higher (vs. lower) customer network centrality. We use the natural logarithm of the degree of centrality as a measure of network centrality, and the higher the degree of centrality, the closer the firm is to the center of the network. Next, we conduct a test by groups based on the median value of network centrality. As shown in columns (1) and (3) of Table 11, in groups with higher customer network centrality, the coefficients of *Cus_esg* are 0.229 and 0.282, which are both significant at the 1 % level. This sug-

Table 11
Heterogeneity analysis: Based on the perspective of customer supply chain network position.

Variable	(1)	(2)	(3)	(4)
	High network centrality	Low network centrality	High network centrality	Low network centrality
	Diver	*Break*	*Diver*	*Break*
Cus_esg	0.229***	0.037	0.282***	0.041
	(3.36)	(0.82)	(3.36)	(0.72)
Sup_size	0.428***	–0.107	0.437**	–0.166
	(2.66)	(–0.86)	(2.31)	(–1.04)
Sup_age	0.162	–0.190	0.201	–0.196
	(0.84)	(–0.62)	(0.89)	(–0.52)
Sup_lev	–0.574	–0.495	–0.351	–0.639
	(–0.82)	(–0.63)	(–0.44)	(–0.63)
Sup_roa	0.343	1.445**	0.917	2.122***
	(0.38)	(2.42)	(0.90)	(2.61)
Sup_growth	–0.118	–0.163	–0.207	–0.167
	(–0.95)	(–1.24)	(–1.46)	(–0.96)
Sup_rd	2.787	–5.005***	5.061***	–5.247**
	(1.51)	(–2.71)	(2.69)	(–2.37)
Sup_nwc	0.178	–0.720	0.359	–0.917
	(0.36)	(–1.02)	(0.64)	(–0.99)
Sup_soe	–0.218	2.096**	–0.130	2.124*
	(–0.38)	(2.19)	(–0.19)	(1.83)
Sup_top1	–0.544	–0.070	–0.725	–0.054
	(–1.27)	(–0.17)	(–1.53)	(–0.01)
Sup_msh	–0.208	–0.046	–0.290	–0.065
	(–1.14)	(–0.32)	(–1.31)	(–0.37)
Sup_board	0.061	0.333*	–0.043	0.507*
	(0.27)	(1.75)	(–0.16)	(1.72)
Sup_gdp	–0.665	–0.371	–0.755	–0.320
	(–1.38)	(–0.51)	(–1.38)	(–0.37)
Cus_size	0.294*	0.005	0.380**	0.086
	(1.91)	(0.02)	(2.02)	(0.28)
Cus_age	–0.155	–0.456	–0.295	–0.556*
	(–0.79)	(–1.63)	(–1.30)	(–1.75)
Cus_roa	1.076	–0.134	1.042	0.128
	(1.11)	(–0.08)	(0.93)	(0.06)
Cus_growth	–0.133	–0.251	–0.101	–0.306
	(–0.77)	(–1.30)	(–0.53)	(–1.36)
Cus_vol	0.004	0.023**	0.005	0.022**
	(0.55)	(2.40)	(0.69)	(2.01)
Year/Ind/Pair FE	Yes	Yes	Yes	Yes
Constant	–9.238	7.231	–10.476	6.393
	(–1.34)	(0.74)	(–1.30)	(0.53)
R^2	0.114	0.075	0.126	0.061
N	1,329	800	1,329	800

gests that the closer a customer's supply chain network position is to the center, the more it can promote improvements in the supplier's green innovation quality through competitive mechanisms, in line with the ESG development demands of the customers.

6.3. Can suppliers identify customers' greenwashing behavior?

The proposal of the dual carbon goal reflects China's emphasis on the transformation of its economy toward green economic development and the achievement of sustainability, which involves redefining corporate behavior. Firms need to focus not only on their economic effects but also on enhancing their low-carbon, green and sustainable development capabilities. ESG embodies a sustainable development value that balances economic, environmental, social and governance benefits. Under the dual carbon concept, firms strive for competitive advantages through proactive ESG performance to attract external stakeholders' attention and enhance their corporate value (Fatemi et al., 2015; Tran and Coqueret, 2023). However, some scholars observe that firms engage in "greenwashing," using ESG as marketing to maximize their self-interest without genuinely fulfilling their corporate social responsibilities (Yi et al., 2022). In particular, firms with a high divergence in ESG ratings are more likely to engage in greenwashing (Hu et al., 2023). A key question is, can suppliers, as stakeholders, identify customers engaging in greenwashing behavior? In other words, does a customer's ESG performance truly prompt suppliers to improve their green innovation quality only when there is genuine commitment to ESG, indicated by a small divergence in ESG ratings?

Table 12
Heterogeneity analysis: Based on suppliers' perceptions of whether customers engage in greenwashing.

Variable	(1)	(2)	(3)	(4)
	Low ESG divergence	High ESG divergence	Low ESG divergence	High ESG divergence
	Diver	*Diver*	*Break*	*Break*
Cus_esg	0.347***	0.057	0.387***	0.052
	(3.01)	(0.63)	(2.80)	(0.49)
Sup_size	0.105	–1.198***	–0.094	–1.412***
	(0.50)	(–3.25)	(–0.35)	(–3.38)
Sup_age	0.402	0.508	0.572	0.586
	(0.80)	(1.23)	(0.99)	(1.18)
Sup_lev	–1.307	1.916*	–1.017	2.555*
	(–1.15)	(1.79)	(–0.73)	(1.91)
Sup_roa	–0.149	–0.950	0.137	–0.444
	(–0.19)	(–0.40)	(0.14)	(–0.15)
Sup_growth	–0.120	–0.172	–0.200	–0.170
	(–0.42)	(–0.91)	(–0.55)	(–0.77)
Sup_rd	9.784*	–3.767	7.433	–3.200
	(1.66)	(–0.83)	(1.14)	(–0.62)
Sup_nwc	0.478	–0.141	0.492	–0.080
	(0.44)	(–0.09)	(0.36)	(–0.04)
Sup_soe	–1.544	2.857	–1.858	2.725
	(–0.98)	(1.53)	(–0.89)	(1.29)
Sup_top1	0.546	0.450	0.645	0.440
	(1.59)	(0.61)	(1.46)	(0.51)
Sup_msh	0.156	0.312	0.216	0.383
	(0.86)	(0.95)	(0.97)	(0.97)
Sup_board	0.199	–0.112	0.191	–0.108
	(0.85)	(–0.57)	(0.64)	(–0.47)
Sup_gdp	–2.480***	–0.067	–2.554**	–0.105
	(–2.82)	(–0.09)	(–2.23)	(–0.11)
Cus_size	–0.227	–0.084	–0.197	–0.071
	(–0.69)	(–0.38)	(–0.49)	(–0.28)
Cus_age	–0.845*	–0.069	–1.057*	–0.514
	(–1.73)	(–0.09)	(–1.79)	(–0.53)
Cus_roa	–1.356	0.444	–1.005	–0.384
	(–0.64)	(0.21)	(–0.36)	(–0.15)
Cus_growth	0.165	0.018	0.076	0.035
	(0.66)	(0.05)	(0.23)	(0.09)
Cus_vol	0.024**	–0.001	0.027*	–0.003
	(2.04)	(–0.04)	(1.93)	(–0.23)
Year/Ind/Pair FE	Yes	Yes	Yes	Yes
Constant	29.452**	26.800*	34.110*	32.338*
	(2.00)	(1.89)	(1.80)	(1.91)
R^2	0.194	0.079	0.167	0.073
N	393	330	393	330

To address this issue, following Hu et al. (2023), we select six types of ESG rating methods, namely the Huazheng ESG rating index, WIND ESG rating index, the Shangdao Ronglu ESG rating index, the Menglang FIN–ESG rating index, the Bloomberg ESG rating score and the FTSE Russell ESG rating score, to assign values and calculate standard deviations to measure ESG rating divergence. As rating companies com-

Table 13
Economic consequences of customer ESG performance for improving supplier green innovation quality.

Variable	(1)	(2)
	Env	*Env*
Cus_esg	0.031	0.038
	(0.90)	(1.10)
Diver	–0.221**	
	(–2.20)	
Cus_esg × *Diver*	0.048**	
	(2.12)	
Break		–0.170**
		(–2.09)
Cus_esg × *Break*		0.034*
		(1.89)
Sup_size	–0.119	–0.115
	(–1.24)	(–1.20)
Sup_age	0.396**	0.396**
	(2.30)	(2.30)
Sup_lev	–0.492	–0.495
	(–1.08)	(–1.09)
Sup_roa	–0.584	–0.550
	(–0.87)	(–0.82)
Sup_growth	0.059	0.055
	(0.61)	(0.58)
Sup_rd	1.565	1.538
	(0.99)	(0.98)
Sup_nwc	–0.245	–0.247
	(–0.76)	(–0.77)
Sup_soe	0.446	0.444
	(0.74)	(0.74)
Sup_top1	0.352	0.357
	(1.43)	(1.45)
Sup_msh	–0.092	–0.094
	(–0.83)	(–0.85)
Sup_board	0.134	0.139
	(0.82)	(0.85)
Sup_gdp	0.427	0.428
	(0.95)	(0.95)
Cus_size	0.064	0.069
	(0.48)	(0.52)
Cus_age	0.765***	0.762***
	(4.22)	(4.20)
Cus_roa	–1.453	–1.465
	(–1.39)	(–1.41)
Cus_growth	0.024	0.027
	(0.21)	(0.23)
Cus_vol	0.007	0.007
	(1.15)	(1.17)
Year/Ind/Pair FE	Yes	Yes
Constant	–4.375	–4.583
	(–0.89)	(–0.93)
R^2	0.354	0.353
N	2,129	2,129

menced operating in 2018, the study sample is limited to the period from 2018 to 2021. As shown in columns (1) and (3) of Table 12, the coefficients of *Cus_esg* are 0.347 and 0.387, respectively, which are both significant at the 1 % level. This suggests that when the customer's ESG rating divergence is lower (higher), meaning that the customer is not engaged (is engaged) in greenwashing behavior, the impact of customer ESG performance on the supplier's green innovation quality is more (less) significant. In other words, suppliers can identify the true ESG performance of customer firms, confirming that only those customers that genuinely practice the concept of sustainable development can promote the improvement of suppliers' green innovation quality.

6.4. The economic consequences of customer ESG performance for enhancing suppliers' green innovation quality

Currently, the need for low-carbon development is a global consensus, with major economies worldwide setting carbon peak and carbon neutrality targets and strengthening the low-carbon management of firms to achieve green transformation. Given that customer ESG performance can promote the enhancement of green innovation quality along the supply chain, we ask: Can this spillover effect lead to green co-governance of the supply chain, ultimately improving the environmental performance of suppliers and driving the green development transformation of businesses? According to the "Guidelines for the Preparation of Corporate Environmental Reports" issued by the Chinese Ministry of Environmental Protection, a firm's environmental performance is defined by measurable results in resource utilization, environmental protection and pollution control. Drawing from Yi et al. (2022), we use the ecological benefit method to measure a firm's environmental performance (*Env*), where ecological benefit = output of products or services/environmental impact. We utilize business total revenue to reflect the firm's operational results, and pollution fees to measure the firm's environmental impact. Pollution fee data are manually compiled from pollution fee details disclosed in the "payment of other cash related to operating activities" section of listed firms' annual reports. The higher the value of this indicator, the better the environmental performance of the enterprise. In this study, the dependent variable in Model (4) is replaced with firm environmental performance (*Env*), and the interaction variable *Z* replaces green technology diversification (*Diver*) and green innovation breakthrough (*Break*) for another regression. As shown in Table 13, the coefficients of *Cus_esg* × *Diver* and *Cus_esg* × *Break* are 0.048 and 0.034, respectively, which are significant at the 5 % and 10 % levels, respectively. This demonstrates that after customer ESG performance produces a spillover effect along the supply chain on suppliers, it prompts suppliers to pursue diversified green innovation and explore breakthrough innovations, leading to further improvement in suppliers' environmental performance.

7. Conclusion and implications

7.1. Conclusion

This paper selects A-share listed companies during the period from 2009 to 2022 to construct "customer–supplier-year" paired samples and explore the spillover effect of customer ESG performance at the supply chain level. Based on the analysis, we find that customer ESG performance can promote the improvement of supplier green innovation quality. Mechanism testing reveals that customer ESG performance improves supplier green innovation quality through suppliers' green learning and competitive effects. Further analysis characterizes the relationship between customers and suppliers in terms of the dimensions of quality and status and reveals that the higher the degree of stickiness of the relationship between customers and suppliers and the more central the position of the customer in the supply chain network, the more significant are the impacts of customer ESG performance on supplier green innovation quality. In addition, by using ESG rating divergence to depict whether customers engage in greenwashing behavior, the group test reveals that suppliers can identify customers' greenwashing behavior and respond accordingly. Finally, the study demonstrates that the spillover effects of customer ESG performance on suppliers ultimately help improve suppliers' environmental performance.

7.2. Implications

Emerging market countries, as the main battlegrounds for implementing low-carbon strategic goals globally, are crucial breakthrough points for achieving global sustainable development goals. The Chinese government's emphasis on achieving its dual carbon goals and its determination to build a "Beautiful China" have prompted Chinese firms to actively practice green development. The accumulated experience in green and low-carbon transformation in China can provide valuable insights and references for other emerging market firms. This experience indicates that, first, upstream and downstream firms in the supply chain should implement green co-governance, leveraging the leadership role of customer firms in sustainable development concepts to drive suppliers' green innovation in response to customer demands. Second, companies in the supply chain should share elements such as green development information and technologies and collaborate to achieve the overall green transformation in the supply chain.

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Conflict of interest statement

The authors confirm that there are no relevant financial or non-financial competing interests to report.

Data availability statement

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

CRediT authorship contribution statement

Yani Sun: Data curation, Writing – original draft, Writing – review & editing. **Yuezhe Shen:** Data curation. **Qingmei Tan:** Conceptualization, Supervision, Funding acquisition, Writing – review & editing.

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Corrigendum

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