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Personal data security and stock crash risk: Evidence from China's Cybersecurity Law

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ABSTRACT

Using China's Cybersecurity Law (CSL) as an exogenous shock, I examine how personal data security affects stock crash risk. I find that the stock crash risk of treatment firms (which collect personal data) significantly decreases after the CSL, and such decrease is larger when firms face greater personal data breach risk and have less transparent information environments before the CSL. Furthermore, treatment firms increase their investment in personal data protection after the CSL. Finally, enhanced personal data security increases firm value and promotes firms' social responsibility to stakeholders. Overall, I provide evidence of the importance of data security for the digital economy from the perspective of capital market stability, which may present implications for data security policy worldwide.

1. Introduction

The past decade has been an era of rapid development for the digital economy, leading firms to gather vast quantities of personal data. Simultaneously, personal data insecurity increasingly threatens various stakeholders. In the United States, over 1,000 firms report data breaches each year, involving hundreds of millions of consumers, with an average cost of millions of US dollars per incident (Foerderer and Schuetz, 2022).[1] In 2014, two-thirds of a sample of Chinese consumers reported having their personal information leaked.[2] For firms whose products and services are directly targeted at consumers and end users (hereafter referred

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[1] See the ITRC Annual Data Breach Report for 2020, which can be found at https://www.idtheftcenter.org/notified.

[2] See the Report for Consumers' Personal Data Security in 2014, which can be found at https://m.news.cntv.cn/2015/03/13/ARTI1426222419386790.shtml (in Chinese).

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to as "TOC firms"), personal data security could be a risk factor in the digital economy (Gordon et al., 2015; Amir et al., 2018; Foerderer and Schuetz, 2022).

Anecdotes show that firms' stock prices crash after personal data breaches in global capital markets. For example, in September 2018, Meta's stock price suddenly dropped by 10 % after its announcement of a personal data breach affecting over 87 million users, and Zuckerberg's wealth shrank by US$6 billion within several days.[3] However, despite these anecdotes, whether and how personal data security affects stock crash risk are largely unknown (Martin et al., 2017; Amir et al., 2018; Janakiraman et al., 2018; Kamiya et al., 2021; Foerderer and Schuetz, 2022). This is surprising, given that cyber risk has become a primary concern for investors (PricewaterhouseCoopers, 2018).

Managers have incentives to strategically withhold bad news from investors. When bad news accumulates beyond a certain threshold, it is released to the market all at once, leading to a stock price crash (Jin and Myers, 2006; Kim et al., 2011a).[4] Previous studies examine the determinants of stock crash risk within the traditional agency framework, and I extend this strand of the literature by investigating how a key feature related to digital economy development, namely personal data security, affects stock crash risk.

Firm-level personal data security and stock crash risk could both be endogenously determined by firms' fundamental characteristics, making it empirically challenging to establish a causal relationship between them. To enhance causal inference, I use a regulatory shock in China (i.e., the 2016 Cybersecurity Law [CSL]) that mandates firm protections for personal data as a natural experiment. As the first and fundamental law regulating China's digital economy, the CSL clarifies firms' responsibility to ensure personal data security and the corresponding measures they should take. The CSL also prohibits unauthorized access to the personal data held by firms. In addition, the CSL stipulates the penalties that regulators can impose on firms after personal data breaches, reinforcing the responsibility of firms to secure their personal data.

I posit that before the CSL, firms that collected personal data (i.e., TOC firms) had higher stock crash risk because they faced greater risk of a personal data breach and their mangers had the ability to withhold bad news related to personal data security. Before the CSL, managers lacked incentives to protect personal data because of the undefined property rights regarding personal data and the externalities of personal data protection. Because managers were not required to report data breaches to regulators before the CSL, they could suppress data breaches below a certain threshold, leading negative information on firms' personal data security (i.e., internal control weakness or underinvestment in user rights protection) to accumulate. Such accumulated negative information could eventually lead to large-scale data breaches that cannot be covered up by managers and are thus discovered by stakeholders (i.e., consumers, users and employees). The stock price would crash with the sudden release of such accumulated negative information regarding personal data security (Jin and Myers, 2006; Kim et al., 2011a). However, the CSL reduces the stock crash risk faced by TOC firms by clarifying property rights, internalizing the externalities related to personal data protection and inhibiting managers' ability to withhold information about data breaches.

To empirically examine the impact of personal data security on stock crash risk, I use the CSL as an exogenous shock that strengthens firms' personal data security to construct a difference-in-differences (DID) model. I first identify firms affected by the CSL (i.e., treatment firms) as those in consumer-sensitive industries that also have WeChat Official Accounts (WCOAs) numbers higher than the industry median (i.e., TOC firms that possess personal data). After validating my identification of treatment firms, I obtain a sample of 17,195 firm–year observations for A-share listed firms from 2013 to 2020. I find that treatment firms exhibit significant lower stock crash risk than firms unaffected by the CSL (i.e., control firms). My baseline results are supported by a battery of robustness checks, including the use of a propensity score-matched sample, parallel trend analysis and alternative variable definitions.

[3] China's capital market has similar anecdotes. For example, in February 2003, China Life's (stock code: 601628) stock price dropped by 11% in five days after a data breach involving 800,000 insurance customers was announced. In February 2023, Yuantong Express (stock code: 600233) was suspected to have suffered a breach of 4.5 billion pieces of personal data, which led directly to a 7% plunge in its stock price on the day and a 15% drop over the following three trading days.

[4] This strand of literature points out that the key intuition underlying stock crash risk is the failure of the stock price to fully account for negative information; such failure is caused by both managerial incentives to hide bad information and firms' information environment opacity. Such managerial incentives include obtaining compensation, pursuing political promotion, maintaining reputation and avoiding litigation (Kothari et al., 2009; Kim et al., 2011b; Piotroski et al., 2015).

I supplement my main findings with two cross-sectional tests. First, the effect of the CSL on stock crash risk is stronger when treatment firms have a higher ex ante personal data breach risk, as proxied by (lower) internal control quality and (less) managerial attention to personal data security. Second, the effect is also stronger when information asymmetry between firms and investors is greater before the CSL, as proxied by lower analyst coverage and fewer media reports. The results of these cross-sectional tests are consistent with my argument that the CSL reduces firm-level personal data security risk and limits managers' ability to hide bad news relating to personal data security.

I further investigate firms' actions on personal data security as responses to the CSL. My additional analysis shows that compared with control firms, treatment firms invest more in personal data security and deploy more background IT managers in top management teams. Consistent with the effects of the CSL on stock crash risk, the capital market reacts positively to the passage of the CSL. My final analysis indicates that treatment firms exhibit better corporate social responsibility (CSR) performance after the CSL, particularly for consumers and employees, than do control firms, indicating that that promoting data security has implications for stakeholders other than investors.

Overall, my study makes several important contributions. First, it enriches the literature on the economic consequences of data security by demonstrating the importance of personal data security to capital market stability (Martin et al., 2017; Janakiraman et al., 2018; D'Arcy et al., 2020; Kamiya et al., 2021), providing implications for the global digital economy. Personal data is a core element of the digital economy; thus, understanding the economic consequences of data security is crucial. While a growing literature focuses on the effects of data breaches on corporate operations and managers' strategic choices in data breach disclosure (i.e., D'Arcy et al., 2020; Foerderer and Schuetz, 2022), this study, to the best of my knowledge, is among the first to reveal the positive effects of strengthening personal data security on the capital market.

Second, my study adds to the literature on stock crash risk by documenting a new determinant in the context of digital economy. While the development of the digital economy has changed firms' operations and business modes, the literature on stock crash risk focuses on its determinants within the traditional agency framework between managers and investors (i.e., Kim and Zhang, 2014, 2016) and pays little attention to the increasing importance of consumers, users and their data security as sources of risk for firms. Scant research addresses the governance of stock crash risk that involves the role of legal institutions. By showing how the CSL affects firms' stock crash risk, my study provides evidence of the causes and regulation of stock crash risk in the digital economy.

Finally, my study is related to the emerging literature seeking to understand the effectiveness of data security regulations (Amir et al., 2018; Ashraf, 2022). Differing from studies of the actions managers and regulators take after a data breach, my study provides evidence of the real effects of the ex ante regulation of data security by exploiting the implementation of the CSL in China as a regulatory shock. This study is also timely, informing the recent considerations of global regulators and policymakers to advance legislation on personal data protection.

The rest of this paper is organized as follows: Section 2 reviews the literature, describes the institutional background and provides a theoretical analysis. Section 3 presents the research design. Sections 4 and 5 present the empirical analyses. Section 6 concludes the paper.

2. Literature review and hypothesis development

2.1. Review of the literature on personal data breaches

Personal data breaches occur when unauthorized third parties obtain personal data from a data-holding entity (Foerderer and Schuetz, 2022).[5] TOC firms hold hundreds of types of personal data gathered through their daily operation such as selling goods or providing services to consumers or users. TOC firms are thus

[5] According to the CSL, personal data are defined as any information recorded in electronic or other form that can identify an individual, either alone or in combination with other information. Examples of personal data include identity data, transaction records, travel records and call logs. Generally, third parties acquire personal data for illegal purposes, including extorting the data holder, conducting telecom fraud, engaging in malicious competition and selling personal data for gains.

likely to be targets of data attacks. Generally, third parties illegally obtain personal data for purposes such as extorting the data-holding entity, committing telecom fraud, engaging in malicious competition and selling personal data for profit. The most common reason for data breaches is firms' lack of attention to personal data security and their internal control weaknesses, particularly failures in information and data security system construction (D'Arcy et al., 2020; Kamiya et al., 2021). Investment in personal data security could be a large cost for public firms under market pressure. For example, Chen et al. (2019) find that firms under greater earnings pressure are more likely to cut investment in data security and experience more subsequent data breaches as a result.

The literature documents several economic consequences of data breaches, which are related to my study on stock crashes. First, data breaches reduce the trust that consumers and users have in firms, leading to customer attrition and a long-term competitive disadvantage for affected firms (Martin et al., 2017; Amir et al., 2018; Janakiraman et al., 2018). Janakiraman et al. (2018) find that consumers spend less at the retailers after a data breach and are more likely to switch to other retailers that do not experience data breaches. Second, firms suffer reputational damage and remediation costs after data breaches (Janakiraman et al., 2018; Lending et al., 2018; Kamiya et al., 2021).[6] For instance, Equifax, one of the three major global credit agencies, fired its CEO to quell user outrage and paid US$700 million in settlement fees after a 2017 data breach involving 140 million users. Third, data breaches cause negative reactions in capital markets (Malhotra and Kubowicz Malhotra, 2011; Kamiya et al., 2021; Tosun, 2021). Kamiya et al. (2021) find that US firms experience an average cumulative abnormal return of –1% in the three trading days surrounding the publicizing of a data breach, corresponding to an average loss of US$500 million in shareholder wealth.

Given such negative consequences, managers have strong incentives to hide data breaches from stakeholders. Amir et al. (2018) find that managers tend not to disclose data breaches below a certain threshold and withhold information on more severe data breaches. Foerderer and Schuetz (2022) find that managers strategically choose busy media days to disclose data breaches, thereby minimizing the attention the data breaches receive.

2.2. Institutional background

The past two decades have witnessed the rapid development of China's digital economy, bringing millions of users' personal data into the possession of firms. However, weak institutions and enforcement in China's digital economy have lead to many personal data breaches. For example, in 2012, a data breach involving millions of Chinese Internet users raised public concerns regarding personal data security.[7] Cainxin reported that many firms held data from millions of their consumers, product users and employees but paid little attention to the security of these data. How to reconstruct the legal system to protect personal data has become an urgent problem at that time.[8] The Chinese government has attached great importance to this issue. In April 2016, President Xi Jinping initiated cybersecurity legislation. On 7 November 2016, the National People's Congress of China passed the CSL, which formally came into effect on 1 June 2017.

The CSL consists of seven chapters and 79 articles covering cybersecurity and personal data regulation. Chapter III of the CSL prohibits obtaining personal data, including stealing data, from a data-holding entity. In Chapters III and IV, the CSL clearly defines the responsibility of firms to protect personal data and the precautions they should take in their daily operations.[9] In Chapters IV and V, the CSL specifies the remedial actions that should be taken after data breaches. Chapter VI specifies the regulatory authorities in charge of data protection enforcement, as well as the penalties that could be imposed by the regulators. In addition, the

[6] The remediation costs include those related to data ransoming, litigation, customer relationship maintenance, reputational damage repair, regulatory fines and executive turnover.

[7] Firms involved in the data leak include CSDN, Tianya, Renren (PRC Internet site), 360, Sina Weibo, JD, Bank of Communications and Minsheng Bank.

[8] For details, see "The Great Cyber Leak" in *Caixin Weekly*'s report from 9 January 2012, which can be found at https://magazine.caixin.com/2012-01-06/100346334.html?p1.

[9] Specifically, those actions include establishing a cybersecurity department, using network firewalls and performing data encryption in their daily operations to safeguard personal data.

CSL requires firms to report data breaches to the cybersecurity regulatory authorities so that they can take joint action to remedy the impact of such breaches.

The CSL has been strongly enforced as regulators have paid closer attention to data security. Anecdotal evidence suggests that Chinese regulators have penalized firms for underperformance in personal data protection. For example, in 2018, the public security authorities investigated Datatang (stock code: 831428) for a personal data leak; in 2021, the Agricultural Bank of China (stock code: 601288) was penalized for its information system weakness and failure to report data breaches in a timely manner.[10] Correspondingly, firms have increased their investment in personal data security. In a 2018 survey by Ernst and Young on global data security, all Chinese firms reported that they had increased their investment in cybersecurity after the CSL, and more than half of those firms reported preventing data breaches as a prioritized task.[11]

2.3. Hypothesis development

Data breaches undermine the trust that stakeholders, including consumers, have in firms; thus, managers have incentives to hide related bad news. Managers also had the ability to hide news on data breaches before the CSL because they were not required to disclose data breach events. Managers could withhold data breaches below a certain threshold, allowing data breach risk to accumulate (Amir et al., 2018). Such risk accumulation can lead to large-scale data breaches that are hard to hide from stakeholders.[12] Correspondingly, stock prices will crash when such accumulated negative information is released to the capital market.

Data breach risk is caused by poorly defined property rights for personal data and the externalities of personal data protection in China's digital economy. First, because of poorly defined property rights, personal data are a public good affected by the tragedy of the commons; thus, who should bear the responsibility to protect personal data remains unclear. Firms could not claim property rights to personal data in financial statements until recently. Therefore, managers did not have strong incentives to protect personal data.

Second, personal data protection generates externalities for firms, reducing the value-enhancing effect of personal data security. While firms bear all the costs associated with personal data protection, the benefits are shared between firms and consumers. China's institutions do not require firms to disclose their investment in personal data protection. As a result, consumers, as well as investors, cannot directly observe firms' investment in personal data protection, and they will not attribute their data security to firms' efforts. Instead, because greater investment in data protection is reflected only by higher expenses and lower earnings on income statements, managers tend to delay or even cut investment in personal data security (Gordon et al., 2015). This externality is more pronounced for firms under capital market pressure (Chen et al., 2019). In addition, there is a data protection externality for peer firms due to the spillover effects of data breaches. Specifically, when a firm's stock price falls because of a data breach, the stock prices of other firms also fall (Corbet and Gurdgiev, 2019). Therefore, firms investing heavily in data protection could also suffer negative effects caused by peer firms neglecting data security. The above externalities reduce the value-enhancing effect of data protection and weaken managers' incentives to protect personal data.

Unclear property rights and the externalities of personal data protection are market failures typical of the development of China's digital economy. Preventing bad news and suppressing managers' ability to hide bad news are effective governance mechanisms to reduce stock crash risk. I argue that the CSL reduces firms' stock crash risk by reducing their data breach risk and curbing managers' ability to hide bad news.

First, the CSL specifies that firms should bear the responsibility for personal data security. It also specifies the actions firms should take in their daily operations as well as after data breaches, attenuating the negative externality of personal data protection because firms' actions to promote data security are more observable to stakeholders. The attenuation of this externality means that firms could gain more benefit from protecting personal data and that managers are more willing to invest in personal data protection. The CSL also prohibits the acquisition of personal data through theft and other means, further reducing data breach risk. Second, the

[10] Information source: https://m.thepaper.cn/baijiahao_11034904 (in Chinese).
[11] Information source: https://finance.takungpao.com/q/2018/0328/3555997.html (in Chinese).
[12] For example, stolen data could be held for ransom from firms, and consumers would learn of data breaches.

CSL requires firms to report data breaches to cybersecurity regulators and consumers, curbing managers' ability to hide related bad news.

Based on the above analysis, I propose the following hypothesis, H1: *Compared with non-TOC firms, TOC firms experience lower stock crash risk after the CSL.*

3. Research design

3.1. Variable definitions and model construction

3.1.1. Stock crash risk

Following Kim et al. (2011b) and Chen et al. (2001), respectively, I use negative conditional return skewness ($NCSKEW_{i,t}$) and down-to-up volatility ($DUVOL_{i,t}$) based on weekly returns to measure stock crash risk.

First, I calculate the firm-specific weekly return, denoted by $W_{i,j}$, as the natural log of 1 plus the residual return from the expanded market, as in Model (1):

$$R_{i,j} = \beta_0 + \beta_1 R_{m,j-2} + \beta_2 R_{m,j-1} + \beta_3 R_{m,j} + \beta_4 R_{m,j+1} + \beta_5 R_{m,j+2} + \varepsilon_{i,j} \tag{1}$$

$R_{i,j}$ is the return on stock i in week j, and $R_{m,j}$ is the value-weighted market return in week j. Lead and lag terms for the market return are included to allow for nonsynchronous trading (Dimson, 1979). The market-adjusted return for stock i in week j is calculated as $W_{i,j} = \ln(1 + \varepsilon_{i,j})$.

Next, I calculate the negative conditional return skewness for a given firm in a fiscal year by taking the negative of the third moment of the firm-specific weekly returns $W_{i,j}$ for each sample year and dividing it by the standard deviation of the firm-specific weekly returns $W_{i,j}$ raised to the third power. Specifically, $NCSKEW_{i,t}$ is calculated using Model (2) as follows:

$$NCSKEW_{i,t} = -\frac{n(n-1)^{3/2}\sum W_{i,j}^3}{(n-1)(n-2)(\sum W_{i,j}^2)^{3/2}} \tag{2}$$

Here, n represents the number of trading weeks for stock i in year t. A higher $NCSKEW_{i,t}$ value represents higher stock crash risk.

To construct the down-to-up volatility variable, $DUVOL_{i,t}$, I separate all the weeks with firm-specific weekly returns below the annual mean ("down" weeks) from those with firm-specific returns above the annual mean ("up" weeks) and calculate the standard deviation for each of these subsamples. I define $DUVOL_{i,t}$ for stock i in year t as the log of the ratio of the standard deviation of the down weeks to the standard deviation of the up weeks, as in Model (3):

$$DUVOL_{i,t} = Ln\left(\sum_{Down}\frac{W_{i,j}^2}{(n_u-1)} \Big/ \sum_{Up}\frac{W_{i,j}^2}{(n_d-1)}\right) \tag{3}$$

3.1.2. Identification of treatment firms

In my study, treatment firms are those firms whose products or services are directly aimed at consumers or end users and that have the ability to collect personal data (i.e., TOC firms). I follow the literature to identify treatment firms first by identifying consumer-sensitive industries based on China Securities Regulatory Commission (CSRC) industry codes. Firms in consumer-sensitive industries are likely to have products or services directly aimed at individual consumers or end users. Appendix A displays the names and CSRC codes of consumer-sensitive industries, as well as their correspondence with 4-digit Standard Industrial Classification codes.

I further identify firms' ability to collect personal data, a key characteristic of my treatment firms, based on the number of WCOAs owned by the firms. This identification strategy is rooted in China's institutional background and the definition of my treatment group. WCOAs have become a necessary means for TOC firms to reach their consumers and a representative channel for collecting personal data. After its launch in 2012, WeChat reached nearly 900 million users by 2016 and nearly 1.3 billion by 2022, making it the most used social software platform in China. Because of the vast user network and comprehensive functions of WeChat,

WCOAs enable firms to conduct business activities directly targeted at consumers and end users, such as product introductions, activity promotions and news publication through daily posts. Firms can also provide after-sales service and implement community operations using the interactive functions of WCOAs, as well as user registration, product purchases and store navigation. Firms with more WCOAs can conduct more types of business activities. More importantly, WCOAs provide firms with the ability to collect personal data (Lin, 2020; McKinnon and Wei, 2020). For example, the first step for users of the mini-programs of WCOAs is to consent to firms' collection of their personal data.

Therefore, I argue that TOC firms that collect personal data should be in consumer-sensitive industries and have a number of WCOAs. Accordingly, I define treatment firms as those in consumer-sensitive industries that have asset-standardized WCOAs in the top 30 % of the industry in 2016.[13]

3.1.3. Regression model

Following Bao et al. (2018), I construct DID Model (4) to examine the impact of the CSL on firm-level stock crash risk:

$$CrashRisk_{t+1} = \beta_0 + \beta_1 Treat + \beta_2 Treat \times Post + Controls_t + YearFE + IndustryFE + \delta \quad (4)$$

The dependent variable in Model (4) is firm-level stock crash risk, which is proxied by either negative conditional return skewness ($NCSKEW_{i,t+1}$) or down-to-up volatility ($DUVOL_{i,t+1}$). *Treat* is a dummy variable indicating treatment firms. *Post* is a dummy variable that equals 1 for years after the passage of the CSL (2017 and after). Following the literature, I control for firm-level stock crash risk in year t ($NCSKEW_t$) and other stock characteristics and financial and corporate governance variables. Among stock characteristics, I control for average weekly returns in year t (RET_t), the volatility of weekly returns in year t ($SIGMA_t$), the average weekly turnover rate in year t (HSL_t) and the book-to-market ratio (BM_t). Among financial variables, I control for firm size ($Size_t$), leverage ratio (Lev_t), return on assets (ROA_t) and operating cash flow (FCF_t). Among corporate governance variables, I control for discretionary accruals (DA_t), the shareholding percentage of the largest shareholder ($First_t$) and whether the firm is a state-owned enterprise (SOE, Soe_t). Year and industry fixed effects are also included in Model (4). Detailed variable definitions are provided in Appendix B. All continuous variables are winsorized at the top and bottom 1 % to eliminate extreme values.

3.2. Sample selection and data source

I compile my sample of Chinese listed firms from the Chinese Research Data Service. I initially sample all Chinese listed firms from 2013 to 2020, obtaining 24,538 firm–year observations for 4,083 unique firms. The sample period begins in 2013 because WCOAs were created in 2012. I choose 2020 as the end of my sample period to avoid the potential impact of two personal data security related laws passed in 2021. I obtain WCOA data from Tianyancha.com and then supplement these data with the financial and stock return data from the China Stock Market and Accounting Research database. In addition, I exclude financial and special treatment (ST) firms because of their unique reporting and regulatory requirements. After excluding observations with missing values for key variables, I obtain a final sample of 17,195 firm–year observations for 2,385 unique firms, comprising 375 treatment and 2,010 control firms.

4. Empirical results

4.1. Descriptive statistics

Table 1 provides the descriptive statistics of the main variables. In Panel A, the mean values of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ are –0.315 and –0.230, which are consistent with the literature on stock crash risk (Chen et al., 2018). Treatment firms account for 13.6 % of my sample. In terms of firm characteristics,

[13] Although TOC firms can also obtain personal data through other channels such as Weibo or even the firm's own app, such tools were not popular in 2016.

the mean values of $Size_t$ and Lev_t are 22.43 and 43.1 %, respectively. In addition, 39.5 % of my sample firms are SOEs. The descriptive statistics of the control variables are consistent with those in the literature.

Panel B provides the DID results for firm-level stock crash risk before and after the CSL. Before the CSL, treatment firms have significantly higher stock crash risk than control firms, whereas after the CSL, treatment and control firms have similar $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ values, which provide initial evidence that enhancing personal data security helps to reduce firm-level stock crash risk.

4.2. Validation tests for treatment identification

Before conducting empirical analysis, it is necessary to validate my identification of treatment firms, that is, to confirm that my treatment firms are TOC firms. I conduct three analyses, based on the textual, financial and operational characteristics of the sample firms, expecting treatment firms to behave more in line with consumer interests.

First, I compare the MD&A in the annual reports of treatment firms with the MD&A in those of control firms. Considering the importance of consumers to TOC firms, such firms should use more consumer-related words in their MD&A. I calculate the frequency of three key words, namely *consumers* (*xiaofeizhe* in Chinese), *customers* (*guke* in Chinese) and *users* (*yonghu* in Chinese), in MD&A sections. Panel A of Appendix C presents a comparison of the frequencies of those key words in the treatment and control firm MD&A sections, revealing that treatment firms use consumer-related words more frequently in their MD&A.

Second, in terms of financial characteristics, TOC firms should have a higher proportion of sales conducted online as online sales have become an important channel for such firms to sell to individual consumers because of the rapid development of the Internet. In addition, TOC firms should have a higher proportional advertis-

Table 1
Descriptive Statistics.

Panel A: Descriptive Statistics of Main Variables

Variable	Obs.	Mean	STD	Min	P25	Median	P75	Max
$NCSKEW_{t+1}$	17,195	–0.315	0.732	–2.549	–0.711	–0.272	0.120	1.765
$DUVOL_{t+1}$	17,195	–0.230	0.482	–1.421	–0.551	–0.230	0.087	1.020
Treat	17,195	0.136	0.343	0.000	0.000	0.000	0.000	1.000
Post	17,195	0.528	0.499	0.000	0.000	1.000	1.000	1.000
$NCSKEW_t$	17,195	–0.325	0.720	–2.502	–0.715	–0.280	0.107	1.710
RET_t	17,195	0.004	0.010	–0.015	–0.003	0.002	0.009	0.034
$SIGMA_t$	17,195	0.064	0.026	0.025	0.045	0.058	0.075	0.154
HSL_t	17,195	0.082	0.058	0.008	0.039	0.068	0.109	0.288
BM_t	17,195	0.623	0.255	0.122	0.428	0.610	0.815	1.184
$Size_t$	17,195	22.430	1.290	20.060	21.520	22.250	23.160	26.390
Lev_t	17,195	0.431	0.200	0.059	0.271	0.425	0.582	0.876
ROA_t	17,195	0.035	0.057	–0.248	0.013	0.034	0.062	0.185
FCF_t	17,195	0.049	0.065	–0.143	0.011	0.047	0.086	0.234
DA_t	17,195	0.052	0.055	0.001	0.016	0.036	0.068	0.304
$First_t$	17,195	0.340	0.148	0.085	0.225	0.318	0.438	0.742
Soe_t	17,195	0.395	0.489	0.000	0.000	0.000	1.000	1.000

Panel B: DID Test Results

Variable	Time	Treatment firms		Control firms		*Mean diff*	*DID tests*
		Obs	Mean	Mean	Obs		
$NCSKEW_t$	$Post = 0$	1251	–0.224	6857	–0.338	0.113^{***}	-0.113^{***}
	$Post = 1$	1460	–0.362	7627	–0.363	0.001	
$DUVOL_t$	$Post = 0$	1251	–0.158	6857	–0.228	0.070^{***}	-0.069^{***}
	$Post = 1$	1460	–0.240	7627	–0.241	0.001	

This table reports the key descriptive statistics of the analytical sample. The summary statistics of the key variables are reported in Panel A; the DID test results for key stock crash risk variables are reported in Panel B. Detailed variable definitions are presented in Appendix A.

ing expenditure because advertisements are another important channel for TOC firms to promote their products to individual consumers. I collect firms' 2016 online sales revenue in 2016 from the Wind database and 2016 advertising expenditure from the footnote of sales expenses and calculate the ratio of each to total sales revenue. The results in Panel B of Appendix C indicate that treatment firms have higher online sales revenue and advertising expenditures relative to their total sales revenue, which are features of TOC firms.

Third, in terms of operational characteristics, TOC firms should have a low ratio of sales revenue from large customers because their customers are likely to be diverse, individual consumers that pay relatively low amounts for individual orders. For example, Hefei Department Store (stock code: 000417) states in its annual report that "the company is mainly engaged in commodity retailing, and the customers are mainly individual consumers and extremely dispersed, so [they] do not have top five customers." Column C of Appendix C presents the ratio of the sales revenue from the top five customers to total sales revenue. I find consistent evidence that this ratio is lower for treatment firms than for control firms.

In summary, my treatment firms have characteristics consistent with TOC firms: They are likely to use consumer-related words in the MD&A sections of their annual reports and to have high proportions of their sales revenue attributed to online sales, large ratios of advertising expenditure to sales revenue and low sales revenue from large customers. While the characteristics mentioned above provide evidence from different dimensions validating my identification of TOC firms, no single characteristic is sufficient to comprehensively and accurately identify TOC firms that collect personal data. For example, although online sales revenue may be associated with personal data, the Wind database provides online sales revenue for only certain industries, limiting its ability to be used to identify all TOC firms.

4.3. Baseline results

Table 2 provides the baseline regression results for Model (4). I find that the coefficients of $Treat \times Post$ are negative and significant at the 1 % level for both $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ as the firm-level stock crash risk measure. These findings suggest that treatment firms experience a decrease in their stock crash risk after the CSL, consistent with my hypothesis. In terms of economic significance, after the passage of the CSL, the $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ of TOC firms decrease by approximately 29.5 % (0.093/0.315 = 0.2952) and 25.6 % (0.059/0.230 = 0.2565), respectively. Therefore, the CSL reduces firm-level stock crash risk both statistically and economically.

4.4. Robustness checks

4.4.1. Parallel trend test

A key assumption of the DID approach is that the dependent variable should show parallel trends for the treatment and control groups before the shock. To validate the parallel trend assumption for my sample, I construct Model (5) as follows:

$$\begin{aligned} CrashRisk_{t+1} = {} & \beta_0 + \beta_1 Treat + \beta_2 Treat \times Before3 + \beta_3 Treat \times Before2 + \beta_4 Treat \times Before1 + \beta_5 Treat \times After1 \\ & + \beta_6 Treat \times After2 + \beta_7 Treat \times After3 + \beta_8 Treat \times After4 + Controls_t + YearFE + IndustryFE + \gamma \end{aligned} \quad (5)$$

Beforei (*i* equals 1, 2 and 3) and *Afteri* (*i* equals 1, 2, 3 and 4) are series of dummy variables that respectively represent *i* years before and after the CSL. Panel A of Table 3 presents the regression results. The coefficients of *Treat* × *Before3*, *Treat* × *Before2* and *Treat* × *Before1* are all nonsignificant, suggesting that the firm-level stock risk of the treatment and control firms satisfies the parallel trend assumptions. In addition, the estimated coefficients for *Treat* × *Afteri* are negative and significant, and their economic magnitude increases over time, indicating that the CSL reduces firm-level stock crash risk and that the effects become stronger over time.

4.4.2. Placebo tests

One concern with my analysis is that the results might be driven by unobserved firm characteristics or factors that coincide with the sample period. I conduct falsification tests to rule out those possibilities. If the

Table 2
Baseline Results.

Variable	$NCSKEW_{t+1}$		$DUVOL_{t+1}$	
	(1)	(2)	(3)	(4)
Treat	0.097***	0.046*	0.057***	0.019
	(3.65)	(1.82)	(3.09)	(1.08)
Treat* × *Post	**–0.124*** **	**–0.093*** **	**–0.079*** **	**–0.059*** **
	(–3.75)	**(–2.96)**	**(–3.58)**	**(–2.75)**
$NCSKEW_t$		0.055***		0.034***
		(6.94)		(6.44)
RET_t		11.208***		7.564***
		(11.87)		(11.91)
$SIGMA_t$		–0.488		–0.679**
		(–1.18)		(–2.46)
HSL_t		–0.425***		–0.305***
		(–3.05)		(–3.34)
BM_t		–0.061*		0.016
		(–1.71)		(0.70)
$Size_t$		–0.015**		–0.029***
		(–2.29)		(–6.34)
Lev_t		–0.184		–0.082
		(–1.51)		(–1.02)
ROA_t		–0.052		–0.022
		(–1.38)		(–0.89)
FCF_t		0.006		–0.054
		(0.07)		(–0.88)
DA_t		0.182*		0.089
		(1.73)		(1.29)
$First_t$		–0.064		–0.036
		(–1.58)		(–1.31)
Soe_t		–0.049***		–0.031***
		(–3.85)		(–3.70)
Constant	–0.262***	0.162	–0.172***	0.494***
	(–6.46)	(1.12)	(–5.24)	(5.00)
FE	Year & Industry	Year & Industry	Year & Industry	Year & Industry
Observations	17,195	17,195	17,195	17,195
Adj R^2	0.040	0.067	0.041	0.067

This table reports the baseline results indicating the effect of the CSL on firms' stock crash risk. In the first two columns, the dependent variable is $NCSKEW_{t+1}$, which is negative conditional return skewness (Kim et al., 2011b). In the last two columns, the dependent variable is $DUVOL_{t+1}$, which is down-to-up volatility (Chen et al., 2001). *Treat* is a dummy variable that equals 1 for TOC firms, that is, firms in consumer-sensitive industries that have WCOAs scaled by total assets in 2016 in the top tercile of the industry. *Post* is a dummy variable that equals 1 for the period after the CSL is passed and 0 otherwise. Year and industry fixed effects are included in all regressions. Detailed variable definitions are presented in Appendix B. *t* statistics based on robust standard errors clustered at the firm level are reported in parentheses. Coefficients marked with *, ** and *** are significant at the 10 %, 5 % and 1 % levels, respectively.

observed decrease in stock crash risk for TOC firms is indeed caused by the enforcement of the CSL, then my results should disappear when I use a different year as a pseudo-CSL. For Panel B of Table 3, I set either 2015 or 2017 as the year of the pseudo-CSL event. *Post_Pseudo* is a dummy variable that equals 1 for years after the pseudo-CSL, and 0 otherwise. I find no evidence that the firm-level stock crash risk decreases after the pseudo-CSL.

4.4.3. Propensity score matching

I use propensity score matching (PSM) to rule out the possibility that my results are driven by a fundamental difference between the treatment and control groups. Specifically, I first estimate the probability that a firm belongs to the treatment group by using logit regression with the same control variables used in Model (4). I

Table 3
Robustness Tests.

Panel A: Parallel Trend Tests

Variable	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)
Treat	0.059	0.053
	(1.25)	(1.64)
Treat × *Before3*	–0.036	–0.032
	(–0.65)	(–0.82)
Treat × *Before2*	0.072	–0.002
	(1.10)	(–0.05)
Treat × *Before1*	0.042	–0.010
	(0.68)	(–0.24)
Treat × *After1*	–0.103*	–0.081*
	(–1.75)	(–1.95)
Treat × *After2*	–0.112*	–0.076*
	(–1.82)	(–1.91)
Treat × *After3*	–0.134**	–0.084**
	(–2.19)	(–2.00)
Treat × *After4*	–0.132**	–0.104***
	(–2.21)	(–2.63)
Controls	Y	Y
Year FE	Y	Y
Industry FE	Y	Y
Observations	17,195	17,195
Adj R^2	0.041	0.041

Panel B: Placebo Tests

Variable	$NCSKEW_{t+1}$		$DUVOL_{t+1}$	
	(1)	(2)	(3)	(4)
Placebo Shock Year	2013	2014	2013	2014
Treat	0.015	0.003	0.036	0.013
	(0.30)	(0.08)	(1.07)	(0.57)
Treat×*Post_Pseudo*	–0.021	–0.008	–0.054	–0.034
	(–0.43)	(–0.24)	(–1.60)	(–1.34)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Observations	17,195	17,195	17,195	17,195
Adj R^2	0.066	0.066	0.067	0.067

Panel C: PSM

Variable	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)
Treat	0.061	0.030
	(1.58)	(1.15)
Treat×*Post*	–0.055***	–0.058***
	(–2.04)	(–3.47)
Controls	Y	Y
Year FE	Y	Y
Industry FE	Y	Y
Observations	4,180	4,180
Adj R^2	0.051	0.048

(*continued on next page*)

Table 3 (*continued*)

Panel D: Sensitivity Tests for Treatment Identification

Variable	WCOAs plus Weibo in the top industry tercile		WCOAs above industry median		Number of WCOAs	
	(1)	(2)	(3)	(4)	(5)	(6)
	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Treat_New	0.044*	0.017	–0.008	–0.017	0.233***	0.111*
	(1.79)	(1.02)	(–0.34)	(–1.09)	(2.72)	(1.92)
Treat_New×Post	–0.121***	–0.064***	–0.081***	–0.039**	–0.307**	–0.169*
	(–3.97)	(–3.10)	(–2.97)	(–2.15)	(–2.26)	(–1.91)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Observations	17,195	17,195	17,195	17,195	17,195	17,195
Adj R^2	0.067	0.068	0.067	0.068	0.067	0.068

Panel E: Using Online Sales to Identify Treatment Firms

Variable	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)
OnlineSale	0.024	0.039**
	(1.53)	(2.32)
OnlineSale × Post	–0.035*	–0.061***
	(–1.67)	(–2.69)
Controls	Y	Y
Year FE	Y	Y
Industry FE	Y	Y
Observations	17,195	17,195
Adj R^2	0.067	0.069

Panel F: Alternative Fixed Effects

Variable	Year and firm fixed effects		Year, industry and province fixed effects		Year, industry and year×industry fixed effects	
	(1)	(2)	(3)	(4)	(5)	(6)
	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$	$NCSKEW_{t+1}$	$DUVOL_{t+1}$
Treat×Post	–0.123***	–0.076***	–0.094***	–0.059***	–0.084***	–0.057***
	(–3.87)	(–3.62)	(–2.98)	(–2.77)	(–2.60)	(–2.69)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	N	N	N	N
Province FE	N	N	Y	Y	N	N
Industry FE	N	N	Y	Y	Y	Y
Year FE× Industry FE	N	N	N	N	Y	Y
Observations	17,195	17,195	17,195	17,195	17,195	17,195
Adj R^2	0.097	0.091	0.067	0.067	0.065	0.063

Table 3 (*continued*)

Panel G: Tail Risk	
Variable	$TailRisk_t$
	(1)
Treat	0.005
	(0.25)
Treat×*Post*	–0.061**
	(–2.19)
Controls	Y
Year FE	Y
Industry FE	Y
Observations	17,195
Adj R^2	0.129

This table reports the results of robustness tests. The dependent variables in all Panels except Panel G are either negative conditional return skewness ($NCSKEW_{t+1}$) or down-to-up volatility ($DUVOL_{t+1}$). *Treat* is a dummy variable that equals 1 for TOC firms, that is, firms in consumer-sensitive industries that have WCOAs scaled by total assets in 2016 in the top tercile of the industry. *Post* is a dummy variable that equals 1 for the period after the CSL is passed, and 0 otherwise. Panel A provides the results of parallel trend tests, where the benchmark year is 2013 (*Before3*). *Beforei* (*i* equals 1, 2 or 3) and *Afteri* (*i* equals 1, 2, 3 or 4) are series of dummy variables that respectively represent *i* years before and after the CSL. Panel B reports the results of placebo tests. For columns (1) and (3), *Post_Pseudo* equals 1 for 2015 and after, and 0 before 2015. For columns (2) and (4), *Post_Pseudo* equals 1 for year 2017 and after, and 0 before 2017. Panel C provides the results of the PSM analysis. I first conduct logit regression to estimate the probability of a firm being a treatment firm using data from 2016. The control variables in Model (4) are included in the logit regression. I match each treatment firm with the control firm with the closest propensity score. Panel D provides the results of various sensitive sensitivity tests for the treatment identification. For columns (1) and (2), *Treat_New* equals 1 for firms in consumer-sensitive industries that have ratios of WCOAs plus Sina Weibo to total assets in the top tercile of the industry in 2016, and 0 for all other firms. For columns (3) and (4), *Treat_New* equals 1 for firms in consumer-sensitive industries with ratios of WCOAs to total assets above the industry median in 2016, and 0 for all other firms. For columns (5) and (6), *Treat_New* equals the number of WCOAs scaled by total assets for firms in consumer-sensitive industries, and 0 for other firms. In Panel E, *OnlineSale* is a dummy variable that equals 1 if the firm is in a consumer-sensitive industry and has online sales revenue in 2016, and 0 otherwise. Panel F provides the results of controlling for alternative fixed effects. Finally, Panel G provides the results indicating the impact of the CSL on firms' tail risk. Detailed variable definitions are presented in Appendix B. *t* statistics based on robust standard errors clustered at the firm level are reported in parentheses. Coefficients marked with *, ** and *** are significant at the 10 %, 5 % and 1 % levels, respectively.

match each treatment firm observation with the control firm observation that has the closest propensity score in the same year. The results in Panel C of Table 3 indicate that my main results are robust.

4.4.4. Other robustness checks

I conduct several sensitivity tests for the identification of treatment firms and obtain results indicating the robustness of main tests. First, I use other mobile apps to capture firms' ability to collect personal data. In 2016, Sina Weibo was an important way for firms to interact with consumers and conduct business activities, in addition to WCOAs. Greater Weibo exposure reflects closer proximity of firms to consumers and users. I obtain Sina Weibo data for my sample firms from Tianyancha.com and define an alternative treatment group for firms that are in consumer-sensitive industries with ratios of WCOAs plus Sina Weibo to total assets in the top tercile of the industry. Second, I define treatment firms as those in consumer-sensitive industries that also have a ratio of WCOAs to total assets above the industry median. Third, I use the number of WCOAs to identify treatment firms. In the last two columns of Panel D in Table 3, *Treat_New* indicates the number of WCOAs scaled by total assets for firms in consumer-sensitive industries and 0 for other firms. Lastly, I use the presence of online sales revenue to identify treatment firms. In Panel E of Table 3, *OnlineSale* is a dummy variable that equals 1 if the firm is in a consumer-sensitive industry and has online sales revenue in 2016, and 0 otherwise.

I also test the robustness of my baseline results by using alternative fixed effects, including (1) firm and year fixed effects; (2) industry, year and province fixed effects; and (3) industry, year and industry × year fixed effects. The results in Panel F of Table 3 indicate that my baseline results are robust.

Lastly, I examine the impact of the CSL on firms' tail risk, which is the probability of a sharp stock price decline in a certain period. Following Atilgan et al. (2020), I use the maximum value of the cumulative decline over two consecutive trading days in year t–1 to measure tail risk in year t ($TailRisk_t$). The results in Panel G of Table 3 illustrate that the tail risk of treatment firms declines after the CSL, which is consistent with the explanation that the CSL reduces the possibility of large data breaches and the likelihood of negative news being released to the market, thus reducing the tail risk.

4.5. Cross-sectional tests

Stock crash risk increases when firms have bad news that can be withheld by managers. I argue that the CSL reduces firms' personal data breach risk by increasing firms' investment in data security and limiting managers' ability to hide bad news related to data breaches, leading to a decrease in stock crash risk. Therefore, I expect the effect indicated by my baseline results to be stronger for firms with a greater data breach risk or more opaque information environment before the CSL.

4.5.1. Data breach risk

Data breach risk is largely determined by firms' internal control quality and whether managers take data security seriously. Data breaches are mainly due to insider leaks or external attacks, which are both related to firms' internal control weaknesses (D'Arcy et al., 2020).[14] Firms can significantly reduce their data breach risk by implementing effective internal control systems, such as the strict separation of the authority and responsibility to avoid data breaches during daily operations and the establishment of strong firewalls and complex encryption systems to defend against external attacks. Accordingly, I expect the effect of the CSL to be stronger for firms with lower internal quality before the CSL, and I use two variables as proxies for firms' internal control quality. First, I use the DIB Internal Control Index to directly measure firms' internal control quality and divide my sample into two groups based on whether its value in 2016 is higher than the industry median. Second, audit quality could have a direct impact on firms' internal control quality and thus on firms' data breach risk. Liu (2024) conducts surveys of audit partners and find that they are concerned about their clients' data breach risk because data breaches indicate audit and internal control failures.[15] Higher audit quality is therefore associated with higher internal control quality and lower data breach risk. I divide my sample firms into two groups based on whether their 2016 audit firm is among the top five as ranked by the Chinese Institute of Certified Public Accountants. These top five audit firms are expected to provide higher audit quality. The cross-sectional regression results are displayed in Panel A and Panel B of Table 4, showing that my baseline results are stronger for firms with lower internal control quality before the CSL.

Second, managers' attention to data security could directly impact firms' investment in data security and thus their data breach risk. Recent studies show that managers are more prone to cut investment in data security when they are under earnings pressure (Chen et al., 2019), as a consequence of managerial myopia and inattention to data breach risk. I check whether firms experience sales declines in two consecutive years (2015 and 2016) before the CSL to measure firms' earnings pressure and divide my sample into two groups. The results in Panel C of Table 4 indicate that the role of the CSL is more pronounced for firms under higher earnings pressure (i.e., firms that have successive sale decreases).

[14] Insider leaks include intentional data breaches caused by employees or irregularities in the daily operation of enterprises. External attacks are usually successful because of weaknesses in firms' information systems.

[15] Audit partners expressed three reasons to Liu (2024) for attaching importance to the risk of personal data breaches at their client firms. First, a high risk of data breaches implies low internal control quality. Second, data breaches directly damage the auditor's reputation. Third, because personal data are an important asset for firms, data breaches also affect firms' operational and financial conditions.

Table 4
Cross-sectional Analysis on Data Breach Risk.

Panel A: Internal Control Quality

Variable	$NCSKEW_{t+1}$		$DUVOL_{t+1}$	
	(1)	(2)	(3)	(4)
	IC index: high	IC index: low	IC index: high	IC index: low
Treat	0.015	0.056*	–0.003	0.027
	(0.41)	(1.66)	(–0.11)	(1.17)
Treat × *Post*	–0.084**	–0.106***	–0.045	–0.064**
	(–2.19)	(–2.62)	(–1.59)	(–2.31)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Observations	8,010	9,185	8,010	9,185
Adj R^2	0.072	0.063	0.072	0.066
Diff-tests (*P* value)	0.104		0.122	

Panel B: Audit Quality

Variable	$NCSKEW_{t+1}$		$DUVOL_{t+1}$	
	(5)	(6)	(7)	(8)
	Big 5	Non-Big 5	Big 5	Non-Big 5
Treat	0.025	0.042	–0.008	0.025
	(0.57)	(1.38)	(–0.28)	(0.97)
Treat×*Post*	–0.083	–0.103***	–0.032	–0.069**
	(–1.26)	(–3.00)	(–0.86)	(–2.53)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Observations	5,586	11,609	5,586	11,609
Adj R^2	0.072	0.064	0.077	0.058
Diff-tests (*P* value)	0.093*		0.084*	

Panel C: Earnings Pressure

Variable	$NCSKEW_{t+1}$		$DUVOL_{t+1}$	
	(1)	(2)	(3)	(4)
	High	Low	High	Low
Treat	0.072	0.030	0.038	0.007
	(1.44)	(1.04)	(1.08)	(0.35)
Treat×*Post*	–0.150**	–0.085**	–0.090**	–0.044**
	(–2.51)	(–2.52)	(–2.14)	(–1.97)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Observations	4,450	12,745	4,450	12,745
Adj R^2	0.062	0.068	0.060	0.071
Diff-tests (*P* value)	0.004***		0.022**	

This table presents the cross-sectional analysis results. The dependent variable is either negative conditional return skewness ($NCSKEW_{t+1}$) or down-to-up volatility ($DUVOL_{t+1}$). *Treat* is a dummy variable that equals 1 for TOC firms, that is, firms in consumer-sensitive industries with WCOAs scaled by total assets in 2016 in the top tercile of the industry. *Post* is a dummy variable that equals 1 for the period after the CSL is passed, and 0 otherwise. For Panel A, I divide the sample firms into two groups based on whether the DIB Internal Control (IC) Index of the firm in 2016 is higher than the industry median. For Panel B, I divide the sample firms into two groups based on whether they are audited by one of the Big 5 auditing firms in 2016. For Panel C, I divide the sample firms into two groups based on whether the firm faces high earnings pressure before the CSL. A firm faces high earnings pressure if it experiences sale declines in two consecutive years (i.e., 2015 and 2016). The same set of control variables is included as in the regressions for Table 2 but not reported for brevity. Year and industry fixed effects are included in all regressions. *P* values from Fisher's permutation test (*F* test) of the equality of the coefficient of *Treat* × *Post* across the two subsamples are also presented. Detailed variable definitions are presented in Appendix B. *t* statistics based on robust standard errors clustered at the firm level are reported in parentheses. Coefficients marked with *, ** and *** are significant at the 10 %, 5 % and 1 % levels, respectively.

Table 5
Cross-Sectional Analysis of the Information Environment.

Panel A: Analyst Coverage				
Variable	$NCSKEW_{t+1}$		$DUVOL_{t+1}$	
	(1)	(2)	(3)	(4)
	High	Low	High	Low
Treat	0.018	0.050	–0.003	0.026
	(0.54)	(1.37)	(–0.12)	(1.06)
Treat × Post	–0.100	–0.116***	–0.039	–0.082***
	(–1.55)	(–2.59)	(–1.50)	(–2.72)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Observations	7,567	9,628	7,567	9,628
Adj R^2	0.075	0.063	0.076	0.066
Diff-tests (*P* value)	0.226		0.052*	
Panel B: Media Coverage				
Variable	$NCSKEW_{t+1}$		$DUVOL_{t+1}$	
	(5)	(6)	(7)	(8)
	High	Low	High	Low
Treat	0.032	0.062*	0.014	0.024
	(0.89)	(1.87)	(0.63)	(0.95)
Treat×Post	–0.075*	–0.133***	–0.042*	–0.072**
	(–1.78)	(–3.22)	(–1.93)	(–2.15)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Observations	8,157	9,038	8,157	9,038
Adj R^2	0.074	0.064	0.078	0.061
Diff-tests (*P* value)	0.042**		0.128	

This table presents cross-sectional analysis results. The dependent variable is either negative conditional return skewness ($NCSKEW_{t+1}$) or down-to-up volatility ($DUVOL_{t+1}$). *Treat* is a dummy variable that equals 1 for TOC firms, that is, firms in consumer-sensitive industries with WCOAs scaled by total assets in 2016 in the top tercile of the industry. *Post* is a dummy variable that equals 1 for the period after the CSL is passed, and 0 otherwise. For Panel A, I divide the sample firms into two groups based on whether the logarithm of the number of analysts issuing forecasts for the firm in 2016 is above the industry median. For Panel B, the sample firms are divided into two groups based on whether the logarithm of the number of media reports for the firm in 2016 is above the industry median. The same set of control variables is included as in the regressions for Table 2 but not reported for brevity. Year and industry fixed effects are included in all regressions. *P* values from Fisher's permutation test (*F* test) of the equality of the coefficient of *Treat* × *Post* across the two subsamples are also presented. Detailed variable definitions are presented in Appendix B. *t* statistics based on robust standard errors clustered at the firm level are reported in parentheses. Coefficients marked with *, ** and *** are significant at the 10 %, 5 % and 1 % levels, respectively.

4.5.2. Information environment

Managers are more likely to hide bad news from the market when their firms' information environments are more opaque, that is, when the severity of data breaches that managers can hide is higher and more negative relating to the stock price can accumulate, leading to a higher stock crash risk. If the CSL reduces firms' stock crash risk by curbing mangers' ability to hide data breaches, my results should be stronger for firms that have lower information transparency before the CSL. I use analyst and media coverage in 2016 to measure firms' information transparency, where firms with greater analyst and media coverage have more transparent information environments.[16] As in the above cross-sectional analysis, I separately divide my sample into two groups based on whether the analyst coverage (number of media reports) in 2016 is higher than

[16] I use the number of analyst teams that issue earnings forecasts for the firm in 2016 and the number of media reports as empirical proxies.

the industry median. The results in Panel A and Panel B of Table 5 suggest that firms with more opaque information environments experience larger stock crash risk decreases after the CSL.

5. Additional analyses

5.1. Mechanism tests

I further investigate whether the CSL promotes firms' investment in personal data security, which could be a direct channel for the decrease in stock crash risk as treatment firms should have less bad news about data security after the CSL. I consider both human and nonhuman capital investments. First, recent labor economy literature shows that the labor skill that firms demand reflects their investment in human capital (Darendeli et al., 2022). Therefore, if firms increase their investment in data security, they should hire employees, particularly managers, with IT-related skills. I use three empirical variables as proxies for firms' human capital investment in data security: CXO_t is a dummy variable that equals 1 if the firm has at least one of chief technology officer (CTO), chief information officer (CIO) or chief digital officer (CDO), and 0 otherwise; $IT\_Manager_t$ is a dummy variable that equals 1 if there are managers with IT backgrounds among the top management, and 0 otherwise; and $IT\_ManRatio_t$ equals the ratio of the number of managers with IT backgrounds to the total number of top managers.

Second, directly measuring firms' nonhuman capital investment is difficult because it is not disclosed in financial reports. However, enhancing data security requires firms to increase investment in their information systems (i.e., IT), including databases, encryption software, internal control systems and servers. Therefore, I use firms' investment in IT hardware and software divided by total assets (IT_Invest_t) to measure their investment in personal data security.

I replace the dependent variables in Model (4) with the above mechanism variables. Table 6 provides the regression results. In Columns (1) to (4), the coefficients are all positive and significant, suggesting that treatment firms are more likely to hire CTOs, CIOs or CDOs after the CSL and that treatment firms increase their

Table 6
CSL and Firms' Investment in Personal Data Security.

Variable	IT_Invest_t	CXO_t	$IT\_Manager_t$	$IT\_ManRatio_t$	DB_Risk_t
	(1)	(2)	(3)	(4)	(5)
Treat	0.016	–0.002	–0.015	–0.004	0.125***
	(1.29)	(–0.37)	(–0.89)	(–1.03)	(3.29)
Treat × *Post*	0.031***	0.006*	0.031**	0.009**	–0.101***
	(2.67)	(1.81)	(2.14)	(2.48)	(–2.59)
$Controls_t$	Y	Y	Y	Y	Y
Year *FE*	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Observations	17,195	17,195	17,195	17,195	17,195
Adj/Pseudo-R^2	0.081	0.018	0.143	0.115	0.134

This table reports the results for the effect of the CSL on firms' investment in personal data security. For column (1), the dependent variable is firms' investment in IT hardware and software divided by total assets (IT_Invest_t). For column (2), the dependent variable is a dummy variable (CXO_t) that equals 1 if the firm has at least one CTO, CIO or CDO, and 0 otherwise. For column (3), the dependent variable is a dummy variable ($IT\_Manager_t$) that equals 1 if there are managers with IT backgrounds on the top management team, and 0 otherwise. For column (4), the dependent variable is the ratio of the number of managers with IT backgrounds to the total number of top managers ($IT\_ManRatio_t$). For column (5), the dependent variable is the number of data security-related words divided by the total number of words in the texts of firms' MD&A sections, conference calls and investors' site visits, multiplied by 100 (DB_Risk_t). *Treat* is a dummy variable that equals 1 for TOC firms, that is, firms in consumer-sensitive industries with WCOAs scaled by total assets in 2016 in the top tercile of the industry. *Post* is a dummy variable that equals 1 for the period after the CSL is passed, and 0 otherwise. The same set of control variables is included as used in the regression for Table 2 but not reported for brevity. Year and industry fixed effects are included in all regressions. Detailed variable definitions are presented in Appendix B. *t* statistics based on robust standard errors clustered at the firm level are reported in parentheses. Coefficients marked with *, ** and *** are significant at the 10%, 5% and 1% levels, respectively.

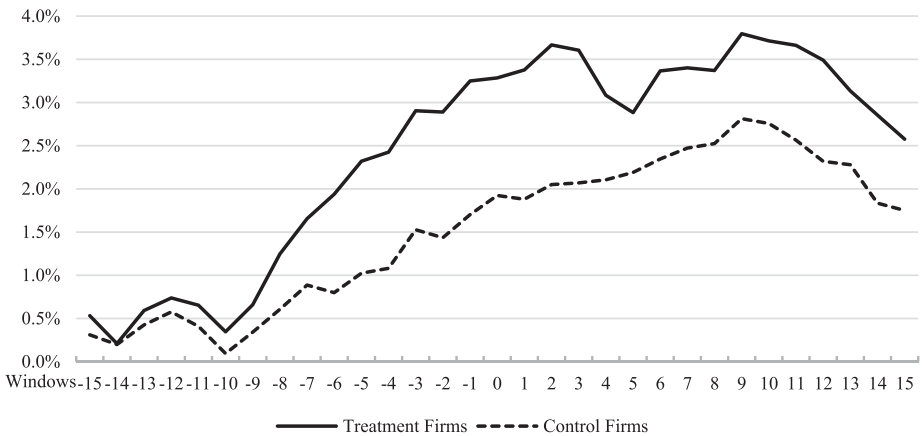

Fig. 1. Market Reaction to the CSL**.** This figure illustrates the average cumulative abnormal returns in a 30-day window around the passage of the CSL for the treatment and control groups. Day 0 is 7 November 2016, the day that the CSL was passed. The cumulative abnormal returns equal the sum of daily abnormal returns. The daily abnormal return equals the firm's daily return minus the market's daily return.

investment in IT. To further investigate whether such investment could reduce firms' data breach risk, I use textual analysis to construct a firm-level data breach risk measure, DB_Risk_t, based on the texture of firms' MD&A, conference calls and investor site visits, and find that it is positively associated with firms' data security risk.[17] As presented in Column (5) of Table 6, I find that the data breach risk of treatment firms decreases after the CSL. Unreported results indicate that treatment firms with greater data security investment have a lower data breach risk after the CSL. Overall, the above results suggest that the CSL reduces firms stock crash risk by promoting investment in personal data protection, reducing data breach risk.

5.2. Market reaction to the CSL

A question begged by my results is how the market reacts to the CSL. To answer this question, I calculate the cumulative abnormal returns (*CAR*) for individual stocks in the three (five) days surrounding the passage of the CSL (7 November 2016), where the daily abnormal return of an individual stock equals the firm's daily return minus the market return. Fig. 1 illustrates the average *CAR* of the treatment and control firms. I find that treatment firms have higher positive abnormal returns than control firms on the days surrounding the passage of the CSL. I also conduct empirical analysis (Table 7); the results of a *CAR* difference test and regression test are both consistent with the results in Fig. 1. These market reaction tests provide evidence that the CSL increases shareholder wealth.

5.3. Economic consequences for other stakeholders

In the era of the digital economy, the bonding of personal data makes consumers, users and employees important stakeholders who, by allowing firms to collect and use their personal data, tacitly agree based on an implicit contract that the firm should take the responsibility for the security of their data. A major reason for stock crashes in my research setting is that data breaches undermine the trust that such stakeholders have in firms because firms do not fulfill their social responsibility to protect personal data. If the CSL requires

[17] Specifically, I first select *cyber*-, *data*- and *information system*-related words based on the CSL, Personal Information Protection Law and Data Security Law as seed words. I use a Python algorithm to train word vectors from the corresponding texture of listed firms' reports and construct a key word dictionary. Finally, I calculate the number of data security-related words divided by the total number of words in this texture, multiplied by 100, as a firm-level measure of data breach risk.

Table 7
Market Reaction to the CSL.

Panel A: Difference Tests					
Window	Treatment firms		Control firms		*Mean difference*
	Mean	Median	Mean	Median	
[–1,+1]	0.006	0.002	0.004	0.002	0.002*
[–2,+2]	0.008	0.005	0.003	0.003	0.008***

Panel B: Regression Analysis		
Variable	*CAR*[–1,+1]	*CAR*[–2,+2]
	(1)	(2)
Treat	0.0003**	0.0012**
	(2.02)	(2.34)
Controls	Y	Y
Industry FE	Y	Y
Observations	2,189	2,189
Adj R^2	0.049	0.057

This table reports the market reaction to the CSL. Panel A reports the cumulative abnormal returns in the three- and five-day windows surrounding the passage of the CSL for the treatment and control groups. Cumulative abnormal returns equal the sum of daily abnormal returns in the corresponding window, where the daily abnormal return is the firm's daily return minus the market daily return. Panel B provides the regression results of market reactions for the CSL. *Treat* is a dummy variable that equals 1 for TOC firms, that is, firms in consumer-sensitive industries with WCOAs scaled by total assets in 2016 in the top tercile of the industry. The same set of control variables is included as in the regressions for Table 2 but not reported for brevity. Industry fixed effects are included in both regressions. Detailed variable definitions are presented in Appendix B. *t* statistics based on robust standard errors clustered at the firm level are reported in parentheses. Coefficients marked with *, ** and *** are significant at the 10%, 5% and 1% levels, respectively.

firms to uphold their responsibility to ensure data security, does the CSL improve TOC firms' CSR performance?

I use the CSR score from Hexun.com ($Total\_Score_t$) to measure firms' CSR performance. The CSR score from Hexun.com evaluates multiple subdimensions, such as CSR to employees, customers and shareholders, allowing me to identify the impact of the CSL on firms' CSR to different stakeholders. I replace the dependent variables in Model (4) with a series of CSR score variables and report the regression results in Table 8. As

Table 8
CSL and CSR performance.

Variable	$Total\_Score_t$	$Staff\_Score_t$	SSC_Score_t	$Shareholder\_Score_t$	$Social\_Score_t$
	(1)	(2)	(3)	(4)	(5)
Treat	0.031	–0.093**	–0.069	0.013	0.250***
	(1.23)	(–2.58)	(–1.52)	(0.68)	(7.49)
Treat × *Post*	0.075***	0.082***	0.108**	0.028	0.004
	(2.95)	(2.99)	(2.41)	(1.46)	(0.16)
$Controls_t$	Y	Y	Y	Y	Y
Year *FE*	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Observations	17,195	17,195	17,195	17,195	17,195
Adj. R^2	0.495	0.170	0.174	0.575	0.275

This table reports the results for the effect of the CSL on firms' CSR performance. For column (1), the dependent variable is the CSR score from Hexun.com ($Total\_Score_t$). For columns (2), (3), (4) and (5), the dependent variable is the CSR score for employees ($Staff\_Score_t$), customers (SSC_Score_t), shareholders ($Shareholder\_Score_t$) and society ($Social\_Score_t$), respectively. *Treat* is a dummy variable that equals 1 for TOC firms, that is, firms in consumer-sensitive industries that have WCOAs scaled by total assets in 2016 in the top tercile of the industry. *Post* is a dummy variable that equals 1 for the period after the CSL is passed, and 0 for all other firms. The same set of control variables is included as in the regression for Table 2 but not reported for brevity. Year and industry fixed effects are included in all regressions. Detailed variable definitions are presented in Appendix B. *t* statistics based on robust standard errors clustered at the firm level are reported in parentheses. Coefficients marked with *, ** and *** are significant at the 10%, 5% and 1% levels, respectively.

Column (1) reveals, I find that treatment firms have better CSR performance than control firms as the coefficient of *Treat* × *Post* is positive and significant. For Columns (2), (3), (4) and (5), firms' CSR to employees ($Staff\_Score_t$), customers (SSC_Score_t), shareholders ($Shareholder\_Score_t$) and society ($Social\_Score_t$), respectively, is the dependent variable. I find that the better overall CSR performance of treatment firms is mainly derived from their superior CSR to employees and customers and not that to shareholders or society. These findings are consistent with the notion that enhancing data security promotes firms' social responsibility to stakeholders in the digital economy.

6. Conclusions, implications and limitations

In this paper, I exploit a natural experiment, namely the passage of the CSL in China, to study the economic effects of enhancing personal data security on the capital market. My results indicate that the CSL significantly reduces the stock crash risk of TOC firms that hold personal data in the digital economy. This finding is proven robust to a series of tests, including parallel trend and placebo tests. Cross-sectional analyses reveal that the impact of the CSL is more pronounced for firms with a higher ex ante data breach risk, that is, firms that have weaker internal control, pay less attention to data security and have more opaque information environments. Additional analyses reveal that the CSL adds value to TOC firms as those treatment firms experience positive market reactions around the passage of the CSL. Furthermore, enhancing personal data security protects consumers and employees and improves these parties' trust in firms, resulting in better CSR performance for these stakeholders. Overall, my results are consistent with the notions that personal data constitute an important asset and source of risk in the digital economy and that promoting data security is important for firms and a variety of stakeholders.

While my study contributes to the literature on both data breaches and stock crash risk, it has several limitations, which could be overcome by further research. First, constrained by current disclosure regulations, I am unable to obtain data on actual investment in data security and therefore unable to directly test the determinants and consequences of data security investment. Second, because listed firms are not required to disclose their data breaches, my study does not focus on the effect of the CSL on the actual data breaches, including incidents and loss amounts. Finally, my conclusion does not necessarily mean that the CSL can totally eliminate data breach risk. Large-scale data breaches at listed firms have occurred in recent years. Effectively preventing data breaches relies on the joint efforts of firms, regulators and users. My study provides only initial evidence of the positive effects of the CSL in strengthening data security from the perspective of capital market stabilization. Future research could explore other effects, including the negative effects, of the CSL.

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. Consumer-Sensitive Industries

This appendix provides the CSRC industry codes and names for customer-sensitive industries based on the industry classification by Lev et al. (2009).

CSRC code	CSRC name	Corresponding Standard Industrial Classification code
A01–A04	Agriculture, forestry, animal husbandry and fishery	0000–0999, 5150–5159
C13	Farm and sideline food processing	5140–5149
C14	Food manufacturing	5140–5149
C15	Manufacturing of wine, beverages and refined tea	5140–5149
C18	Apparel and finished products from fabrics	2300–2399
C19	Leather and leather products	3100–3199
C21	Furniture and home furnishings	2500–2599, 5700–5799
C23	Printing, publishing and allied industries	2700–2799
C24	Cultural product manufacturing	2700–2799
C27	Medicine	2830–2839, 3850–3859
C36	Motor industry	5010–5019
F52	Retail industry	3870–3879, 5900–5999
H	Hotel and catering sectors	5800–5899, 7000–7099
I63	Telecommunications and radio and satellite transmission services	4830–4849
I64	Internet and related services	4830–4849
K	Realty business	6531
N78	Public facility management	9100–9799
O	Service	7200–7599, 8100–8399
P	Education	8299
Q	Health	8099, 8322
R	Culture, sports and entertainment	4830–4849

Appendix B. Variable Definitions

Variable	Detailed definition
NCSKEW	Negative conditional return skewness
DUVOL	Down-to-up volatility
Treat	Dummy variable that equals 1 if the firm belongs to a consumer-sensitive industry and its WCOAs scaled by total assets in 2016 are in the top tercile of the industry, and 0 otherwise
Post	Dummy variable that equals 1 if the year is in the post-CSL period (2017, 2018 or 2019), and 0 otherwise
RET	Average weekly holding return
SIGMA	Standard deviation of weekly return
HSL	Average weekly turnover rate
BM	Book-to-market ratio
Size	Natural logarithm of total assets
Lev	Ratio of total debt to total assets
ROA	Ratio of net profit to total assets
FCF	Sum of cash flow from operation and investment activities, divided by total assets

(*continued on next page*)

(*continued*)

Variable	Detailed definition
DA	Discretionary accruals measured as the residuals calculated from the Jones model
First	Shareholding ratio of the largest shareholders
Soe	Dummy variable that equals 1 for SOEs, and 0 otherwise

Appendix C. Validation Tests for Treatment Identification

This appendix provides the results of the validation tests for treatment identification. Panel A compares the frequency of consumer-related key words in the MD&A sections of treatment and control firms' reports. Panel B compares the proportion of sales revenue attributable to online sales and the ratio of advertising expenditure to total sales revenue in the treatment and control groups. Panel C compares the ratio of the sales revenue from the top five customers to total sales revenue in the treatment and control groups.

Panel A: Textual Analysis

Key word	Treatment firms		Control firms		*Mean diff*
	Obs.	Mean	Obs.	Mean	
Consumers (*xiaofeizhe* in Chinese)	350	0.162	1839	0.033	0.129***
Customers (*guke* in Chinese)	350	0.101	1839	0.068	0.033***
Users (*yonghu* in Chinese)	350	0.026	1839	0.006	0.020***
Total	350	0.289	1839	0.107	0.182***

Panel B: Financial Indicators

Indicator	Treatment firms		Control firms		*Mean diff*
	Obs.	Mean	Obs.	Mean	
Online sales ratio	350	0.054	1839	0.007	0.047**
Advertising expenditure	350	0.033	1839	0.006	0.027***

Panel C: Operating Characteristic

Characteristic	Treatment firms		Control firms		*Mean diff*
	Obs.	Mean	Obs.	Mean	
Top five customers	350	0.221	1839	0.297	0.076***

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Overseas operations and corporate financial asset allocation

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ABSTRACT

Using data on Chinese listed companies for 2008–2018, we find that firms participating in overseas operations, proxied by overseas subsidiaries, generally have higher financial asset allocations than other firms. At the micro level, the effects are more pronounced when the parent company faces serious financing constraints, has no overseas returned executives, has a business that is inconsistent with that of its overseas subsidiaries and has overseas subsidiaries that experience losses. At the macro level, the effects are more pronounced when overseas operations are in OECD and Belt and Road countries, or in areas with higher economic or political risks and greater investment opportunities. Financial asset allocation helps mitigate cash flow fluctuations and operational risks for multinational firms. This study advances research on the determinants of financial asset allocation and has implications relevant to the Chinese government's "Go Global" and Belt and Road strategies and its efforts to realize a developed financial sector to service the Chinese economy.

1. Introduction

Increasing globalization and enhanced cross-border economic cooperation increase the potential for rapid transmission of operational risks from overseas subsidiaries to parent companies. However, the literature on the headquarters–subsidiary relationship in multinational corporations primarily focuses on how the parent company influences the location selection and operational performance of overseas subsidiaries, with a particular emphasis on how the parent company facilitates the establishment of operational advantages for

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subsidiaries through trust and knowledge acquisition (Li et al., 2006; Li et al., 2010; Zhang et al., 2022). Thus, there is limited research analyzing how foreign subsidiaries reciprocally impact their parent companies.

Against the backdrop of momentous global events—including Brexit, the surge of anti-globalization and anti-free trade movements in the United States and other nations, public health crises and the Ukraine–Russia conflict—the global political and economic landscape is characterized by unprecedented uncertainty, which profoundly impacts overseas operations (Cumming and Zahra, 2016; Mohr et al., 2020). The inherent volatility of the external environment gives rise to significant spillover effects, such that operational risks originating from overseas subsidiaries reverberate throughout their parent companies. Although divestment by the parent company (such as withdrawal from the subsidiary) is an obvious consequence of overseas operational risks, an unanswered question is whether parent companies implement responsive measures and preventive strategies following their perception of risks emanating from their overseas subsidiaries, particularly regarding asset allocation.

Financial assets, a crucial category of asset allocation, play a significant role in corporate operations. Firms invest in financial assets with lower liquidity but higher excess returns to share in the financial industry's supernormal profits, thus achieving capital arbitrage objectives. In addition, they allocate idle funds to financial assets as capital reserves, thereby mitigating the adverse effects of production and operational disruptions (Liang and Xu, 2021). Studies examine how both internal factors within a single firm and industry-level factors influence financial asset allocation based on these two major motives, but do not consider the role of overseas operations at a remote geographical distance from the parent company. The complex factors inherent in overseas operational environments can lead to operational risks that are likely to generate spillover effects on parent companies, thereby influencing the demand for financial asset allocation for arbitrage or reserves.

In this study, we argue that the relationship between overseas operations and financial asset allocation is unclear. On the one hand, overseas operations may promote the allocation of funds to financial assets. Firms engaging in overseas operations need to consider not only the various risks in the home country, but also the political, economic and cultural risks in the host country. Because allocating funds to financial assets can reduce earnings volatility, enterprises can avoid an operational crisis by using hedging strategies (Smith and Stulz, 1985; Campello et al., 2011). Moreover, firms can convert financial assets into cash when they experience cash flow shortages, thereby avoiding illiquidity. On the other hand, overseas operations may inhibit firms allocating funds to financial assets. Financial asset allocation can crowd out real investment and exacerbate the linkage between the company and capital market risks (Duchin et al., 2017). Therefore, whether and how overseas operations affect financial asset allocation is an empirical question.

The availability of data on Chinese subsidiaries and the Chinese context offers unique opportunities for researching this issue. Chinese firms provide detailed information about their subsidiaries, including revenue and business type. This allows for an exploration of the impact of subsidiary operations on firm decision-making, expanding beyond the conventional perspectives that focus on segments or divisions when studying corporate valuation and decision-making dynamics (Chen and Zhang, 2003; Harris and Raviv, 2005). Specifically, this study extends the literature on the parent–subsidiary relationship by investigating the influence of subsidiary operational activities on the financial asset allocation strategies adopted by the parent company, introducing a novel dimension to the research on financial asset allocation. Moreover, this study enriches the understanding of the consequences of overseas operations from an investment perspective, in contrast with studies that focus on the foreign subsidiaries' entry mode and performance (Martin, 2013).

Since its reform and opening up, China has participated in economic globalization and actively engaged in cooperative investments with other countries worldwide based on equality and mutual benefit. Since the 18th Communist Party of China (CPC) National Congress, the CPC Central Committee, with President Xi Jinping at its core, has attached great importance to outbound investment, encouraging enterprises to utilize both domestic and foreign markets and to further open the economy. According to the Report on the Development of China's Outbound Investment Cooperation released by China's Ministry of Commerce in 2020, the country's outbound industry-wide direct investment in 2019 amounted to US$136.91 billion, accounting for 10.4 % of the global share and ranking China the second highest in the world. At the end of 2019, 27,500 Chinese enterprises had established 44,000 overseas subsidiaries with 3,744,000 employees in 188 countries/regions. Clearly, Chinese enterprises' overseas business activities have far-reaching effects globally. Therefore, under-

standing the impact of overseas subsidiaries on Chinese enterprises' behavior is important (Wei et al., 2016; Hao et al., 2017) and will yield insights for Chinese enterprises' international partners.

The downturn in China's real economy has led many non-financial listed companies to become involved in the more prosperous financial industry. There is no general agreement about whether excessive financialization has occurred (Du et al., 2017; Hu et al., 2017; Peng et al., 2018b). Compared with financial powerhouses such as the United Kingdom and the United States, China's financial industry accounts for a low proportion of the national economy, and its financial market is lagging in its development and suffers from financial inhibition (Luo et al., 2016). The financialization of real enterprises can help address the problem of financial resource mismatch to a certain extent and act as an important buffer in times of need (Liu et al., 2018). Therefore, clarifying the causes of financialization is important in determining whether real enterprises are overly financialized and in guiding the synergistic development of the financial industry and the real economy.

Using data on Chinese listed companies for the 2008–2018 period, this paper finds that enterprises participating in overseas operations have a higher level of financial asset allocation than their peers without overseas operations. The results hold after several robustness tests, including introducing firm fixed effects, instrumental variables and alternative measures of key variables. A heterogeneity analysis at the micro level shows that overseas operations promote both hedged and non-hedged financial assets. The relationship between overseas operations and financial asset allocation mainly exists when the parent company faces serious financing constraints, has no overseas returned executives, has a business that is inconsistent with that of the overseas subsidiaries and when its overseas subsidiaries experience losses. Furthermore, a heterogeneity analysis at the macro level shows that overseas operations in OECD countries and in Belt and Road countries have a higher level of financial asset allocation than their counterparts in non-OECD and non-Belt and Road countries. Overseas operations mainly play a role in promoting financial asset allocation in cases of high economic and political risks and when there are numerous investment opportunities in areas where overseas operations are located. An economic analysis shows that financial asset allocation is beneficial for reducing cash flow fluctuations and the operational risk of multinational enterprises.

This study's contributions are threefold. First, it enriches research on the economic consequences of overseas operations. With the acceleration of China's opening up to the outside world, an increasing number of overseas mergers and acquisitions (M&As) are occurring. Overseas operations have become an important means through which Chinese enterprises can develop. An extensive literature examines topics such as risk prevention in relation to overseas M&As, entry modes of overseas operations, social networks and knowledge spillovers. However, little attention is paid to how firms prevent long-term business risks and support internationalization strategies through financial strategies. This study suggests that firms respond to future risks by allocating funds to financial assets, enriching research on the impact of overseas operations on firms' financial decisions from the perspective of preventing long-term business risks.

Second, this study extends consideration of the motivations for financial asset allocation beyond China's macro environment, examining this motivation from the perspective of the risk of overseas operations' locations. Studies on the drivers of financial asset allocation for real enterprises begin with economic consequences or domestic macro influences. Most such studies consider the surge in financial assets triggered by derealization to virtualization to be negative, arguing that it increases the enterprises' risks and affects the stability of the capital market. In contrast, this study focuses on the emerging trend of enterprises' overseas business activities and provides a new explanation for the causes of the surge in financial assets from the perspective of the risks of overseas business locations. Specifically, it shows that firms are motivated, at least in part, to allocate funds to financial assets because of risk aversion rather than expansionary motives, thus contributing to a more comprehensive understanding of the causes of financial asset allocation.

Third, this study provides insights into enterprises' overseas operations. The "going out" of Chinese enterprises has become an important feature of the new era and is crucial for the development of China's economy. However, Chinese enterprises' risk awareness and practical experience in this context are insufficient. They are easily affected by all types of potential risk factors, which hinders their globalization. This study shows that enterprises can mitigate overseas risks by allocating funds to financial assets and provides insights into realizing cross-border operations and coping with business risks.

2. Literature review and hypothesis development

2.1. Literature review

2.1.1. Influencing factors and economic consequences of corporate financial asset allocation

Financial asset allocation has been a clear trend in the economic development of developed countries since the 1980s and is a topic of strong interest in academic research. Studies mainly explore the economic consequences of financial asset allocation and the factors influencing it. First, considering the economic consequences, the literature examines the impact of financial asset allocation on corporate investment behavior, future performance and the stock market. Most studies posit that allocating funds to financial assets has a crowding-out effect on physical investment. Because of resource limitations, financial and physical investments act as substitutes; that is, given resource limitations, if firms spend more funds on short-term financial assets, less funds are available for long-term, irreversible physical investment. Orhangazi (2008) analyzes the relationship between the rate of physical investment in non-financial firms in the United States and investment in financial assets, and finds that financial asset investments have a significant negative impact on physical investment. Wang et al. (2017) conclude that the financialization of enterprises crowds out investment in innovation and reduces enterprises' incentives to undertake technological innovation. Zhang and Zhang (2016) construct a model of microenterprise investment decision-making in a financialization environment. From a macro perspective, they find that the financialization of the economy reduces the physical investment rate and weakens the ability of monetary policy to boost the real economy.

Studies report different findings regarding the impact of financial asset allocation on enterprise performance. Wang et al. (2017) show that financial asset allocation by enterprises significantly improves their operating performance in the next period. Du et al. (2017) observe that enterprises' investment in financial assets negatively affects their main business performance in the future by suppressing innovation and physical capital investments. Li and Ma, 2017 find that the allocation of bridge loans to small and medium enterprises does not significantly affect performance. In terms of the stock market, Yan and Chen (2018) find that stock returns are negatively affected by firms in the industrial sector holding of financial assets, and Peng et al. (2018b) find that when listed firms hold financial assets to hide negative information, it enhances the probability of a collapse of the firm's stock price.

Second, regarding the literature on factors influencing financial asset allocation, most studies focus on enterprises' recognition and identification of capital arbitrage and reserve motives. The capital arbitrage motive refers to enterprises sharing excess profits in the financial industry by investing in financial assets with low liquidity but excess returns. The capital reserve motive refers to enterprises allocating idle funds to financial assets as a capital reserve to reduce the negative impact of a stoppage in production and operation activities (Liang and Xu, 2021). Using data from Argentina, Mexico and Turkey, Demir (2009) finds that the more significant the gap between the return on investments in fixed and financial assets, and the higher the macro-exchange rate uncertainty, the more firms tend to invest in financial assets. Using the Penman–Nissim method, Song and Lu (2015) remove financial assets and returns from total assets and earnings, and find that corporate performance and the proportion of financial assets have a U-shaped relationship. Specifically, higher-performing firms increase financial investment because of abundant funds, whereas lower-performing firms invest their limited funds in financial assets to compensate for the losses of their main business. Han et al., 2017 show that changes in the macroeconomic environment, brought about by the slowdown in economic growth and reductions in social fixed asset investments, intensify the trend for non-financial enterprises to enter shadow banking. Further, combining macro data analysis, Hu et al. (2017) find that corporate financial asset allocation is negatively and significantly correlated with the GDP cycle and the growth rate of the stock index, and positively and significantly correlated with the M2 cycle and legal reserve ratio. Thus, the authors suggest that corporate financial asset allocation is based on the capital reserve motive.

Finally, some studies consider policy uncertainty as a factor influencing financial asset allocation. Peng et al. (2018a) find that an increase in economic policy uncertainty significantly inhibits corporate financialization. After distinguishing the structures of financial assets, the authors find that corporations increase their holdings of relatively value-protecting long-term financial assets and sell liquid short-term financial assets,

suggesting that they invest in financial assets to chase profits. Nie et al. (2020) show that firms that perceive rising policy uncertainty increase their financial asset allocation.

2.1.2. Relevant works on overseas operations

In today's era of economic globalization, overseas operations are a strategically important international economic activity for both individual enterprises and countries in general (Liu et al., 2017). By establishing overseas subsidiaries and operations, enterprises can expand their market, obtain economies of scale, reduce unit product costs and improve their profitability. Fierce competition in overseas markets accelerates the frequency with which new products are introduced and technological upgrades occur. For instance, the overseas enterprises of developing countries can invest in developed countries and absorb and learn the advanced knowledge of the host country through technology diffusion, talent training, personnel mobility, information exchange and other means, and thus benefit from positive technological spillover effects. This can promote innovative inputs and outputs by the enterprise (Li and Yu, 2016). Moreover, outward foreign direct investment (OFDI) can alleviate financing constraints through direct and indirect effects, such as productivity and export effects. However, OFDI by China's enterprises remains nascent; the country's OFDI experience remains limited, and the awareness of external risk avoidance is not strong. Furthermore, political, economic, industry and business risks in the investing country often cause investment failures or huge losses for Chinese enterprises (Jiang, 2015; Sun and Qin, 2018). Some studies design early warning models for overseas investment risks (Miller, 1992; Li, 2016), or conduct empirical tests for the impact of a specific risk type on overseas investment, including institutional barriers (Morck et al., 2008; Zhang and Zhau, 2010), cultural risk (Guiso et al., 2009) and political risk (Bekaert et al., 2014).

In summary, overseas operations, as an important strategic investment of Chinese enterprises in recent years, are attracting extensive scholarly attention. However, few studies focus on how overseas operations affect a company's own financial behaviors or examine the impact of overseas operations on different types of asset allocation decisions. Next, we discuss the possible impact of overseas operations on firms' financial asset allocation.

2.2. Hypothesis development

This study argues that an enterprise's engagement in overseas operations may have two different effects on financial asset allocation. Overseas operations may promote financial asset allocation, which we refer to as the promotion effect. First, financial asset allocation can reduce earnings volatility. When entering a new market, firms face irreversible fixed costs, such as those associated with gathering market information, establishing transportation systems and adjusting product characteristics. Significant turbulence in the global market environment, which is characterized by volatility, uncertainty, complexity and ambiguity, can make it difficult for firms to predict and control their business environment. Thus, they must consider not only the various risks in the home country but also the political, economic and cultural risks in the host country (Buckley et al., 2007; Yu, 2015; Lv et al., 2019). For example, Yu (2015) observes that the lower the level of financial development of the host country, the lower the OFDI of Chinese enterprises. Tang and Liu (2017) show that political corruption in a host country has a significant inhibitory effect on Chinese overseas investment. Therefore, when the host country's macro-level risk rises and other adverse situations occur, overseas subsidiaries are negatively affected. However, enterprises can smooth profits in each period, reduce the costs of financial distress and avoid operational crises using hedging strategies, such as derivative instruments (Smith and Stulz, 1985; Guo, 2012). The smoothing of profits also helps improve the confidence of creditors and investors, enhances the financing ability of enterprises and assists them to improve the performance of their daily overseas business activities (Campello et al., 2011; Hao and Liang, 2019).

Second, financial asset allocation can help enterprises cope with liquidity pressures. By converting financial assets into cash when they experience cash flow shortages, enterprises can avoid illiquidity. Thus, financial assets act as a reservoir for enterprises (Liu et al., 2018; Liu et al., 2019a; Nie et al., 2020). Enterprises operating overseas have numerous physical investment opportunities, including the acquisition of scarce resources, development of overseas markets and learning about advanced technology. To take the initiative when competing in such markets, these enterprises tend to implement market-dominant investment strategies to increase

their market share; that is, they increase capital expenditure and R&D investments. However, the adoption of these strategies stimulates a strong demand for capital (Barclay and Smith, 1995; Yang et al., 2016). Information asymmetry between financial institutions and firms in the host country and difficult financing conditions in the host country can lead to insufficient exogenous financing. Consequently, firms will elevate their liquidity preferences and allocate more of their funds to liquid assets (Kim et al., 1998; Almeida et al., 2004).

However, in contrast with the arguments presented above, overseas operations may inhibit firms from allocating funds to financial assets, which we refer to as the crowding-out effect.[1] First, non-financial enterprises are less capable of recognizing, managing and controlling the risks associated with financial assets than non-financial assets. Financial asset allocation can exacerbate the linkages between the company and the risks of the capital market. Then, volatility in the financial market can also increase the uncertainty of the company's future cash flow. This can hurt daily operations, trigger a stock price collapse and even lead to corporate bankruptcy (Li and Han, 2019; Yu et al., 2021). Second, financial asset allocation can crowd out real investment (Du et al., 2017), weakening enterprises' ability to adjust their capital structure promptly (Liu et al., 2019b), thus reducing enterprises' value and increasing their financial risks (Huang et al., 2018; Li et al., 2019). Finally, according to the resource-based view, enterprises have limited funds for investment. Considering that financing is difficult and expensive in general for Chinese enterprises (Meng et al., 2020), their cash flow tends to be tight when they invest overseas. This reduces their ability to allocate funds to financial assets.

Summarizing the above two views, this study proposes the following competing hypotheses:

H1a: Ceteris paribus, if the promotion effect dominates the crowding-out effect, enterprises that operate overseas will have a higher financial asset allocation than those that do not operate overseas.

H1b: Ceteris paribus, if the crowding-out effect dominates the promotion effect, enterprises that operate overseas will have a lower financial asset allocation than those that do not operate overseas.

3. Research design and descriptive statistics

3.1. Model construction and variable definition

We construct Model (1) to test the impact of overseas operations on corporate financial asset allocation. The explained variable is corporate financial asset allocation (*Fininv*), whereas the explanatory variable is overseas operations (*OS_dum*). The control variables (*Control*) include several corporate and macro characteristic variables that may affect financial asset allocation. If H1a holds, α_1 should be positive and significant, whereas if H1b holds, α_1 should be negative and significant.

$$Fininv_{it} = \alpha_0 + \alpha_1 OS\_dum_{it} + \sum Control_{it} + \sum Year + \sum Industry + \varepsilon_{it} \quad (1)$$

The variables are defined as follows.

3.1.1. Explained variable: Financial asset allocation

Following Du et al. (2017) and Hu et al. (2017), we use the ratio of financial assets to total assets to measure the level of corporate financial asset allocation (*Fininv*). We define financial assets as including trading financial assets, net loans and advances granted, available-for-sale financial assets, derivative financial assets and net held-to-maturity investments. In a robustness test, we use alternative variables to measure financial asset allocation.

3.1.2. Explanatory variable: Overseas operations

Overseas operations are not explicitly defined in the literature. When an enterprise owns overseas subsidiaries, it will have involvements regarding local raw materials, products and personnel. The parent company

[1] It should be pointed out that prior studies have focused on financial asset investment and observed its "crowding out" of physical investment. This study adopts this term but focuses on real investment to observe whether there is a crowding-out effect on financial asset investment. Thus, the crowding-out effect in this study and that in the literature have different starting points but share the same logic.

Table 1
Variable Definitions.

Variable type	Variable	Variable definitions
Explained variable	*Fininv*	Financial asset allocation, financial assets as a percentage of total assets.
Explanatory variable	*OS_dum*	Overseas operations, dummy variable that takes the value of 1 if the firm has overseas subsidiaries in the year, and 0 otherwise.
Control	*Size*	Firm size, measured as the natural logarithm of total assets.
	Roa	Profitability, calculated as net income divided by total assets.
	Lev	Leverage ratio, calculated as total debt divided by total assets.
	Turnover	Asset turnover ratio, calculated as sales revenue divided by total assets.
	Tq	Tobin's q, calculated as the market value divided by total assets.
	Growth	Growth capacity, calculated as sales revenue in year t minus sales revenue in year t–1 divided by sales revenue in year t–1.
	East	Registration area, dummy variable, that takes the value of 1 if firms registered in the eastern region, otherwise 0.
	Soe	Nature of property rights, dummy variable, SOEs take the value of 1, otherwise 0.
	Gdp_p	The level of economic development of the firm's location, GDP per capita of the province where the enterprise is located (ten thousand yuan).

will be able to obtain information on the management and operation of overseas subsidiaries, which will help it make targeted investment decisions (Luo, 2003; Phene and Almeida, 2008). In addition, firms with overseas subsidiaries are more sensitive to the host country's supply and demand markets, and have a better understanding of local institutional changes and cultural practices, than firms without overseas operations (Jiang et al., 2012; Julio and Youngsuk, 2016). Therefore, having overseas subsidiaries indicates whether a firm has overseas operations. *OS_dum* is defined as a dummy that equals one if the firm has an overseas subsidiary in the current year and zero otherwise.

3.1.3. Control variables

Following Demir (2009), Hu et al. (2017) and Peng et al. (2018a), we incorporate the following control variables into our model: firm size (*Size*); profitability (*Roa*); gearing ratio (*Lev*); asset turnover (*Turnover*); Tobin's Q (*Tq*); growth capacity (*Growth*); registration area (*East*)[2]; the nature of property rights, that is, whether enterprises are state-owned (*Soe*); and the level of economic development of the firm's location (*Gdp_p*). In addition, year (*Year*) and industry dummy variables (*Industry*) are added to control for year and industry fixed effects, respectively.

Table 1 presents definitions and descriptions of the main variables. To eliminate the effects of extreme values, all continuous variables are winsorized at the 1st and 99th percentiles.

3.2. Sample selection and data sources

In 2007, China implemented a new accounting standard that significantly modified the classification, recognition and measurement of financial assets. To ensure the comparability of our financial assets data, we commence our period of analysis in 2008. We set the end year as 2018 to avoid the influence of the Sino–US trade war, which commenced in 2018, and the COVID-19 outbreak in 2020, both of which would affect enterprises' overseas investment and financial asset allocation.

We process the data on A-share listed companies for the 2008–2018 period by excluding: (1) financial and real estate industries, (2) samples with missing control variables, and (3) outliers (e.g., samples for which the gearing ratio exceeds one). This yields 19,497 firm-year observations. Firm financial data are sourced from the

[2] If the enterprise is located in Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong or Hainan, *East* equals one, and zero otherwise.

Table 2
Descriptive Statistics and Correlation Coefficient Matrix.

Panel A: Descriptive Statistics for Key Variables

Variable	N	Mean	Min	Max	SD	Q25	Median	Q75
Fininv	19,497	0.0176	0.0000	0.3857	0.0428	0.0000	0.0005	0.0126
OS_dum	19,497	0.2427	0.0000	1.0000	0.4287	0.0000	0.0000	0.0000
Size	19,497	22.1349	18.7245	26.2313	1.2955	21.2402	21.9976	22.8731
ROA	19,497	0.0337	−0.6556	0.2360	0.0679	0.0113	0.0329	0.0633
Lev	19,497	0.4618	0.0470	0.9981	0.2068	0.3022	0.4598	0.6175
Turnover	19,497	0.6784	0.0446	3.0374	0.4700	0.3721	0.5710	0.8419
Tq	19,497	2.1149	0.8092	19.3802	1.6506	1.2355	1.6068	2.3420
Growth	19,497	0.1878	−0.6977	5.9850	0.5430	−0.0269	0.1028	0.2586
East	19,497	0.6125	0.0000	1.0000	0.4872	0.0000	1.0000	1.0000
Soe	19,497	0.5073	0.0000	1.0000	0.5000	0.0000	1.0000	1.0000
Gdp_p	19,497	6.1219	0.9855	14.2094	2.9232	3.8572	5.6650	8.1874

Panel B: Descriptive Statistics of Sub-Yearly Means of Corporate Financial Asset Allocation and Overseas Operations

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Fininv	0.0089	0.0129	0.0135	0.0090	0.0088	0.0087	0.0215	0.0239	0.0265	0.0265	0.0230
OS_dum	0.1460	0.1612	0.1867	0.2016	0.2306	0.2533	0.2764	0.2986	0.2492	0.2993	0.2789

Panel C: A Univariate Test of Corporate Financial Asset Allocation and Overseas Operations

Financial Asset Allocation (*FinInv*)	Mean	Median
Overseas Operations: *OS_dum* =1 (N = 4732)	0.0207	0.0030
No Overseas Operations: *OS_dum* = 0 (N = 14765)	0.0166	0.0000
Diff (Overseas Operations – No Overseas Operations)	0.0041***	0.0030***

Panel D: Correlation Coefficient Matrix

	A	B	C	D	E	F	G	H	I	J	K
(A)Fininv	1.0000	0.1367***	0.2701***	−0.0034	0.0131***	−0.0527***	−0.0473**	−0.0422***	0.0972***	0.0520**	0.2629***
(B)OS_dum	0.0410***	1.0000	0.2208	0.0516	0.0574	0.0777	−0.0521	0.0685	0.1794	−0.1102	0.1884
(C)Size	0.0380***	0.2290***	1.0000	0.0103	0.3808	0.0218	−0.5413	0.0909	−0.0082	0.2646	0.1496
(D)ROA	−0.0070	0.0450***	0.0680***	1.0000	−0.4279	0.1988	0.1956	0.3111	0.1186	−0.1361	0.0881
(E)Lev	−0.0880***	0.0530***	0.3620***	−0.3690***	1.0000	0.1201	−0.3156	0.0054	−0.1235	0.2461	−0.1272
(F)Turnover	−0.0770***	0.0680***	0.0330***	0.1070***	0.1380***	1.0000	−0.0213	0.1535	0.0867	0.0352	0.0072
(G)Tq	0.0480***	−0.0540***	−0.4340***	0.0240***	−0.1680***	−0.0340***	1.0000	0.0024	0.0146	−0.1837	−0.0057
(H)Growth	−0.0360***	0.0260***	0.0490***	0.1760***	0.0250***	0.0660***	−0.0100	1.0000	0.0245	−0.0765	0.0091
(I)East	0.0770***	0.1790***	0.0060	0.0830***	−0.1280***	0.0660***	−0.0100	−0.0180**	1.0000	−0.1560	0.6935
(J)Soe	0.0150**	−0.1100***	0.2810***	−0.0770***	0.2440***	0.0530***	−0.1240***	−0.0510***	−0.1560***	1.0000	−0.1444
(K)Gdp_p	0.1500***	0.1760***	0.1640***	0.0390***	−0.1160***	−0.0030	−0.0190***	−0.0170**	0.6520***	−0.1220***	1.0000

Note: *, ** and *** indicate significance levels of 10%, 5% and 1%, respectively.

China Stock Market and Accounting Research database. Data on overseas subsidiaries are collected manually.[3]

3.3. Descriptive statistics and correlation analysis

Panel A in Table 2 reports the descriptive statistics of the main variables in this paper. The results show that the mean and median of *Fininv* are 1.76 % and 0.00 %, respectively, which are close to those estimated by Wang et al. (2021) and Du et al. (2017) The mean value of *OS_dum* is 24.27 %, indicating that nearly 24 % of the observations in the sample conduct overseas operations, and the standard deviation is 0.4287, indicating a large variation in whether different firms conduct overseas operations. All other descriptive statistics are within reasonable intervals compared with those determined in the literature.

Panel B in Table 2 reports the descriptive statistics of corporate financial asset allocation and overseas operations by year. Combined with Panel A, it is evident that there is a considerable upward trend in the financial asset allocation level of listed companies in China, which increased rapidly from 0.87 % to 2.30 % between 2013 and 2018. The high growth in the level of financial assets and the room for further growth enhance the importance of research on the factors influencing corporate financial asset allocation and their economic consequences. Panel B shows an increasing trend year by year in enterprises engaged in overseas operations, with the proportion of such enterprises rising rapidly from 14.60 % in 2008 to 27.89 % in 2018. Therefore, studying the impact of overseas operations is vital to understanding the behavior of listed companies in China.

Panel C in Table 2 reports the results of univariate tests of corporate financial asset allocation and overseas operations. All samples are categorized into two groups based on whether firms conduct overseas operations (*OS_dum = 1*) or do not conduct overseas operations (*OS_dum = 0*), and the mean and median tests are conducted on the financial asset allocations of the samples in both groups. The results show that the mean corporate financial asset allocation in the group with overseas operations is 0.0207 (median 0.0030), whereas the corresponding figures for the group without overseas operations are 0.0166 (mean) and 0.0000 (median). The firms with overseas operations have a higher level of financial asset allocation than firms without such operations, and this difference is significant (the mean and median tests are significant at the 1 % level).

Panel D in Table 2 reports the matrix of correlation coefficients for the main variables in this paper. The Pearson correlation coefficients are shown on the lower left of the diagonal, and the Spearman correlation coefficients are shown on the upper right. We observe that the Pearson and Spearman correlation coefficients between OS_dum and Fininv are 0.0410 and 0.1367, respectively, and both are significant at the 1 % level, consistent with H1a. The Pearson and Spearman correlation coefficients between East and Gdp_p are 0.6520 and 0.6935, respectively. All other correlation coefficients between the remaining variables are within 0.5. We conduct a variance inflation factor (VIF) test, which reveals that the VIFs of each variable are less than 4, and thus the problem of multicollinearity does not interfere greatly with the regression results in this paper.

4. Empirical results

4.1. Hypothesis testing results

Table 3 provides the results for Model (1). The explained variable is *Fininv*. Column (1) reports the results with only control variables.[4] The coefficients of *Turnover* and *Growth* are negative and significant at the 1 % level. Firms with higher asset turnover and growth capacity have more opportunities for physical investment, a tendency toward low levels of risk aversion and correspondingly lower levels of financial asset allocation than firms with lower asset turnover and growth capacity. The coefficients of *East* and *Soe* are positive and significant. Eastern China has higher levels of regional financial development than other regions of China. Consequently, firms registered in the east are more likely to have higher levels of funding and thus may allocate more of their funds to financial assets than firms in other regions, which is consistent with the findings of

[3] Due to the data timeframe, the sample used for some subsidiary characteristics tests ends in 2015.

[4] To avoid coefficients that are too small, the coefficients of the regression results in subsequent tables are expressed in percentage terms (%). In addition, the results hold even after extending the sample to 2020.

Table 3
Overseas Operations and Corporate Financial Asset Allocation.

Variable	(1) Full sample	(2) Full sample	(3) Full sample
	Fininv	*Fininv*	*Fininv*
OS_dum		**0.3093*** **	**0.3245*** **
		(4.32)	**(4.32)**
Size	0.2092***		0.1769***
	(7.04)		(5.89)
ROA	−2.3720***		−2.3766***
	(−4.13)		(−4.14)
Lev	−2.3289***		−2.3482***
	(−12.13)		(−12.22)
Turnover	−0.6749***		−0.6931***
	(−9.81)		(−10.06)
Tq	0.1119***		0.1079***
	(3.75)		(3.61)
Growth	−0.1859***		−0.1868***
	(−3.51)		(−3.52)
East	0.1574*		0.1198
	(1.65)		(1.25)
Soe	0.3151***		0.3572***
	(4.47)		(4.98)
Gdp_p	0.1010***		0.0999***
	(4.61)		(4.57)
Constant	−2.9487***	0.4966***	−2.2629***
	(−4.70)	(2.89)	(−3.56)
Year & Ind	Yes	Yes	Yes
Obs#	19,497	19,497	19,497
Adj-R^2	0.0725	0.0517	0.0733

Note: t-values adjusted for standard errors based on firm-level clustering are in parentheses; *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, the same below.

Hu et al. (2017). The managers of state-owned enterprises (SOEs) have a high level of risk aversion and a higher likelihood of allocating funds to financial assets than non-SOEs.

Column (2) contains the results with only explanatory variables. The coefficient of *OS_dum* is 0.3093 and significant at the 1 % level. Thus, firms that conduct overseas operations have higher financial asset allocations than firms without overseas operations.

Column (3) contains the results with both explanatory and control variables, which are generally in line with the findings in column (1). The coefficients of *Turnover* and *Growth* are negative and significant at the 1 % level, and the coefficients of *East* and *Soe* are positive. The coefficient of *OS_dum* is 0.3245 and significant at the 1 % level. In other words, even after controlling for company characteristics, firms with overseas operations have higher financial asset allocations than firms without such operations. Thus, H1a is supported. Economically, firms with overseas operations have financial assets that are 18.44 % higher as a percentage of total assets (relative to the overall mean) than do firms with no overseas operations. Thus, the effect is economically significant.

4.2. Robustness tests

4.2.1. Discussion of endogeneity issues

Sor far, our results indicate that firms with overseas operations have higher levels of financial asset allocation than firms without overseas operations. However, this finding is not sufficient to generalize the active effect of overseas operation on firms' financial asset allocation, and endogeneity issues such as causal inversion and omitted variables need to be considered. We mitigate the impact of endogeneity problems using the following five methods.

Table 4
Robustness Tests: Endogeneity Tests.

Variable	(1) Fixed effects	(2) One-period lag	(3) First-order differences	(4) PSM	(5) Instrumental variables	(6) Control for corporate governance characteristics
	Fininv	*Fininv*	*Fininv*	*Fininv*	*Fininv*	*Fininv*
OS_dum	**0.1520****			**0.3995*****	**0.6764*****	**0.3282*****
	(2.11)			**(4.00)**	**(3.23)**	**(4.30)**
L.OS_dum		**0.3798*****				
		(4.35)				
D.OS_dum			**0.1440****			
			(2.06)			
Size	−0.0389	0.1144***	0.1296	0.2258***	0.1990***	0.2501***
	(−0.67)	(3.28)	(0.85)	(4.43)	(5.49)	(7.20)
ROA	−1.8057***	−1.8959***	−1.2018**	−3.8499***	−2.2084***	−1.8580***
	(−4.24)	(−2.82)	(−2.50)	(−3.54)	(−3.51)	(−3.17)
Lev	−1.8587***	−2.5668***	−0.9490***	−2.8225***	−1.4480***	−2.4828***
	(−8.44)	(−11.47)	(−2.94)	(−7.93)	(−7.86)	(−12.59)
Turnover	−0.4221***	−0.7948***	−0.1824	−0.6285***	−0.5199***	−0.6198***
	(−4.10)	(−9.92)	(−1.15)	(−5.41)	(−7.42)	(−9.03)
Tq	0.0783***	0.0737**	0.0023	0.0996**	0.1154***	0.1073***
	(3.65)	(2.23)	(0.07)	(1.99)	(7.05)	(3.53)
Growth	−0.0570	−0.2164***	−0.0659*	−0.0966	−0.2365***	−0.1926***
	(−1.33)	(−3.50)	(−1.66)	(−0.97)	(−3.98)	(−3.60)
East		0.1787		0.2092	0.0756	0.1232
		(1.63)		(1.37)	(0.87)	(1.31)
Soe	0.0458	0.3096***	0.3032	0.3187**	0.5724***	0.3947***
	(0.31)	(3.87)	(1.43)	(2.41)	(8.24)	(5.51)
Gdp_p	0.2782***	0.1033***	0.0610	0.0702**	0.0000***	0.1120***
	(8.30)	(4.24)	(1.02)	(2.09)	(5.93)	(5.02)
Rind						−0.2107
						(−0.42)
*Top*1						−0.0132***
						(−6.26)
Agency						0.0215
						(0.85)
M_pay						−0.1465***
						(−2.61)
Constant	1.4644	−0.5363	−0.4280***	−3.1520***	−3.5700***	−1.3456*
	(1.17)	(−0.71)	(−3.39)	(−2.80)	(−4.57)	(−1.75)
Firm	Yes	No	No	No	No	No
Ind	No	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs#	19,497	16,404	16,404	6,880	14,386	19,497
Adj-R^2/R^2	0.1108	0.0752	0.0306	0.0830	0.0522	0.0754

(1) Adopting the fixed effects model for testing. To mitigate the impact of unobservable firm-level factors on our conclusions, we control for firm fixed effects for robustness testing. The results are shown in column (1) of Table 4. The coefficient of overseas operations remains positive and significant at the 5 % level.
(2) Using the previous period's overseas operations in the regression. To mitigate the endogeneity problem of causal inversion between overseas operations and firms' financial asset allocation, we regress firms' financial asset allocation in the current period on overseas operations in the previous period. The results are shown in column (2) of Table 4. The coefficient of *OS_dum* during the last period remains positive and significant at the 1 % level.
(3) Using first-order differencing. To mitigate the possible impact of the firm's own characteristics on its financial asset allocation, we adopt first-order differencing. The results are shown in column (3) ofTable 4.[5] The coefficient of *OS_dum* remains positive and significant at the 5 % level.
(4) Adopting propensity score matching (PSM). To control for possible selection bias, we adopt the PSM method as a further test. After matching, there are 3,440 firm-year observations in the treatment group and 3,440 firm-year observations in the control group.[6] The regression results are shown in column (4) of Table 4. The coefficient on *OS_dum* remains positive and significant at the 1 % level.
(5) Using an instrumental variable approach. To alleviate the problem of possible omitted variables, we select two variables as instrumental variables for overseas operations. First, we use the number of Confucius Institutes in each country (*Confuzi*) as an instrumental variable,[7] drawing on Xie et al. (2017) and Chen et al., 2017. Second, we use the average value of the overseas operations of other companies in the year of the location of the company (*OS_mean*). The reasons for choosing these two instrumental variables are as follows. First, as the most important way for Chinese culture to "go out," the rapid development of Confucius Institutes not only indicates the general acceptance and recognition of Chinese culture in other countries/regions but also reduces the transaction costs and communication costs arising from cultural differences and promotes the development of China's outbound investment. Therefore, the greater the number of Confucius Institutes in a country, the more likely it is that a company will make overseas investments and carry out overseas operations. At the same time, the Confucius Institutes in a country will not directly affect the investments of domestic listed companies in financial assets, thus passing the test for an acceptable instrumental variable. Second, the labor supply, corporate governance and other corporate characteristics of companies in the same region are similar, and thus the overseas operations of a specific company are related to the overseas operations of the region. However, the regional overseas operations do not have a direct impact on the financial asset allocation activities of a specific company, and thus the mean value of regional overseas operations can be used as an instrumental variable.[8] The regression results using the instrumental variable approach are shown in column (5) of Table 4. The coefficient of overseas operations remains positive and significant at the 1 % level.
(6) Adding control variables at the level of corporate governance. Financial assets have arbitrage attributes, and this may increase the incentives of self-interested executives or major shareholders to allocate funds to financial assets, that is, the level of corporate governance is an important factor affecting the allocation of financial assets. Therefore, to avoid the interference of omitted variables on the results, we add four control variables to the original model as a robustness test, namely the proportion of shares held by the largest shareholder, the proportion of independent directors, the agency cost and executive compensation. We measure agency cost as the ratio of administrative expenses to operating income, and exec-

[5] The control variables in this column are all first differences.
[6] The matching variables for all control variables (*Size, ROA, Lev, Turnover, Tq, Growth, East, Soe* and *Gdp_p*) are matched using a 1:1 matching method. This study's PSM matching method satisfies the balance test. We do not report specific test results to save space.
[7] Data are sourced from Hanban and Confucius Institute conference collation.
[8] The unreported regression results of the first stage show that the adjusted partial R^2 is 0.1169, and the minimum eigenvalue of *Confuzi* and *OS_mean* is 950.219. This shows that the above variables are not weak tools. In addition, we conduct an overrecognition test and find that the value of the Sargan statistic is 1.585 and the *p* value is 0.2081, indicating that the selected instrumental variables meet the exogenous conditions.

utive compensation by the natural logarithm of the compensation of the top three executives. The regression results when these corporate governance-level control variables are presented in column (6) of Table 4. The coefficient on overseas operations remains positive and significant at the 1 % level.

4.2.2. Alternative measures of key variables

To further improve the robustness of the conclusions, we adopt alternative measures for each of the key variables. For the explanatory variable *OS_dum*, we adopt the number of overseas subsidiaries, using the natural logarithm (*OS_num*) by taking the value of the number of overseas subsidiaries owned by the enterprise plus one. We consider the impact of overseas revenue[9] to test the relationship between the presence of overseas business revenue (*Oversales_Dum*), the proportion of overseas revenue (*Oversales_Prop*) and the allocation of the financial assets of enterprises. The specific results are shown in Panel A of Table 5. The coefficients of *OS_num, Oversales_Dum* and *Oversales_Prop* are all positive and significant, indicating that our main findings remain robust.

For the explanatory variable *Fininv*, we use the measures of financial assets in Hu et al. (2017), Peng et al. (2018a), and Liu et al. (2018), with the regression results shown in Panel B ofTable 5.[10] As the table shows, the coefficient of *OS_dum* remains positive and significant at the 1 % level under these different measures, indicating the robustness of our conclusions. In addition, to avoid foreign currencies influencing our conclusions, we exclude foreign currency funds from total assets and recalculate the ratio of financial assets to total assets (*Fininv_F*), presenting the regression results in column (4) of Panel B in Table 5. The coefficient on *OS_dum* remains positive and significant at the 1 % level.

To consider the effect of cash holdings, one important component of financial assets, on the robustness of conclusions, we also test the relationship between overseas operations and cash holdings.[11] Referring to Zhang and Wu (2014), the ratio of cash to non-cash assets (*Cash*) is used to measure the level of cash holdings, with cash defined as including money funds and short-term investments, and non-cash assets referring to total assets minus cash. We also control for *Size*, *Roa*, *Lev*, *Turnover*, *Tq*, *Growth*, *East*, *Soe* and *Gdp_p*. Panel C of Table 5 reports the test results. The coefficient of *OS_dum* is positive and significant at the 1 % level for both current and lagged explanatory variables. This indicates that firms with overseas subsidiaries hold more cash to guard against possible future operational risks than firms without overseas operations. This finding is consistent with the research logic of this paper.

4.2.3. Other robustness tests

We conduct the following additional robustness tests. (1) Considering the skewed distribution of the proportion of financial assets and the proportion of overseas operations, we utilize a quantile regression. (2) Considering the impact of the financial crisis, we exclude observations for 2008 and 2009. (3) We adding control

[9] Export income refers to the business income of enterprises selling export goods or services to foreign buyers and receiving foreign exchange. Overseas income refers to income derived from foreign countries, including export income, and it can also be derived from the local operations of overseas subsidiaries.

[10] *Fininv_H* = (cash + financial derivatives + short-term investments + trading financial assets + interest receivable + buy-back financial assets + available-for-sale financial assets + hold-to-maturity investment + long-term receivables)/total assets. *Fininv_P* = (tradable financial assets + derivative financial assets + available-for-sale financial assets + held-to-maturity investment + investment real estate)/total assets. *Fininv_L* = (money funds + held-to-maturity investments + trading financial assets + derivative financial assets + available-for-sale financial assets + long-term equity investments + dividends receivable + interest receivable)/total assets.

[11] In this paper, cash is not included in the test of the main results, which are mainly considered in the following three aspects. First, one of the research motives of this paper is to explore whether the current surge of financial assets of Chinese enterprises is driven mainly by their overseas operations to provide a new explanation of the causes of corporate financial asset allocation. Second, monetary funds are closely related to the daily business activities of enterprises, whereas it is difficult to accurately identify and measure monetary funds used for financial asset transactions (Song and Lu, 2015; Du et al., 2017). Third, this paper attempts to enrich the relevant theories of financial asset allocation; separating monetary funds for testing highlights the research purpose and contribution of this paper (Hu et al., 2017).

Table 5
Robustness Tests: Alternative Measures of Key Variables.

Panel A: Other Measures of Overseas Operations

Variable	(1) Full sample	(2) Full sample	(3) Full sample
	Fininv	*Fininv*	*Fininv*
OS_num	0.1557**		
	(2.04)		
Oversales_Dum		0.1463**	
		(2.10)	
Oversales_Prop			0.3948**
			(2.15)
Size	0.2007***	0.2005***	0.2083***
	(6.70)	(6.72)	(7.01)
ROA	−2.3786***	−2.3433***	−2.3293***
	(−4.14)	(−4.08)	(−4.07)
Lev	−2.3339***	−2.3370***	−2.3282***
	(−12.15)	(−12.16)	(−12.14)
Turnover	−0.6794***	−0.6818***	−0.6751***
	(−9.84)	(−9.90)	(−9.81)
Tq	0.1105***	0.1139***	0.1135***
	(3.70)	(3.81)	(3.80)
Growth	−0.1851***	−0.1852***	−0.1864***
	(−3.49)	(−3.49)	(−3.52)
East	0.1477	0.1330	0.1310
	(1.54)	(1.41)	(1.36)
Soe	0.3208***	0.3322***	0.3285***
	(4.55)	(4.65)	(4.60)
Gdp_p	0.1013***	0.1007***	0.1005***
	(4.63)	(4.59)	(4.59)
Constant	−2.7664***	−2.7701***	−2.9502***
	(−4.36)	(−4.41)	(−4.70)
Year & Ind	Yes	Yes	Yes
Obs#	19,497	19,497	19,497
Adj-R^2	0.0723	0.0726	0.0727

Panel B: Alternative Measures of Financial Asset Allocation

Variable	(1) Full sample	(2) Full sample	(3) Full sample	(4) Full sample
	Fininv_H	*Fininv_P*	*Fininv_L*	*Fininv_F*
OS_dum	0.0097***	0.0046***	0.0115***	0.0040***
	(4.68)	(2.79)	(4.98)	(4.65)
Size	0.0021**	0.0030***	0.0060***	0.0020***
	(2.12)	(3.72)	(5.47)	(5.83)
ROA	0.1816***	−0.0623***	0.1473***	−0.0288***
	(10.50)	(−4.10)	(7.21)	(−4.38)
Lev	−0.1773***	−0.0645***	−0.2308***	−0.0306***
	(−28.46)	(−12.41)	(−32.67)	(−13.70)
Turnover	0.0012	−0.0373***	−0.0123***	−0.0083***
	(0.53)	(−19.34)	(−4.73)	(−10.52)
Tq	0.0085***	0.0058***	0.0122***	0.0013***
	(9.69)	(8.22)	(12.49)	(3.61)
Growth	−0.0006	−0.0073***	−0.0076***	−0.0024***
	(−0.31)	(−4.89)	(−3.64)	(−3.98)
East	−0.0011	0.0046*	−0.0042	0.0021*
	(−0.39)	(1.93)	(−1.33)	(1.95)
Soe	0.0111***	0.0193***	0.0214***	0.0038***
	(5.53)	(11.35)	(9.48)	(4.62)
Gdp_p	0.0033***	0.0032***	0.0049***	0.0007***
	(5.60)	(6.31)	(7.57)	(2.86)

Table 5 (*continued*)

Panel B: Alternative Measures of Financial Asset Allocation				
Variable	(1) Full sample	(2) Full sample	(3) Full sample	(4) Full sample
	Fininv_H	*Fininv_P*	*Fininv_L*	*Fininv_F*
Constant	0.1598***	0.0185	0.1371***	−0.0234***
	(7.55)	(1.13)	(5.82)	(−3.19)
Year & Ind	Yes	Yes	Yes	Yes
Obs#	19,497	19,497	19,497	19,497
Adj-R^2	0.181	0.138	0.199	0.0685

Panel C: Impact of Overseas Operations on the Level of Cash Holdings		
Variable	(1) Current explanatory variables	(2) One-period lagged explanatory variables
	Cash	*Cash*
OS_dum	0.0060***	0.0068***
	(3.21)	(3.43)
Size	−0.0004	0.0007
	(−0.47)	(0.70)
ROA	0.2072***	0.2005***
	(13.06)	(11.31)
Lev	−0.1542***	−0.1353***
	(−27.15)	(−22.43)
Turnover	0.0164***	0.0173***
	(7.89)	(7.76)
Tq	0.0066***	0.0082***
	(8.72)	(10.04)
Growth	0.0003	0.0014
	(0.17)	(0.73)
East	−0.0015	−0.0037
	(−0.58)	(−1.35)
Soe	0.0052***	0.0090***
	(2.91)	(4.76)
Gdp_p	0.0016***	0.0016***
	(3.10)	(2.93)
Constant	0.1957***	0.1700***
	(10.11)	(7.94)
Year&Ind	Yes	Yes
Observations	19,497	16,404
Adj-R2	0.190	0.177

variables reflecting overseas demand to the model to alleviate the possible impact of overseas demand on the conclusions.[12] (4) We retain only the samples of enterprises from the manufacturing industry for the test because the vast majority of Chinese listed enterprises come from the manufacturing industry. The regression results, shown in Table 6, indicate that the coefficient of *OS_dum* remains positive and significant at the 1 % level for tests (1)–(3), and at the 5 % level for test (4).

5. Further analysis

The theoretical analysis and empirical results in this paper show that the impact of overseas operations on corporate financial asset allocation depends on the trade-off between the financial asset risks and the physical investment risks. In general, overseas operations have a "boosting effect" on financial assets. Thus, the

[12] The literature has not yet developed an authoritative opinion on how to measure firms' overseas demand. This paper argues that firms demand for overseas markets is greater when they struggle to grow domestically and are located in industries with insufficient growth. Therefore, drawing on Yang et al. (2016), the median *Tobin's Q* for each year and industry is used to measure the growth of the industry. The lower the industry growth, the stronger is the company's demand for overseas investment.

Table 6
Robustness Tests: Other Robustness Tests.

Variable	(1) Quantile regression	(2) Excluding years of financial crisis	(3) Adding control variables	(4) Manufacturing enterprises
	Fininv	*Fininv*	*Fininv*	*Fininv*
OS_dum	0.2787***	0.3011***	0.3254***	0.1789**
	(3.70)	(3.78)	(4.33)	(2.20)
Size	0.0923***	0.1757***	0.1811***	0.1987***
	(4.83)	(5.31)	(6.02)	(5.75)
ROA	−0.4365**	−2.4276***	−2.3161***	−1.9048***
	(−2.41)	(−3.70)	(−4.05)	(−3.08)
Lev	−0.3950***	−2.3212***	−2.3545***	−1.6211***
	(−4.12)	(−11.17)	(−12.25)	(−7.70)
Turnover	−0.0393*	−0.7491***	−0.6916***	−0.5812***
	(−1.73)	(−9.67)	(−10.04)	(−7.38)
Tq	0.0596***	0.1200***	0.1181***	0.0638*
	(2.65)	(3.76)	(3.90)	(1.93)
Growth	−0.0195	−0.1741***	−0.1836***	−0.1788***
	(−1.64)	(−3.04)	(−3.46)	(−2.73)
East	−0.0316	0.1496	0.1159	−0.1324
	(−1.23)	(1.40)	(1.21)	(−1.20)
Soe	0.0731***	0.3344***	0.3589***	0.1814**
	(3.97)	(4.20)	(5.00)	(2.24)
Gdp_p	0.0556***	0.0874***	0.1009***	0.1013***
	(3.79)	(3.77)	(4.61)	(3.99)
OS_demand			−0.5646***	
			(−3.35)	
Constant			−0.8256***	
			(−6.78)	
Year & Ind	Yes	Yes	Yes	Yes
Obs#	19,497	16,796	19,497	12,956
Adj-R^2	0.0762	0.0743	0.0739	0.0369

"promotion effect" on financial assets is more pronounced when the risk faced by overseas subsidiaries rises and the risk of investing in financial assets is relatively low. Conversely, the "crowding-out effect" is more pronounced when the risk to foreign subsidiaries declines and the risk of physical investments is relatively low. To further strengthen the main logic of this paper, we analyze the heterogeneity in both micro-level operating characteristics and the macro-level operating environment. We also test the economic consequences of financial asset allocation.

5.1. Analyzing heterogeneity under different conditions: Micro-operational characteristics

5.1.1. Heterogeneity analysis by parent company financing constraints

Liu et al. (2018) show that firms with stronger financing constraints are more inclined to use financial assets for preventive savings than those with weaker constraints. Similarly, the theoretical analysis in this study points out that listed companies conducting overseas operations increase their financial asset allocations to prevent future cash flow fluctuations. Therefore, we argue that when facing stronger financing constraints, firms are more inclined to allocate funds to financial assets and to use financial assets as a buffer to cope with possible future liquidity crises.

To test this inference, following the literature (Deng et al., 2020; Wang et al., 2021), we adopt the KZ index to measure firms' financing constraints. The larger the value of the KZ index, the more serious are the financing constraints faced by firms. Compared with a single index, the KZ index more comprehensively portrays the financing constraints of listed companies. Specifically, we group firms into high (*High_FC*) and low (*Low_FC*) financing constraint groups based on whether their KZ index is above or below the annual industry median, respectively. The results, presented in Table 7, reveal that the coefficients of *OS_dum* are 0.1308 and nonsignif-

Table 7
Heterogeneity Analysis Based on Parent Company Financing Constraints.

Variable	(1) Financing constraints low group	(2) Financing constraints high group
	Fininv	*Fininv*
OS_dum	0.1308	0.5302***
	(1.35)	(4.77)
Size	0.3357***	0.0605
	(7.32)	(1.31)
ROA	−1.0742	−1.8453***
	(−1.13)	(−2.78)
Lev	−2.0624***	−3.9592***
	(−6.85)	(−14.13)
Turnover	−0.5066***	−0.8289***
	(−5.12)	(−8.18)
Tq	0.0850*	0.0570**
	(1.93)	(2.05)
Growth	−0.2132***	−0.1473
	(−3.19)	(−1.51)
East	0.1315	0.1728
	(1.00)	(1.25)
Soe	0.0775	0.5430***
	(0.84)	(5.48)
Gdp_p	0.0917***	0.0951***
	(3.50)	(3.41)
Constant	−6.0750***	1.5050
	(−6.20)	(1.48)
Year & Ind	Yes	Yes
Obs#	9,659	9,838
Adj-R^2	0.0839	0.0805

icant for the lower financing constraint group, and 0.5302 and significant for the higher financing constraint group. Therefore, the impact of overseas operations on financial asset allocation is more evident when corporate financing constraints are more (vs. less) severe, consistent with the theoretical analysis.

5.1.2. Heterogeneity analysis by parent company talent structure

Recent research suggests that executives returning from overseas subsidiaries serve as an important bridge between local firms and overseas subsidiaries (Dai and Kong, 2017). If executives have experienced studying and acquiring knowledge abroad, or have rich experience working in overseas enterprises, these experiences can enhance their cognitive abilities, enabling them more effectively to solve the various problems that arise in the process of outbound investment, reduce the cost of international transactions and communication and enhance the degree of enterprise internationalization. Moreover, executives with overseas experience more effectively capture potential investment opportunities and improve investment efficiency than executives who lack such experiences (Dai and Kong, 2017). Therefore, compared with enterprises in which executives lack overseas experience, the enterprises with returnee executives may have a more accurate perception of the risks of overseas operations and better grasp investment opportunities, thus reducing the risk of physical investment. In turn, this can reduce the need for financial asset allocation.

To test these inferences, drawing on Giannetti et al. (2015) and Dai and Kong, 2017, we define executive overseas experience (*OS_exp*) as a dummy variable that equals one if the firm has executives with overseas study or work experience in the current year, and zero otherwise. Next, according to the executives' overseas

Table 8
Heterogeneity Analysis Based on Executives' Overseas Experience.

Variable	(1) *OS_exp = 1*	(2) *OS_exp = 0*
	Fininv	*Fininv*
OS_dum	0.1501	0.3894***
	(1.64)	(3.66)
Size	0.1535***	0.1437***
	(3.43)	(3.12)
ROA	0.3229	−1.8835**
	(0.35)	(−2.20)
Lev	−0.6383**	−2.0039***
	(−2.32)	(−8.26)
Turnover	−0.3603***	−0.4853***
	(−3.50)	(−5.32)
Tq	0.0540**	−0.0056
	(2.29)	(−0.21)
Growth	−0.1872**	−0.2460***
	(−2.20)	(−3.06)
East	0.4110***	0.2359*
	(3.10)	(1.95)
Soe	0.4868***	0.5090***
	(5.04)	(5.54)
Gdp_p	−0.0298	0.1221***
	(−1.03)	(4.07)
Constant	−3.3556***	−1.8879*
	(−3.42)	(−1.91)
Year & Ind	Yes	Yes
Obs#	5,734	8,652
Adj-R^2	0.0871	0.0732

experience, we divide the sample into groups with overseas experience (*OS_exp = 1*) and without such experience (*OS_exp = 0*) and report the regression results for each in columns (1) and (2) of Table 8, respectively. The coefficient of *OS_dum* is positive and nonsignificant for the group with overseas experience, but positive and significant at the 1 % level for the group without overseas experience.[13] Thus, our results demonstrate that executives' overseas experience affects the relationship between overseas operations and financial asset allocation. Further, the positive effect of overseas operations on financial asset allocation is weakened when firms have returnee executives, which is consistent with the theoretical analysis indicating that these executives seize physical investment opportunities that reduce the need for financial asset allocation.

5.1.3. Heterogeneity analysis by the business scope of overseas subsidiaries

The scope of business operations between overseas subsidiaries and their parent companies is an important factor affecting the operational risks of overseas subsidiaries. The economic, cultural and institutional environments of the host and home countries can vary considerably. When the business environment differs, the subsidiary, as a new entrant, needs to establish new sales channels, design and develop new products, recruit new employees and familiarize itself with the new competitive environment in the host market. The knowledge and experience accumulated by the parent company cannot be transferred effectively to the subsidiary. This increases the complexity of matching the subsidiary with the host country and increases business risks. Therefore, we argue that if the main results hold, when the business between the parent and subsidiary is aligned, the risk of overseas operations is relatively low, and firms' motivation to guard against risk decreases, which, in turn, reduces the need for financial asset allocation.

[13] The test of the difference in coefficients between the groups shows that the Chi^2 (1) value for the comparison of the *OS_dum* coefficients between the groups with and without overseas experience is 3.37, with a *p* value of 0.07.

Table 9
Heterogeneity Analysis Based on the Main Business of Overseas Subsidiaries.

Variable	(1) Full sample	(2) Full sample
	Fininv	*Fininv*
OS_match1	−0.3166**	
	(−2.21)	
OS_match2		−0.6123***
		(−3.37)
Size	0.2777***	0.2888***
	(4.59)	(4.75)
ROA	−4.7919***	−4.6632***
	(−2.90)	(−2.82)
Lev	−3.7412***	−3.7358***
	(−6.86)	(−6.83)
Turnover	−0.3886***	−0.3930***
	(−2.75)	(−2.78)
Tq	−0.0774*	−0.0767*
	(−1.69)	(−1.68)
Growth	−0.1667	−0.1573
	(−0.83)	(−0.79)
East	−0.2170	−0.2125
	(−1.08)	(−1.05)
Soe	0.2077	0.2086
	(1.20)	(1.21)
Gdp_p	0.0000*	0.0000*
	(1.69)	(1.73)
Constant	−2.8404**	−2.7867**
	(−2.15)	(−2.12)
Year & Ind	Yes	Yes
Obs#	3,442	3,442
Adj-R^2	0.1262	0.1283

To test this inference, we use original data and a manual comparison method to match the parent company's business type based on its industry classification with the overseas subsidiary's business type based on a description of its main business. After matching, we define cases in three ways: completely inconsistent, completely consistent and partially consistent for overseas subsidiaries. To ensure the robustness of the conclusions, we use two matching criteria. First, as long as an overseas subsidiary's main business is different from that of the parent company, we consider it inconsistent with the parent company's business. We define a dummy variable *OS_Match1* as equal to one for consistency and zero for inconsistency. Second, as an alternative matching criteria, we define overseas subsidiaries as being inconsistent with the parent company's business only when all of the subsidiaries have a different main business from that of the parent company. Then, the dummy variable *OS_Match2* equals one for consistency and zero for inconsistency.

The regression results are presented in Table 9. The explanatory variables in columns (1) and (2) are *OS_Match1* and *OS_Match2*, respectively. The coefficients of the explanatory variables are negative and significant at the 1 % or 5 % levels, regardless of the criteria used for the measure. Thus, when the business between the parent and subsidiary companies is the same, the parent company's product technology and production experience can be transferred to the subsidiary company. This can effectively reduce the operating risks of overseas subsidiaries. Hence, with relatively lower physical investment risk, financial asset allocation is lower. This finding provides evidence that both the promotion and crowding-out effects exist simultaneously.

5.1.4. Heterogeneity analysis by profitability of overseas subsidiaries

This study argues that a parent company's need for financial asset allocation arises because it must protect itself against the operational and financial risks faced by its overseas subsidiaries. From the perspective of overseas subsidiaries' profitability levels, when overseas subsidiaries experience operational difficulties and

Table 10
Heterogeneity Analysis Based on Profitability Level of Overseas Subsidiaries.

Variable	(1) Current explanatory variables	(2) One period lagged explanatory variables
	Fininv	*Fininv*
OS_loss	0.3302**	0.3548*
	(2.04)	(1.82)
Size	0.3346***	0.3511***
	(4.60)	(3.60)
ROA	−2.6240	−2.0619
	(−1.39)	(−0.84)
Lev	−2.6637***	−3.2931***
	(−4.82)	(−4.13)
Turnover	−0.0499	0.0701
	(−0.33)	(0.35)
Tq	0.0495	0.0305
	(0.64)	(0.30)
Growth	−0.1131	−0.4490*
	(−0.71)	(−1.76)
East	−0.0874	−0.0944
	(−0.41)	(−0.33)
Soe	0.0179	−0.2314
	(0.10)	(−1.01)
Gdp_p	0.0000	0.0000
	(0.35)	(0.16)
Constant	−4.9503***	−4.8265**
	(−2.69)	(−2.20)
Year & Ind	Yes	Yes
Obs#	1,894	1,217
Adj-R^2	0.2371	0.2862

incur losses, they are more likely to suffer from cash flow shortfalls and experience liquidity difficulties in future. In this situation, the risk of physical investment by enterprises is relatively high, and the motivation to prevent risk is strong. This manifests in the enterprise increasing its financial asset allocation.

To test this inference, by manually organizing the data,[14] this study constructs a dummy variable on whether overseas subsidiaries are losing money (*OS_loss*). This dummy variable equals one when the net profit of overseas subsidiaries is negative, and zero otherwise. The regression results are presented in Table 10. *OS_loss* serves as the explanatory variable in column (1). The coefficient of this variable is positive and significant at the 5 % level. The explanatory variable in column (2) is the profitability of overseas subsidiaries lagged by one period. The coefficient of the explanatory variable remains positive and significant at the 10 % level. Thus, the lack of profitability of overseas subsidiaries further strengthens firms' incentives for future risk prevention, which manifests itself in an increased financial asset allocation.

5.2. Heterogeneity analysis under different conditions: Macro business environment

5.2.1. Heterogeneity analysis by the location of overseas operations

The economic, political and operational risks faced by enterprises in their overseas operations differ by the location of these enterprises. As pointed out in the hypothesis development section, the impact of overseas operations on financial asset allocation is based on a comparison and trade-off between the risks of financial assets and real investment, and the impact varies depending on the risk situation.

To examine these issues, we collect information on the locations of overseas subsidiaries manually. First, we separate OECD and non-OECD overseas operations into groups depending on whether the parent enterprise

[14] Data on the profitability of subsidiaries is manually collected and organized from the sections of annual reports of listed companies titled "Analysis of major holding and participating companies."

Table 11
Heterogeneity Analysis of Overseas Operating Locations.

Variable	(1) Full sample	(2) Full sample	(3) Full sample
	Fininv	*Fininv*	*Fininv*
OS_o	0.1744**		
	(2.07)		
OS_no	0.5685***		
	(3.31)		
OS_o&no	−0.7221***		
	(−3.37)		
OS_br		0.5474***	
		(3.35)	
OS_nbr		0.2167**	0.2164**
		(2.43)	(3.34)
OS_br&nbr		−0.8493***	−0.8426***
		(−4.23)	(−4.21)
OS_bra			1.5269*
			(1.95)
OS_bre			0.2078**
			(2.32)
OS_bra&e			−1.6428**
			(−1.98)
Size	0.1406***	0.1437***	0.1449***
	(4.95)	(5.03)	(5.06)
ROA	−0.9604	−0.9592	−0.9765
	(−1.50)	(−1.50)	(−1.52)
Lev	−1.4666***	−1.4697***	−1.4760***
	(−7.62)	(−7.63)	(−7.67)
Turnover	−0.4349***	−0.4346***	−0.4339***
	(−6.55)	(−6.54)	(−6.53)
Tq	0.0173	0.0175	0.0173
	(0.70)	(0.70)	(0.70)
Growth	−0.2256***	−0.2259***	−0.2251***
	(−4.45)	(−4.46)	(−4.44)
East	0.3007***	0.3014***	0.3046***
	(3.33)	(3.34)	(3.37)
Soe	0.5440***	0.5444***	0.5445***
	(7.45)	(7.46)	(7.46)
Gdp_p	0.0532**	0.0533**	0.0525**
	(2.23)	(2.24)	(2.20)
Constant	−2.1621***	−2.2205***	−2.2451***
	(−3.67)	(−3.75)	(−3.78)
Year & Ind	Yes	Yes	Yes
Obs#	14,386	14,386	14,386
Adj-R^2	0.0707	0.0710	0.0711

has overseas subsidiaries only in OECD countries or only in non-OECD countries. We define two dummy variables on this basis. The dummy variable *OS_o* equals one if the parent enterprise has overseas subsidiaries only in OECD countries in a particular year, and zero otherwise. The dummy variable *OS_no* equals one if the parent enterprise has overseas subsidiaries only in non-OECD countries in a particular year, and zero otherwise. In addition, we define a third dummy variable for a parent enterprise that has overseas operations in both OECD and non-OECD countries; *OS_o&no* equals one if the firm has both OECD and non-OECD over-

seas subsidiaries in that year, and zero otherwise. Column (1) of Table 11 presents the test results. The coefficient of *OS_o* is positive and significant at the 5 % level, whereas the coefficient of *OS_no* is positive and significant at the 1 % level. Thus, enterprises with non-OECD overseas operations have stronger contributions to firms' financial asset allocations[15] than enterprises with OECD overseas operations only. In addition, the coefficient of *OS_o&no* is negative and significant at the 1 % level. This may be because when firms conduct overseas operations in both OECD and non-OECD countries, the diversification of business channels also diversifies risk, or because such enterprises have strong experience in overseas investment. Thus, the actual risks faced by their overseas operations are relatively small, and the allocation of financial assets may be reduced accordingly.

To further analyze the impact of the location of investment on financial asset allocation, we categorize overseas operations into Belt and Road countries only, non-Belt and Road countries only and both types of countries. Specifically, we construct the following three dummies: *OS_br* equals one if overseas operations are only in Belt and Road countries, and zero otherwise; *OS-nbr* equals one if overseas operations are only in non-Belt and Road countries, and zero otherwise; and *OS_br&nbr* equals one if overseas operations are based in both types of countries, and zero otherwise. The regression results are reported in column (2) of Table 11. The coefficients of *OS_br* and *OS_nbr* are positive and significant at the 1 % and 5 % levels, respectively. The coefficient of *OS_br&nbr* is negative and significant at the 1 % level.

Further analysis is conducted by classifying overseas operations in only Belt and Road countries into two further categories: Belt and Road Asian countries, and Belt and Road European countries. Thus we construct dummies for[16] Belt and Road Asia-only overseas operations (*OS-bra* = 1, and 0 otherwise), Belt and Road Europe-only overseas operations (*OS-bre* = 1, and 0 otherwise), and overseas operations in both categories of countries (*OS-bra&e* = 1, and 0 otherwise). The results are reported in column (3) of Table 11. The coefficients of *OS_bra* and *OS_bre* are positive and significant at the 10 % and 5 % levels, respectively. The coefficient of *OS_bra&e* is negative and significant at the 5 % level.[17]

Together, these results suggest that overseas operations located in Belt and Road countries, specifically those located in Asian Belt and Road countries, have a stronger effect on firms' financial asset allocations than other overseas operations in other locations.[18] In addition, similar to findings regarding the OECD-based categories, for firms operating only in Belt and Road countries, only in non-Belt and Road countries, only in Asian Belt and Road countries and only in European Belt and Road countries, these locations have a stronger impact on their financial asset allocation than is the case for enterprises with overseas operations in the other locations analyzed. Specifically, when firms have overseas operations in both Belt and Road and non-Belt and Road countries, or in both Asian and European Belt and Road countries, overseas operations dampen firms' financial asset allocations. These results suggest that firms weigh the risks associated with financial assets and real investments when making investment decisions. For these enterprises with deep participation in international markets and broad investment opportunities, the risk of overseas investment is relatively low, which reduces their demand for financial assets. This manifests as lower financial asset allocations. Meanwhile, when enterprises are deeply involved in overseas markets, their overseas investment needs—to develop sales chan-

[15] At present, there are 35 member countries of the OECD: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States. Compared with OECD countries, non-OECD countries have a higher degree of institutional imperfections and greater political, economic and financial risks.

[16] At present, there is no strict definition of the countries involved in the Belt and Road Initiative. Following Fan and Huang (2017), Chen et al. (2017) and Liu et al. (2018), we consider such countries as comprising a total of 64 countries in the six segments of Central Asia, Mongolia, Russia, Southeast Asia, Central and Eastern Europe, South and West Asia and the Middle East. Furthermore, the Belt and Road Asian countries are defined as 41 countries in Central Asia, Mongolia, Southeast Asia, South Asia, West Asia and the Middle East. The Belt and Road European countries are the 23 countries in Russia and Central and Eastern Europe.

[17] The within-group coefficient difference test shows that the F value for the comparison of the coefficients of *OS_bra* and *OS_bre* is 4.49, with a *p* value of 0.03.

[18] The possible reasons for this are poorer economic fundamentals, underdeveloped financial markets and exchange rate risks in Belt and Road countries/regions compared with non-Belt and Road countries/regions, and in Belt and Road countries/regions in Asia compared with Belt and Road countries/regions in Europe (Yin et al., 2018). This leads to a stronger "facilitation effect" of overseas subsidiaries on financial assets.

Table 12
Heterogeneity Analysis Based on Economic Risks of Overseas Operating Locations.

Variable	(1) Current explanatory variables	(2) One-period lagged explanatory variables
	Fininv	*Fininv*
OS_ER	0.5006***	0.4384**
	(3.25)	(2.03)
Size	0.2872***	0.2821***
	(4.78)	(4.00)
ROA	−5.1930***	−4.8607**
	(−3.07)	(−2.46)
Lev	−3.6929***	−4.4654***
	(−6.73)	(−6.34)
Turnover	−0.3949***	−0.4277***
	(−2.85)	(−2.76)
Tq	−0.0607	−0.0650
	(−1.33)	(−1.18)
Growth	−0.1759	−0.3353
	(−0.92)	(−1.45)
East	−0.2182	−0.3521
	(−1.09)	(−1.47)
Soe	0.1902	0.1122
	(1.13)	(0.57)
Gdp_p	0.0000*	0.0000
	(1.87)	(1.50)
Constant	−4.0710***	−3.1302**
	(−3.07)	(−2.10)
Year & Ind	Yes	Yes
Obs#	3,412	2,524
Adj-R^2	0.1302	0.1624

nels, hire local employees and spend time understanding local policies—are high. Thus, with limited capital, a substitution relationship may exist between the two forms of investment. Thus, while these findings mainly support the promotion effect, some results also support the crowding-out effect.

5.2.2. Heterogeneity analysis by economic risks of overseas operations

As noted previously, the uncertainty and risk of the external environment faced in overseas operations is an important reason to promote financial asset allocation by enterprises. Research shows that the economic risk of a host country's location is an important factor in the internationalization of business operations. Therefore, if the main logic of this study is valid, the higher the economic risk in the overseas subsidiary's location, the higher the risk of physical investment compared with the risk of financial assets, and the more incentives the parent company has to prevent risk by allocating funds to financial assets.

To test this inference, we measure the economic risk of a region where overseas operations are located based on an index of economic policy uncertainty calculated by Baker et al. (2016). However, Baker et al. (2016) only calculate economic policy uncertainty for select countries.[19] Therefore, we divide the locations of the overseas operations by continent as Europe, Asia, North America and South America. We adopt the economic policy uncertainty indexes of the major countries in these continents as a substitute for uncertainty regarding the specific locations of overseas operations. For Asia, we use the mean value of the economic

[19] Source: https://www.policyuncertainty.com/global_monthly.html. These countries include Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, United Kingdom and United States, as well as the European Union. As no countries in Africa are included, samples with foreign subsidiaries located only in Africa are excluded, and samples without foreign subsidiaries are also excluded. In addition, the uncertainty calculated by Baker et al. (2016) is based on monthly data, and this paper takes the annual mean for the calculation. To avoid the regression coefficients being too small, the uncertainty data are divided by 100.

Table 13
Heterogeneity Analysis Based on Political Risk in Overseas Operating Locations.

Variable	(1) Current explanatory variables	(2) One-period lagged explanatory variables
	Fininv	*Fininv*
OS_PR	2.3446**	2.1650*
	(2.41)	(1.85)
Size	0.3038***	0.2918***
	(5.19)	(4.15)
ROA	−3.1237**	−3.0819*
	(−2.35)	(−1.77)
Lev	−2.9464***	−3.7182***
	(−6.54)	(−6.24)
Turnover	−0.1921	−0.2170
	(−1.38)	(−1.36)
Tq	−0.0644	−0.0714
	(−1.51)	(−1.33)
Growth	−0.0638	−0.2502
	(−0.45)	(−0.94)
East	0.1085	−0.0793
	(0.60)	(−0.35)
Soe	−0.0039	−0.1296
	(−0.02)	(−0.66)
Gdp_p	0.0000	0.0000
	(1.04)	(1.22)
Constant	−5.6718***	−4.2596***
	(−4.40)	(−2.75)
Year & Ind	Yes	Yes
Obs#	2,859	2,085
Adj-R^2	0.1471	0.1872

policy uncertainty indexes of Hong Kong, Japan, South Korea and Singapore; Europe is proxied by the mean value of the index for the European Union; North America is proxied by the mean value of the indexes for the United States and Canada; and South America is proxied by the mean values of the indexes of Brazil, Chile and Mexico. The mean value of economic risk (*OS_ER*) is used in the regression.[20]

The regression results are presented in Table 12. The explanatory variable in column (1) is the economic risk of overseas operations' locations (*OS_ER*). Its coefficient is positive and significant at the 1 % level. The explanatory variable in column (2) is the lagged one-period economic risk of overseas operations' locations. The coefficient remains positive and significant at the 5 % level. Thus, the higher the economic risk of the country/region in which overseas operations are located, the higher the risk of real investment, the stronger the firm's incentive to allocate funds to financial assets and the higher its financial asset allocation.

5.2.3. Heterogeneity analysis by political risk of overseas operations

Owing to the irreversibility of investments, high political risk is a key factor affecting enterprises' overseas operations. For example, Lv et al. (2019) find that the Belt and Road Initiative does not have a significant promotional effect on investment in economies with high political risk. Therefore, if the key argument of this study is valid, the higher the political risk of the location of overseas subsidiaries, the higher the risk of physical investment compared with investment in financial assets and the stronger the demand for financial asset al-

[20] To ensure the robustness of this paper's conclusions and avoid the limitations of a single indicator, we adopt the risk ratings of overseas investment countries in the Report on Risk Ratings of China's Overseas Investment Countries compiled by the International Investment Research Office of the Institute of World Economics and Politics of the Chinese Academy of Social Sciences as a measure of the risk of overseas operations. Source: https://www.iwep.org.cn/ Because this report has been published only since 2012, its use would result in a large reduction in sample size, and therefore it is used only in the robustness test. The results show that the lower the risk rating, the higher the firm's financial asset allocation, consistent with the findings of the literature. The regression results are available on request.

Table 14
Heterogeneity Analysis Based on Enterprises' Overseas Investment Opportunities.

Variable	(1) Current explanatory variables	(2) One-period lagged explanatory variables
	Fininv	*Fininv*
OS_InvO	3.7327***	3.0887**
	(2.86)	(2.21)
Size	0.3133***	0.3038***
	(5.24)	(4.40)
ROA	−5.3544***	−5.7904***
	(−3.25)	(−2.75)
Lev	−3.7642***	−3.9276***
	(−6.89)	(−5.64)
Turnover	−0.3877***	−0.4162***
	(−2.80)	(−2.80)
Tq	−0.0609	−0.1437
	(−1.35)	(−1.60)
Growth	−0.1382	−0.2654
	(−0.72)	(−1.64)
East	−0.1220	−0.1848
	(−0.61)	(−0.80)
Soe	0.1793	0.1940
	(1.06)	(0.98)
Gdp_p	0.0000	0.0000
	(1.53)	(1.49)
Constant	−4.1001***	−3.1824**
	(−3.12)	(−2.07)
Year & Ind	Yes	Yes
Obs#	3,439	2,544
Adj-R^2	0.1292	0.1373

location. This inference is further discussed in this section. Drawing on Lv et al. (2019), the political risk of the location of overseas subsidiaries is measured using four indicators—government stability, the political risk of investment projects, religious and political risks and the degree of democratization—published in the International Country Risk Guide database by the PRS Group.[21]

The regression results are presented in Table 13. The explanatory variable in column (1) is the political risk of the location of the overseas operations (*OS_PR*). Its coefficient is positive and significant at the 5 % level. The explanatory variable in column (2) is the lagged one-period political risk of the location of the overseas operations. Its coefficient remains positive and significant at the 10 % level. Thus, the higher the political risk of the country in which the overseas operations are located, the higher the risk of real investment compared with that of investment in financial assets and hence, the stronger the firm's incentive to allocate funds to financial assets and the higher its financial asset allocation level.

5.2.4. Heterogeneity analysis by investment opportunities in overseas operations

The previous two-part test supports the notion that the risk mechanism plays an important role in the relationship between overseas operations and financial asset allocation from the perspectives of economic and political risks. In the theoretical analysis, we note that, in addition to business risks, potential investment opportunities prompt overseas operations to invest in financial assets. Then, the question arises: is it true that the more potential investment opportunities exist, the stronger the contribution of overseas operations to an enterprise's financial asset allocation? We examine this question in this section. When a country's economic growth rate is rapid and all sectors are booming, enterprises tend to face plentiful investment opportunities. Therefore, we determine the GDP of the locations of overseas subsidiaries in past years, calculate their growth

[21] The PRS model is an effective system for predicting and quantifying political and country risk. Many scholars test the accuracy and practical relevance of the model, which provides valid predictions for 100 countries. Source: https://www.prsgroup.com/explore-our-products/international-country-risk-guide/.

Table 15
Impact of Financial Asset Allocation on Liquidity Risk and Operational Risk of Multinational Firms.

Variable	(1) Full sample	(2) Full sample
	CFO_VOL	*ROA_VOL*
*OS_dum*Fininv*	−0.0128**	−0.0351*
	(−2.05)	(−1.88)
Fininv	−0.0170	0.0059
	(−1.20)	(0.61)
OS_dum	−0.0027	0.0003
	(−0.47)	(0.35)
Size	−0.0061***	−0.0037***
	(−11.30)	(−9.97)
ROA	−0.0688***	−0.1107***
	(−6.82)	(−16.12)
Lev	0.0341***	0.0137***
	(10.89)	(6.44)
Turnover	0.0118***	−0.0023***
	(10.10)	(−2.90)
Tq	0.0031***	0.0025***
	(8.91)	(10.71)
Growth	0.0044***	0.0020***
	(4.94)	(3.28)
East	−0.0012	0.0005
	(−0.80)	(0.45)
Soe	−0.0052***	−0.0038***
	(−4.62)	(−4.95)
Gdp_p	0.0001	−0.0004*
	(0.34)	(−1.78)
Constant	0.1657***	0.1161***
	(14.23)	(14.67)
Year & Ind	Yes	Yes
Obs#	13,742	13,742
Adj-R^2	0.0644	0.0901

rates and average the three-year growth rate to obtain the average value of investment opportunities for enterprises with overseas operations (*OS_InvO*).[22]

The regression results are shown in Table 14. The explanatory variable in column (1) is *OS_InvO*, and the coefficient of this variable is positive and significant at the 1 % level. The explanatory variable in column (2) is the economic growth rate of the location of overseas operation in the advance period, and the coefficient remains positive and significant at the 5 % level. These regression results indicate that the faster the economic growth rate of the country or region in which overseas operations are located, the higher the financial asset allocation level of firms. This further supports the logic of this paper from the perspective of investment opportunities.

5.3. Further analysis: Economic consequences test

The theoretical analysis and heterogeneity tests in this paper show that multinational firms increase their financial asset allocations mainly for the purposes of risk hedging and precautionary savings. Therefore, a high financial asset allocation should be conducive to reducing the liquidity risk and overall business risk of multinational sub-firms. To test this inference, we conduct an economic consequence analysis. Drawing

[22] We also measure the external risk of a firm's investment using the economic volatility (standard deviation of GDP growth) of the location of its overseas subsidiaries over the past three years, and test these results. The results show that the higher the economic volatility of the country/region where the overseas operation is located, the higher the firm's financial asset allocation, consistent with the established findings.

on Liu and Zhao, 2019, the standard deviation of a firm's cash flow from operating activities over the next three years is used to measure the firm's liquidity risk (*CFO_VOL*), and the standard deviation of the firm's return on total assets over the next three years is used to measure the firm's overall risk (*ROA_VOL*). We define cash flow from operating activities as equal to net cash flow from operating activities divided by total assets and the return on total assets as equal to net profit divided by total assets. The specific model is shown below:

$$CFO\_VOL_{it}/ROA\_VOL_{it} = \alpha_0 + \alpha_1 OS\_dum_{it} * Fininv_{it} + \alpha_2 OS\_dum_{it} + \alpha_3 Fininv_{it} + \sum Control_{it} + \varepsilon_{it} \quad (2)$$

The regression results are presented in Table 15. It can be observed that the coefficient of the interaction term *OS_dum*Fininv* is negative and significant, indicating that the allocation of financial assets by listed companies conducting overseas operations can suppress cash flow and net profit fluctuations and mitigate the liquidity and operational risks of enterprises. Therefore, the results in Table 15 further support the theoretical hypotheses of the article. In addition, the results in Table 15 rule out the alternative explanation that multinational firms take advantage of capital to hold more financial assets for investment benefits.

6. Conclusion

Exploring the motives influencing the corporate financial asset allocations of real enterprises is of considerable significance because it helps to guide the development of both the real economy and the financial sector, and provides financial services for the real economy. In contrast with studies that focus on the impact of macro factors on corporate financial asset allocations, in this paper, we test the impact of overseas operations on corporate financial asset allocations using data on China's A-share listed companies for the 2008–2018 period. We find that the level of financial asset allocation is higher for enterprises with overseas operations than for their counterparts without such operations. These results continue to hold after conducting robustness tests, including fixed effects, instrumental variables and PSM, and replacing measures of core variables. Further analysis based on enterprises' micro-operating characteristics shows that the promotion effect of overseas operations on financial asset allocations mainly exists when the parent company has severe financing constraints, no overseas executives, a business that is inconsistent with that of the subsidiary company and an overseas subsidiary company that is losing money. Further analysis based on the macro business environment shows that the level of financial asset allocation is higher when overseas subsidiaries are located in non-OECD (vs. OECD) countries, and in Belt and Road Initiative countries (vs. non-Belt and Road Initiative countries). Furthermore, the level of financial asset allocation is higher for enterprises with overseas operations in Belt and Road Initiative countries than for those with non-OECD operations. The promotion effect of overseas operations on financial asset allocations mainly exists in regions with high economic or political risks and high investment opportunities. Finally, the economic consequences test shows that high financial asset allocations help reduce the cash flow fluctuations and business risk of multinational enterprises and serve as a reservoir.

The findings of this paper have implications for policy. Opening up to the outside world is an essential component of China's national policy and, under the Belt and Road development strategy, promoting enterprises to "go global" has become an important prerequisite to ensure China's sustained and stable economic growth. From the unique perspective of financial asset allocation, this paper examines the important function of risk prevention played by financial assets in the process of "going out," which has certain insights for Chinese enterprises making global investments in the future. However, most studies consider financial asset allocation by enterprises to be driven by short-term arbitrage purposes, which will adversely affect the value of the firms. However, the research in this paper suggests that enterprises may increase their financial asset allocation for risk aversion purposes. In the context of high uncertainty in the external market environment, allocating part of their capital to financial assets can help overseas subsidiaries prevent future operational and financial risks and simultaneously grasp potential investment opportunities. Relevant regulatory authorities should comprehensively examine the financialization of enterprises in the light of many factors, such as enterprise characteristics, sources of funds, the external environment and economic cycles.

Although we find that overseas operations generally have a "facilitating effect" on financial asset allocation, this does not mean that an enterprise should solely or necessarily pursue a strategy of financialization. An enterprise must compare and weigh the risks of physical investment and financial assets when making invest-

ment decisions, and financial assets must meet certain internal and external conditions to fulfill their risk prevention function. A research issue that deserves attention in the future is how a host country's close economic ties with China, its degree of trade friction with China and its level of financial development affect financial asset allocation. Due to data disclosure limitations, it is difficult to explore whether an increase in financial asset allocation is due to an increase in overseas or domestic financial asset allocation. With the deepening of financial reform, an important question will be how to promote the healthy development of the real economy and a financial virtuous circle in light of the global economic environment. In particular, entrepreneurs should combine their own characteristics, macroeconomic policies and overseas market environment to maximize the ''risk prevention'' function of financial assets, avoid over-financialization, pursue reasonable allocation of financial assets and assist the combined development of the real economy and the financial market to realize the great strategic concept of the ''Belt and Road Initiative'' for China.

Conflict of Interest

We all have no actual or potential conflict of interest including any financial, personal or other relationships with other people or organizations within three years of beginning the submitted work that could inappropriately influence, or be perceived to influence, their work.

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Voluntary resignation of independent directors and auditor responses: Empirical evidence from Chinese A-share listed firms

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ABSTRACT

We examine auditor responses to the voluntary resignation of independent directors. We show that auditors respond by increasing audit fees or rescinding engagement with their clients, but not by increasing their audit effort. Mechanism tests reveal that independent directors' voluntary resignation leads to increased regulatory sanctions and negative media coverage, these relationships are more pronounced after the New Securities Law. Auditor response strategies follow an order of priority: at an acceptable level of perceived risk, auditors increase audit fees; when perceived risk exceeds this level, auditors will discontinue the client relationship. Auditors associate greater risk with firms that have (vs. have not) experienced consecutive voluntary resignations by independent directors. Mandatory resignation has no such effect.

1. Introduction

The board of directors plays a crucial role in corporate governance. The proportion of independent directors on the board is an important metric of the effectiveness of board supervision, which is emphasized by regulatory authorities (Zhu et al., 2016). The independent director system was initially established to mitigate agency problems between shareholders and management (Fama and Jensen, 1983; Dai et al.,

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2014). Independent directors also supervise, advise and provide support in the form of resources for listed companies (Fama and Jensen, 1983; Liu et al., 2018; Zhou et al., 2021). What signals are sent by the voluntary resignation events of independent directors? Can auditors identify the risks involved? How do auditors respond? We explore this series of questions.

Typically, the resignation events of independent directors are categorized as mandatory or voluntary. Mandatory resignation occurs when independent directors are required to step down from their roles under regulatory pressure; voluntary resignation occurs when independent directors proactively relinquish their positions, judging that the benefits of those positions do not compensate for the risks incurred. According to signaling theory, the voluntary resignation of independent directors signals company risk to external parties (Gupta and Fields, 2009; Lin et al., 2012; Bar-Hava et al., 2021; Cao et al., 2023), such as poor company performance (Arthaud-Day et al., 2006), high levels of earnings management (Zhi and Tong, 2005) or elevated legal risks (Yang and Huang, 2015). This paper focuses on the responses of auditors, as stakeholders in listed companies, to the voluntary resignation of independent directors.

On 1 March 2020, the newly revised Securities Law of the People's Republic of China (2019 Revision) (hereinafter "the New Securities Law") officially came into effect. The new law required listed companies to expand the scope of their information disclosure, including the disclosure of dissenting votes on the board of directors, and increased the penalties for violations. As a result, independent directors now face a higher risk of receiving substantial penalties due to a listed company's violations (Guo, 2022; Li et al., 2022; Tang et al., 2023). Under the new law, therefore, independent directors bear a higher level of risk but receive fewer benefits. This imbalance has contributed to an increase in resignations by independent directors of listed companies (Zhang et al., 2023), which has attracted attention from all sectors of society and provides a good scenario for this study to explore the signaling effect of the resignation of independent directors.

To test the risk control strategies adopted by auditors in response to the voluntary resignation of independent directors, we focus on a sample of listed firms on the Chinese A-share market from 2018 to 2021. We find that listed firms experiencing voluntary resignations by independent directors, compared with those not experiencing such resignations, are charged higher audit fees and have a higher probability of audit firm change. However, we find no evidence that such voluntary resignations have a significant impact on audit effort. Mechanism tests show that the voluntary resignation of listed companies' independent directors signals to the outside world that the companies are at risk of regulatory penalties. As a result, there is also an increase in negative media coverage of the companies, which increases auditors' perception of risk and thus affects their response behavior. Further analysis indicates that since the implementation of the New Securities Law, the voluntary resignation of independent directors has conveyed a stronger risk signal and the risk perceived by auditors has increased, making the positive effect of voluntary resignation on abnormal audit fees more pronounced. Additionally, we find that in response to the risk brought about by the voluntary resignation of independent directors, auditors tend to charge higher audit fees when they believe the risk to be at an acceptable level; however, when they believe that the risk outweighs the benefits, they will seek to avoid risk by discontinuing the client relationship.

Our paper makes the following contributions. First, it enriches the literature on the economic consequences of the voluntary resignation of independent directors. Most previous studies explore this topic from the perspectives of investors and listed firms, with few discussing auditors. This paper takes auditor responses as a starting point, offering a new perspective on the economic consequences of the voluntary resignation of independent directors.

Second, our paper expands research on the factors influencing auditor response behavior. While the literature explores the impact of factors such as fraud risk, the executive team and policy implementation on auditor response behavior, few studies systematically explore such behavior from the perspective of the voluntary resignation of independent directors. In contrast with previous studies, most of which consider only a single auditor behavior, this paper uses the sequential analysis method proposed by Krishnan et al. (2013) to make the study of auditor responses more systematic and comprehensive.

Third, this study provides new evidence of how systemic risk factors such as laws and regulations affect auditors' risk perception, thus enhancing understanding of auditor response behavior and providing empirical support for the effectiveness of the implementation of the New Securities Law.

The remainder of the paper proceeds as follows. Section 2 reviews the literature. Section 3 develops our hypothesis. Section 4 describes the data, variables and research design. Section 5 provides the empirical results and reports on a series of robustness tests. Section 6 presents the mechanism analysis. Section 7 describes further analyses. Section 8 presents the heterogeneity analysis. Section 9 concludes the paper.

2. Literature review

2.1. Voluntary resignation of independent directors

Studies show that listed companies whose independent directors voluntarily resign have significant deficiencies in internal control (Shang and Hu, 2016); an increased probability of financial misconduct and regulatory penalties (Dai et al., 2014; Goodell et al., 2023); reduced investment in research and development and reduced innovation efficiency (Le et al., 2020; Cao et al., 2023); and increased levels of cash holdings (Tian and Wang, 2019). The economic consequences of the voluntary resignation of independent directors are primarily explored from the perspectives of investors and listed companies.

From the perspective of investors, voluntary resignation is a way for independent directors to "vote with their feet" to avoid risk, signaling to the market that a company is experiencing risks and/or governance deficiencies. The voluntary resignation of independent directors can reduce the corporate value and operational performance of listed companies (Bazerman and Schoorman, 1983; Tang and Ma, 2012; Huang and Chan, 2018; Bar-Hava et al., 2021; Zhang et al., 2023). In China, these effects have been especially pronounced since the judgment of the first Special Representative Securities Action case following the implementation of the New Securities Law, namely the Kangmei Pharmaceutical case. After this judgment, the market reaction around the dates of voluntary resignations of independent directors showed a significant (3.9 %) decrease (Xie et al., 2023).

From the perspective of listed firms, independent directors mainly play supervisory and advisory roles. After the voluntary resignation of independent directors, the newly appointed independent directors have lower supervisory and advisory capabilities than their predecessors, due to the influence of a learning effect (Gupta and Fields, 2009). This reduces the governance capabilities and internal control quality of listed firms and affects their standardized operations (Guo, 2022).

Few studies explore the impact of the voluntary resignation of independent directors on auditor behavior. Shang and Hu (2016) find that auditors are more likely to issue qualified audit opinions for listed companies that have experienced voluntary resignations by independent directors. Xie et al. (2023) show that auditors pay attention to the market reaction to the voluntary resignation of independent directors and adopt corresponding strategies to adjust key aspects of the audit process.

2.2. Auditor responses

Auditor responses mainly depend on the magnitude of risks associated with client companies. Auditors conduct a risk assessment of a client company before entering into a contract and adjust their audit plan, audit effort and audit fees according to the level of risk identified (Johnstone, 2000). The literature on the factors influencing auditor responses focuses on two main factors: corporate executives and enterprise risk.

From the perspective of corporate executives, when the executive team is less stable and management is overconfident, auditors will charge higher audit fees to address potential risks. If such risks exceed the auditors' tolerance threshold, they will choose to avoid risk by discontinuing the client relationship, leading to auditor change (Cai et al., 2015; Liu et al., 2018; Wang et al., 2022). Changes in a company's executive team create uncertainty about the future operating conditions and financial policies of the company (Miller, 1993). In such circumstances, auditors are also likely to adopt risk mitigation measures such as increasing audit fees or terminating the audit (Simunic, 1980; Jiang et al., 2007; Wang et al., 2021; Zhu and Liu, 2022).

From the perspective of enterprise risk, the higher the risk associated with a company, the greater the risk of audit failure and the more extensive auditor responses become (Wang et al., 2022). Specifically, when clients have higher levels of earnings management, lower-quality internal control and higher litigation risks, auditors are more likely to take measures such as increasing audit fees and effort, issuing unqualified opinions with

reservations and canceling the audit agreement based on their risk perception (Krishnan and Krishnan, 1997; Elder et al., 2009; Krishnan et al., 2013). Aspects of the external environment and policy implementation, such as media attention (Liu et al., 2014), tax policies (Hu et al., 2022) and environmental regulations (Ji et al., 2022), also affect auditors' risk perception, leading to auditor responses such as increasing audit fees.

2.3. Critical review

Most previous studies explore the economic consequences of the voluntary resignation of independent directors from the perspectives of investors and listed firms. Given China's current context, following the implementation of the New Securities Law, which has increased the perceived risk faced by auditors, there is a need for more research on this topic from the perspective of auditors' risk perception. In addition, research on the factors influencing auditors' risk response strategies typically considers individual actions taken by auditors, such as increasing audit fees or effort or discontinuing the client relationship. Little research organically links the voluntary resignation of independent directors with auditors' systematic strategies in response to risk.

3. Theoretical analysis and hypothesis

In recent years, with the gradual refinement of China's independent director system, the mechanism of governance of Chinese independent directors has become a hot topic of research. Many scholars explore the voluntary resignation events of independent directors. Kaplan and Reishus (1990) and Gilson (1990) argue that the voluntary resignation of an independent director due to poor company performance affects the director's reputation, making it more difficult for them to find employment in the future. Tan et al. (2006) and Dai et al. (2014) also note that legal risks and reputational losses are important factors influencing the decision of independent directors to voluntarily resign. Therefore, this decision can be assumed to be well considered. Accordingly, such resignation events reflect the risks facing listed companies to a certain extent.

The independent director system was originally established to alleviate the principal–agent problem faced by enterprises (Fama and Jensen, 1983). Compared with non-independent directors, independent directors have access to more internal information about listed companies and are better positioned to detect risks, due to their supervisory and consultative roles. In reality, however, because of their personal relationships, independent directors rarely opt to resign voluntarily. When they identify corporate governance flaws, they often choose to remain silent out of courtesy, which significantly undermines their supervisory role. In such circumstances, independent directors may face fines for failing to perform their duties diligently, which can severely impact their reputation (Xin et al., 2013). Based on this, we argue that independent directors only choose to resign when the risk of corporate penalties is particularly high, and such resignation events can signal to the market that the listed companies involved may be at risk.

Auditors are highly sensitive to the risks associated with listed companies, but as outsiders, they face challenges in identifying all of these risks due to information asymmetry. Consequently, the abrupt voluntary resignation of an independent director may serve as a warning to auditors to maintain a prudent audit approach. First, auditors may harbor suspicions about the reasons for the independent director's resignation. To guard against the inherent risk of material misstatement (Zhu and Liu, 2022), they will remain skeptical about the compliance of certain business and accounting treatments. Second, auditors may question whether the company's newly appointed independent directors can effectively fulfill their supervisory and advisory roles (Liang and Li, 2022). This will lead to an increase in both control risk and audit risk.

DeAngelo (1981) points out that in a competitive market environment, auditors often hope to earn quasi-rents by maintaining long-term relationships with clients. When a listed company has higher inherent and control risks, auditors will engage in additional audit procedures and increase their audit effort to reduce their own legal and reputational risk to an acceptable level (Chen et al., 2019). Upon identifying the risk signals conveyed by the voluntary resignation of independent directors, auditors will charge higher audit fees based on the increased audit effort or risk premium (Simunic, 1980). However, when auditors perceive the voluntary resignation of independent directors to convey a level of risk that exceeds an acceptable threshold, they will

choose to terminate their engagement with the client company (Johnstone and Bedard, 2003). Based on this, we propose the following hypothesis:

H1. The voluntary resignation of independent directors prompts various auditor responses.

4. Data and research design

4.1. Data

We select A-share listed companies in China from 2018 to 2021 as our sample, excluding those in the financial industry and those with missing data. We ultimately obtain 14,887 firm-year observations. The new Code of Corporate Governance for Listed Companies was issued in 2018, imposing new regulations on the responsibilities of independent directors. We select 2018 as the starting year to mitigate potential endogeneity issues. The sample of voluntary resignations of independent directors is manually compiled from the Cninfo website, summarizing 1508 voluntary resignation events involving 1261 listed companies from 1 January 2018 to 31 December 2021. After the aforementioned data processing, the final sample of voluntary resignations for regression analysis comprises 1073 firm-year observations. Audit data, financial data and corporate governance data are sourced from the China Stock Market & Accounting Research database, and data on negative media coverage come from the Chinese Research Data Services database. To mitigate the impact of extreme values, we apply 1 % up and down winsorization for all continuous variables.

4.2. Variable definitions

4.2.1. Voluntary resignation of independent directors

Following Xie et al. (2023), a dummy variable (*INResign*) is introduced to measure the voluntary resignation of independent directors. *INResign* takes the value of 1 if a listed company experiences the voluntary resignation of an independent director, and 0 otherwise.

4.2.2. Audit effort

Audit effort is measured by audit delay (*LnAlag*), following Li and Chen (2023). *LnAlag* is defined as the natural logarithm of the number of days between the balance sheet date and the date of issuance of the audit report.

4.2.3. Abnormal audit fees

Referring to Cai and Zhang (2022), we measure abnormal audit fees (*ABFEE*) by calculating the residual term of Model (1):

$$\begin{aligned} LNFEE_{it} = {} & \alpha + \beta_0 Size_{it} + \beta_1 Lev_{it} + \beta_2 ROA_{it} + \beta_3 Loss_{it} + \beta_4 Growth_{it} + \beta_5 LnAlag_{it} + \beta_6 Accr_{it} + \beta_7 Inv_{it} \\ & + \beta_8 Current_{it} + \beta_{10} Big4_{it} + \beta_{11} Extra_{it} + \beta_{12} Cata_{it} + \sum Industry + \sum year + \varepsilon_{it} \end{aligned} \quad (1)$$

where *LNFEE* represents the natural logarithm of audit fees for the current year, controlling for factors such as the company's size (*Size*), debt ratio (*Lev*) and return on assets (*ROA*); whether the company is incurring a loss (*Loss*); the company's growth potential (*Growth*); audit effort (*LnAlag*); the ratio of accounts receivable to total assets (*Accr*); the ratio of inventory to total assets (*Inv*); the current ratio (*Current*); whether the auditor is one of the Big Four (*Big4*); the ratio of operating income to net profit (*Extra*); and the ratio of current assets to total assets (*Cata*).

4.2.4. Auditor change

Auditor change (*Change*) takes the value of 1 if the audit firm of the listed company changes in the current year, and 0 otherwise, excluding cases of firm renaming, merger or split.

4.3. Research design

To explore auditors' responses to the voluntary resignation of independent directors, we construct the following model:

$$Response_{it} = \alpha + \beta_0 INResign_{it} + \beta_1 Controls + \sum Industry + \sum year + \varepsilon_{it} \quad (2)$$

Specifically, we use audit effort (*LnAlag*), abnormal audit fees (*ABFEE*) and auditor change (*Change*) to measure the dependent variable (*Response*). Model (2) includes control variables selected with reference to Liang and Li (2022) and Shang and Hu (2016), which encompass firm size (*Size*), debt ratio (*Lev*), return on assets (*ROA*), firm age (*Age*), growth potential (*Growth*), proportion of independent directors (*Indep*), board size (*Board*), whether the firm is experiencing a loss (*Loss*), affiliation with one of the Big Four audit firms (*Big4*) and the combination of CEO and chairman roles (*Dual*). For detailed variable definitions, see Table 1.

5. Empirical results

5.1. Descriptive statistics

Table 2 provides the reasons for the voluntary resignation of independent directors and the number of observations in our sample. The majority of the observations show independent directors resigning for personal reasons, accounting for 72.32 % of the voluntary resignation sample. Table 3 illustrates the distribution of listed companies that experienced voluntary resignations by independent directors from 2018 to 2021. The table shows that the number of companies experiencing the voluntary resignation of independent directors increased year by year during this period, with the proportion of such companies reaching its highest value, at 7.91 % of the total sample, in 2021.

Table 4 shows the results of descriptive statistical analysis of the variables. The mean of audit effort (*LnAlag*) is 4.639, with a minimum value of 2.833, a maximum value of 5.220 and a standard deviation of 0.178, indicating a significant variation in audit effort between companies. The mean of abnormal audit fees (*ABFEE*) is –0.001, with a minimum value of –0.962 and a maximum value of 1.016, spanning 1.978. The mean of audit firm change (*Change*) is 0.104, indicating that 10.4 % of the sampled companies changed their audit firms between 2018 and 2021. The mean of the independent director voluntary resignation variable (*INResign*) is 0.072, indicating that 7.2 % of the companies in the sample experienced voluntary resignations by independent directors during the sample period. In terms of the control variables, the minimum and maximum values of firm size (*Size*) are 19.753 and 26.372, respectively, indicating a large variation in the size of the

Table 1
Variable definitions.

Variable	Definition
LnAlag	Natural logarithm of the number of days between the balance sheet date and the audit report issuance date.
ABFee	Residuals from Model (1).
Change	Dummy variable that takes the value of 1 if there is a change in the audit firm hired in a given year, and 0 otherwise.
INResign	Dummy variable that takes the value of 1 for listed companies experiencing the voluntary resignation of independent directors, and 0 otherwise.
Size	Natural logarithm of year-end asset balance.
Lev	Year-end total liabilities divided by year-end total assets.
ROA	Net profit to total assets ratio.
Age	Natural logarithm of the difference between the current year and the year of listing.
Growth	Percentage change in operating revenue from the previous year.
Indep	Ratio of independent directors to total board members.
Board	Natural logarithm of the number of board members.
Loss	Dummy variable that takes the value of 1 if the current year's net profit is less than 0, and 0 otherwise.
Big4	Dummy variable that takes the value of 1 if the company is audited by one of the Big Four audit firms, and 0 otherwise.
Dual	Dummy variable that takes the value of 1 if the chairman and general manager are the same person, and 0 otherwise.

Table 2
Reasons for resignation.

Reason for Resignation	Event Count	Proportion
Health-/Age-Related	38	3.54 %
Work-Related	233	21.71 %
Personal	776	72.32 %
Unspecified	16	1.49 %
Inability to Fulfill Duties	4	0.37 %
Mutual Agreement for Company-Related Reasons	4	0.37 %
Doubts About Company's Regular Related-Party Transactions	1	0.09 %
Change in Management Relationship in Personal Workplace	1	0.09 %
Total	1,073	100.00 %

Table 3
Independent director resignation sample statistics.

Year	Total Sample	Voluntary Resignation	
		Sample Size	Proportion
2018	3,297	245	7.51 %
2019	3,495	234	6.77 %
2020	3,799	251	6.85 %
2021	4,296	343	7.91 %
Total	14,887	1,073	7.28 %

Table 4
Summary statistics.

Variable	N	Mean	Median	SD	Min	25th pct	75th pct	Max.
LnAlag	14,887	4.639	4.710	0.178	2.833	4.511	4.762	5.220
ABFEE	14,887	–0.001	–0.004	0.382	–0.962	–0.254	0.244	1.016
Change	14,887	0.104	0.000	0.306	0.000	0.000	0.000	1.000
INResign	14,887	0.072	0.000	0.259	0.000	0.000	0.000	1.000
Size	14,887	22.279	22.081	1.308	19.753	21.343	23.009	26.372
Lev	14,887	0.422	0.411	0.207	0.059	0.258	0.565	0.962
ROA	14,887	0.035	0.040	0.087	–0.384	0.013	0.076	0.239
Age	14,887	2.073	2.303	0.969	0.000	1.386	2.944	3.367
Growth	14,887	0.157	0.105	0.393	–0.643	–0.027	0.266	2.401
Indep	14,887	0.379	0.364	0.054	0.333	0.333	0.429	0.571
Board	14,887	2.100	2.197	0.196	1.609	1.946	2.197	2.639
Loss	14,887	0.141	0.000	0.348	0.000	0.000	0.000	1.000
Big4	14,887	0.060	0.000	0.237	0.000	0.000	0.000	1.000
Dual	14,887	0.321	0.000	0.467	0.000	0.000	1.000	1.000

listed companies in the sample. The mean of the debt ratio (*Lev*) is 0.422, indicating a moderate overall debt ratio for the sampled companies. The results of the descriptive statistical analysis are similar to those reported in previous studies, with no significantly abnormal values detected.

5.2. Correlation analysis

Table 5 presents the Pearson correlation coefficients for the variables. The voluntary resignation of independent directors (*INResign*) is positively and significantly correlated with audit effort, abnormal audit fees and auditor change, providing preliminary support for H1. In terms of the control variables, the maximum absolute value of the correlation coefficients is 0.571, indicating that there is no severe problem of multicollinearity among the variables.

Table 5
Correlation analysis.

	LnAlag	*ABFEE*	*AFchange*	*INResign*	*Size*	*Lev*	*ROA*	*Age*	*Growth*	*Indep*	*Board*	*Loss*	*Big4*
ABFEE	0.040***	1.000											
AFchange	0.063***	0.017**	1.000										
INResign	0.026***	0.024***	0.043***	1.000									
Size	–	–	–0.016*	–	1.000								
	0.046***	0.022***		0.038***									
Lev	0.016**	0.030***	0.011	0.038***	0.019**	1.000							
ROA	–	–0.018**	–	–	0.031***	–	1.000						
	0.107***		0.051***	0.076***		0.488***							
Age	–	–0.008	0.042***	0.041***	0.407***	0.063***	–	1.000					
	0.022***						0.139***						
Growth	–0.004	0.009	0.018**	–0.005	0.003	0.000	0.030***	–0.013	1.000				
Indep	0.026***	0.026***	0.014*	–0.002	–0.013	0.001	–0.016**	–0.002	–0.011	1.000			
Board	–	–	–0.014*	0.000	0.273***	0.013	0.012	0.150***	0.019**	–	1.000		
	0.044***	0.024***								0.571***			
Loss	0.183***	0.019**	0.073***	0.082***	–	0.064***	–	0.155***	–0.004	0.033***	–	1.000	
					0.079***		0.408***				0.050***		
Big4	–	–	–0.003	–0.018**	0.314***	0.007	0.024***	0.025***	0.046***	0.021**	0.083***	–	1.000
	0.101***	0.033***										0.040***	
Dual	0.050***	0.047***	–0.019**	–0.011	–	–	0.025***	–	0.001	0.107***	–	–0.007	–
					0.197***	0.025***		0.263***			0.177***		0.053***

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

5.3. Main results

Table 6 displays the regression results for Model (2). Column (1) shows the results of regressing the voluntary resignation of independent directors on audit effort. The coefficient of the voluntary resignation of independent directors (*INResign*) is 0.005, but it does not pass the significance test. Therefore, there is no evidence that auditors increase audit effort for listed companies experiencing voluntary resignations by independent directors (see Table 7).

In Column (2), the coefficient of the voluntary resignation of independent directors (*INResign*) is 0.029, which is significant at the 5 % level. This indicates that auditors perceive risk signals to be conveyed by listed companies experiencing the voluntary resignation of independent directors. Therefore, auditors charge significantly higher audit fees for listed companies experiencing voluntary resignations by independent directors than for their counterparts not experiencing such resignations.

Table 6
Voluntary resignation of independent directors and auditor responses.

	(1)	(2)	(3)
Variable	*LnAlag*	*ABFEE*	*Change*
INResign	0.005	0.029**	0.373***
	(0.920)	(2.180)	(3.910)
Size	0.006***	–0.002	–0.095***
	(2.608)	(–0.280)	(–3.323)
Lev	0.013	0.055	0.484***
	(1.096)	(1.565)	(2.821)
ROA	–0.303***	–0.179**	–1.324***
	(–10.895)	(–2.390)	(–2.880)
Age	–0.015***	–0.002	0.096***
	(–6.378)	(–0.305)	(2.653)
Growth	–0.023***	0.006	0.280***
	(–4.779)	(0.579)	(3.911)
Indep	0.019	0.128	0.413
	(0.459)	(1.001)	(0.639)
Board	–0.011	0.000	–0.133
	(–0.895)	(0.002)	(–0.688)
Loss	0.035***	–0.021	0.267**
	(6.248)	(–1.357)	(2.486)
Big4	–0.073***	–0.044	0.096
	(–7.886)	(–1.622)	(0.753)
Dual	0.013***	0.035***	–0.099
	(3.187)	(3.324)	(–1.534)
Cons	4.564***	–0.030	–1.663*
	(86.722)	(–0.185)	(–1.673)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	14,887	14,887	14,887
F/chi2	80.402	3.141	5,768.482
Adj-R^2/Pseudo R^2	0.097	0.005	0.049

Note: Figures in parentheses are robust standard errors, obtained by clustering at the firm level. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively, as below.

Table 7
Common support test.

Group	Outside Common Support Area	Inside Common Support Area	Total
Control Group	101	13,713	13,814
Experimental Group	7	1,066	1,073
Total	108	14,779	14,887

In Column (3), the coefficient for listed companies experiencing the voluntary resignation of independent directors (*INResign*) is 0.373, which is significant at the 1 % level. Economically, this suggests that listed companies with (vs. without) voluntary resignations by independent directors are 45.16 % more likely to experience a change in audit firms. This indicates that the audit contract relationship between auditors and listed companies with (vs. without) such resignations is less stable and the likelihood of a change of audit firm is greater. In summary, H1 is supported.

5.4. Robustness tests

5.4.1. Propensity score matching

To eliminate the impact of company-specific characteristics on the research conclusions, we use propensity score matching (PSM) to test the main findings of the paper. First, we select firm size (*Size*), debt ratio (*Lev*), return on assets (*ROA*), firm age (*Age*), growth potential (*Growth*), whether the firm is loss-making (*Loss*), affiliation with one of the Big Four audit firms (*Big4*) and the combination of CEO and chairman roles (*Dual*) as covariates for PSM matching. Table 8 and Fig. 1 display the results of a PSM balance test, indicating that there are no significant differences between the two groups for any of the control variables after PSM. Therefore, the balance test is passed.

Using the propensity score-matched sample, we retest Model (2). Column (1) of Table 9 shows that the regression coefficient of the voluntary resignation of independent directors (*INResign*) is positive (0.007) but does not pass the significance test. Column (2) shows that the regression coefficient of *INResign* is positive (0.031) and significant at the 5 % level. Column (3) shows that the regression coefficient of *INResign* is positive (0.320) and significant at the 1 % level. These results are consistent with the previous research findings.

5.4.2. Two-stage least squares estimation with instrumental variable

We select the natural logarithm of the number of deaths from natural disasters in each province per year (*Death*) as an exogenous instrumental variable and conduct two-stage least squares (2SLS) regression to address potential endogeneity issues arising from omitted variables and bidirectional causality. A large number of deaths from natural disasters in a province indicates that the province frequently experiences natural disasters, which implies a greater physical risk for independent directors traveling to listed companies in that province to fulfill their duties. Consequently, independent directors are less willing to serve at listed companies in such provinces, meeting the requirement of relevance for the instrumental variable. However, the number of deaths from natural disasters in each province does not have a direct relationship with auditors' responses to a

Table 8
PSM balance test.

Variable	Sample	Mean		Standard Error (%)	Reduction in Standard Error (%)	T-test	
		Treatment Group	Control Group			T	P>|T|
Size	U	22.107	22.292	–14.7	86.7	–4.460	0.000
	M	22.121	22.097	2.0		0.470	0.640
Lev	U	0.458	0.419	18.1	86.0	5.960	0.000
	M	0.455	0.449	2.5		0.570	0.566
ROA	U	0.003	0.038	–33.8	98.4	–12.690	0.000
	M	0.005	0.005	–0.5		–0.110	0.912
Age	U	2.213	2.062	16.6	85.7	4.950	0.000
	M	2.207	2.186	2.4		0.570	0.568
Growth	U	0.125	0.159	–8.4	81.7	–2.790	0.005
	M	0.125	0.131	–1.5		–0.350	0.728
Loss	U	0.243	0.133	28.6	99.7	10.080	0.000
	M	0.238	0.239	–0.1		–0.020	0.984
Big4	U	0.045	0.061	–7.3	81.7	–2.180	0.029
	M	0.045	0.042	1.3		0.340	0.734
Dual	U	0.304	0.323	–4.1	88.6	–1.280	0.200
	M	0.305	0.307	–0.5		–0.110	0.914

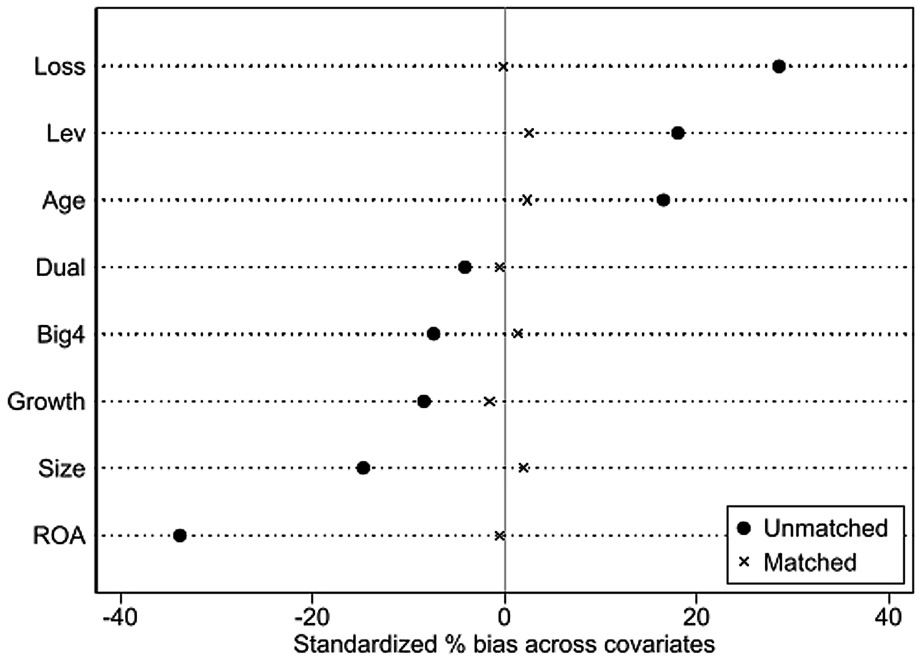

Fig. 1. PSM balance test.

particular company, thus meeting the requirement of exogeneity for the instrumental variable. Table 10 shows the test results. In Column (2), the coefficient of the voluntary resignation of independent directors (*INResign*) is positive and significant at the 1 % level, consistent with the conclusions described earlier. The Wu–Hausman test, whose results are reported in Column (3), confirms that the variable is exogenous and there is no need to use the instrumental variable method to address endogeneity.

5.4.3. Heckman two-stage method

As factors such as firm size, profitability and debt-paying ability may affect both the decision of independent directors to voluntarily resign and the responses of auditors to that decision, we re-estimate the results using the Heckman two-stage method to address this potential endogeneity issue. In the first stage, the voluntary resignation of independent directors (*INResign*) is taken as the dependent variable, and the control variables from Model (2) and the instrumental variable (*Death*) mentioned above are used as independent variables. A probit model is used to conduct a regression to calculate the inverse Mills ratio (*IMR*). In the second stage, the value of *IMR* estimated from the first stage is included in the regression analysis in Model (2).

Table 11 presents the results of the Heckman two-stage method. The coefficient of *IMR* in Column (2) is significant at the 1 % level, indicating the presence of endogeneity. After eliminating endogeneity using the Heckman two-stage method, the coefficient of the voluntary resignation of independent directors (*INResign*) remains positive (0.028) and is significant at the 10 % level, further verifying the conclusion that listed companies experiencing the voluntary resignation of independent directors are charged higher audit fees. The estimated coefficient of *IMR* in Column (3) is statistically nonsignificant, indicating that the model does not suffer from severe endogeneity, and the estimated coefficient of the voluntary resignation of independent directors (*INResign*) is positive (0.378) and significant at the 1 % level, again reaffirming the paper's conclusion.

5.4.4. Sensitivity analysis of independent variable

The independent director resignation events in our sample are categorized as voluntary or nonvoluntary based on the reasons for resignation. To assess the sensitivity of the classification of voluntary resignation, we reclassify the reasons for the voluntary resignation of independent directors to include only health- and

Table 9
Robustness test: Propensity score-matched.

	(1)	(2)	(3)
Variable	*LnAlag*	*ABFEE*	*Change*
INResign	0.007	0.031**	0.320***
	(1.237)	(2.231)	(3.172)
Size	0.004	–0.021**	–0.122***
	(1.344)	(–2.495)	(–2.800)
Lev	0.019	0.078*	0.378
	(1.222)	(1.755)	(1.504)
ROA	–0.287***	–0.104	–1.604***
	(–7.355)	(–1.121)	(–2.621)
Age	–0.018***	0.006	0.113*
	(–5.302)	(0.678)	(1.890)
Growth	–0.024***	–0.004	0.333***
	(–3.038)	(–0.238)	(3.231)
Indep	–0.010	0.034	0.462
	(–0.186)	(0.217)	(0.430)
Board	–0.010	–0.005	0.172
	(–0.584)	(–0.113)	(0.553)
Loss	0.035***	–0.025	0.077
	(4.072)	(–1.202)	(0.493)
Big4	–0.066***	–0.100***	0.176
	(–4.958)	(–2.649)	(0.763)
Dual	0.007	0.025*	–0.002
	(1.242)	(1.794)	(–0.020)
Cons	4.611***	0.411**	–1.466
	(62.493)	(2.098)	(–0.918)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	5,252	5,252	5,235
F/*chi*^{2}	40.138	2.938	2,069.271
Adj-R^2/*Pseudo* R^2	0.114	0.013	0.051

Note: The reduced sample size in Column (3) is due to the logit regression with controlled industry fixed effects.

age-related reasons, work-related reasons, personal reasons and doubts about the company's regular related-party transactions. A new indicator of the voluntary resignation of independent directors (*INResign_r*) is constructed and Model (2) is re-estimated. The results are shown in Table 12. In Column (1), the coefficient of voluntary resignation is positive but not significant. In Column (2), the coefficient of voluntary resignation of independent directors is 0.029 and significant at the 5 % level. In Column (3), the regression coefficient for voluntary resignation of independent directors is 0.379 and significant at the 1 % level, consistent with the previous conclusions. That is, listed companies experiencing the voluntary resignation of independent directors face higher audit fees and a higher likelihood of change in audit firms. However, Table 12 provides no evidence of a significant increase in audit effort for such companies.

5.4.5. Alternative measure of dependent variable

Following Quan and Lu (2016), we use audit workload (*ARL*) as an alternative measure of audit effort (*LnAlag*), defined as 1 if the audit report date for the current year is later than that for the previous year for the same period, and 0 otherwise. Referring to Cai and Zhang (2022), we use the natural logarithm of audit fees (*LNFEE*) as an alternative variable for abnormal audit fees (*ABFEE*). Model (2) is re-estimated using these alternative variables, and the regression results are presented in Table 13. The regression coefficient of the voluntary resignation of independent directors (*INResign*) in Column (1) of Table 13 does not pass the significance test. In Column (2), the regression coefficient of the voluntary resignation of independent

Table 10
IV-2SLS results.

	(1)	(2)	(3)
Variable	*INResign*	*ABFEE*	*Change*
Death	–0.046***		
	(–2.929)		
INResign		1.801***	0.297*
		(5.435)	(1.699)
Size	–0.104***	0.017**	–0.006
	(–5.518)	(2.384)	(–1.615)
Lev	0.412***	–0.032	0.021
	(3.785)	(–0.851)	(1.063)
ROA	–0.879***	0.110	–0.140**
	(–3.057)	(0.984)	(–2.381)
Age	0.084***	–0.022***	0.003
	(3.786)	(–2.973)	(0.817)
Growth	–0.037	0.005	0.027***
	(–0.760)	(0.335)	(3.487)
Indep	–0.049	0.032	0.032
	(–0.113)	(0.258)	(0.491)
Board	0.153	–0.059*	–0.023
	(1.292)	(–1.651)	(–1.202)
Loss	0.077	–0.044**	0.023**
	(1.172)	(–1.993)	(1.985)
Big4	–0.010	–0.042	0.013
	(–0.108)	(–1.641)	(0.928)
Dual	–0.026	0.035***	–0.010
	(–0.669)	(2.995)	(–1.543)
Cons	0.078	–0.304*	0.153
	(0.137)	(–1.659)	(1.580)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	13,194	12,690	12,690
F/chi^2	209.924	82.226	468.017
Wu–Hausman F (1,12655)		70.158***	2.23323
Shea's partial R^2		0.004	0.004
Minimum eigenvalue statistic		48.584	48.584
2SLS size of nominal 5 % Wald test (10 %)		16.38	16.38

Note: The reduction in sample size is due to the presence of missing values for the *Death* variable.

directors (*INResign*) is positive and passes the significance test at the 5 % level, which is in line with the findings of previous research.

5.4.6. Auditor responses in the subsequent period

In the context of audit practice, listed companies may sign engagement letters with audit firms before the balance sheet date to determine audit fees (Yu et al., 2020). Therefore, the voluntary resignation of an independent director between the signing of the engagement letter and the balance sheet date will not affect audit fees or the likelihood of a change in audit firms for the current period. However, it may have an impact on audit fees and the likelihood of audit firm change in the subsequent period. Consequently, we replace the audit effort (*LnAlag*), abnormal audit fees (*ABFEE*) and change in audit firm (*Change*) variables in Model (2) with the corresponding variables for the $t + 1$ period, namely future audit effort (*FLnAlag*), future abnormal audit fees (*FABFEE*) and future change in audit firm (*FChange*), and re-estimate the model. This approach also helps to mitigate endogeneity issues within the model. The regression results are presented in Table 14.

The results in Column (1) of Table 14 show that the regression coefficient of the voluntary resignation of independent directors (*INResign*) is positive but statistically nonsignificant (0.008), indicating that there is no evidence that the voluntary resignation of independent directors leads to significantly increased audit effort in

Table 11
Heckman two-stage method.

	(1)	(2)	(3)
Variable	*INResign*	*ABFEE*	*Change*
IMR		–0.321***	–0.406
		(–3.308)	(–0.606)
INResign		0.028*	0.378***
		(1.954)	(3.615)
Death	–0.046***		
	(–2.899)		
Size	–0.104***	0.021*	–0.064
	(–5.948)	(1.934)	(–0.971)
Lev	0.412***	–0.047	0.242
	(4.170)	(–0.956)	(0.824)
ROA	–0.879***	0.033	–1.122
	(–3.275)	(0.316)	(–1.623)
Age	0.084***	–0.027***	0.046
	(3.889)	(–2.712)	(0.727)
Growth	–0.037	0.010	0.256***
	(–0.827)	(0.846)	(3.041)
Indep	–0.049	0.052	0.365
	(–0.125)	(0.387)	(0.510)
Board	0.153	–0.065	–0.247
	(1.353)	(–1.568)	(–1.073)
Loss	0.077	–0.043**	0.232*
	(1.199)	(–2.448)	(1.903)
Big4	–0.010	–0.036	0.135
	(–0.114)	(–1.127)	(0.906)
Dual	–0.026	0.039***	–0.104
	(–0.696)	(3.430)	(–1.472)
Cons	0.078	0.330*	–0.885
	(0.148)	(1.871)	(–0.743)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	13,194	12,690	12,690
F/chi^2	229.333	3.741	463.490
Adj-R^2*/Pseudo R*^{2}	0.033	0.009	0.051

the subsequent period (*FLnAlag*). Column (2) shows that the regression coefficient of the voluntary resignation of independent directors (*INResign*) is positive (0.026) and significant at the 5 % level, indicating that the voluntary resignation of independent directors also significantly increases abnormal audit fees in the subsequent period (*FABFEE*). Column (3) shows that the regression coefficient of the voluntary resignation of independent directors (*INResign*) is 0.204 and significant at the 5 % level. This indicates that listed companies with (vs. without) voluntary resignations by independent directors are also more likely to experience a change in audit firms in the subsequent period, further substantiating the conclusions of this study.

6. Mechanism analysis

Based on the theoretical analysis in the previous section, the voluntary resignation of independent directors may affect auditors' strategies by signaling the risk of potential regulatory penalties to external stakeholders and increasing negative media coverage. Next, we examine the authenticity of these two potential mechanisms. Following Di Giuli and Laux (2022), we use a two-stage method to conduct mechanism testing. The first stage estimates the impact of the voluntary resignation of independent directors (*INResign*) on the mechanism variable (*M*); the second stage analyzes the impact of the predicted mechanism variable (*M*) obtained from the first stage on auditors' responses (abnormal audit fees, *ABFEE*, and change in audit firm, *Change*). Specifically, the two-stage test is implemented by estimating the following system of equations:

Table 12
Sensitivity analysis of independent variable.

	(1)	(2)	(3)
Variable	*LnAlag*	*ABFEE*	*Change*
INResign_r	0.006	0.029**	0.379***
	(1.080)	(2.177)	(3.950)
Size	0.006***	–0.002	–0.095***
	(2.613)	(–0.280)	(–3.321)
Lev	0.013	0.055	0.482***
	(1.090)	(1.563)	(2.808)
ROA	–0.303***	–0.179**	–1.324***
	(–10.889)	(–2.390)	(–2.873)
Age	–0.015***	–0.002	0.096***
	(–6.381)	(–0.303)	(2.658)
Growth	–0.023***	0.006	0.280***
	(–4.780)	(0.578)	(3.909)
Indep	0.019	0.129	0.413
	(0.459)	(1.001)	(0.638)
Board	–0.011	0.000	–0.133
	(–0.896)	(0.003)	(–0.687)
Loss	0.035***	–0.021	0.268**
	(6.250)	(–1.352)	(2.494)
Big4	–0.073***	–0.044	0.095
	(–7.888)	(–1.624)	(0.747)
Dual	0.013***	0.035***	–0.098
	(3.188)	(3.326)	(–1.529)
Cons	4.564***	–0.030	–1.665*
	(86.723)	(–0.185)	(–1.675)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	14,887	14,887	14,887
F/chi^2	80.418	3.135	5,765.772
Adj-R^2*/Pseudo* R^2	0.097	0.005	0.049

$$M_{it} = \alpha + \beta_0 INResign_{it} + \beta_1 Controls + \sum Industry + \sum year + \varepsilon_{it} \quad (3)$$

$$Response_{it} = \alpha + \beta_0 M_{it} + \beta_1 Controls + \sum Industry + \sum year + \varepsilon_{it} \quad (4)$$

Here, M represents the mechanism variable, with all other variables consistent with the baseline model.

6.1. Regulatory sanction risk mechanism

Regulatory sanction risk (*Violation*) is defined following Liao and Su (2021), taking the value of 1 if the listed company receives a penalty announcement in that year, and 0 otherwise. In the first stage of the regression, as shown in Columns (1) and (4) of Table 15, the coefficients of the voluntary resignation of independent directors are 0.094 and 0.046, respectively, both of which are significant at the 1 % level. This indicates that the voluntary resignation of a listed company's independent directors signals to the outside world that the company has a higher risk of regulatory penalties than its counterparts not experiencing such resignation events. As a result, the probability of being penalized in the following year increases for companies with voluntary resignations by independent directors. The second-stage regression results are presented in Columns (2), (3), (5) and (6) of Table 15. The estimated coefficients of M are all positive and significant, suggesting that the signal of higher regulatory penalty risk conveyed by the voluntary resignation of independent directors increases the litigation risk perceived by auditors. This affects auditors' risk perception and in turn leads to increased audit fees and a heightened likelihood of a change in audit firms.

Table 13
Alternative dependent variable.

	(1)	(2)
Variable	*ARL*	*LNFEE*
INResign	–0.024	0.031**
	(–1.620)	(2.290)
Size	0.004	0.339***
	(1.310)	(49.318)
Lev	–0.005	0.217***
	(–0.241)	(5.876)
ROA	–0.230***	–0.625***
	(–3.488)	(–8.055)
Age	0.049***	–0.005
	(12.555)	(–0.765)
Growth	0.035***	0.010
	(3.256)	(0.940)
Indep	0.040	0.143
	(0.525)	(1.064)
Board	–0.023	0.001
	(–1.030)	(0.032)
Loss	0.037**	0.066***
	(2.355)	(4.150)
Big4	–0.044***	0.570***
	(–2.979)	(19.549)
Dual	0.019***	0.036***
	(2.586)	(3.370)
Cons	0.269***	6.241***
	(3.065)	(36.143)
Year	Yes	Yes
Industry	Yes	Yes
N	14,887	14,887
F	31.882	567.441
Adj-R^2	0.106	0.629

6.2. Negative media coverage mechanism

Following Wu and Ye (2020), we measure negative media coverage (*NMedia*) as the natural logarithm of the number of negative news articles about each company per year. A higher value of *NMedia* indicates that there is a larger volume of negative media coverage of the listed company. The regression results are shown in Table 16. In the first stage, as shown in Columns (3) and (4) of Table 16, the regression coefficients of the voluntary resignation of independent directors are 0.065 and 0.037, respectively, significant at the 1 % and 10 % levels. This indicates that companies experiencing voluntary resignations by independent directors receive more negative media coverage than do companies not experiencing such resignations. The second-stage regression results presented in Columns (2), (3), (5) and (6) of Table 16 show that the estimated coefficients of *NMedia* are all positive and significant. This suggests that the increase in negative media reporting triggered by the voluntary resignation of independent directors affects auditors' risk perception. Auditors respond by charging higher audit fees to account for the increased risk and may terminate their audit engagement with client companies as a risk avoidance strategy.

7. Further analysis

7.1. The effect of the new securities law

Based on the theory of audit risk elements, the implementation of the New Securities Law increased the legal responsibilities of listed companies, making the external regulatory environment more stringent and

Table 14
Auditor responses in the subsequent period.

	(1)	(2)	(3)
Variable	*FLnAlag*	*FABFEE*	*FChange*
INResign	0.008	0.026**	0.204**
	(1.619)	(1.967)	(2.092)
Size	0.003	0.004	–0.051*
	(1.262)	(0.682)	(–1.701)
Lev	0.031**	0.020	0.338*
	(2.527)	(0.574)	(1.945)
ROA	–0.165***	–0.556***	–1.571***
	(–5.768)	(–7.532)	(–3.354)
Age	–0.014***	–0.020***	0.121***
	(–5.845)	(–3.115)	(3.247)
Growth	–0.013***	0.023**	0.137*
	(–3.353)	(2.287)	(1.728)
Indep	–0.022	0.119	0.911
	(–0.535)	(0.913)	(1.493)
Board	–0.021*	–0.001	0.026
	(–1.687)	(–0.017)	(0.144)
Loss	0.015**	0.066***	0.319***
	(2.535)	(4.329)	(2.946)
Big4	–0.078***	–0.035	–0.276*
	(–8.581)	(–1.309)	(–1.958)
Dual	0.015***	0.036***	–0.122*
	(3.937)	(3.387)	(–1.906)
Cons	4.664***	–0.109	–3.355***
	(89.205)	(–0.659)	(–3.552)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	14,672	14,672	14,672
F/chi2	28.669	23.271	13,270.873
Adj-R^2/Pseudo R^2	0.060	0.031	0.049

Note: The reduction in sample size is due to the presence of missing values for the following variables in the $t+1$ period: audit effort (*FLnAlag*), abnormal audit fees (*FABFEE*) and auditor change (*FChange*).

raising inherent risk. The resignation of independent directors to avoid risks reduces the independence of the board, lowers the quality of corporate internal control and increases the likelihood that the listed company will be penalized for violations (Beasley, 1996). It may also attract more media attention to the company and thus lead to an increase in the publication of negative news related to the company, drawing the attention of regulatory authorities and in turn increasing the possibility of audit failure (Wu and Ye, 2020). Based on the above analysis, since the implementation of the New Securities Law, the risk perception of auditors has increased significantly and auditors have become more sensitive to the voluntary resignation of independent directors.

To explore the changes in the impact of the voluntary resignation of independent directors on the responses of auditors before and after the implementation of the New Securities Law, we construct the following model:

$$Response_{it} = \alpha + \beta_0 INResign_{it} + \beta_1 INResign_{it} \times Policy_{it} + \beta_2 Controls_{it} + \sum Industry + \sum year + \varepsilon_{it} \quad (5)$$

In Model (5), the variable indicating the implementation of the New Securities Law (*Policy*) is a dummy variable measured as 1 for years after 2020 (because the promulgation date of the New Securities Law was 1 March 2020), and 0 otherwise. As Model (5) includes time fixed effects, the *Policy* variable is not added separately to the model. The regression results are shown in Table 17.

Column (1) of Table 17 presents the results of regressing the interaction term between the voluntary resignation of independent directors (*INResign*) and the implementation of the New Securities Law (*Policy*)

Table 15
Regulatory sanction risk mechanism.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	*Violation*	*ABFEE*	*Change*	*FViolation*	*FABFEE*	*FChange*
INResign	0.094***			0.046***		
	(7.213)			(3.739)		
$\widehat{Violation}$		0.304**	3.971***			
		(2.180)	(3.910)			
$\widehat{FViolation}$					0.531*	4.495**
					(1.864)	(2.140)
Size	–0.024***	0.006	0.001	–0.015***	0.011	0.016
	(–6.880)	(0.752)	(0.030)	(–4.129)	(1.478)	(0.369)
Lev	0.174***	0.002	–0.209	0.148***	–0.056	–0.329
	(7.311)	(0.053)	(–0.838)	(6.242)	(–1.019)	(–0.912)
ROA	–0.499***	–0.027	0.658	–0.482***	–0.298*	0.529
	(–7.889)	(–0.263)	(0.948)	(–7.106)	(–1.923)	(0.470)
Age	0.042***	–0.015*	–0.069	0.020***	–0.029***	0.040
	(12.387)	(–1.669)	(–1.228)	(5.720)	(–3.404)	(0.692)
Growth	–0.006	0.008	0.304***	–0.003	0.023**	0.126
	(–0.679)	(0.756)	(4.212)	(–0.352)	(2.289)	(1.609)
Indep	–0.050	0.144	0.610	–0.027	0.131	1.007*
	(–0.696)	(1.114)	(0.937)	(–0.356)	(1.006)	(1.659)
Board	–0.064***	0.019	0.120	–0.072***	0.036	0.310
	(–3.112)	(0.490)	(0.587)	(–3.326)	(0.812)	(1.346)
Loss	0.067***	–0.041**	0.001	0.156***	–0.018	–0.396
	(4.753)	(–2.299)	(0.007)	(10.241)	(–0.389)	(–1.138)
Big4	–0.021*	–0.037	0.180	–0.032***	–0.009	–0.117
	(–1.895)	(–1.372)	(1.387)	(–2.780)	(–0.311)	(–0.745)
Dual	0.012*	0.031***	–0.147**	0.009	0.032***	–0.174***
	(1.808)	(2.941)	(–2.260)	(1.260)	(2.899)	(–2.630)
Cons	0.673***	–0.235	–4.337***	0.522***	–0.366	–5.655***
	(8.088)	(–1.229)	(–3.491)	(6.134)	(–1.643)	(–3.992)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	14,887	14,887	14,887	14,848	14,654	14,713
F/chi2	81.573	3.141	5,768.482	73.585	23.106	13,367.595
Adj-R^2/Pseudo R^2	0.095	0.005	0.049	0.104	0.031	0.050

Note: The change in sample size is due to the presence of missing values for the future period's regulatory penalty variable (*FViolation*).

(hereinafter "the interaction term") on audit effort. The results indicate that the regression coefficient of the interaction term (*INResign* × *Policy*) on audit effort (*LnAlag*) is negative, but it does not pass the significance test. Thus, there is no evidence that the positive relationship between the voluntary resignation of independent directors of listed companies and audit effort is significantly stronger after the implementation of the New Securities Law. Next, the regression results in Column (2) of Table 17 show that the regression coefficient of the interaction term (*INResign* × *Policy*) is 0.045 and significant at the 10 % level. This indicates that the implementation of the New Securities Law had a deterrent effect on auditors, increasing their sensitivity to risk and heightening their attention to the risk signals conveyed by the voluntary resignation of independent directors of client companies. This in turn increased auditors' risk perception and led them to charge higher audit fees to compensate for increased risk. Column (3) of Table 17 shows that the regression coefficient of the interaction term (*INResign* × *Policy*) is 0.104, but it is not statistically significant. Therefore, there is no evidence to indicate that the positive relationship between the voluntary resignation of independent directors in listed companies and the change in audit firms has become significantly stronger since the implementation of the New Securities Law. This lack of significance might be attributable to the intensified competition in the audit industry caused by the New Securities Law, which could have made audit firms more reluctant to terminate their engagements with client companies.

Table 16
Negative media coverage mechanism.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	*NMedia*	*ABFEE*	*Change*	*FNMedia*	*FABFEE*	*FChange*
INResign	0.065***			0.037*		
	(2.784)			(1.674)		
$\widehat{NMedia}$		0.440**	5.745***			
		(2.180)	(3.910)			
$\widehat{FNMedia}$					0.660*	5.581**
					(1.864)	(2.140)
Size	0.267***	–0.119**	–1.630***	0.261***	–0.168*	–1.504**
	(22.492)	(–2.196)	(–4.157)	(22.621)	(–1.819)	(–2.216)
Lev	0.120**	0.002	–0.208	0.050	–0.011	0.056
	(2.050)	(0.055)	(–0.835)	(0.902)	(–0.277)	(0.253)
ROA	0.177	–0.256***	–2.341***	0.262**	–0.727***	–3.100***
	(1.336)	(–3.094)	(–4.486)	(2.058)	(–6.088)	(–3.814)
Age	–0.161***	0.069**	1.024***	–0.140***	0.074	0.911**
	(–13.204)	(2.101)	(4.282)	(–11.852)	(1.481)	(2.491)
Growth	0.003	0.005	0.265***	0.003	0.020*	0.096
	(0.152)	(0.460)	(3.698)	(0.179)	(1.937)	(1.221)
Indep	1.233***	–0.414	–6.674***	1.096***	–0.606	–5.233*
	(5.408)	(–1.509)	(–3.524)	(4.981)	(–1.496)	(–1.774)
Board	0.183***	–0.081	–1.186***	0.207***	–0.139*	–1.166**
	(2.694)	(–1.548)	(–3.567)	(3.179)	(–1.682)	(–2.026)
Loss	0.325***	–0.164**	–1.601***	0.338***	–0.159	–1.583*
	(11.069)	(–2.430)	(–3.258)	(11.975)	(–1.313)	(–1.775)
Big4	0.412***	–0.225***	–2.270***	0.380***	–0.276**	–2.381**
	(6.759)	(–2.587)	(–3.689)	(6.437)	(–2.028)	(–2.380)
Dual	0.083***	–0.002	–0.575***	0.093***	–0.025	–0.654***
	(4.319)	(–0.077)	(–4.219)	(5.030)	(–0.725)	(–2.591)
Cons	–3.694***	1.595**	19.561***	–3.591***	2.281*	16.736*
	(–12.062)	(2.104)	(3.586)	(–12.214)	(1.782)	(1.771)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	14,703	14,887	14,887	14,701	14,654	14,713
F/chi2	88.639	3.141	5,768.483	86.875	23.106	13,367.590
Adj-R^2/Pseudo R^2	0.244	0.005	0.049	0.249	0.031	0.050

Note: The change in sample size is due to missing values for the negative media coverage mechanism variables (*NMedia* and *FNMedia*).

7.2. Priority order of auditor responses

Referring to Krishnan et al. (2013), we test the order of response choices made by auditors in response to the voluntary resignation of independent directors by constructing an ordered logit model.

$$Order_{it} = \alpha + \beta_0 INResign_{it} + \beta_1 Controls + \sum Industry + \sum year + \varepsilon_{it} \quad (6)$$

In Model (6), the dependent variable *Order* represents the priority order of auditor responses. It is measured such that if the listed company experiences a change in its audit firm, it takes the value of 2; if there is no change in the audit firm but the auditor charges higher abnormal audit fees (above the annual median of abnormal audit fees), it takes the value of 1; if there is neither a change in the firm nor an increase in abnormal audit fees, it takes the value of 0.

Table 18 illustrates the sequence of auditors' responses to the voluntary resignation of independent directors. The regression results in Column (1) indicate that the voluntary resignation of independent directors (*INResign*) is significantly and positively correlated with *Order*, suggesting that auditors follow an order of priority in responding to the risk signals conveyed by the voluntary resignation of independent directors. When responding to the risks indicated by the voluntary resignation of independent directors, auditors will first consider increasing audit fees to take on the risk; however, when the perceived risk exceeds a level

Table 17
The effect of the New Securities Law.

	(1)	(2)	(3)
Variable	*LnAlag*	*ABFEE*	*Change*
INResign	0.005	0.004	0.323**
	(0.654)	(0.183)	(2.430)
INResign × *Policy*	–0.000	0.045*	0.104
	(–0.046)	(1.813)	(0.555)
Size	0.006***	–0.002	–0.095***
	(2.605)	(–0.265)	(–3.310)
Lev	0.013	0.055	0.482***
	(1.095)	(1.550)	(2.811)
ROA	–0.303***	–0.178**	–1.323***
	(–10.895)	(–2.391)	(–2.878)
Age	–0.015***	–0.002	0.096***
	(–6.376)	(–0.320)	(2.644)
Growth	–0.023***	0.006	0.280***
	(–4.779)	(0.583)	(3.912)
Indep	0.019	0.127	0.409
	(0.459)	(0.990)	(0.633)
Board	–0.011	0.000	–0.134
	(–0.895)	(0.000)	(–0.689)
Loss	0.035***	–0.020	0.268**
	(6.247)	(–1.337)	(2.497)
Big4	–0.073***	–0.044	0.095
	(–7.888)	(–1.634)	(0.747)
Dual	0.013***	0.035***	–0.099
	(3.186)	(3.325)	(–1.534)
Cons	4.564***	–0.031	–1.672*
	(86.691)	(–0.192)	(–1.683)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	14,887	14,887	14,887
F/chi^2	73.765	3.155	5,761.159
Adj-R^2*/Pseudo R*^{2}	0.097	0.005	0.049

acceptable to the auditor, the contractual relationship between the auditor and the listed company becomes more unstable and the likelihood of a change in audit firms increases.

7.3. Multiple consecutive years of voluntary resignations by independent directors and auditor responses

We construct Model (7) to further explore changes in auditor responses when companies experience consecutive years of voluntary resignations by independent directors.

$$Response_{it} = \alpha + \beta_0 Over1_{it} + \beta_1 Over2_{it} + \beta_2 Controls_{it} + \sum Industry + \sum year + \varepsilon_{it} \quad (7)$$

Over1 represents a dummy variable that takes the value of 1 if the company experiences the voluntary resignation of independent directors in one consecutive year, and 0 otherwise. *Over2* represents a dummy variable that takes the value of 1 if the company experiences such events in two or more consecutive years, and 0 otherwise. The regression results are presented in Table 19.

As shown in Column (1) of Table 19, the regression results reveal positive coefficients of both *Over1* and *Over2* (0.010 and 0.048), which are significant at the 5 % and 1 % levels, respectively. The coefficient of *Over2* is greater than that of *Over1*, suggesting that auditors invest more effort in auditing companies with (vs. without) multiple consecutive years of voluntary resignations. The regression results in Column (2) of Table 19 show that while *Over1*′s coefficient (0.020) is not statistically significant, *Over2*′s coefficient (0.105) is positive and significant at the 5 % level, indicating that auditors charge higher audit fees for companies with (vs. with-

Table 18
Priority order of auditor responses.

Variable	(1) *Order*
INResign	0.173***
	(2.691)
Size	–0.017
	(–0.707)
Lev	0.130
	(0.923)
ROA	–0.900***
	(–2.669)
Age	–0.004
	(–0.167)
Growth	–0.018
	(–0.414)
Indep	0.594
	(1.143)
Board	–0.088
	(–0.579)
Loss	–0.000
	(–0.005)
Big4	0.013
	(0.115)
Dual	0.057
	(1.193)
Year	Yes
Industry	Yes
N	14,887
Chi^2	972.500
Pseudo R^2	0.006

out) multiple consecutive years of voluntary resignations. Column (3) of Table 19 shows positive and significant coefficients for both *Over1* and *Over2* at the 1 % level (0.332 and 0.447, respectively), with *Over2*′s coefficient being greater than that of *Over1*. This indicates that companies with (vs. without) multiple consecutive years of voluntary resignations by independent directors are more likely to experience a change in their audit firms. In summary, companies with multiple consecutive years of voluntary resignations by independent directors, compared with their counterparts without such resignations, convey stronger risk signals to auditors, which significantly impact auditors' response behavior.

7.4. Mandatory resignation of independent directors and auditor responses

To further determine whether the impact of the voluntary resignation of independent directors on auditor responses is due to the risk signals conveyed to external stakeholders, rather than merely because auditors see the impact of resignation events on market perception and respond accordingly, we re-estimate Model (2) by introducing a variable measuring the mandatory resignation of independent directors (*PasResign*). *PasResign* takes the value of 1 for listed companies experiencing the mandatory resignation of independent directors (that is, excluding the sample of voluntary resignations), and 0 otherwise. The regression results are presented in Table 20. We observe that the coefficients of mandatory resignation (*PasResign*) on *LnAlag*, *ABFEE* and *Change* are nonsignificant, showing that the mandatory resignation of independent directors does not significantly affect auditor responses. In other words, only voluntary resignation, not mandatory resignation, conveys risk signals to auditors and influences their behavior.

Table 19
Consecutive resignations and auditor responses.

	(1)	(2)	(3)
Variable	*LnAlag*	*ABFEE*	*Change*
Over1	0.010**	0.020	0.332***
	(1.994)	(1.415)	(5.208)
Over2	0.048***	0.105**	0.447***
	(5.151)	(2.481)	(2.988)
Size	0.006***	–0.001	–0.086***
	(2.915)	(–0.083)	(–2.982)
Lev	0.011	0.051	0.457***
	(0.881)	(1.443)	(2.675)
ROA	–0.296***	–0.167**	–1.264***
	(–10.608)	(–2.245)	(–2.738)
Age	–0.016***	–0.003	0.085**
	(–6.607)	(–0.481)	(2.343)
Growth	–0.024***	0.005	0.274***
	(–4.843)	(0.514)	(3.832)
Indep	0.015	0.119	0.312
	(0.360)	(0.930)	(0.481)
Board	–0.013	–0.003	–0.169
	(–1.015)	(–0.074)	(–0.870)
Loss	0.034***	–0.023	0.260**
	(6.080)	(–1.496)	(2.422)
Big4	–0.073***	–0.043	0.102
	(–7.868)	(–1.608)	(0.795)
Dual	0.013***	0.035***	–0.096
	(3.224)	(3.344)	(–1.501)
Cons	4.552***	–0.050	–1.714*
	(86.495)	(–0.305)	(–1.733)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	14,887	14,887	14,887
F/chi^2	76.315	3.129	5,755.401
Adj-R^2*/Pseudo* R^2	0.099	0.007	0.051

8. Heterogeneity analysis

8.1. Voluntary resignation of independent directors, auditors' industry expertise and auditor responses

Auditors with industry expertise, compared with their counterparts without such expertise, have stronger professional skills and are better able to uncover financial irregularities and illegal activities within client companies. Therefore, audits of financial statements conducted by auditors with industry expertise can lead to higher-quality accounting information (Fan et al., 2013), reduce information asymmetry and mitigate the negative signaling effect of the voluntary resignation of independent directors, thereby lowering the risk perceived by auditors. This may in turn reduce the positive impact of the voluntary resignation of independent directors on abnormal audit fees and the likelihood of a change in audit firms. Conversely, when auditors lack industry expertise, their relatively weak professional skills may make them more sensitive to the negative signals conveyed by independent directors' resignation, leading to a higher risk premium and a greater likelihood that auditors will abandon their clients. This increases the likelihood of higher audit fees and a change in audit firms. Accordingly, we posit that the positive effect of the voluntary resignation of independent directors on abnormal audit fees and the likelihood of audit firm change is more pronounced when auditors possess industry expertise than when they do not possess such expertise.

Following Fan et al. (2013), we use the industry portfolio share method to measure auditors' industry expertise. The sample is divided into groups with and without industry expertise based on the annual median

Table 20
Mandatory resignation and auditor responses.

	(1)	(2)	(3)
Variable	*LnAlag*	*ABFEE*	*Change*
PasResign	0.006	–0.025	0.235
	(0.579)	(–1.159)	(1.385)
Size	0.006***	0.003	–0.091***
	(2.600)	(0.437)	(–2.941)
Lev	0.011	0.044	0.410**
	(0.886)	(1.213)	(2.251)
ROA	–0.314***	–0.171**	–1.416***
	(–10.174)	(–2.184)	(–2.881)
Age	–0.016***	–0.003	0.086**
	(–6.439)	(–0.549)	(2.247)
Growth	–0.025***	0.011	0.251***
	(–4.741)	(1.062)	(3.227)
Indep	0.020	0.149	0.255
	(0.475)	(1.127)	(0.374)
Board	–0.010	0.007	–0.110
	(–0.765)	(0.173)	(–0.536)
Loss	0.034***	–0.017	0.283**
	(5.800)	(–1.085)	(2.509)
Big4	–0.074***	–0.043	0.036
	(–8.055)	(–1.576)	(0.268)
Dual	0.013***	0.036***	–0.124*
	(3.242)	(3.337)	(–1.820)
Cons	4.557***	–0.151	–1.605
	(82.442)	(–0.909)	(–1.536)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
N	13,814	13,814	13,814
F/chi^2	69.491	2.550	5,311.446
Adj-R^2*/Pseudo* R^2	0.093	0.004	0.049

within the industry. The regression results in Table 21 show that for the group with industry expertise, the coefficients of the voluntary resignation of independent directors (*INResign*) are nonsignificant. However, for the group without industry expertise, the coefficients of the voluntary resignation of independent directors (*INResign*) are significant and positive. This indicates that the positive influence of the voluntary resignation of independent directors on abnormal audit fees and the likelihood of changes in audit firms is more pronounced in the group without industry expertise, corroborating the aforementioned analysis.

8.2. Voluntary resignation of independent directors, the legal environment and auditor responses

Perceived risk is a major reason for independent directors to voluntarily resign (Tang and Luo, 2007). When listed companies are in a weaker legal environment, i.e., an environment with lower legal standards, they face less regulatory pressure and a lower likelihood of regulatory penalties. Therefore, the independent directors of these companies may perceive less corporate risk, reducing the likelihood of their voluntary resignation. If, under such circumstances, an independent director does resign voluntarily, stakeholders (especially auditors) receive a stronger signal that the listed company faces a high risk of regulatory penalties. This can lead to a higher risk premium for auditors, thereby increasing audit fees and the probability of a change in audit firms. From this perspective, the positive effects of voluntary resignation on abnormal audit fees and accounting firm changes may be more pronounced when legal standards are lower. In addition, regulatory risk can increase audit fees and lead to changes in audit firms (Liu and Zhou, 2007; Cai and Zhang, 2022). When listed companies are in a stronger legal environment, i.e., an environment with higher legal standards, the voluntary resignation of independent directors is more likely to attract the attention of

Table 21
Auditors' industry expertise.

Variable	(1) *With Expertise ABFEE*	(2) *Without Expertise ABFEE*	(5) *With Expertise Change*	(6) *Without Expertise Change*
INResign	0.009	0.049***	0.189	0.440***
	(0.477)	(2.822)	(1.111)	(3.840)
Size	0.015*	–0.020**	–0.026	–0.113***
	(1.670)	(–2.329)	(–0.545)	(–3.059)
Lev	0.031	0.071	0.131	0.571***
	(0.620)	(1.590)	(0.449)	(2.700)
ROA	–0.134	–0.214**	–1.489*	–1.093*
	(–1.142)	(–2.301)	(–1.865)	(–1.931)
Age	–0.008	0.009	0.184***	0.007
	(–0.913)	(1.108)	(2.873)	(0.162)
Growth	–0.010	0.014	0.473***	0.172*
	(–0.634)	(1.107)	(4.179)	(1.917)
Indep	–0.014	0.245	0.412	0.594
	(–0.073)	(1.547)	(0.384)	(0.716)
Board	–0.016	0.010	0.076	–0.203
	(–0.275)	(0.206)	(0.232)	(–0.853)
Loss	–0.017	–0.022	0.188	0.308**
	(–0.751)	(–1.104)	(1.018)	(2.302)
Big4	–0.038	–0.009	–0.309	0.062
	(–0.603)	(–0.310)	(–0.946)	(0.446)
Dual	0.027*	0.039***	–0.289***	0.015
	(1.832)	(2.810)	(–2.697)	(0.185)
Cons	–0.271	0.241	–3.173**	–0.191
	(–1.143)	(1.194)	(–2.317)	(–0.166)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	6,944	7,943	6,899	7,943
F/chi2	0.968	4.043	336.692	3,148.367
Adj-R^2/Pseudo R^2	0.006	0.015	0.076	0.043
P-value		0.040**		0.062*

Note: P-values indicate the significance of the difference in the estimated coefficients of the voluntary resignation of independent directors (*INResign*) between groups, obtained through 1,000 bootstrap replications, as below.

the government and regulatory bodies, increasing the regulatory pressure faced by auditors. This in turn can lead to higher audit fees and a greater probability of changes in audit firms.

Based on this, we examine how the legal environment affects auditors' responses to the voluntary resignation of independent directors through grouped regression analysis. Following Tian and Wang (2019), we use the Development of Market Intermediary Organizations and Legal Environment indices from the marketization index system compiled by Fan et al. (2011) to divide the sample into groups with stronger and weaker legal and institutional environments, based on the median value of the Legal Environment index for each region annually. Columns (1) and (2) of Table 22 show that for the group with a weaker legal environment, the coefficient of the voluntary resignation of independent directors (*INResign*) is positive and significant, while for the group with a stronger legal environment, the coefficient of *INResign* is statistically nonsignificant. This indicates that the positive impact of the voluntary resignation of independent directors on abnormal audit fees is more pronounced in the group with a weaker legal environment, suggesting that auditors are more sensitive to the voluntary resignation of independent directors when the listed companies involved are in a weaker legal environment. However, the regression results in Columns (3) to (4) of Table 22 show empirically that the P-value used to test the difference between the coefficients of the voluntary resignation of independent directors (*INResign*) between groups is nonsignificant. This indicates that there is no significant difference in the positive correlation between the voluntary resignation of independent directors (*INResign*) and auditor change (*Change*) between the groups with different legal environments.

Table 22
Impact of legal environment.

Variable	(1) Stronger Legal Environment *ABFEE*	(2) Weaker Legal Environment *ABFEE*	(3) Stronger Legal Environment *Change*	(4) Weaker Legal Environment *Change*
INResign	0.015	0.079**	0.379***	0.378*
	(1.084)	(2.454)	(3.578)	(1.730)
Size	0.006	–0.046***	–0.121***	0.017
	(0.824)	(–3.202)	(–3.778)	(0.267)
Lev	0.096**	–0.025	0.444**	0.434
	(2.529)	(–0.320)	(2.323)	(1.065)
ROA	–0.124	–0.397**	–1.226**	–1.965*
	(–1.514)	(–2.307)	(–2.398)	(–1.806)
Age	0.004	–0.008	0.125***	–0.027
	(0.570)	(–0.532)	(3.120)	(–0.295)
Growth	–0.007	0.059***	0.299***	0.200
	(–0.633)	(2.912)	(3.697)	(1.203)
Indep	0.083	0.705**	0.342	0.369
	(0.598)	(2.397)	(0.483)	(0.232)
Board	0.002	0.137*	–0.117	–0.267
	(0.055)	(1.793)	(–0.548)	(–0.563)
Loss	–0.017	–0.040	0.365***	–0.079
	(–1.026)	(–1.180)	(3.055)	(–0.314)
Big4	–0.074***	0.044	0.149	–0.098
	(–2.657)	(0.531)	(1.098)	(–0.255)
Dual	0.029***	0.037	–0.069	–0.340*
	(2.667)	(1.220)	(–0.996)	(–1.756)
Cons	–0.194	0.389	–1.114	–2.566
	(–1.085)	(1.088)	(–1.047)	(–1.426)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	12,476	2,391	12,476	2362
F/chi^2	3.247	4.616	4,883.218	99.112
Adj-R^2*/Pseudo R*^{2}	0.009	0.062	0.051	0.060
P-value		0.052*		0.405

9. Conclusion

This paper presents an in-depth exploration of auditors' responses to the voluntary resignation of independent directors. The findings reveal that the voluntary resignation of independent directors of a listed company transmits risk signals to auditors that elevate their perception of the risk associated with that company. In response, auditors seek to mitigate this risk by charging higher audit fees or terminating their engagement with the client company. Interestingly, we find no evidence that auditors also increase their audit effort following the voluntary resignation of independent directors, indicating that the higher audit fees charged are due primarily to an increased risk premium, rather than to cost compensation. Mechanism analysis indicates that companies with voluntary resignations by independent directors face an increased risk of regulatory penalties in both the current and subsequent periods, and such companies also receive more negative media coverage.

Further analysis reveals that since the implementation of the New Securities Law, the positive relationship between the voluntary resignation of independent directors and abnormal audit fees has become more pronounced. This suggests that the new law has a deterrent effect on auditors, increasing their perception of risk and leading them to raise audit fees. Moreover, we discover that auditors follow an order of priority in responding to the risk signals conveyed by the voluntary resignation of independent directors: when they perceive the level of corporate risk to be acceptable, they prefer to increase audit fees, but when the risk exceeds their tolerance level, they are likely to terminate the engagement, leading to an auditor change.

Additionally, our results show that auditors exhibit a heightened perception of risk for companies with (vs. without) multiple consecutive years of voluntary resignations by independent directors. We find no evidence that the mandatory resignation of independent directors significantly affects auditors' responses. Our heterogeneity analyses reveal that when auditors have a lower level of expertise and the legal and institutional environment is less robust, the voluntary resignation of independent directors has more pronounced positive effects on abnormal audit fees and the likelihood of auditor change.

The conclusions of this paper offer insights for regulators, auditors and listed companies. First, regulators should be aware that although China's New Securities Law has a certain deterrent effect on auditors, this does not translate into increased audit effort or improved audit quality. Therefore, the government should introduce further policies to urge auditors to perform effective risk assessment of listed companies and enhance their audit quality.

Second, auditors should pay close attention to listed companies whose independent directors have voluntarily resigned and make a full assessment of the risks and potential benefits associated with auditing them. Auditors should increase their audit effort to reduce audit risk and capture audit market share by providing high-quality audit services.

Third, listed companies should be aware that voluntary resignation by independent directors increases a company's administrative costs. Management can reduce the risk perceived by independent directors and minimize the likelihood of their resignation by purchasing director and officer liability insurance, which will allow independent directors to better fulfill their supervisory, consultative and resource support roles.

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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Industrial internet technology, resource reallocation and corporate risk-taking capacity: Evidence from the strategic management perspective

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ABSTRACT

By employing machine learning techniques and the Word2Vec model, we quantify the micro-level implementation of Industrial Internet technology in Chinese manufacturing firms from 2010 to 2022. This provides empirical evidence for understanding how the Industrial Internet technology enhances corporate risk-taking capability. Our study shows that adopting this technology increases risk-taking capacity, mainly through resource reallocation. The information layer empowers improvements in organizational structure, the platform layer optimizes labor resources, and the edge/software layers facilitate the integration of supply chain resources. The effect is more pronounced in firms that are technology- and labor-intensive, particularly in environments of high economic policy uncertainty. In conclusion, the Industrial Internet boosts total factor productivity by fostering increased risk-taking.

1. Introduction

Since the global financial crisis of 2008, economies worldwide have experienced significant slowdowns in growth. Even with the rapid progress and widespread application of digital technology, total factor productivity and gross domestic product trends in the U.S., Japan, South Korea and China reveal the limited efficiency enhancement and economic growth driven by technological advancement (Chen and Cai, 2022); this constitutes the "Solow paradox". China is undergoing momentous changes unseen in a century. It is facing a complex and volatile economic environment, particularly due to the challenges posed by unilateral trade

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policies and a new wave of technological revolution. It is crucial to explore the application of digital technology and its growth-promoting effects, combined with the process of resource reallocation. Doing so would not only help resolve the Solow paradox but also facilitate high-quality development in the manufacturing industry and overall economic growth.

As an essential decision-making strategy for expansion and growth (Banerjee and Gupta, 2017), risk-taking capacity drives continuous performance improvement (Nakano and Nguyen, 2012; Wang et al., 2023). It is a core component of promoting technological progress, enhancing social productivity and maintaining stable macroeconomic operations (De and Summers, 1991; John et al., 2008; Tian et al., 2022). Previous studies focus on agency problems, institutional environments and policy changes to identify the key points for improving investment decisions. Based on neo-Schumpeterian endogenous growth theory, the escalation of demand and the rise of innovative technologies are propelling transformations in technology, structure and models within the supply chain. This dynamic serves as an inexhaustible driving force for the reallocation of manufacturing resources. Advanced technologies and inimitable organizational culture account for sustained competitive advantages and improved corporate performance (Wernerfelt, 1984; Barney, 1991). This circumstance offers new insights, which we explore in our study of the technological drivers behind the enhancement of risk-taking capacity in the context of Industry 4.0.

In November 2017, the State Council released *Guidelines Aimed at Bolstering Industrial Internet's Growth and Development*, emphasizing the need to foster a close fusion between the Industrial Internet, big data, artificial intelligence and the real economy. This integration is intended to propel the advancement of manufacturing and facilitate the optimization and upgrading of traditional industries. China's Industrial Internet technology has witnessed significant progress, leading to a wealth of data resources and numerous practical applications. In August 2023, the Ministry of Industry and Information Technology released the *Eight Major Achievements in the Development of Cross-Industry and Cross-Domain Industrial Internet Platforms*, indicating that China's "double-cross" platform ecosystem is gradually improving, with a healthy, orderly and high-quality growth trend. The 50 selected double-cross platforms have an average connection of 2.18 million industrial devices, serve over 234,000 enterprises and achieve an average revenue of 6.9 billion yuan. The Industrial Internet, serving as a powerful booster for the "Made in China Smart" initiative (China Academy of Industrial Internet, 2021), builds a smart manufacturing system that supports ubiquitous connectivity, flexible supply and efficient allocation of manufacturing resources. It is driving a shift in business models from a "consumer-centric" approach to an approach in which "consumption determines production" (Cai and Qi, 2021; Chen et al., 2022a,b; Du et al., 2022; Sun et al., 2022), thus enabling "zero-distance" communication across manufacturing, supply chain and retail operations (Lyubic et al., 2018; Ma et al., 2020; Wei and Li, 2020; Lu and Chen, 2023).

Furthermore, the implementation of the Industrial Internet presents a pivotal opportunity for companies to strengthen their risk-taking capacity. Distinct from the traditional Internet, the Industrial Internet enables holistic interconnection among humans, machines, objects and networks, realizing seamless integration of all factors, chains and value across the entire industrial spectrum. This reflects the embedding of digital elements into the traditional production factor system. The realization of a closed-loop system, encompassing high-skilled labor, smart machines, data collection and analysis platforms, feedback control and intelligent operating systems is significant for the Industrial Internet to achieve the technological empowerment effect. The combination of bottom-up information flows and top-down decision-making streams creates an optimized closed loop, which includes industrial digitalization and the efficient allocation of traditional resources, such as finance, labor and supply chains. This empowerment effect exerts a positive influence on risk-taking capacity.

Accordingly, in this study, we adopt the framework of neo-Schumpeterian endogenous growth theory, using listed manufacturing firms over the 2010–2022 period as our sample, and use the Word2Vec model to gauge the micro-level adoption intensity of Industrial Internet technology. We conduct an empirical investigation into the impact, mechanisms and consequences of Industrial Internet technology in terms of risk-taking capacity. Fundamental tests reveal that Industrial Internet technology significantly enhances risk-taking capability. Mechanism examinations uncover that Industrial Internet technology boosts risk-taking capacity through resource reallocation, with (1) information-as-a-service (IaaS) layer technology exerting an informational empowerment effect to optimize corporate organizational structures; (2) platform-as-a-

service (PaaS) layer technology exerting an empowerment effect to enhance the efficiency of labor resource allocation; and (3) edge layer and software-as-a-service (SaaS) layer technology exerting an algorithm empowerment effect to facilitate the integration of supply chain resources. Heterogeneity tests show that the effect of Industrial Internet technology on risk-taking capacity is more pronounced in firms with high levels of technology intensity and labor force intensity and in firms in environments with high economic policy uncertainty. The main contributions of this study are detailed below.

First, grounded in the framework of neo-Schumpeterian endogenous growth theory, we illuminate the effect of Industrial Internet technology in augmenting corporations' risk-taking capacity, thereby furnishing micro-evidence for innovation-driven development within the context of China's manufacturing sector. The level of risk tolerance represents a pivotal strategic element underlying corporate expansion and growth, functioning as a vital impetus for regional and macroeconomic growth. The literature predominantly focuses on the influences of agency issues, institutional environments and policy shifts on corporate risk-taking propensity or willingness. Departing from this, our investigation from the supply-side perspective examines how digital technological innovations empower the allocation of operational resources, bolstering corporate risk-taking capability and enhancing total factor productivity. This analysis offers theoretical guidance and practical insights for China's manufacturing industry in its transition from investment-driven to innovation-driven evolution.

Second, by separately validating the information empowerment, technological empowerment and algorithm empowerment effects realized through the Industrial Internet's IaaS, PaaS, edge and SaaS layers, we elucidate the mechanistic pathways through which the Industrial Internet bolsters firms' capacity to take risk, thereby furnishing empirical evidence of the Industrial Internet's empowerment of China's manufacturing sector to transcend the Solow paradox. Amid the application of digital technology innovations, inadequacies in technology maturity and delays in technology implementation alongside organizational restructuring can trigger the manifestation of the Solow paradox. We dissect the Industrial Internet and its distinct layers of technology, outlining the mechanisms by which they facilitate the efficient allocation of production factors, examining the concrete scenarios in which manufacturing transcends this paradox and unearthing the black box of how Industrial Internet augments corporate risk-taking capabilities. We thereby lay a theoretical foundation for how the Industrial Internet propels high-quality development in manufacturing.

Third, adopting machine learning techniques, we use the Word2Vec model to quantify the extent of Industrial Internet technology's micro-level implementation, thereby furnishing empirical support for understanding how Industrial Internet technology enhances corporate risk-taking capability. While the roles of Industrial Internet technology in refining business models, aligning with market demands, enhancing operational management and stimulating innovation capabilities within the manufacturing sector are broadly acknowledged, research in this domain predominantly relies on theoretical analyses and case studies due to a scarcity of quantitative methodologies. We leverage machine learning methodologies to systematically measure the granularity of Industrial Internet technology adoption, providing fresh empirical evidence of the influence, mechanisms and outcomes of Industrial Internet technology on corporate risk appetite. In doing so, we enhance the application scope of machine learning within the field of management science.

The remainder of this paper is structured as follows. Section 2 provides a review of the literature and a theoretical analysis. Section 3 presents our research design. Section 4 presents our empirical tests and analyses. Section 5 concludes the paper.

2. Theoretical foundations and hypothesis formulation

2.1. Analysis of factors driving corporate risk-taking

Corporate risk-taking, which reflects a firm's risk preference and control in investment decisions, constitutes a vital foundation for securing long-term competitive advantages and sustainable development. Early research primarily explains levels of corporate risk-taking within the agency theory framework, positing that executives tend to curb corporate risk-taking to avoid wealth and reputation losses. Corporate governance enhancements elevate corporate risk-taking (Acharya et al., 2011; Kini and Williams, 2012; Nakano and Nguyen, 2012). Firms whose shares are jointly held by spouses exhibit significantly lower risk-taking (Xiao

et al., 2018). Pyramid ownership structures positively influence the rise in corporate risk-taking (Gao and Liu, 2019). Firms with multiple large shareholders demonstrate increased risk-taking (Gao et al., 2020; Wang et al., 2020). Executives' psychological states, experience and cognitive biases, among other irrational traits, reinforce risk appetites (Eisenbach and Schmalz, 2015). Overconfidence among executives is positively correlated with corporate risk-taking (Yu et al., 2013). Older executives are more likely to shy away from risks, reducing corporate risk-taking (Serfling, 2014). Firms led by male CEOs exhibit higher risk-taking than those with female CEOs (Faccio et al., 2016; Khaw et al., 2016). CEOs with early-life exposure to extreme disasters are more risk-averse, leading to more conservative decision-making (Bernile et al., 2018).

Furthermore, high-risk investments, being resource-intensive activities, are subject to a company's capacity to secure financing, indicating an element of resource dependency (Zhang et al., 2015). During economic downturns, tightened credit policies exacerbate the funding constraints faced by firms, thereby inhibiting their risk-taking capacity. Conversely, the relaxation of banking regulations significantly bolsters corporate risk-taking capacity (Yan et al., 2019). Favorable institutional environments aid in mitigating the impact of societal conflicts on corporate risk-taking capacity (Yang et al., 2017). An increase in minimum wage levels notably decreases the risk-taking level of listed companies (Liu and He, 2020). The value-added tax refund reform incentivizes firms to undertake higher risks (Wu et al., 2022). Strengthened accountability systems dampen state-owned enterprises' (SOEs') excessive risk-taking inclinations (Chen et al., 2022a,b). The introduction of green credit policies significantly enhances corporate risk-taking in green project investments (Li et al., 2023). The enactment of the Bankruptcy Law and Property Law restrains firms' willingness to take risks (Wang et al., 2023). The recentralization of SOEs fosters an improvement in corporate risk-taking capabilities (Peng et al., 2020). Firms occupying central positions in supply chain networks demonstrate elevated risk-taking capacity (Lv et al., 2023).

The literature predominantly focuses on the impacts of agency issues, institutional contexts and policy dynamics on corporate risk-taking, with less emphasis on the perspective of technological innovation. Neo-Schumpeterian endogenous growth theory recognizes innovation as the fountainhead of economic growth (Romer, 1986; Aghion and Howitt, 1992), representing firms' voluntary investments in new knowledge and technologies in pursuit of expansion (Winter, 2006; Hanusch and Pyka, 2007), not only ensuring supply but also efficiently meeting market demands. This theory forms the bedrock for studies on innovation-driven development and provides theoretical guidance for our examination of how Industrial Internet technology influences, through its mechanisms, corporate risk-taking capabilities and their consequences. Amid the deep integration of digital technology into the real economy, the Industrial Internet, characterized by ubiquitous connectivity, comprehensive sensing, intelligent optimization and robust security, has emerged as a strategic asset, significantly contributing to competitive advantage and sustained growth capabilities. By examining corporate risk-taking through the lens of digital technology innovation, we aim to illuminate the influences and operational processes affecting this capacity, thereby furnishing empirical evidence within the context of China's manufacturing sector for the innovation-driven development paradigm. This endeavor has crucial theoretical implications for and practical insights into achieving high-quality development in the manufacturing industry.

2.2. Micro-level economic consequences of Industrial Internet technology

In 2017, the notion of *Leveraging the Industrial Internet to Facilitate High-Quality Development in Manufacturing* was incorporated into the central government's work report,[1] marking the transition of Industrial Internet technology from conceptual formation to practical promotion. Core to the Industrial Internet is its broader and deeper connectivity, enabling comprehensive sensing of industrial systems; through the modeling and analysis of vast industrial data, it facilitates intelligent decision-making, fueling value creation for

[1] On 27 November 2017, the State Council officially issued the *Guiding Opinions on Deepening the Development of Industrial Internet in the Context of "Internet Plus Advanced Manufacturing."* This document outlines the three-stage development goals, corresponding main tasks and supportive measures for the development of a domestic Industrial Internet. It emphasizes the construction of cross-industry and cross-domain platforms; the establishment of a group of enterprise-level platforms to support the digitalization, networking and intelligent transformation of enterprises; and the improvement of requirements for a smart manufacturing ecosystem.

enterprises. The technology promotes efficient alignment of corporate resources and services with customer needs, enhancing the business models of the manufacturing sector (Gierej, 2017; Leminen et al., 2020). It transforms the pathways of knowledge transfer in production processes and adjusts the value connection methods between upstream and downstream firms in the supply chain (Cai and Qi, 2021). By boosting product and service innovation, it strengthens enterprises' competitive prowess (Babu et al., 2022) and fosters a co-creation of value model (Ma et al., 2020). Furthermore, it significantly enhances the capacity for value generation (Lv et al., 2019; Ma et al., 2020; Wei and Li, 2020; Lu and Chen, 2023).

The above analysis focuses on the paths through which Industrial Internet technology empowers the business models, operational management and value creation of enterprises, with less emphasis on the impact of its adoption on corporate risk-taking capacity. Neo-Schumpeterian endogenous growth theory posits that an innovation-driven development system places knowledge and technology at the core of its resource perspective, emphasizing the creation, accumulation, diffusion and application of new knowledge via learning processes. Establishing such a system necessitates the orderly flow of knowledge and technology, facilitating their sharing among individuals, organizations and regions. Industrial Internet technology fosters comprehensive interconnectivity of production factors within firms, across industries and throughout regions, shaping five core competencies: ubiquitous sensing, intelligent decision-making, agile responsiveness, global collaboration and dynamic optimization. This interconnectivity creates the technological prerequisites for the flow of resources internally, across industries and in different regions, thereby promoting an enhancement in firms' capacity to assume risk.

2.3. Industrial Internet technology, resource reallocation and risk-taking capacity

The effect of Industrial Internet technology in empowering a company's ability to take risks is significant. At the macroeconomic level, total factor productivity is influenced by input–output factors and hinges on the allocation of production factors among different economic entities. Macroscopically, resource reallocation refers to the government's recombination of resources among firms, under the principle of market-driven allocation, to increase the market share of high-growth enterprises, thereby enhancing industry-wide productivity. From a microeconomic perspective grounded in resource-based theory, ample evidence highlights the prevalent heterogeneity among economic agents. This heterogeneity, stemming from variations in productivity (Syverson, 2004; Jian, 2011), energy efficiency (Lyubic et al., 2018; Chen and Chen, 2019) and scale (Becker et al., 2013), forms the fundamental rationale behind resource reallocation among firms (Folta et al., 2016). At the macroeconomic level, capacity constraints amplify the significance of resource reallocation practices by firms. Amid technological innovations (Kaul, 2012) and shocks to external factor markets (Berry and Kaul, 2021), firms can redeploy resources from low-profit or low-growth ventures to those with higher profitability or growth potential, thereby reducing unit costs and realizing economies of scope over time. This realignment of production resources serves as a means to gain competitive advantage (Helfat and Peteraf, 2003).

According to neo-Schumpeterian endogenous growth theory, knowledge and technology, as factor inputs, directly contribute to productivity, reinforcing firms' core competitiveness and enabling novel combinations of production elements, thereby fostering transformative productivity enhancements (Romer, 1986; Lundvall and Johnson, 1994). Distinguishing itself from conventional Internet technologies, Industrial Internet technology unites the potent functionalities of IaaS (as the foundational infrastructure layer), PaaS (as the core layer), edge layer and SaaS layer (Guth et al., 2016), encompassing three major systems of networking, data and security and embodying four application models: intelligent manufacturing, networked collaboration, personalized customization and service extension. As Fig. 1 shows, the PaaS layer, as the core layer, utilizes industry-specific knowledge, production processes, technical principles and experiential data to achieve industrial mechanism modeling and big data modeling, thereby constructing a smart manufacturing system. The IaaS layer comprises fundamental generic modules of servers, storage, networking and virtualization resources, forming the backbone of cloud computing. The edge layer, through controllers or sensors, realizes real-time data acquisition, simulating physical entity behaviors via digital twin technology, monitoring changes in customer and supplier demands and relaying this information to the core technology layer and

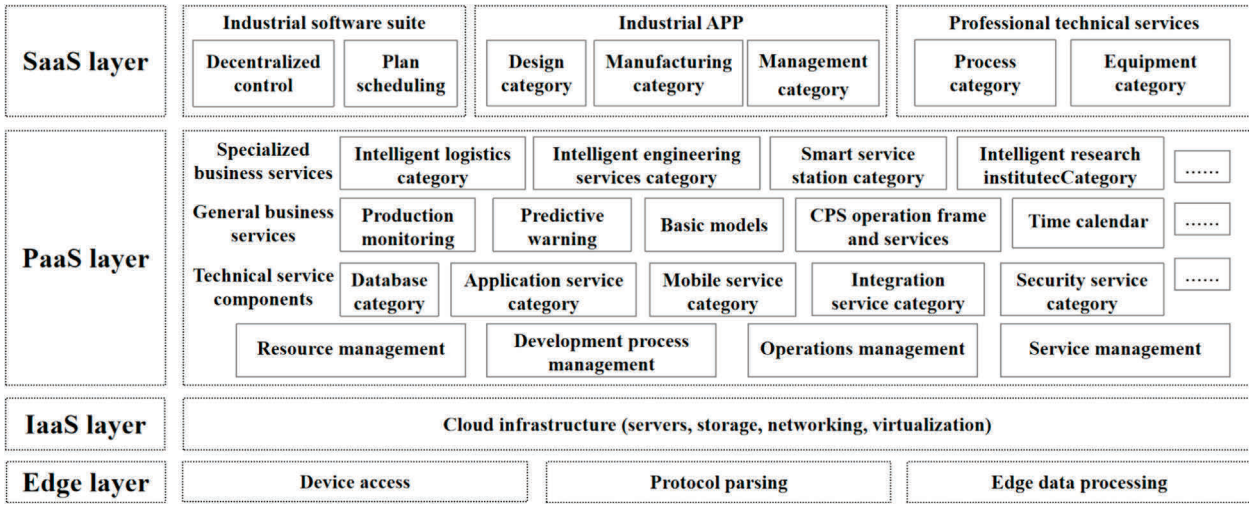

Fig. 1. Architecture diagram of the Industrial Internet.

the SaaS layer. Lastly, the SaaS layer furnishes clients with application software and solutions across the production, design, management and service domains.

Industrial Internet technology forms an optimized closed loop for digital industrial application, integrating bottom-up information flows and top-down decision-making processes. This facilitates the optimization of traditional resources, such as organizational structures, labor and supply chains, presenting a pivotal opportunity for resource realignment within enterprises. First, the varying layers of Industrial Internet technology, through resource reallocation, enhance the efficiency and convenience of information exchange both internally within firms and externally across industries and regions. This elevates the intrinsic demand for organizational structure optimization, laying the necessary groundwork for increasing corporate risk-taking capacity. Second, Industrial Internet technology harnesses data from industry expertise, production processes, technical principles and empirical knowledge to establish industrial mechanism models and big data models, thereby constructing a smart manufacturing ecosystem. It complements and substitutes traditional labor resources, reinforcing the adjustment and optimization of labor and thereby boosting corporate risk-taking capabilities. Lastly, the Industrial Internet bolsters firms' predictive abilities concerning changes in supplier and customer needs, augments collaboration among supply chain participants, accelerates response and delivery times to market shifts and demands and, through the discovery and integration of resources, ameliorates risk-taking capacity. Hence, we propose the following hypothesis:

H1: Industrial Internet technology significantly enhances corporate risk-taking capacity.

Leveraging Industrial Internet technology, enterprises are able to restructure and to reallocate resources effectively, ultimately enhancing their risk-taking capacity. The impetus for organizational change in companies often lies in novel institutional frameworks and challenges posed by both internal and external environments; this process is collectively known as *creative destruction*. Since the 1990s, the adoption of computer and network technologies has served as a key catalyst in the evolution of corporate organizational structures. Due to the adoption of information technology, the cost of processing and transmitting information has been greatly reduced. This enhancement in information flow efficiency among various levels and departments has blurred the traditional boundaries of organizational structures. As a result, we have witnessed a transition from traditional hierarchical structures to matrix-based departmental structures and further toward flattened alliance-oriented models, incorporating new paradigms such as platformization, ecology, modularization and virtualization. Furthermore, with the reduced cost of external information acquisition and the introduction of

new product development and competition, enterprises are increasingly motivated to undergo organizational transformations to establish specialized risk warning systems, knowledge management capacity, inherent flexibility mechanisms and adaptive data intelligence solutions. The information-driven IaaS layer of the Industrial Internet boosts traditional manufacturing business models and organizations, empowering structural reforms and risk-taking abilities. Composed of servers, storage, networks and virtualization, the IaaS layer serves as the basis for cloud computing. It enhances data collection, integration and modeling analysis, enabling flexible resource allocation, collaboration and groundbreaking business models, thus achieving capabilities beyond traditional automation and information technology. With this as a foundation, corporate decision-making spans wider, and organizational structures increasingly feature modularity, flattening and global collaboration (Kim and Park, 2016), evolving from a linear to a networked model (Hu and Wang, 2020). Such resource reallocation improves efficiency, quality and operations, enabling swift internal and external responses. Given the information above, we propose the following hypothesis:

H2: The IaaS layer technology of the Industrial Internet exerts an information empowerment effect on organizational structure improvement, thus enhancing corporate risk-taking capacity.

Through optimized labor structures, Industrial Internet technology enables the improvement of resource reallocation and risk-taking capacity. Labor economics highlights the role of labor investment in asset pricing, as labor costs constitute a form of leverage that shapes business risks (Donangeloa et al., 2019). During China's manufacturing boom, a stable labor supply is essential. However, with economic growth and demographic changes, rural labor migration has slowed, leading to faster labor cost increases in manufacturing compared with developed economies (Bai and Yu, 2019). As a result, China's manufacturing industry has lost some of its competitive advantage, causing a surge in business risks. In terms of technological empowerment, the intelligent manufacturing framework in the Industrial Internet architecture is a crucial factor in optimizing labor structures while revolutionizing productivity. As the core technology level, the PaaS layer uses industry insights, production techniques, technological principles and experience to develop industrial mechanism modeling and big data modeling, constructing a robust intelligent manufacturing system. The digital technology in the intelligent manufacturing system, due to its technological bias (Autor and Dorn, 2013), automates programmatic tasks and activities and collects and stores data. It can substitute for physical demand and repetitive work that relies on low-level cognitive effort (Acemoglu and Restrepo, 2018; Graetz and Michaels, 2018), reducing reliance on low-skilled labor, enhancing productivity, cutting labor costs and strengthening resilience to external risks. Furthermore, with the integration of smart manufacturing technology into traditional manufacturing, it complements high-skilled labor (Flug and Hercowitz, 2000; Acemoglu and Autor, 2011; Weinberger, 2014), driving structural changes in daily work, creating new job opportunities and directing skilled workers toward innovative activities. This synergistic innovation effect enables labor resources to adapt flexibly to new workflows and organizational models (Hitt and Brynjolfsson, 1997; Bresnahan et al., 2002; Wang et al., 2006), enhancing adjustment and optimization, thus further strengthening risk-taking capacity. In light of this, we propose the following hypothesis:

H3: The PaaS layer technology of the Industrial Internet exerts a technology empowerment effect on labor force structure optimization, thus enhancing corporate risk-taking capacity.

With the integration of supply chain resources, Industrial Internet technology facilitates resource reallocation, elevating risk-taking capacity. Being involved in the procurement and sales aspects of production and operations, suppliers and customers have a profound impact on a company's production costs, revenue and, ultimately, its competitive positioning and risk-taking capacity. As supply chain concentration increases, production efficiency and resource utilization are boosted (Patatoukas, 2012; Irvine et al., 2016). Nonetheless, the differing interests and objectives of upstream and downstream partners create a continuous negotiation process throughout their cooperation. Excessive concentration of suppliers decreases supply chain resilience, leading to supply–demand fluctuations and increasing the risk of stock market crashes (Gao et al., 2023). Over-reliance on major customers weakens bargaining power, forcing companies into a disadvantaged position and leading to potential losses from customer disruptions (Li et al., 2018). Additionally, earnings volatil-

ity from suppliers and clients spreads to companies (Kolay et al., 2016; Chen and Liu, 2020), intensifying business risk. In terms of algorithmic empowerment, the edge and SaaS layers of the Industrial Internet exhibit strong algorithm capabilities. These allow for neural network–based predictions of customer and supplier demand shifts, fostering better coordination among supply chain stakeholders, accelerating the response and delivery processes and optimizing supply chain resources through the discovery and integration of resources. Featuring sensors and controllers, edge layer technology creates digital twins of physical systems, enabling real-time online analysis and optimization. With its dynamic monitoring of supplier and customer operational data, it significantly boosts supply chain resource management efficiency. The SaaS layer delivers diverse service software apps, efficiently underpinning the operations, development, administration and maintenance of intelligent apps and services. This improves the flow of information between companies, suppliers and customers, shifting competitive dynamics to collaborative partnerships and fostering technological innovation (Mathews and Cho, 2000). These resource reallocation methods help enterprises quickly mobilize resources for production, flexibly respond to external market demands and enhance risk-taking capacity. Given this foundation, we propose the following hypothesis:

H4: The edge layer and SaaS layer technology of the Industrial Internet exert an algorithm empowerment effect on supply chain resource integration, thus enhancing corporate risk-taking capacity.

3. Research design

3.1. Sample selection

Our initial sample consists of public manufacturing firms listed on the Chinese A-share market over the 2010–2022 period. We take the following steps to obtain the final research sample. First, we delete observations classified as special treatment (labeled as ST/*ST/PT). Second, we exclude firms with less than 3 consecutive years of observations to ensure that we can capture dynamic changes. Third, we delete observations from the initial public offering (IPO) year. Fourth, we exclude firms that have changed industries. This process yields a final sample that consists of 11,172 firm-year observations. We obtain financial information from the China Stock Market & Accounting Research database and annual reports from the CNINFO Network. All continuous variables are winsorized at the 1st and 99th percentiles to reduce the effects of outliers.

3.2. Variable construction

3.2.1. Measures of risk-taking capacity

Previous studies document that riskier investments and decisions result in more volatile returns of capital. Following Zhou et al. (2019), we consider two measures to proxy for risk-taking capacity: (1) the volatility of return on assets (ROA) adjusted by the industry average over the 3-year period from year t to $t + 2$ and (2) the maximum deviation of ROA adjusted by the industry average over the 3-year period from year t to $t + 2$. These measures are computed as follows:

$$Adj\_Roa_{i,n} = \frac{EBIT_{i,n}}{Assets_{i,n}} - \frac{1}{X_n}\sum_{k=1}^{X}\frac{EBIT_{k,n}}{Assets_{k,n}} \tag{1}$$

$$RISK1_i = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\left(Adj\_Roa_{i,n} - \frac{1}{N}\sum_{N=1}^{N}Adj\_Roa_{i,n}\right)^2}\ /N = 3 \tag{2}$$

$$RISK2_i = Max(Adj\_Roa_{i,n}) - Min(Adj\_Roa_{i,n})|_{N=3} \tag{3}$$

Adj_Roa is the ROA adjusted by the industry average as shown in Eq. (1), where *i* denotes the firm, *n* denotes the year, *X* denotes the total number of firms in the same industry, *EBIT* represents earnings before interest and taxes, and *Assets* represents average total assets. *RISK1* is the volatility of ROA calculated by the rolling window of the industry mean-adjusted ROA from year *t* to *t* + *2*, as shown in Eq. (2). *RISK2* is the maximum difference value of the industry mean-adjusted ROA from year *t* to *t* + 2, as shown in Eq. (3).

3.2.2. Measures of Industrial Internet technology

We proxy for Industrial Internet technology using the Word2Vec natural language processing method.

First, we extract high-frequency keywords related to Industrial Internet technology. In 2017, the State Council issued *Deepening Internet + Advanced Manufacturing*. In 2018, the Central Economic Work Conference categorized the Industrial Internet platform, 5G, artificial intelligence and the Internet of Things (IoT) as new infrastructure. In 2020, the Ministry of Industry and Information Technology issued the *Notice on Promoting the Development of Industrial Internet* for further specific planning. In accordance with these national policies, we select *Industrial Internet*, *network interconnection*, *communication modules*, *applications*, *network virtualization*, *production control networks*, *gateways*, *software-defined networks*, *narrowband IoT*, *computing technology*, *new infrastructure*, *blockchain*, *data interoperability*, *identification carriers*, *identification resolution* and *passive optical networks* as constituting the seed vocabulary of Industrial Internet technology.

Then, we expand the seed vocabulary. To avoid the subjectivity problem of "talking much and doing little," we use the Word2Vec natural language processing method to search the seed vocabulary of Industrial Internet technology and their synonyms in the core competitiveness section of annual reports, so as to enhance the reliability of the measurement method. The top 10 words with the highest similarity scores are selected as a set of similar words.

Next, we calculate the frequency of words related to Industrial Internet technology from the core competitiveness sections of the annual reports over the 2010–2022 period and standardize the effective words after removing invalid words from the text of the core competitiveness sections.

Finally, we test the validity of our measure of Industrial Internet technology. The Word2Vec natural language processing method uses dense real-valued vectors to represent words according to the context. These vectors generate a word vector space. Within this space, the distance between word vectors represents the semantic similarity of the words. A shorter distance between word vectors indicates that the words are more semantically similar. As Fig. 2 shows, the keywords with dense word vectors are *Industrial Internet*, *deep learning*, *data center*, *edge computing*, *storage chip*, *simulated data* and *near field communication*, which is consistent with the definition of Industrial Internet technology in the *Guidelines for the Construction and Promotion of Industrial Internet Platforms* issued by the Ministry of Industry and Information Technology and close to the description of technical architectures in the Industrial Internet Architecture (Version 1.0), indicating the validity of our measure.

3.2.3. Control variables

Studies reveal several liability factors and firm characteristics that affect risk-taking capacity. Following prior research, we control for an array of firm-level financial and manager characteristics to capture confounding factors that may bias our estimation: firm size (*Size*), firm age (*Age*), leverage (*Lev*), rate of return on investment (*ROI*), gross profit margin (*Profit_M*), administrative expenses (*Overhead_E*), the proportion of fixed assets (*Fix_A*), the share of fixed assets in revenue (*Fix_S*), sustainable growth (*Sustainable_G*), executive compensation (*Top3*) and the nature of property rights (*SOE*). Table 1 presents all of the variable definitions.

3.3. Model specification

We estimate the following models to investigate the effect of Industrial Internet technology on risk-taking capacity:

$$RISKi,t = \beta 0 + \beta 1 \times IITi,t + \sum \beta jControli,t + \sum Year + \sum Industry + \varepsilon i,t \quad (4)$$

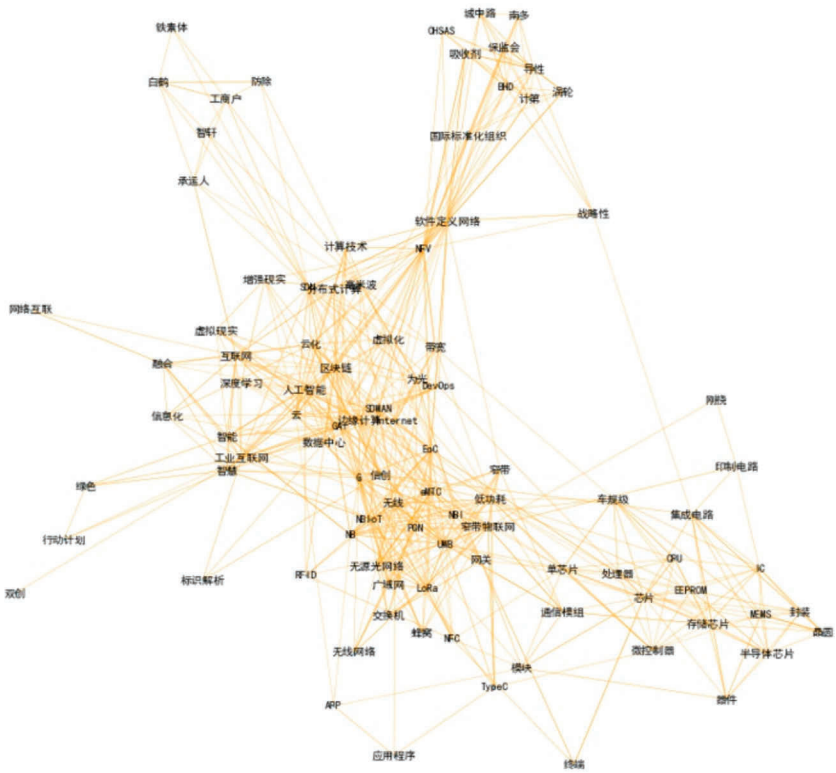

Fig. 2. Network graph of similar Industrial Internet technology words.

$$RISKi,t = \beta 0 + \beta 1 \times IITi,t + \beta 2 \times IITi,t \times Structure\_Ri,t+1 + \beta 3 \times Structure\_Ri,t+1 + \sum \beta jControli,t + \sum Year + \sum Industry + \varepsilon i,t \quad (5)$$

$$RISKi,t = \beta 0 + \beta 1 \times IITi,t + \beta 2 \times IITi,t \times Labor\_Ri,t+1 + \beta 3 \times Labor\_Ri,t+1 + \sum \beta jControli,t + \sum Year + \sum Industry + \varepsilon i,t \quad (6)$$

$$RISKi,t = \beta 0 + \beta 1 \times IITi,t + \beta 2 \times IITi,t \times Supplier\_Rt+1/Customer\_Ri,t+1 + \beta 3 \times Supplier\_Rt+1/Customer\_Ri,t+1 + \sum \beta jControli,t + \sum Year + \sum Industry + \varepsilon i,t \quad (7)$$

where i denotes the firm and t denotes the year. $RISK_{i,t}$ represents risk-taking capacity. $IIT_{i,t}$ represents Industrial Internet technology. $Control_{i,t}$ is a vector of firm-level financial and manager characteristics. The variables *Year* and *Industry* refer to year- and industry- fixed effects, respectively, which are used to control for time-variant macroeconomic factors and time-invariant heterogeneity across industries.

Eq. (4) tests the association between Industrial Internet technology and risk-taking capacity. To test the information empowerment mechanism, we use the frequency of the keywords (i.e., *server*, *storage*, *network* and *virtualization resource technology*) related to the IaaS layer technology of the Industrial Internet derived from the core competitiveness description sections of the annual reports to proxy for IaaS layer technology (*IIT_I*). Furthermore, we measure the reform of organizational structure ($Structure\_R_{i,t+1}$) with a dummy variable that equals 1 if the firm reforms its organizational structure in year $t + 1$, and 0 otherwise. Eq. (5) interacts Industrial Internet technology (*IIT*) with $Structure\_R_{i,t+1}$, and we estimate Eq. (5) for the two subsamples partitioned according to the median of *IIT_I*.

To test the technology empowerment mechanism, we use the frequency of the keywords (i.e., *intelligent production*, *basic models* and *data analysis*) related to the PaaS layer technology of the Industrial Internet derived

from the core competitiveness description sections of the annual reports to proxy for PaaS layer technology (*IIT_P*). Furthermore, we measure the optimization of labor force structure ($Labor\_R_{i,t+1}$) by the proportion of production personnel relative to all staff in year $t + 1$. Eq. (6) interacts Industrial Internet technology (*IIT*) with $Labor\_R_{i,t+1}$, and we estimate Eq. (6) for the two subsamples partitioned according to the median of *IIT_P*.

To test the algorithm empowerment mechanism, we use the frequency of the keywords (i.e., *device access*, *edge computing*, *app* and *software*) related to the edge layer and SaaS layer technology of the Industrial Internet derived from the core competitiveness description sections of the annual reports to proxy for edge layer and SaaS layer technology (*IIT_E*). Furthermore, we measure the adjustment of supply chain resources by the proportion of the purchase amount of the largest supplier relative to the total purchase amount in year $t + 1$ ($Supplier\_R_{i,t+1}$) and the proportion of the sales amount of the largest customer relative to the total sales amount in year $t + 1$ ($Customer\_R_{i,t+1}$). Eq. (7) interacts Industrial Internet technology (*IIT*) with $Supplier\_R_{i,t+1}$/$Customer\_R_{i,t+1}$, and we estimate Eq. (7) for the two subsamples partitioned according to the median of *IIT_E*.

4. Empirical results

4.1. Descriptive statistics and correlation analysis

Table 2 reports the descriptive statistics of the main variables. *IIT* has a mean (median) value of 0.0070 (0.0014) and a standard deviation of 0.0047. *RISK1* has a mean (median) value of 0.0366 (0.0101) and a standard deviation of 0.0195. *RISK2* has a mean (median) value of 0.0511 (0.0064) and a standard deviation of 0.0262. These results suggest that there is no substantial variation in risk-taking capability across the different firms.

Table 1
Variable definitions.

Variable	Definition
RISK1	The the volatility of ROA adjusted by industry average over the 3-year period from year t to $t + 2$.
RISK2	The maximum deviation of ROA adjusted by industry average over the 3-year period from year t to $t + 2$.
IIT	The frequency of keywords related to Industrial Internet technology, derived from the core competitiveness description sections of annual reports.
IIT_I	The frequency of keywords related to IaaS layer technology of the Industrial Internet, derived from the core competitiveness description sections of annual reports.
IIT_P	The frequency of keywords related to PaaS layer technology of the Industrial Internet, derived from the core competitiveness description sections of annual reports.
IIT_E	The frequency of keywords related to Edge layer and SaaS layer technology of the Industrial Internet, derived from the core competitiveness description sections of annual reports.
Structure_R	A dummy variable that equals 1 if the firm reforms organizational structure in year $t + 1$, and 0 otherwise.
Labor_R	The proportion of production personnel to all staff in year $t + 1$.
Supplier_R	The proportion of the purchase amount of the largest supplier to the total purchase amount in year $t + 1$.
Customer_R	The proportion of the sales amount of the largest customer to the total sales amount in year $t + 1$.
Size	The natural logarithm of total assets.
Age	The natural logarithm of the fiscal year minus a firm's IPO year.
Lev	The ratio of total liabilities to total assets.
ROI	The ratio of investment income to the sum of trading financial assets, other equity instrument investments, derivative financial assets, debt investments, other debt investments and long-term equity investments.
Profit_M	The ratio of operating profit to operating income.
Overhead_E	The ratio of administrative expenses to operating income.
Fix_A	The ratio of fixed assets to total assets.
Fix_S	The ratio of fixed assets to operating income.
Sustainable_G	The ROE divided by retention rate.
Top3	The natural logarithm of the sum of top three executives' compensation.
SOE	A dummy variable that equals 1 if the firm is state-owned enterprise, and 0 otherwise.

Table 2
Descriptive statistics.

	N	mean	sd	P25	P50	P75
RISK1	11,172	0.0366	0.0195	0.0531	0.0101	0.0379
RISK2	11,172	0.0511	0.0262	0.0824	0.0064	0.0555
IIT	11,172	0.0070	0.0047	0.0080	0.0014	0.0095
IIT_I	11,172	0.0016	0.0028	0.0002	0.0006	0.0018
IIT_P	11,172	0.0061	0.0037	0.0015	0.0037	0.0081
IIT_E	11,172	0.0001	0.0007	0.0000	0.0000	0.0000
Size	11,172	22.1193	21.9267	1.2740	21.2083	22.8081
Age	11,172	1.9307	2.0794	0.9550	1.3863	2.7081
Lev	11,172	0.4057	0.3925	0.2055	0.2413	0.5518
ROI	11,172	0.4526	0.0319	2.3606	0.0000	0.1334
Profit_M	11,172	0.2994	0.2644	0.1812	0.1690	0.3908
Overhead_E	11,172	0.0901	0.0711	0.0762	0.0446	0.1106
Fix_A	11,172	0.1975	0.1689	0.1431	0.0861	0.2790
Fix_S	11,172	0.4366	0.3063	0.4582	0.1546	0.5462
Sustainable_G	11,172	0.0721	0.0603	0.0598	0.0305	0.0986
Top3	11,172	14.5356	14.5116	0.7084	14.0744	14.9565
SOE	11,172	0.0866	0.0000	0.2812	0.0000	0.0000

Note: This table provides the summary statistics of the key variables. The sample size, mean, standard deviation (SD), 25th percentile (P25), median (P50), and 75th percentile (P75) are reported. The sample spans the 2010–2022 period and includes 11,172 firm-year observations. All continuous variables are winsorized at the 1st and 99th percentiles.

Table 3 summarizes the magnitudes and significance levels of the main variables' correlation coefficients. The results reveal no strong correlations between the variables, thus avoiding the risk of estimation errors due to multicollinearity. From the correlation coefficients of *RISK1*/*RISK2* and *IIT*, we tentatively determine that Industrial Internet technology promotes risk-taking capacity.

4.2. Baseline regression results

Table 4 reports the baseline regression results pertaining to the effect of Industrial Internet technology on risk-taking capacity. Columns (1) and (2) present the regression results without including the control variables. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.2908$, $t = 5.29$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 1.4214$, $t = 18.28$). Columns (3) and (4) present the regression results of Eq. (4). The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 10 % level ($\beta = 0.2384$, $t = 1.75$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.5437$, $t = 2.64$). Taken together, these results show that Industrial Internet technology increases risk-taking capacity, which is consistent with our hypotheses.

4.3. Mechanism tests

Table 5 reports the mechanism test results pertaining to the reform of organizational structure. Columns (1) and (2) present the regression results for the full sample. The coefficient on *IIT***Structure_R* when using *RISK1* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.7530$, $t = 2.57$), and the coefficient on *IIT***Structure_R* when using *RISK2* as the dependent variable is positive and significant at the 5 % level ($\beta = 1.1554$, $t = 2.34$). These results indicate that Industrial Internet technology enhances risk-taking capacity through organizational structure reform. Columns (3) and (4) present the regression results for the subsample with a high *IIT_I*. The coefficient on *IIT***Structure_R* when using *RISK1* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.8402$, $t = 2.48$), and the coefficient on *IIT***Structure_R* when using *RISK2* as the dependent variable is positive and significant at the 5 % level ($\beta = 1.2827$, $t = 2.26$). Columns (5) and (6) present the regression results for the subsample with a low *IIT_I*. The coefficients on

Table 3
Correlation analysis.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
RISK1 (*A*)	1.0000																	
RISK2 (*B*)	0.988***	1.0000																
IIT (*C*)	0.065***	0.154***	1.0000															
Structure_R(D)	0.015**	0.0060	−0.013**	1.0000														
Labor_R(E)	0.035***	−0.020***	−0.170***	−0.010	1.0000													
Supplier_R(F)	0.035***	0.022***	−0.028***	−0.012	−0.005	1.0000												
Customer_R(G)	0.030***	0.005	−0.038***	0.003	0.084***	0.198***	1.0000											
Size (*H*)	−0.070***	−0.085***	−0.022***	−0.042***	0.105***	−0.109***	−0.031***	1.0000										
Age (*I*)	0.087***	0.044***	−0.038***	−0.052***	0.040***	−0.054***	−0.085***	0.472***	1.0000									
Lev (*J*)	0.092***	0.059***	−0.040***	−0.006	0.121***	−0.085***	−0.009	0.487***	0.402***	1.0000								
ROI (*K*)	0.033***	0.034***	0.0030	−0 014**	0.014**	−0.005	0.013*	−0.023***	0.0040	−0.0030	1.0000							
Profit_M (*L*)	−0.022***	−0.0060	0.095***	0.015**	−0.389***	−0.008	−0.055***	−0.212***	−0.255***	−0.470***	−0.020***	1.0000						
Overhead_E (*M*)	0.180***	0.167***	0.061***	0.007	−0238***	−0.005	0.015*	−0.306***	−0.044***	−0.183***	0.023***	0.334***	1.0000					
Fix_A (*N*)	−0.054***	−0.035***	−0.139***	−0.010	0.437***	0.034***	−0.030***	0.118***	0.163***	0.120***	−0.0080	−0.212***	−0.110***	1.0000				
Fix_S (*O*)	0.015**	0.0090	−0.093***	−0.010	0.191***	0.052***	0.078***	0.100***	0.113***	0.053***	−0.0100	0.0070	0.237***	0.679***	1.0000			
Sustainable_G (*P*)	−0.382***	−0.279***	0.014**	−0.008	0.008	−0.012	−0.016**	0.089***	−0.130***	−0.234***	−0.0010	0.246***	−0.250***	−0.054***	−0.167***	1.0000		
Top3 (*Q*)	−0.040***	−0.096***	0.035***	0.016**	−0.097***	−0.055***	−0.004	0.442***	0.116***	0.073***	−0.022***	0.126***	−0.120***	−0.103***	−0.110***	0.149***	1.0000	
SOE (*R*)	−0.067***	−0.052***	−0.013*	−0.015**	0.011	0.004	0.053***	0.195***	0.113***	0.135***	−0.0100	−0.106***	−0.057***	0.080***	0.082***	0.0001	0015**	1.0000

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

Table 4
Baseline results from analysis of the effect of Industrial Internet technology on risk-taking capacity.

	RISK1 (1)	*RISK2* (2)	*RISK1* (3)	*RISK2* (3)
IIT	0.2908***	1.4214***	0.2384*	0.5437***
	(5.29)	(18.28)	(1.75)	(2.64)
Size	–	–	−0.0091***	−0.0131***
	–	–	(−7.17)	(−7.69)
Age	–	–	0.0069***	0.0107***
	–	–	(5.35)	(5.85)
Lev	–	–	0.0554***	0.1151***
	–	–	(13.92)	(19.72)
ROI	–	–	0.0701***	0.0899***
	–	–	(10.85)	(9.99)
Profit_M	–	–	−0.0000	−0.0000
	–	–	(−0.03)	(−0.11)
Overhead_E	–	–	−0.0039	0.0044
	–	–	(−0.47)	(0.40)
Fix_A	–	–	0.0556***	−0.0298***
	–	–	(3.72)	(−19.72)
Fix_S	–	–	−0.0318***	−0.0524***
	–	–	(−2.63)	(−3.27)
Sustainable_G	–	–	−0.0436***	−0.0929***
	–	–	(−7.51)	(−11.15)
Top3	–	–	−0.0044***	−0.0058***
	–	–	(−6.67)	(−5.93)
SOE	–	–	−0.0033*	−0.0025
	–	–	(−1.84)	(−1.01)
_cons	0.0320***	0.0392***	0.2252***	0.3072***
	(54.79)	(51.20)	(8.28)	(8.19)
Year	–	–	Yes	Yes
Industry	–	–	Yes	Yes
N	11,172	11,172	11,172	11,172
AdjR²	0.0020	0.0191	0.2171	0.1915

Note: This table presents the baseline regression results pertaining to the effect of Industrial Internet technology on risk-taking capacity. Our sample spans the 2010–2022 period and includes 11,172 firm-year observations. Columns (1) and (2) reports the regression results without including the control variables. Columns (3) and (4) reports the regression results of Eq. (4). These results show that Industrial Internet technology increases risk-taking capacity.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

*IIT*Structure_R* are not significant. These results indicate that the IaaS layer technology of the Industrial Internet plays an information empowerment role in the reform of organizational structure, thus improving corporate risk-taking capacity.

Table 6 reports the mechanism test results pertaining to the optimization of labor force structure. Columns (1) and (2) present the regression results for the full sample. The coefficient on *IIT*Labor_R* when using *RISK1* as the dependent variable is negative and significant at the 1 % level ($\beta = -0.0114$, $t = -4.03$), and the coefficient on *IIT*Labor_R* when using *RISK2* as the dependent variable is negative and significant at the 1 % level ($\beta = -0.0206$, $t = -4.34$). These results indicate that Industrial Internet technology enhances risk-taking capacity by optimizing the labor force structure. Columns (3) and (4) present the regression results for the subsample with a high *IIT_P*. The coefficient on *IIT*Labor_R* when using *RISK1* as the dependent variable is negative and significant at the 1 % level ($\beta = -0.0103$, $t = -3.23$), and the coefficient on *IIT*Labor_R* when using *RISK2* as the dependent variable is negative and significant at the 1 % level ($\beta = -0.0191$, $t = -3.63$). Columns (5) and (6) present the regression results for the subsample with a low *IIT_P*. The coefficients on *IIT*Labor_R* are not significant. These results indicate that the PaaS layer technology of the Industrial Internet plays a technology empowerment role in the optimization of labor force structure, thus improving corporate risk-taking capacity.

Table 5
Results of mechanism tests: Reform of organizational structure.

	Reform of organizational structure					
	Full sample		High *IIT_I*		Low *IIT_I*	
	RISK1	*RISK2*	*RISK1*	*RISK2*	*RISK1*	*RISK2*
	(1)	(2)	(3)	(4)	(5)	(6)
IIT	0.0848	0.1862**	0.0376	0.1074	0.0335	0.1025
	(1.53)	(1.98)	(0.55)	(0.94)	(0.30)	(0.54)
*IIT*Structure_R*	0.7530**	1.1554**	0.8402**	1.2827**	0.1844	0.4449
	(2.57)	(2.34)	(2.48)	(2.26)	(0.25)	(0.35)
Structure_R	−0.0040	−0.0064	−0.0056	−0.0093	0.0011	0.0012
	(−1.33)	(−1.27)	(−1.46)	(−1.45)	(0.21)	(0.12)
Size	−0.0024***	−0.0042***	−0.0024***	−0.0040***	−0.0020***	−0.0037***
	(−4.56)	(−4.63)	(−3.00)	(−3.02)	(−2.96)	(−3.09)
Age	0.0031***	0.0051***	0.0034***	0.0056***	0.0022***	0.0039***
	(5.81)	(5.74)	(4.58)	(4.46)	(3.12)	(3.15)
Lev	0.0152***	0.0256***	0.0172***	0.0294***	0.0081**	0.0130**
	(5.41)	(5.39)	(4.18)	(4.26)	(2.24)	(2.07)
ROI	−0.0000	−0.0000	0.0000	0.0000	−0.0000	−0.0000
	(−1.07)	(−1.13)	(0.47)	(0.35)	(−0.86)	(−0.91)
Profit_M	0.0143***	0.0253***	0.0252***	0.0418***	−0.0104**	−0.0131
	(4.01)	(4.19)	(5.13)	(5.09)	(−2.06)	(−1.50)
Overhead_E	0.0485***	0.0779***	0.0322**	0.0561**	0.0944***	0.1468***
	(4.89)	(4.65)	(2.46)	(2.56)	(6.17)	(5.54)
Fix_A	−0.0161***	−0.0285***	−0.0239***	−0.0417***	−0.0077	−0.0143
	(−3.11)	(−3.26)	(−3.07)	(−3.20)	(−1.19)	(−1.27)
Fix_S	0.0031	0.0060*	0.0021	0.0038	0.0055**	0.0102**
	(1.60)	(1.83)	(0.75)	(0.82)	(2.13)	(2.27)
Sustainable_G	0.0129***	0.0197***	0.0092***	0.0138***	0.0323***	0.0514***
	(9.39)	(8.52)	(5.73)	(5.09)	(11.18)	(10.29)
Top3	−0.0023***	−0.0038***	−0.0025**	−0.0042**	−0.0015	−0.0025
	(−3.14)	(−3.14)	(−2.31)	(−2.39)	(−1.64)	(−1.57)
SOE	−0.0061***	−0.0106***	−0.0073***	−0.0129***	−0.0050***	−0.0086***
	(−4.04)	(−4.16)	(−3.06)	(−3.23)	(−2.82)	(−2.78)
_cons	0.0918***	0.1608***	0.0916***	0.1596***	0.0742***	0.1345***
	(8.03)	(8.32)	(5.32)	(5.53)	(5.02)	(5.26)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	9260	9260	5475	5475	3785	3785
AdjR²	0.0836	0.0911	0.0787	0.0949	0.1504	0.1359

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

Table 7 reports the mechanism test results pertaining to the adjustment of supplier resources. Columns (1) and (2) present the regression results for the full sample. The coefficient on *IIT*Supplier_R* when using *RISK1* as the dependent variable is negative and significant at the 5 % level ($\beta = -0.0496$, $t = -1.98$), and the coefficient on *IIT*Supplier_R* when using *RISK2* as the dependent variable is negative and significant at the 10 % level ($\beta = -0.0694$, $t = -1.81$). These results indicate that Industrial Internet technology enhances risk-taking capacity by adjusting supplier resources. Columns (3) and (4) present the regression results for the subsample with a high *IIT_E*. The coefficient on *IIT*Supplier_R* when using *RISK1* as the dependent variable is negative and significant at the 10 % level ($\beta = -0.0157$, $t = -1.86$), and the coefficient on *IIT*Supplier_R* when using *RISK2* as the dependent variable is negative and significant at the 10 % level ($\beta = -0.0177$, $t = -1.71$). Columns (5) and (6) present the regression results for the subsample with a low *IIT_E*. The coefficients on *IIT*Supplier_R* are not significant. These results indicate that the edge layer and SaaS layer technology of the Industrial Internet play an algorithm empowerment role in the adjustment of supplier resources, thus improving corporate risk-taking capacity.

Table 6
Results of mechanism tests: Optimization of labor force structure.

	Optimization of labor force structure					
	Full sample		High *IIT_P*		Low *IIT_P*	
	RISK1 (1)	*RISK2* (2)	*RISK1* (3)	*RISK2* (4)	*RISK1* (5)	*RISK2* (6)
IIT	0.6491***	1.2033***	0.5527***	1.0654***	0.5932	1.0863
	(4.27)	(4.71)	(3.25)	(3.79)	(1.37)	(1.46)
*IIT*Labor_R*	−0.0114***	−0.0206***	−0.0103***	−0.0191***	−0.0039	−0.0074
	(−4.03)	(−4.34)	(−3.23)	(−3.63)	(−0.50)	(−0.55)
Labor_R	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(1.33)	(1.55)	(0.47)	(0.72)	(0.66)	(0.68)
Size	−0.0060***	−0.0101***	−0.0066***	−0.0108***	−0.0046***	−0.0083***
	(−10.21)	(−10.34)	(−8.56)	(−8.54)	(−5.07)	(−5.32)
Age	0.0040***	0.0069***	0.0030***	0.0052***	0.0058***	0.0101***
	(6.69)	(6.89)	(3.94)	(4.10)	(5.92)	(6.01)
Lev	0.0457***	0.0751***	0.0514***	0.0830***	0.0347***	0.0595***
	(15.19)	(14.88)	(12.80)	(12.50)	(7.60)	(7.58)
ROI	−0.0000	−0.0000	−0.0000	−0.0000	0.0000**	0.0000***
	(−1.33)	(−1.38)	(−1.49)	(−1.54)	(2.55)	(3.09)
Profit_M	−0.0110***	−0.0185***	−0.0025	−0.0037	−0.0185***	−0.0315***
	(−2.78)	(−2.78)	(−0.45)	(−0.40)	(−3.26)	(−3.22)
Overhead_E	0.0925***	0.1470***	0.0934***	0.1457***	0.0890***	0.1446***
	(13.43)	(12.73)	(10.01)	(9.44)	(8.72)	(8.25)
Fix_A	−0.0205***	−0.0375***	−0.0237***	−0.0428***	−0.0168**	−0.0318**
	(−3.57)	(−3.90)	(−2.96)	(−3.24)	(−2.04)	(−2.24)
Fix_S	0.0084***	0.0159***	0.0055**	0.0107**	0.0118***	0.0221***
	(4.35)	(4.89)	(2.12)	(2.49)	(4.02)	(4.38)
Sustainable_G	−0.0029***	−0.0049***	−0.0089***	−0.0138***	−0.0020***	−0.0037***
	(−6.14)	(−6.26)	(−6.86)	(−6.40)	(−4.10)	(−4.33)
Top3	−0.0019**	−0.0032**	−0.0011	−0.0018	−0.0029**	−0.0050**
	(−2.34)	(−2.36)	(−0.96)	(−1.02)	(−2.41)	(−2.36)
SOE	−0.0072***	−0.0125***	−0.0072***	−0.0129***	−0.0072***	−0.0119***
	(−4.28)	(−4.40)	(−3.12)	(−3.35)	(−2.92)	(−2.84)
_cons	10,016	10,016	6004	6004	4012	4012
	0.1276	0.1354	0.1396	0.1499	0.1393	0.1412
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	11,173	11,173	6004	6004	5169	5169
AdjR²	0.1276	0.1354	0.1396	0.1499	0.1393	0.1412

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

Table 8 reports the mechanism test results pertaining to the adjustment of customer resources. Columns (1) and (2) present the regression results for the full sample. The coefficient on *IIT*Customer_R* when using *RISK1* as the dependent variable is negative and significant at the 5 % level ($\beta = -0.0446$, $t = -2.39$), and the coefficient on *IIT*Customer_R* when using *RISK2* as the dependent variable is negative and significant at the 5 % level ($\beta = -0.0660$, $t = -2.30$). These results indicate that Industrial Internet technology enhances risk-taking capacity by adjusting customer resources. Columns (3) and (4) present the regression results for the subsample with a high *IIT_E*. The coefficient on *IIT*Customer_R* when using *RISK1* as the dependent variable is negative and significant at the 1 % level ($\beta = -0.0742$, $t = -2.79$), and the coefficient on *IIT*Customer_R* when using *RISK2* as the dependent variable is negative and significant at the 1 % level ($\beta = -0.1418$, $t = -3.01$). Columns (5) and (6) present the regression results for the subsample with a low *IIT_E*. The coefficients on *IIT*Customer_R* are not significant. These results indicate that the edge layer and SaaS layer technology of the Industrial Internet play an algorithm empowerment role in the adjustment of customer resources, thus improving corporate risk-taking capacity.

Table 7
Results of mechanism tests: Adjustment of supplier resources.

	Adjustment of supplier resources					
	Full sample		High *IIT_E*		Low *IIT_E*	
	RISK1 (1)	*RISK2* (2)	*RISK1* (3)	*RISK2* (4)	*RISK1* (5)	*RISK2* (6)
IIT	0.7252	1.1524*	0.2829*	0.3624*	0.1823	0.4210
	(1.60)	(1.66)	(1.81)	(1.78)	(0.24)	(0.37)
*IIT*Supplier_R*	−0.0496**	−0.0694*	−0.0157*	−0.0177*	0.0114	0.0245
	(−1.98)	(−1.81)	(−1.86)	(−1.71)	(0.27)	(0.39)
Supplier_R	0.0013***	0.0018***	0.0003***	0.0003**	0.0010***	0.0013***
	(5.23)	(4.88)	(3.09)	(2.54)	(3.04)	(2.82)
Size	0.0052*	0.0029	−0.0036**	−0.0040***	0.0158***	0.0188***
	(1.87)	(0.68)	(−2.50)	(−2.71)	(5.01)	(3.98)
Age	0.0025	0.0055	0.0031**	0.0020	0.0055*	0.0107**
	(0.91)	(1.33)	(2.30)	(1.30)	(1.72)	(2.23)
Lev	0.0567***	0.0975***	−0.0094***	0.0525***	0.0402**	0.0743***
	(4.12)	(4.62)	(−2.65)	(6.72)	(2.55)	(3.15)
ROI	−0.0002	−0.0002	0.0641***	0.0003***	−0.0005	−0.0006
	(−0.24)	(−0.13)	(8.87)	(3.83)	(−0.52)	(−0.43)
Profit_M	−0.0438***	−0.0825***	0.0017***	0.0001	0.0402**	0.0555*
	(−2.66)	(−3.28)	(4.10)	(0.69)	(2.07)	(1.90)
Overhead_E	0.4717***	0.6223***	0.0353***	0.0647***	0.7471***	1.0409***
	(46.52)	(40.03)	(4.62)	(6.60)	(64.10)	(59.42)
Fix_A	0.3664***	0.4882***	0.1085***	−0.0533***	0.5376***	0.7483***
	(18.72)	(16.27)	(5.75)	(−3.84)	(24.49)	(22.68)
Fix_S	−0.1650***	−0.2174***	0.0053	−0.0021***	−0.2617***	−0.3645***
	(−46.39)	(−39.89)	(0.44)	(−5.47)	(−64.00)	(−59.31)
Sustainable_G	−0.0093***	−0.0155***	−0.0154***	−0.0167***	−0.0042*	−0.0076**
	(−4.41)	(−4.77)	(−8.83)	(−7.74)	(−1.89)	(−2.27)
Top3	−0.0210***	−0.0271***	−0.0031	−0.0005	−0.0379***	−0.0540***
	(−5.67)	(−4.79)	(−1.49)	(−0.21)	(−9.11)	(−8.62)
SOE	−0.0116	−0.0212	−0.0084	−0.0107**	−0.0066	−0.0135
	(−1.37)	(−1.64)	(−1.63)	(−1.98)	(−0.72)	(−0.98)
_cons	0.0894	0.1963**	0.0894	0.1742**	0.0540	0.1585
	(1.46)	(2.10)	(1.46)	(2.43)	(0.78)	(1.52)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	11,172	11,172	11,172	11,172	9485	9485
AdjR²	0.3095	0.2825	0.3095	0.2825	0.5146	0.4960

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

4.4. Robustness tests

4.4.1. Alternative measure of risk-taking capacity

In the baseline regressions, we use earnings before interest and taxes (*EBIT*) adjusted by the industry average to calculate risk-taking capacity. In this section, we use the sum of *EBIT* and depreciation adjusted by the industry average to calculate risk-taking capacity. Columns (1) and (2) of Table 9 report the results. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 10 % level ($\beta = 0.3016$, $t = 1.82$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.6242$, $t = 2.41$). These results show that our baseline results hold after using the alternative measure of risk-taking capacity.

4.4.2. Adjustment of sample period

In baseline regressions, we use the volatility of ROA over the 3-year period from year t to $t + 2$ to proxy for risk-taking capacity. In this section, we use the volatility of ROA over the 5-year period from year t to $t + 4$ to

Table 8
Results of mechanism tests: Adjustment of customer resources.

	Adjustment of customer resources					
	Full sample		High *IIT_E*		Low *IIT_E*	
	RISK1 (1)	*RISK2* (2)	*RISK1* (3)	*RISK2* (4)	*RISK1* (5)	*RISK2* (6)
IIT	0.7021*	1.1838*	0.7414*	1.4797**	0.7670	1.3198
	(1.74)	(1.91)	(1.81)	(2.03)	(1.23)	(1.41)
*IIT*Customer_R*	−0.0446**	−0.0660**	−0.0742***	−0.1418***	−0.0438	−0.0597
	(−2.39)	(−2.30)	(−2.79)	(−3.01)	(−1.54)	(−1.39)
Customer_R	0.0009***	0.0014***	0.7414*	1.4797**	0.0008***	0.0012***
	(4.93)	(4.71)	(1.81)	(2.03)	(3.46)	(3.22)
Size	0.0043*	0.0018	−0.0093**	−0.0164**	0.0135***	0.0158***
	(1.72)	(0.46)	(−2.39)	(−2.36)	(4.82)	(3.73)
Age	0.0022	0.0052	−0.0002	−0.0015	0.0042	0.0089**
	(0.87)	(1.36)	(−0.05)	(−0.22)	(1.48)	(2.05)
Lev	0.0511***	0.0887***	0.0992***	0.1968***	0.0403***	0.0736***
	(4.04)	(4.57)	(21.45)	(23.71)	(2.85)	(3.45)
ROI	−0.0003	−0.0003	0.0602***	0.1052***	−0.0005	−0.0006
	(−0.44)	(−0.31)	(3.19)	(3.12)	(−0.58)	(−0.47)
Profit_M	−0.0408***	−0.0766***	0.0016	0.0030	0.0362**	0.0505*
	(−2.68)	(−3.27)	(1.41)	(1.47)	(2.05)	(1.90)
Overhead_E	0.4712***	0.6219***	−0.1328***	−0.2639***	0.7399***	1.0312***
	(48.44)	(41.66)	(−6.34)	(−7.08)	(66.97)	(62.03)
Fix_A	0.3626***	0.4843***	0.2526***	0.4952***	0.5303***	0.7395***
	(20.05)	(17.45)	(6.48)	(7.09)	(26.61)	(24.66)
Fix_S	−0.1648***	−0.2173***	−0.2498***	−0.4897***	−0.2592***	−0.3611***
	(−48.31)	(−41.52)	(−8.47)	(−9.30)	(−66.87)	(−61.92)
Sustainable_G	−0.0098***	−0.0162***	0.0019	0.0051	−0.0043**	−0.0078**
	(−4.87)	(−5.23)	(0.32)	(0.47)	(−2.07)	(−2.48)
Top3	−0.0211***	−0.0273***	0.0165***	0.0332***	−0.0366***	−0.0520***
	(−6.20)	(−5.25)	(3.18)	(3.59)	(−9.76)	(−9.23)
SOE	−0.0126	−0.0224*	−0.0193	−0.0357*	−0.0095	−0.0173
	(−1.64)	(−1.90)	(−1.63)	(−1.68)	(−1.14)	(−1.39)
_cons	0.1148**	0.2314***	−0.0013	−0.0449	0.0880	0.2027**
	(2.11)	(2.77)	(−0.02)	(−0.29)	(1.45)	(2.22)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	11,172	11,172	11,172	11,172	9485	9485
AdjR²	0.3087	0.2817	0.6139	0.6397	0.5098	0.4910

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

proxy for risk-taking capacity. Columns (3) and (4) of Table 9 report the results. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.3800$, $t = 2.27$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.8808$, $t = 3.11$). These results show that our baseline results remain robust after adjusting the sample period.

4.4.3. Excluding the top 10 % firms by risk-taking capacity

The baseline results may be driven by firms with high risk-taking capacity. We exclude the top 10 % of firms by risk-taking capacity from the sample. Columns (5) and (6) of Table 9 report the results. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.0534$, $t = 2.29$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.1254$, $t = 3.35$). These results show that our baseline results remain robust after removing the sample of firms with high risk-taking capacity.

Table 9
Results of robustness tests.

	Alternative measure of corporate risk-taking		Adjustment of sample period		Excluding the top 10 % firms by risk-taking capacity		White test	
	RISK1 (1)	*RISK2* (2)	*RISK1* (3)	*RISK2* (4)	*RISK1* (5)	*RISK2* (6)	*RISK1* (7)	*RISK2* (8)
IIT	0.3016*	0.6242**	0.3800**	0.8808***	0.0534**	0.1254***	0.3462**	0.6823**
	(1.82)	(2.41)	(2.27)	(3.11)	(2.29)	(3.35)	(2.08)	(2.40)
Size	−0.0044***	−0.0045*	−0.0042***	−0.0095***	−0.0016***	−0.0020***	−0.0029**	−0.0040**
	(−2.73)	(−1.93)	(−2.73)	(−4.06)	(−7.15)	(−6.12)	(−2.48)	(−2.33)
Age	0.0070***	0.0102***	0.0073***	0.0121***	0.0006***	0.0003	0.0053***	0.0074***
	(4.40)	(4.41)	(4.59)	(4.81)	(2.71)	(0.98)	(4.14)	(3.75)
Lev	0.0189**	0.0288**	0.0782***	0.1205***	0.0010	0.0010	0.0167*	0.0266**
	(2.24)	(2.35)	(9.90)	(9.72)	(0.81)	(0.55)	(1.95)	(2.11)
ROI	−0.0000	−0.0000	0.0000	−0.0000	−0.0000	−0.0000	−0.0000***	−0.0000***
	(−0.47)	(−0.47)	(0.03)	(−0.00)	(−1.38)	(−1.50)	(−7.47)	(−7.92)
Profit_M	0.0204*	0.0336**	0.0368***	0.0557***	0.0044***	0.0058**	0.0164*	0.0233
	(1.91)	(2.18)	(3.66)	(3.62)	(2.80)	(2.48)	(1.70)	(1.54)
Overhead_E	0.0496*	0.0802*	0.1079***	−0.0000	0.0044	0.0067	0.0546**	0.0893**
	(1.66)	(1.78)	(6.22)	(−0.38)	(1.00)	(0.99)	(2.15)	(2.25)
Fix_A	−0.0154	−0.0179	−0.0612***	−0.1371***	−0.0006	0.0018	−0.0141	−0.0218
	(−1.00)	(−0.80)	(−4.15)	(−6.20)	(−0.27)	(0.54)	(−1.07)	(−1.23)
Fix_S	0.0002	−0.0012	0.0195***	0.0543***	0.0017**	0.0018	0.0014	0.0041
	(0.03)	(−0.14)	(3.83)	(7.74)	(2.09)	(1.47)	(0.32)	(0.67)
Sustainable_G	0.0310***	0.0512***	−0.0032***	−0.0064***	0.0199***	0.0244***	0.0325	0.0538
	(7.69)	(7.85)	(−4.14)	(−4.72)	(9.47)	(7.83)	(1.16)	(1.14)
Top3	−0.0025	−0.0023	−0.0100***	−0.0121***	0.0002	0.0005	−0.0035	−0.0043
	(−1.18)	(−0.72)	(−4.61)	(−3.52)	(0.73)	(1.00)	(−1.47)	(−1.20)
SOE	−0.0073	−0.0127*	−0.0190***	−0.0345***	−0.0018***	−0.0032***	−0.0078***	−0.0124***
	(−1.60)	(−1.87)	(−4.21)	(−4.68)	(−2.96)	(−3.32)	(−5.69)	(−5.94)
_cons	0.1263***	0.1234**	0.2163***	0.3874***	0.0486***	0.0672***	0.1126***	0.1460***
	(3.73)	(2.49)	(6.51)	(7.49)	(10.31)	(9.46)	(4.33)	(3.63)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,172	11,172	11,172	11,172	9485	9485	11,172	11,172
AdjR²	0.0020	0.0191	0.2171	0.1915	0.0790	0.2537	0.2089	0.1858

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

4.4.4. White test

To alleviate the potential concern about heteroscedasticity, we re-estimate Eq. (4) using the White test. Columns (7) and (8) of Table 9 report the results. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.3462$, $t = 2.08$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.6823$, $t = 2.40$). These results show that our baseline results remain robust after alleviating heteroscedasticity.

4.5. Endogeneity tests

4.5.1. Fixed effects model

To alleviate the potential bias of missing variables, we re-estimate Eq. (4) with the inclusion of firm-fixed effects, further controlling for time-invariant firm characteristics that may influence risk-taking capacity. Columns (1) and (2) of Table 10 report the results. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 10 % level ($\beta = 0.3087$, $t = 1.75$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.5836$, $t = 2.35$). These results show that our main results hold after controlling for firm-fixed effects.

Table 10
Results of endogeneity tests.

	Fixed effects model		Instrumental variable method				Propensity score matching	
	RISK1 (1)	*RISK2* (2)	*IIP* (3)	*IIP* (4)	*RISK1* (5)	*RISK2* (6)	*RISK1* (7)	*RISK2* (8)
IIT	0.3087*	0.5836**	–	–	7.6398***	7.6735***	0.3972***	0.7470***
	(1.75)	(2.35)	–	–	(7.19)	(4.26)	(2.73)	(3.46)
Size	0.0093***	0.0126***	–	–	−0.0073***	−0.0162***	−0.0073***	−0.0116***
	(2.75)	(2.63)	–	–	(−4.96)	(−7.01)	(−5.43)	(−6.55)
Age	0.0105***	0.0135**	–	–	0.0049***	0.0110***	0.0053***	0.0083***
	(2.61)	(2.45)	–	–	(2.95)	(4.11)	(3.78)	(4.33)
Lev	−0.0264**	−0.0186	–	–	0.0759***	0.1143***	0.0695***	0.0895***
	(−2.10)	(−1.05)	–	–	(9.42)	(8.74)	(9.88)	(9.34)
ROI	−0.0000**	−0.0001**	–	–	0.0000	0.0000	−0.0000	−0.0000
	(−2.17)	(−2.29)	–	–	(0.36)	(0.15)	(−0.04)	(−0.11)
Profit_M	−0.0162	−0.0394	–	–	−0.0397***	−0.0355***	−0.0210***	−0.0213**
	(−0.85)	(−1.47)	–	–	(−4.67)	(−2.62)	(−2.86)	(−2.16)
Overhead_E	0.0806**	0.1287**	–	–	0.1156***	−0.0002	0.1140***	−0.0000
	(2.20)	(2.36)	–	–	(7.30)	(−0.31)	(7.37)	(−0.35)
Fix_A	0.0187	0.0064	–	–	0.0259	−0.0494*	−0.0258**	−0.0696***
	(0.81)	(0.19)	–	–	(1.50)	(−1.78)	(−2.13)	(−4.46)
Fix_S	−0.0069	−0.0021	–	–	0.0091**	0.0331***	0.0167***	0.0407***
	(−0.85)	(−0.18)	–	–	(2.10)	(5.04)	(3.75)	(7.66)
Sustainable_G	0.0970***	0.1671***	–	–	−0.0008***	−0.0013***	−0.0042***	−0.0057***
	(12.64)	(14.10)	–	–	(−2.93)	(−2.77)	(−5.88)	(−5.41)
Top3	0.0012	0.0006	–	–	−0.0118***	−0.0102**	−0.0013	0.0004
	(0.37)	(0.13)	–	–	(−4.13)	(−2.16)	(−0.69)	(0.14)
SOE	0.0003	−0.0013	–	–	−0.0179***	−0.0315***	−0.0159***	−0.0239***
	(0.06)	(−0.20)	–	–	(−4.11)	(−4.41)	(−3.91)	(−4.16)
IV	–	–	0.0002***	0.0002***	–	–	–	–
	–	–	(17.77)	(17.58)	–	–	–	–
_cons	−0.1505	−0.0501	−0.0079***	−0.0067***	0.2604***	0.4532***	0.1603***	0.2448***
	(−0.90)	(−0.20)	(−4.75)	(−4.22)	(7.62)	(8.29)	(5.71)	(6.44)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EF_YEAR	Yes	Yes	–	–	–	–	–	–
EF_INDUSTRY	Yes	Yes	–	–	–	–	–	–
N	11,172	11,172	11,172	11,172	11,172	11,172	6900	6900
AdjR²	0.1578	0.1714	0.0916	0.0901	–	–	0.0416	0.0506
Wald F stat	–	–	–	–	315.864	309.106	–	–

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

4.5.2. Instrumental variable method

Both Industrial Internet technology application and risk-taking capacity are derived from internal production and operation activities. To address the problem of mutual causality between Industrial Internet technology and risk-taking capacity, we adopt two instrumental variables (IVs) referring to Niu et al. (2023) and Wu and Tian (2022): (1) a dummy variable that equals 1 if the prefecture-level city in which a firm is headquartered has enacted an *Industrial Internet Plan*, and 0 otherwise (*IV1*), and (2) the number of degrees awarded to college students in the province in which the firm is headquartered (*IV2*). A reasonable and effective IV must satisfy the principles of both relevance and exogeneity. Regarding relevance, an Industrial Internet plan can reflect the development level of local Industrial Internet technology and encourage firms to implement Industrial Internet technology. The number of degrees awarded to local college students reflects the supply of talent with higher education backgrounds, facilitating the development and application of Industrial Internet technology in firms. Industrial Internet policy and degrees awarded to local college students hardly affect risk-taking capacity, thus satisfying the exogeneity requirement.

Table 11
Results of excluding alternative explanation: Finance development and executive long-term vision.

	RISK1	*RISK2*	*RISK1*	*RISK2*	*RISK1*	*RISK2*	*RISK1*	*RISK2*
	Finance development				Executive vision			
	High		Low		Long-term		Short-term	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IIT	0.5687***	1.0033***	0.3397**	0.7450***	0.3804*	0.6835**	0.5273***	0.9400***
	(2.70)	(3.14)	(2.17)	(3.00)	(1.68)	(1.97)	(3.36)	(3.91)
Size	−0.0042**	−0.0064**	−0.0028*	−0.0044*	−0.0047**	−0.0065**	−0.0014	−0.0019
	(−2.19)	(−2.36)	(−1.77)	(−1.90)	(−2.48)	(−2.38)	(−0.85)	(−0.78)
Age	0.0048**	0.0061**	0.0046***	0.0069***	0.0028	0.0033	0.0061***	0.0084***
	(2.39)	(2.13)	(3.06)	(3.06)	(1.36)	(1.11)	(3.72)	(3.53)
Lev	0.0201*	0.0342**	0.0139*	0.0211*	0.0322***	0.0462***	0.0046	0.0092
	(1.89)	(2.27)	(1.75)	(1.77)	(2.97)	(2.97)	(0.54)	(0.76)
ROI	−0.0000	−0.0000	0.0000	0.0000	−0.0000	−0.0000	0.0000	0.0000
	(−0.65)	(−0.73)	(0.05)	(0.03)	(−0.53)	(−0.56)	(0.37)	(0.42)
Profit_M	0.0079	0.0110	0.0050	0.0068	−0.0054	−0.0111	−0.0133	−0.0187
	(0.62)	(0.61)	(0.44)	(0.41)	(−0.48)	(−0.69)	(−1.47)	(−1.46)
Overhead_E	0.0895***	0.1493***	0.0306	0.0431	0.0498	0.0725	0.0398	0.0705*
	(2.73)	(3.07)	(0.92)	(0.85)	(1.19)	(1.16)	(1.41)	(1.67)
Fix_A	0.0157	0.0175	−0.0329**	−0.0460**	0.0014	−0.0006	−0.0590***	−0.0818***
	(0.83)	(0.64)	(−2.21)	(−2.08)	(0.08)	(−0.02)	(−3.60)	(−3.49)
Fix_S	−0.0077	−0.0102	0.0130**	0.0194**	0.0076	0.0125	0.0164**	0.0228**
	(−1.08)	(−1.00)	(2.32)	(2.34)	(1.10)	(1.26)	(2.55)	(2.50)
Sustainable_G	0.0289***	0.0489***	0.0923***	0.1338***	0.0309***	0.0522***	0.0916***	0.1224***
	(8.05)	(8.76)	(6.85)	(6.53)	(7.75)	(8.37)	(5.06)	(4.83)
Top3	−0.0012	−0.0013	−0.0033	−0.0038	0.0016	0.0029	−0.0040*	−0.0056*
	(−0.47)	(−0.35)	(−1.50)	(−1.18)	(0.60)	(0.74)	(−1.80)	(−1.75)
SOE	−0.0094*	−0.0144*	−0.0053	−0.0071	−0.0112**	−0.0175**	−0.0094	−0.0135
	(−1.85)	(−1.92)	(−1.13)	(−1.00)	(−2.35)	(−2.48)	(−1.39)	(−1.39)
_cons	0.1017**	0.1481**	0.1035***	0.1476***	0.0749*	0.0977	0.0965***	0.1354***
	(2.51)	(2.57)	(3.06)	(2.91)	(1.82)	(1.64)	(2.83)	(2.78)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5173	5173	5999	5999	5606	5606	5567	5567
AdjR²	0.1722	0.1833	0.2054	0.1558	0.0749*	0.0977	0.0965***	0.1354***

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

To alleviate the problem of over-identification of individual IVs, we use the interaction term of the two variables introduced above as our joint IV (*IV*). Columns (3)–(6) of Table 10 report the results. Columns (3) and (4) reveal that *IV1* and *IV2* are strongly correlated with Industrial Internet technology (*IIT*), suggesting that the IVs meet the correlation requirement. Columns (5) and (6) report the second-stage regression results. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 1 % level ($\beta = 7.6398$, $t = 7.19$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 7.6735$, $t = 4.26$). These results suggest that the association between Industrial Internet technology and risk-taking capacity holds after mitigating the reverse causality problem.

4.5.3. Propensity score matching

To alleviate the concern that firms that do and do not implement Industrial Internet technology may be systematically different, we use the propensity score matching (PSM) approach to alleviate the endogeneity problem. In the first step of the PSM analysis, we estimate the probability of applying digital technology using a logistic model. The dependent variable is an indicator that equals 1 if the firm applies Industrial Internet technology, and 0 otherwise. The control variables include *Size*, *Age*, *Lev*, *ROI*, *Profit_M*, *Overhead_E*, *Fix_A*, *Fix_S*, *Sustainable_G*, *Top3* and *SOE*, which are defined in Table 1. According to the most adjacent matching

Table 12
Results of excluding alternative explanation: Internet technology and adjustment costs.

	RISK1	*RISK2*	*RISK1*	*RISK2*	*RISK1* (*t-t + 2*)	*RISK2* (*t-t + 2*)	*RISK1* (*t-t + 2*)	*RISK2* (*t-t + 2*)	*RISK1* (*t-t + 4*)	*RISK2* (*t-t + 4*)	*RISK1* (*t-t + 4*)	*RISK2* (*t-t + 4*)
	Internet technology				Adjustment costs							
	High		Low		High		Low		High		Low	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IIT	0.3624***	0.7115***	0.5327***	0.9661***	0.0943	0.3270	0.4567**	0.8546**	0.4659**	0.9397**	0.6662***	1.4377***
	(2.63)	(3.28)	(2.94)	(3.63)	(0.53)	(1.26)	(2.16)	(2.50)	(2.00)	(2.50)	(3.37)	(3.60)
Size	−0.0031**	−0.0038**	−0.0031*	−0.0056**	−0.0080***	−0.0117***	−0.0040**	−0.0042	0.0019	0.0012	−0.0029	−0.0050
	(−2.30)	(−1.98)	(−1.89)	(−2.36)	(−4.96)	(−5.56)	(−2.00)	(−1.38)	(0.88)	(0.37)	(−1.54)	(−1.39)
Age	0.0056***	0.0079***	0.0061***	0.0082***	0.0081***	0.0122***	−0.0014	−0.0032	0.0085***	0.0129***	0.0008	0.0005
	(4.26)	(4.11)	(3.77)	(3.45)	(5.24)	(5.81)	(−0.49)	(−0.76)	(4.17)	(4.17)	(0.31)	(0.09)
Lev	0.0174**	0.0283***	−0.0067	−0.0093	0.0678***	0.0872***	0.0598***	0.0700***	0.0327***	0.0625***	0.0279***	0.0487**
	(2.52)	(2.80)	(−0.71)	(−0.68)	(8.23)	(7.84)	(5.76)	(4.46)	(2.83)	(3.59)	(2.69)	(2.46)
ROI	−0.0000	−0.0000	−0.0000	−0.0000	0.0000***	0.0000***	−0.0000	−0.0000	0.0000	0.0001	−0.0000	−0.0000
	(−0.55)	(−0.57)	(−0.22)	(−0.31)	(14.81)	(13.82)	(−0.90)	(−0.86)	(0.77)	(1.15)	(−0.68)	(−0.67)
Profit_M	0.0124	0.0184	0.0088	0.0155	0.0041	0.0198	−0.0480***	−0.0759***	0.0852***	0.1120***	0.0048	0.0096
	(1.40)	(1.44)	(0.75)	(0.91)	(0.40)	(1.46)	(−3.59)	(−3.71)	(5.87)	(5.20)	(0.34)	(0.36)
Overhead_E	0.0677***	0.1068***	0.0269	0.0382	0.0825***	−0.0000	0.3306***	0.4521***	0.0903**	0.1786***	0.0233	0.0520
	(2.80)	(2.90)	(0.65)	(0.63)	(5.17)	(−0.31)	(10.13)	(9.27)	(2.23)	(2.81)	(0.61)	(0.69)
Fix_A	−0.0126	−0.0211	−0.0271	−0.0390	−0.0338**	−0.0663***	0.0004	0.0136	−0.0535**	−0.1109***	−0.0816***	−0.1347***
	(−0.99)	(−1.13)	(−1.54)	(−1.56)	(−2.19)	(−3.36)	(0.02)	(0.45)	(−2.51)	(−3.43)	(−4.33)	(−3.73)
Fix_S	0.0010	0.0046	0.0097	0.0142	0.0188***	0.0377***	−0.0082	−0.0128	0.0143*	0.0354***	0.0103	0.0129
	(0.21)	(0.65)	(1.50)	(1.57)	(3.47)	(5.94)	(−1.23)	(−1.25)	(1.75)	(2.90)	(1.52)	(0.98)
Sustainable_G	0.0298***	0.0496***	0.1370***	0.2223***	−0.0025***	−0.0034***	−0.0087***	−0.0116***	0.0283***	0.0465***	0.0886***	0.1514***
	(9.09)	(9.36)	(11.49)	(12.46)	(−3.15)	(−2.97)	(−7.15)	(−5.81)	(5.83)	(5.77)	(5.30)	(4.62)
Top3	−0.0030*	−0.0034	−0.0071***	−0.0103***	−0.0049**	−0.0046	−0.0015	−0.0005	−0.0127***	−0.0179***	−0.0074***	−0.0122**
	(−1.69)	(−1.32)	(−2.97)	(−2.93)	(−2.14)	(−1.50)	(−0.53)	(−0.12)	(−4.21)	(−3.92)	(−2.88)	(−2.45)
SOE	−0.0080**	−0.0132**	−0.0034	−0.0024	−0.0142***	−0.0213***	−0.0064	−0.0128	−0.0172***	−0.0301***	−0.0123**	−0.0247**
	(−2.21)	(−2.43)	(−0.55)	(−0.26)	(−2.98)	(−3.19)	(−1.10)	(−1.41)	(−2.73)	(−3.09)	(−2.29)	(−2.35)
_cons	0.1055***	0.1278***	0.1851***	0.2907***	0.2223***	0.3044***	0.0937**	0.0904	0.1250***	0.2271***	0.1837***	0.3212***
	(3.77)	(3.11)	(5.11)	(5.53)	(6.47)	(6.64)	(2.13)	(1.34)	(2.68)	(3.24)	(4.47)	(4.04)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8491	10,545	1587	1706	7123	7123	4049	4049	7123	7123	4049	4049
AdjR^2	0.2670	0.2195	0.1173	0.1265	0.2145	0.1745	0.2545	0.2196	0.0942	0.1122	0.3970	0.3626

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

Table 13
The results of heterogeneity analysis.

	Capital-intensive		Technology-intensive		Labor force-intensive		High economic policy uncertainty		Low economic policy uncertainty	
	RISK1 (1)	*RISK2* (2)	*RISK1* (3)	*RISK2* (4)	*RISK1* (5)	*RISK2* (6)	*RISK1* (7)	*RISK2* (8)	*RISK1* (9)	*RISK2* (10)
IIT	0.1303	0.2949	0.3251**	0.3104**	0.5804***	0.6116**	0.5175***	0.9413***	0.1106	0.2711
	(0.78)	(1.15)	(2.24)	(2.02)	(2.59)	(2.51)	(3.30)	(4.40)	(0.58)	(0.83)
Size	−0.0034**	−0.0049**	−0.0028*	−0.0047***	−0.0041*	−0.0068***	−0.0036*	−0.0043**	−0.0023	−0.0030
	(−2.04)	(−2.11)	(−1.85)	(−3.02)	(−1.95)	(−3.01)	(−1.94)	(−1.99)	(−1.55)	(−1.21)
Age	0.0049***	0.0066***	0.0047***	0.0022	0.0069***	0.0032	0.0033*	0.0035*	0.0072***	0.0120***
	(2.98)	(2.79)	(3.11)	(1.35)	(3.15)	(1.36)	(1.88)	(1.65)	(4.85)	(4.70)
Lev	−0.0012	−0.0002	0.0166**	0.0299***	0.0308***	0.0443***	0.0124	0.0148	0.0056	0.0086
	(−0.14)	(−0.02)	(2.06)	(3.53)	(2.67)	(3.60)	(1.22)	(1.26)	(0.74)	(0.67)
ROI	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	0.0000	0.0000	−0.0000	−0.0000
	(−0.49)	(−0.53)	(−0.43)	(−0.54)	(−0.50)	(−0.59)	(0.51)	(0.48)	(−0.57)	(−0.58)
Profit_M	−0.0221**	−0.0423***	0.0296***	0.0183	0.0446***	0.0200	0.0209*	0.0214	−0.0125	−0.0186
	(−1.98)	(−2.70)	(2.71)	(1.64)	(2.88)	(1.23)	(1.71)	(1.53)	(−1.23)	(−1.07)
Overhead_E	0.1141***	0.1977***	0.0445	0.0824**	0.0812*	0.1354**	−0.0225	−0.0204	0.1150***	0.1964***
	(3.04)	(3.56)	(1.43)	(2.25)	(1.76)	(2.43)	(−0.49)	(−0.37)	(4.54)	(4.54)
Fix_A	−0.0139	−0.0271	−0.0231	−0.0101	−0.0383*	−0.0204	−0.0181	−0.0194	−0.0174	−0.0284
	(−0.94)	(−1.28)	(−1.54)	(−0.67)	(−1.78)	(−0.92)	(−0.94)	(−0.88)	(−1.26)	(−1.21)
Fix_S	0.0069	0.0143*	0.0047	0.0013	0.0101	0.0048	0.0003	0.0004	0.0059	0.0107
	(1.28)	(1.86)	(0.80)	(0.22)	(1.21)	(0.53)	(0.04)	(0.05)	(1.14)	(1.22)
Sustainable_G	0.1805***	0.2874***	0.0653***	0.0462***	0.0812***	0.0737***	0.0116***	0.0175***	0.1329***	0.2271***
	(21.17)	(22.04)	(4.58)	(4.31)	(4.06)	(4.50)	(3.34)	(3.56)	(18.60)	(18.63)
Top3	−0.0036*	−0.0041	−0.0011	0.0026	−0.0006	0.0037	−0.0003	0.0007	−0.0065***	−0.0111***
	(−1.73)	(−1.36)	(−0.55)	(1.30)	(−0.22)	(1.24)	(−0.12)	(0.23)	(−3.39)	(−3.37)
SOE	−0.0050	−0.0078	−0.0053	−0.0040	−0.0087	−0.0067	−0.0058	−0.0059	−0.0071*	−0.0132**
	(−1.21)	(−1.30)	(−1.44)	(−1.10)	(−1.60)	(−1.21)	(−0.89)	(−0.79)	(−1.90)	(−2.08)
_cons	0.1175***	0.1576***	0.0737**	0.0639*	0.0964*	0.0938*	0.1139***	0.1345***	0.1280***	0.1974***
	(3.36)	(3.16)	(2.11)	(1.78)	(1.93)	(1.79)	(2.79)	(2.84)	(4.18)	(3.79)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5484	6868	5730	5227	7224	6551	4058	6096	6020	6155
AdjR²	0.2414	0.2114	0.1970	0.3301	0.1758	0.2864	0.1649	0.1465	0.3122	0.3216

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

method, we obtain the samples that have similar firm characteristics, only differing in whether they implement Industrial Internet technology.

We re-estimate Eq. (4) using the matched samples, including 6,900 firm-year observations. Columns (7) and (8) of Table 10 report the results. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.3972$, $t = 2.73$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.7470$, $t = 3.46$). These results suggest that Industrial Internet technology increases corporate risk-taking capacity.

4.6. Excluding alternative explanations

4.6.1. Financial development

Based on resource dependence theory, financial development facilitates corporate risk-taking capacity. To exclude the influence of financial development during the sample period, we use the degree of regional-inclusive finance as a proxy for financial development (*FD*) and re-estimate Eq. (4) for the two subsamples partitioned according to the median of *FD*. Columns (1) and (4) of Table 11 report the results. Columns (1) and (2) present the results for the subsample with a high *FD*. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.5687$, $t = 2.70$), and the coefficient

Table 14
The results of further analysis.

	TFP(t)	*TFP (t)*	*TFP (t + 1)*	*TFP (t + 2)*	*TFP (t + 3)*	*TFP (t)*	*TFP (t + 1)*	*TFP (t + 2)*	*TFP (t + 3)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IIT	0.5250**	0.1328	1.9736***	1.0511	−1.5217	0.2523	1.9737***	1.0348	−1.6239
	(2.27)	(0.50)	(3.02)	(1.10)	(−1.07)	(1.01)	(3.01)	(1.08)	(−1.14)
IIT RISK1*	–	11.4155***	7.4354**	15.9807***	88.6116***	–	–	–	–
	–	(2.80)	(1.97)	(3.05)	(4.19)	–	–	–	–
RISK1	–	−0.2150***	−0.3862***	−0.8709***	−1.8507***	–	–	–	–
	–	(−3.38)	(−5.01)	(−8.08)	(−6.82)	–	–	–	–
IIP RISK2*	–	–	–	–	–	7.0957***	4.1946*	9.0949***	50.9584***
	–	–	–	–	–	(3.00)	(1.95)	(3.03)	(4.37)
RISK2	–	–	–	–	–	−0.1309***	−0.2196***	−0.5017***	−1.0656***
	–	–	–	–	–	(−3.58)	(−5.04)	(−8.26)	(−7.09)
Size	0.6489***	0.6497***	0.6386***	0.6231***	0.6067***	0.6484***	0.6386***	0.6230***	0.6055***
	(187.73)	(184.04)	(116.32)	(80.17)	(60.52)	(187.57)	(116.33)	(80.20)	(60.76)
Age	0.0172***	0.0176***	−0.0003	−0.0095	−0.0146	0.0174***	−0.0003	−0.0094	−0.0143
	(4.12)	(4.16)	(−0.05)	(−1.22)	(−1.47)	(4.17)	(−0.05)	(−1.21)	(−1.44)
Lev	0.1054***	0.1029***	0.1352***	0.0333	−0.0468	0.1059***	0.1351***	0.0334	−0.0366
	(5.66)	(5.42)	(4.65)	(0.82)	(−0.90)	(5.69)	(4.65)	(0.82)	(−0.71)
ROI	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.74)	(0.73)	(0.39)	(0.48)	(0.28)	(0.72)	(0.39)	(0.48)	(0.27)
Profit_M	−0.4286***	−0.4173***	−0.4583***	−0.5668***	−0.6116***	−0.4307***	−0.4581***	−0.5665***	−0.6076***
	(−17.34)	(−16.63)	(−11.96)	(−10.41)	(−8.64)	(−17.43)	(−11.95)	(−10.41)	(−8.61)
Overhead_E	−2.0814***	−2.0661***	−1.8121***	−1.2221***	−1.0116***	−2.0729***	−1.8119***	−1.2192***	−1.0013***
	(−31.38)	(−30.69)	(−18.30)	(−8.97)	(−5.96)	(−31.25)	(−18.30)	(−8.95)	(−5.92)
Fix_A	1.2157***	1.2459***	1.2326***	1.2257***	1.2594***	1.2147***	1.2326***	1.2263***	1.2513***
	(36.17)	(36.28)	(23.31)	(16.78)	(13.48)	(36.15)	(23.31)	(16.79)	(13.45)
Fix_S	−1.2220***	−1.2317***	−1.1421***	−1.0440***	−0.9960***	−1.2205***	−1.1421***	−1.0442***	−0.9936***
	(−96.85)	(−95.27)	(−57.29)	(−37.88)	(−27.94)	(−96.74)	(−57.29)	(−37.90)	(−28.02)
Sustainable_G	0.6819***	0.6910***	0.5763***	0.7607***	0.7581***	0.6935***	0.5775***	0.7624***	0.7703***
	(18.62)	(18.48)	(10.76)	(9.87)	(7.85)	(18.87)	(10.78)	(9.89)	(8.00)
Top3	0.0717***	0.0703***	0.0791***	0.0793***	0.0837***	0.0717***	0.0790***	0.0792***	0.0842***
	(15.19)	(14.66)	(10.72)	(7.75)	(6.43)	(15.19)	(10.71)	(7.74)	(6.50)
SOE	0.0159	0.0136	0.0351**	0.0343*	0.0610**	0.0152	0.0351**	0.0340*	0.0579**
	(1.60)	(1.36)	(2.34)	(1.72)	(2.47)	(1.53)	(2.34)	(1.70)	(2.35)
_cons	−5.6988***	−5.7010***	−5.4821***	−5.1269***	−4.7372***	−5.6858***	−5.4812***	−5.1251***	−4.7279***
	(−76.88)	(−75.51)	(−47.05)	(−31.72)	(−22.86)	(−76.65)	(−47.05)	(−31.72)	(−22.93)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11,172	11,172	7685	6194	4965	11,172	7685	6194	4965
AdjR²	0.9377	0.9376	0.8728	0.7940	0.7295	0.9378	0.8728	0.7941	0.7295

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

on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 1.0033$, $t = 3.14$). Columns (3) and (4) present the results for the subsample with a low *FD*. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.3397$, $t = 2.17$) and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.7450$, $t = 3.00$). Therefore, our baseline results remain robust after considering the influence of financial development.

4.6.2. Executive long-term vision

Higher levels of risk-taking enable firms to grasp investment opportunities with higher return rates and obtain long-term competitive advantage (Low, 2009; Yu et al., 2013). However, the benefits of risk-taking are difficult to realize in the short term, so whether executives have a long-term vision is an important factor

that affects corporate risk-taking capacity. To exclude the influence of executive long-term vision, we use the shareholding ratio of executives as a proxy for executive long-term vision (*ELV*) and re-estimate Eq. (4) for the two subsamples partitioned according to the median of *ELV*. Columns (5)–(8) of Table 11 report the results. Columns (5) and (6) present the results for the subsample with a high *ELV*. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 10 % level ($\beta = 0.3804$, $t = 1.68$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.6835$, $t = 1.97$). Columns (7) and (8) present the results for the subsample of firms with a low *ELV*. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.5273$, $t = 3.36$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.9400$, $t = 3.91$). Therefore, our baseline results hold after considering the influence of executive long-term vision.

4.6.3. Internet technology

Studies find that Internet technology contributes to the development of the real economy. To eliminate the influence of Internet technology on our results, we use the number of mobile phone base stations as a proxy for Internet technology (*IT*) and re-estimate Eq. (4) for the two subsamples partitioned according to the median of *IT*. Columns (1)–(4) of Table 12 report the results. Columns (1) and (2) present the results for the subsample with a high *IT*. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.3624$, $t = 2.63$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.7115$, $t = 3.28$). Columns (3) and (4) present the results for the subsample with a low *IT*. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.5327$, $t = 2.94$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.9661$, $t = 3.63$). Therefore, our baseline results remain robust after considering the influence of Internet technology.

4.6.4. Adjustment costs

Drawing on resource reallocation theory, adjustment costs reduce the benefits brought by resource reallocation. To eliminate the influence of adjustment costs on our results, we use cost stickiness formed by the investment of financial resources and labor resources as a proxy for adjustment costs. Referring to Jang and Yehuda (2021), we apply the following model to measure cost stickiness:

$$\Delta \ln \cos ti, q = \beta 0 + \beta 1 \Delta \ln salei, q + \beta 2 Deci, q \times \Delta \ln salei, q + \varepsilon i, q \tag{8}$$

where i denotes the firm and q denotes the quarter. $cost_{i,t}$ represents quarterly the operating costs. $sale_{i,t}$ represents the quarterly sales revenue. $Dec_{i,t}$ is a dummy variable that equals 1 if the sales revenue in quarter q is less than that in quarter $q-1$, and 0 otherwise. The coefficient β_1 represents the degree of change in operating costs when the sales revenue increases, and the coefficient β_2 represents the degree of change in operating costs when the sales revenue decreases. We use the negative value of the ratio of β_2 to β_1 to measure the adjustment costs, and we partition the total sample into two subsamples according to the median of the adjustment costs.

Columns (5)–(12) of Table 12 report the results. Columns (5)–(8) present the regression results of using *RISK1(t − t + 2)* and *RISK2(t − t + 2)* as the dependent variables. *RISK1(t − t + 2)* is the volatility of ROA adjusted by the industry average over the 3-year period from year t to $t+2$. *RISK2(t − t + 2)* is the maximum deviation of ROA adjusted by the industry average over the 3-year period from year t to $t+2$. Columns (5) and (6) present the regression results for the subsample of firms with high adjustment costs. The coefficients on *IIT* are not significant. Columns (5) and (6) present the regression results for the subsample of firms with low adjustment costs. The coefficient on *IIT* when using *RISK1(t − t + 2)* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.4567$, $t = 2.16$), and the coefficient on *IIT* when using *RISK2(t − t + 2)* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.8546$, $t = 2.50$). These results suggest that adjustment costs constrain the effect of Industrial Internet technology on corporate risk-taking capacity in the short term.

Columns (9)–(12) present the regression results of using *RISK1(t − t + 4)* and *RISK2(t − t + 4)* as the dependent variables. *RISK1(t − t + 4)* is the volatility of ROA adjusted by the industry average over the 5-year period from year t to $t+4$. *RISK2(t − t + 4)* is the maximum deviation of ROA adjusted by the indus-

try average over the 5-year period from year t to $t + 4$. Columns (9) and (10) present the regression results for the subsample of firms with high adjustment costs. The coefficient on *IIT* when using *RISK1*$(t - t + 4)$ as the dependent variable is positive and significant at the 5 % level ($\beta = 0.4659$, $t = 2.00$), and the coefficient on *IIT* when using *RISK2*$(t - t + 4)$ as the dependent variable is positive and significant at the 5 % level ($\beta = 0.9397$, $t = 2.50$). Columns (5) and (6) present the regression results for the subsample of firms with low adjustment costs. The coefficient on *IIT* when using *RISK1*$(t - t + 4)$ as the dependent variable is positive and significant at the 1 % level ($\beta = 0.6662$, $t = 3.37$), and the coefficient on *IIT* when using *RISK2*$(t - t + 4)$ as the dependent variable is positive and significant at the 1 % level ($\beta = 1.4377$, $t = 3.60$). These results suggest that adjustment costs have no impact on the effect of Industrial Internet technology on corporate risk-taking capacity in the long term.

4.7. Heterogeneity analysis

4.7.1. Production factor characteristics

Production factor characteristics vary greatly in different manufacturing firms. The focus of Industrial Internet technology implementation and the pain points that need to be solved are considerably distinct. We use the cash paid for the purchase and construction of fixed assets, intangible assets and other long-term assets to measure capital intensity, and we partition the total sample into two subsamples according to the median of capital intensity. The firms in the subsample with high capital intensity are referred to as "capital-intensive firms." We use the ratio of research and development investment to the operating revenue to measure technology intensity, and we partition the total sample into two subsamples according to the median of technology intensity. The firms in the subsample with high technology intensity are referred to as "technology-intensive firms." We use the cash paid to and on behalf of employees to measure labor force intensity, and we partition the total sample into two subsamples according to the median of labor force intensity. The firms in the subsample with high labor force intensity are referred to as "labor force-intensive firms." Columns (1)–(6) of Table 13 report the results. Columns (1) and (2) present the regression results for the subsample of capital-intensive firms. The coefficients on *IIT* are not significant. Columns (3) and (4) present the regression results for the subsample of technology-intensive firms. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.3251$, $t = 2.24$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.3104$, $t = 2.02$). Columns (5) and (6) present the regression results for the subsample of labor force-intensive firms. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.5804$, $t = 2.59$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.6116$, $t = 2.51$). These results show that the effect of Industrial Internet technology on risk-taking capacity exists in firms with high levels of technology intensity and labor intensity.

4.7.2. Economic policy uncertainty

Economic policy uncertainty has a significant influence on corporate risk-taking capacity. On the one hand, increases in economic policy uncertainty lead to decreases in the amount of credit provided by financial institutions and reduce risk-taking. On the other hand, uncertain economic environments offer many investment opportunities for firms (Bernanke, 1983; Liu et al., 2017), which may enhance their willingness to take risks. Referring to Baker et al. (2016), we use the Economic Policy Uncertainty Index to measure economic policy uncertainty, and we partition the total sample into two subsamples according to the median of economic policy uncertainty. Columns (7)–(10) of Table 13 report the results. Columns (7) and (8) present the results for the subsample of firms with high economic policy uncertainty. The coefficient on *IIT* when using *RISK1* as the dependent variable is positive and significant at the 1 % level ($\beta = 0.5175$, $t = 3.30$), and the coefficient on *IIT* when using *RISK2* as the dependent variable is positive and significant at the 5 % level ($\beta = 0.9413$, $t = 4.40$). Columns (9) and (10) present the results for the subsample of firms with low economic uncertainty. The coefficients on *IIT* are not significant. These results show that the effect of Industrial Internet technology on corporate risk-taking capacity exists in the case of high economic policy uncertainty.

4.8. Further analysis

High levels of risk-taking enable firms to obtain better investment opportunities, improve their future performance and enhance their long-term competitive advantage. We estimate the following models to investigate the economic consequences of the effect of Industrial Internet technology on risk-taking capacity. Total factor productivity (*TFP*) is measured following Levinsohn and Petrin (2003). All of the other variables are defined as in the baseline regressions.

$$TFPi,t = \beta 0 + \beta 1 \times IITi,t + \sum \beta jControli,t + \sum Year + \sum Industry + \varepsilon i,t \tag{9}$$

$$\begin{aligned} TFPi,t = {} & \beta 0 + \beta 1 \times IITi,t + \beta 2 \times IIT \times RISKi,t + \beta 3 \times RISKi,t + \sum \beta jControli,t \\ & + \sum Year + \sum Industry + \varepsilon i,t \end{aligned} \tag{10}$$

Table 14 reports the results. Column (1) presents the regression results for Eq. (9). The coefficient on *IIT* is positive and significant at the 5 % level ($\beta = 0.5250$, $t = 2.27$), indicating that Industrial Internet technology promotes total factor productivity. Columns (2) and (6) present the regression results for Eq. (10). The coefficient on *IIT*RISK1* is positive and significant at the 1 % level ($\beta = 11.4155$, $t = 2.80$), and the coefficient on *IIT*RISK2* is positive and significant at the 1 % level ($\beta = 7.0957$, $t = 3.00$). These results indicate that Industrial Internet technology promotes total factor productivity by increasing corporate risk-taking capacity.

Columns (3) and (7) present the regression results for Eq. (10) when using $TFP_{i,t+1}$ (the total factor productivity in year *t + 1*) as the dependent variable. The coefficient on *IIT*RISK1* is positive and significant at the 5 % level ($\beta = 7.4354$, $t = 1.97$), and the coefficient on *IIT*RISK2* is positive and significant at the 10 % level ($\beta = 4.1946$, $t = 1.95$). Columns (4) and (8) present the regression results for Eq. (10) when using $TFP_{i,t+2}$ (the total factor productivity in year *t + 2*) as the dependent variable. The coefficient on *IIT*RISK1* is positive and significant at the 1 % level ($\beta = 15.9807$, $t = 3.05$), and the coefficient on *IIT*RISK2* is positive and significant at the 1 % level ($\beta = 9.0949$, $t = 3.03$). Columns (5) and (9) present the regression results for Eq. (10) when using $TFP_{i,t+3}$ (the total factor productivity in year *t + 3*) as the dependent variable. The coefficient on *IIT*RISK1* is positive and significant at the 1 % level ($\beta = 88.6116$, $t = 4.19$), and the coefficient on *IIT*RISK2* is positive and significant at the 1 % level ($\beta = 50.9584$, $t = 4.37$). These results show that Industrial Internet technology promotes total factor productivity by increasing risk-taking capacity, which is an effect that occurs in the long term.

5. Conclusion

Risk-taking capacity is a key factor contributing to firms' development and survival. Using a sample of Chinese A-share listed manufacturing firms over the 2010–2022 period, we explore the impact of Industrial Internet technology on corporate risk-taking capacity from the perspective of strategic management. We find that the implementation of Industrial Internet technology increases corporate risk-taking capacity. Our main results hold after a series of robustness and endogeneity tests. The mechanism analysis shows that Industrial Internet technology enhances risk-taking capacity through resource reallocation. Specifically, IaaS layer technology exerts an information empowerment effect on organizational structure improvement. PaaS layer technology exerts a technology empowerment effect on labor resource optimization. Edge layer and SaaS layer technology exert an algorithm empowerment effect on supply chain resource integration. Heterogeneity tests show that the effect of Industrial Internet technology on risk-taking capacity only exists in firms with high levels of technology intensity and labor intensity and in firms operating in environments with high economic uncertainty. Further analysis reveals that Industrial Internet technology significantly improves total factor productivity by enhancing risk-taking capacity.

The practical implications of our findings are as follows. First, alongside their strategic goals, firms should take full advantage of all layers of Industrial Internet technology to optimize resource allocation and improve risk-taking capacity, thus overcoming the Solow paradox and achieving high-quality development. Internally, it is necessary to strengthen interconnections among different machinery, equipment, workforce and business units, implement complementary organizational reforms and optimize the human capital structure. Exter-

nally, firms need to utilize Industrial Internet technology in reducing transaction costs, improving transaction efficiency and integrating resources, thus strengthening their interconnections with supply chain partners.

Second, our results provide inspiration for local governments and relevant departments to formulate policies for the development of Industrial Internet technology. Due to the cross-industry, cross-regional and multi-technology integration characteristics of Industrial Internet technology, it requires a large amount of capital and facilities investment in the short term for platform construction, industry resource diversion and integration. Governments should focus on the most common problems and provide solutions, such as design collaboration, supply chain collaboration, finance support, Industrial Internet platform development and business model innovation acceleration. As firms' foundations and environments for implementing Industrial Internet technology vary, governments should enact targeted policies and implement flexible services to meet the developmental demands of multiple firms.

Declaration of competing interest

According to policy as well as my moral obligation, as the researchers report, there are no potential conflict of interest was reported by the authors.

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Coping strategy of independent directors for job-fulfillment risk under different ownership types and enforced legal environments

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ABSTRACT

Ownership type, legal system evolution and their interaction significantly affect the incentives and behaviors of independent directors. We use the 2019 *Securities Law* revision as an exogenous shock to examine how state-owned enterprises (SOEs) versus non-SOEs and their independent directors respond to variations in regulatory compliance risk. Following the revision, SOEs are more likely to purchase directors' and officers' liability insurance to provide job security for independent directors. Non-SOEs are more likely to compensate for independent directors' fulfillment risk by increasing salaries and their independent directors are more likely to resign to avoid litigation risk. The coping strategies for SOEs, non-SOEs and independent directors are dynamic under different compliance risk stages and are affected by firm-level and director-level characteristics.

1. Introduction

In emerging markets with underdeveloped legal systems and insufficient investor protection, enhancing the legal liability of independent directors and ensuring their commitment to acting on behalf of minority shareholders' interests are matters of common concern for regulators and capital market participants. In developed capital markets such as the United States (U.S.), minority shareholders actively participate in corporate

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governance and exercise their influence in the independent director appointment process (Kang et al., 2020). However, the role of minority shareholders in corporate governance is limited in China's market, and the appointment and compensation of independent directors are heavily influenced by controlling shareholders and management (Firth et al., 2006; Jiang and Kim, 2020). The independence of independent directors is relatively weak (Hwang and Kim, 2009; Ma and Khanna, 2016), and they fail to fulfill their supervisory role effectively (Ye et al., 2011; Jiang and Kim, 2020). At the same time, the costs of and penalties for violations are low (Jiang and Kim, 2015). As such, illegal activities, such as financial fraud, insider trading and market manipulation, persist in China's capital markets, harming investors' interests and protection (Ge et al., 2022).

Starting from scratch, China's legal systems for independent directors have been gradually established and are currently undergoing a dynamic process of continuous improvement. In 1998, during the early stage of the market transition, the *Securities Law* was enacted to regulate the issuance and trading of securities. The introduction of the *Guiding Opinions on Establishing the Independent Director System* by the State Council in 2001 marked a significant step toward mandating the appointment of independent directors in listed companies. It regulated the proportion of independent directors, requiring them to comprise at least one third of listed companies' board members, far less than the 50 % threshold required by the U.S. Securities and Exchange Commission. Following its introduction, most listed companies hired the minimum number of independent directors required by the policy (Jiang and Kim, 2015). The "precise compliance" strategy in the appointment of independent directors has limited both the supervisory and advisory roles of independent directors. The practice, which barely meets regulatory requirements, has also impeded independent directors' capacity to diligently fulfill their duties and protect the rights of minority shareholders. With the development of the capital market and the implementation of the registration system reform, it has become imperative to address the ongoing challenges of low penalties for illegal activities under the old *Securities Law* and the barriers faced by minority investors in seeking judicial remedies. To promote the high-quality development of the capital market and strengthen the due diligence of independent directors, the revised *Securities Law* was passed on 28 December 2019.

This new *Securities Law* has enhanced the compliance risks encountered by independent directors. The legal liabilities of independent directors are reenforced through increased penalties for violations and the establishment of a special representative litigation mechanism. At the same time, considering China's political system, economic status, judicial framework and cultural environments, a blended litigation system has been developed to promote private interests through public enforcement mechanisms (Jiao, 2023). The "opt-out" rule, which allows for implicit participation in lawsuits, maximizes the compensation function of litigation and creates a strong deterrent to misconduct in the securities market.

Independent directors consider a number of factors in job selection, such as compensation (Ghannam et al., 2019), influence within the board of directors (Dou and Zhang, 2020), corporate reputation (Fich and Shivdasani, 2007) and job-fulfillment risks (Tan et al., 2006). Among these considerations, the external regulatory environment, a crucial element of job-fulfillment risks, has a direct and profound impact on the behavior of firms and independent directors. Firms dynamically adjust the proportion of independent directors on the board (Armstrong et al., 2014), the number of female independent directors (Ahern and Dittmar, 2012) and the compensation of independent directors in response to legal regulations and increased job-fulfillment risks (Donelson et al., 2022). Independent directors also proactively modify their strategies based on changes in regulatory compliance risks. These changes include voicing objections more frequently (Li et al., 2022a, 2022b; Hu et al., 2023) and choosing to resign in high-risk scenarios (Naaraayanan and Nielsen, 2021).

In China's transition economy, the legal system of the securities market is continuously evolving, with ownership type playing a crucial role in the process. The interaction between these two factors has a significant impact on the incentives and behaviors of independent directors. However, whether ownership types lead to variations in regulatory compliance risks remains to be explored. State-owned enterprises (SOEs) hold certain advantages over non-SOEs. For example, they have special governance systems, such as the "*ex-ante* discussion" procedure. They also pay more attention to standardized operations and compliance management. These mechanisms and measures help SOEs avoid potential mistakes in decision-making. Additionally, governments tend to offer more political resources and policy preferences to SOEs and assist them in operational crises (Dai et al., 2014). Such advantages may give rise to distinct behaviors among SOEs, non-SOEs and their independent directors when confronted with shifts in the regulatory environment.

In this study, we use the revision of the *Securities Law* as an exogenous policy shock, Chinese A-share listed companies from 2016 to 2022 as the research sample and a difference-in-differences (DID) design to examine the behaviors of SOEs, non-SOEs and their independent directors in response to changes in regulatory compliance risks at each stage following the revision of the *Securities Law*. Three stages, namely the legislation, enforcement and enforcement adjustment stages, are identified based on the typical features and the level of regulatory compliance risk of each stage.

We find that since the revision of the *Securities Law* in 2019, SOEs have demonstrated a stronger awareness of risk management and a greater willingness to comply with regulations. The likelihood of SOEs purchasing directors' and officers' liability insurance (D&O insurance) has also increased significantly compared with that of non-SOEs following the enactment of the law. With the enforcement of the new *Securities Law* in 2021, non-SOEs have increased the salaries of their independent directors as a form of risk compensation, and their independent directors have become more inclined to resign when salary increases do not sufficiently offset their perceived potential loss from regulatory compliance risks. This trend has been significantly mitigated since the introduction of the new judicial interpretations in 2022, clarifying the circumstances under which independent directors may be exempt from legal liability. Further analysis finds that company-level risks increase the probability of non-SOEs purchasing D&O insurance and compel them to increase independent directors' salaries. However, the resignation of independent directors is often not a rational decision based on potential compliance risks; instead, it tends to be an overreaction to reinforced regulatory compliance risks highlighted by the Kangmei Pharmaceutical Co., Ltd. case. Similarly, the individual-level job-fulfillment risks faced by independent directors elevate the propensity of non-SOEs to purchase D&O insurance and lead to an increase in the compensation package offered to independent directors. Furthermore, independent directors in non-SOEs are also more likely to resign when faced with higher individual job-fulfillment risk. Finally, by comparing the individual characteristics of successors before and after the *Securities Law* revision, we find that the enactment has enhanced the competence of successive independent directors, enabling them to fulfil their roles in oversight, decision-making and advisory more effectively.

We contribute to the literature in the following ways. First, we extend the research on ownership type and independent director behavior. The literature fails to systematically investigate the different influences of corporate governance mechanisms between SOEs and non-SOEs and their potential behavioral differences when faced with varying regulatory compliance risks. We emphasize the governance differences between SOEs and non-SOEs and explore the various responses of SOEs, non-SOEs and their independent directors following the revision of the *Securities Law*.

Second, we focus on the detailed legal timeline around the shock of regulatory changes and divide the timeline into legislation, enforcement and enforcement adjustment stages. Previous studies roughly divide the sample period based solely on the enactment of legal provisions or the judgment of litigation cases. We divide the entire sample period into four stages: pre-revision (2016–2018), legislation (2019–2020), enforcement (2021) and enforcement adjustment (2022). This division is based on the unique characteristics and changes in regulatory compliance risks in each stage. Based on the detailed legislative timeline, we examine how listed companies and their independent directors respond to dynamic changes in the regulatory environment and fluctuations in regulatory compliance risks. We also explore the deterrent effect of China's legal system reform from the perspectives of legislation and enforcement.

Third, we extend the research on the regulatory environment and independent director behavior. The literature focuses on single independent director behaviors following an increase in compliance risk, such as changes in compensation (Donelson et al., 2022), diligence (Li et al., 2022a, 2022b) and resignation (Naaraayanan and Nielsen, 2021; Goodell et al., 2023; Lu and Jiang, 2023; Luo et al., 2023). In this study, we systematically examine the impact of the new *Securities Law* on D&O insurance, salary and abnormal resignation, as well as the interaction between these factors. D&O insurance safeguards independent directors in carrying out their responsibilities, salary compensates them for the associated job-fulfillment risk and resignation represents their decision to avoid risk when the costs outweigh the benefits. The purchase of D&O insurance and changes in salary both have an impact on independent directors' resignation decisions.

Finally, our findings also provide policy implications. We analyze the deterrent effect of the legislation, enforcement and enforcement adjustment stages of the new *Securities Law* on strengthening independent directors' personal responsibility, reflecting the two-way interaction and mutual promotion effects between

legislation and enforcement. This provides valuable insights for future legislative and enforcement efforts, as well as for the reform of the independent director system.

2. Background

Emerging markets often confront challenges, such as underdeveloped judicial systems, low violation costs and inadequate investor protection (Jiang and Kim, 2015). In response to the serious imbalance between the benefits gained from illegal activities and the punitive costs under the previous *Securities Law*, a revised *Securities Law* was enacted on 28 December 2019. This revision has enhanced penalties for responsible parties, including independent directors, and established a class action system with uniquely Chinese characteristics, thereby increasing the litigation risk for independent directors. We divide the period following the *Securities Law* revision into three stages, namely the legislative stage (2019–2020), the law enforcement stage (2021) and the law enforcement adjustment stage (2022), based on the rise of representative cases and fluctuations in regulatory compliance risks.

2.1. Legislative stage

Since its enactment on 1 July 1999, the *Securities Law* has undergone three amendments and one revision to accommodate the development of and changes in the capital market and foster the growth of the socialist market economy in China. To steadily advance registration system reform and effectively suppress illegal activities in the capital market, the revised *Securities Law* was passed on 28 December 2019; it has been officially implemented since 1 March 2020.

This latest revision has increased the minimum and maximum fines for illegal activities by liable parties, including independent directors, as detailed in Table 1. Even the lowest penalty for illegal activities has been raised from 30,000 yuan to 200,000 yuan, significantly increasing the costs of various violations.

Beyond the enhanced penalties, another significant feature of the revised *Securities Law* is the establishment of a special representative litigation system that is tailored to Chinese legal practices and serves as China's version of class action lawsuits. This system relies on investor protection institutions as the main litigants.[1] Investors participate in litigation according to the opt-out principle, maximizing the number of plaintiff investors. The system increases compensation, simplifies the litigation process and solves the difficulties faced by plaintiff investors under the old *Securities Law*. This system increases the costs of illegal activities and the litigation compensation risks for liable parties, fosters a legislative and judicial securities framework with Chinese characteristics and reinforces the legal groundwork for safeguarding investors' legitimate rights and interests.

2.2. Law enforcement stage

Although the new *Securities Law* was promulgated in 2019 and implemented in 2020, the first batch of financial fraud cases penalized under the new *Securities Law* did not emerge until 2021.[2] This first batch of cases involved Yihua Lifestyle Technology Co., Ltd., Guangdong Rongtai Industry Co., Ltd. and China Dive Company Limited. The misconduct and punishments of independent directors in each case are detailed in Table 2. These cases provide a reference for the relevant liable entities under the new *Securities Law* regarding the severity of penalties.

The China Securities Regulatory Commission (CSRC) treated the first batch of cases as typical examples, enforcing the law strictly and punishing severely. The penalty results show that the new *Securities Law* significantly increases the punishment for dereliction of duty by independent directors. In these three cases, independent directors faced fines ranging from 500,000 to 600,000 yuan, all exceeding the amounts fined under the previous *Securities Law*.

[1] The investor protection institutions include the China Securities Investor Service Center (CSISC) and the China Securities Investor Protection Fund Corporation.

[2] The CSRC announced the punishment of the first batch of financial fraud cases under the new *Securities Law*: http://www.csrc.gov.cn/csrc/c100028/c3d34146c65c5455fbf430b262e054362/content.shtml.

Table 1
Comparison of violation costs between the Securities Law of 2014 and 2019.

Misconducts	*Securities Law* of 2014	*Securities Law* of 2019
Information disclosure	Directors and other directly responsible persons shall be given a warning and fined between thirty thousand yuan and one hundred thousand yuan.	(1) Information disclosure obligors shall be fined between five hundred thousand yuan and five million yuan. (2) As for independent directors, unless they can prove that they are not at fault, they shall bear joint and several civil liability.
Insider trading	(1) Confiscate the illegal gains and impose a fine of more than one time and up to five times the amount of the illegal gains. (2) If there are no illegal gains or the illegal gains are less than three hundred thousand yuan, a fine of between three hundred thousand yuan and three million yuan shall be imposed.	(1) Confiscate the illegal gains and impose a fine of more than one time and up to ten times the amount of the illegal gains. (2) If there are no illegal gains or illegal gains less than one million yuan, a fine of between one million yuan and ten million yuan shall be imposed.
False information	False statements or misleading information shall be rectified. And a fine between thirty thousand yuan and two hundred thousand yuan is imposed.	(1) Confiscate the illegal gains and impose a fine of between one time and ten times the amount of the illegal gains. (2) If there are no illegal gains or the illegal gains are less than two hundred thousand yuan, a fine of between two hundred thousand yuan and two million yuan shall be imposed.

The sentence for the first class action under the new *Securities Law* on 12 November 2021 further increased the compliance risks faced by independent directors.[3] The Guangzhou Intermediate People's Court ordered Kangmei Pharmaceutical to compensate 52,037 investors represented by the CSISC for losses amounting to 2.459 billion yuan. Independent directors were held liable for compensation ranging from 5 % to 10 % of the total amount, corresponding to 123 million to 246 million yuan, respectively, significantly exceeding the total salaries they received during their tenure.

The first batch of punishment cases under the new *Securities Law* in 2021, along with the judgment for the Kangmei Pharmaceutical lawsuit, marked the formal entry of China's capital market into the law enforcement stage of the new *Securities Law*. From this point onward, independent directors who violate laws or regulations would face heavy penalties that could exceed their entire earnings during their tenure. Furthermore, if a case is subject to a class action suit, independent directors could bear joint and several liabilities amounting to hundreds of millions of yuan, thus significantly increasing the compliance risks they face.

2.3. Law enforcement adjustment stage

To alleviate independent directors' concerns regarding job-fulfillment compliance risk after the Kangmei Pharmaceutical lawsuit, the Supreme People's Court issued the *Provisions on Several Issues Concerning the Trial of Civil Compensation Cases for False Statements in the Securities Market* (*Provisions*) on 21 January 2022. Article 16 of the *Provisions* specifically stipulates the specific grounds for exemption from liability for independent directors to relieve their concerns about diligent duties requirements and avoid a "chilling effect."[4]

[3] The Kangmei Pharmaceutical case, initiated by the CSISC, a public welfare institution subordinated to the CSRC and endorsed by state public power, and representing over 50,000 plaintiffs, is the first class action under the new *Securities Law*.

[4] If an independent director can prove one of the following circumstances, the People's Court shall deem them not at fault:(1) Before signing the relevant information disclosure documents, they failed to discover the problem, even with the assistance of professionals such as accountants and lawyers for issues that are not within their own professional fields.(2) Before the revelation or correction date, when they discovered the false statements, they promptly raised objections to the issuer and supervised the rectification or made a written report to the stock exchange or regulatory authorities.(3) In their independent opinions, they expressed reservations, opposition or an inability to express an opinion on the false statement matter and provided specific reasons, except for voting in favor when reviewing or examining related documents.(4) Due to the issuer's refusal or obstruction of their duties, they were unable to determine whether the information disclosure documents contained false statements and made a timely written report to the stock exchange or regulatory authorities.(5) Other circumstances that can prove diligent performance of duties.

Table 2
First batch of financial fraud cases punished under the new Securities Law.

Company	Illegal acts	Penalty results
Yihua Lifestyle (600978)	From 2016 to 2019, the company inflated its profits by over 2.7 billion yuan through creating fictitious sales transactions and exaggerating sales revenue. It also artificially increased its reported bank funds by 8.6 billion yuan through forging bank documents, omitting transactions or recording false transactions. Additionally, the company failed to disclose fund transfer with related parties amounting to over 32 billion yuan, as required by regulations.	Three independent directors (with an annual salary of 210,000 yuan each) were issued warnings and fined 600,000 yuan each.
Guangdong Rongtai (600589)	From 2018 to 2019, the company inflated its profits by over 55 million yuan through creating fictitious sales collections and fictitious factoring businesses. Moreover, the company failed to disclose the affiliated relationships and daily operational related-party transactions as required by regulations.	Four independent directors (with an annual salary of 60,000 yuan each) were issued warnings and fined 500,000 yuan each.
China Dive (400185)	In 2019, the company artificially increased its operating revenue by over 37.2 million yuan, inflated its operating costs by over 11.5 million yuan, resulting in an exaggerated operating profit of over 25.7 million yuan. Additionally, the 2019 annual report failed to disclose related-party transactions as required by regulations, and the announcements released in 2020 contained misleading statements.	Three independent directors (with an annual salary of 60,000 yuan each) were issued warnings and fined 500,000 yuan each.

Meanwhile, China's class action system is a public enforcement mechanism with specific purposes, aimed at achieving the social function of deterring misconduct (Jiao, 2023). Therefore, in judicial practice, the special representative litigation procedure follows a rigorous standard for selecting cases, and the CSISC is also very cautious about whether to initiate it. In 2022, this special representative litigation system was not applied in any cases.

The regulatory compliance risks faced by independent directors have significantly decreased compared to 2021. The *Provisions* clearly stipulate the grounds for exemption from liability for independent directors. The special representative litigation procedure was not activated in securities civil dispute cases in 2022. Independent directors only need to pay fines for their dereliction of duty in accordance with the standards of the new *Securities Law* and do not need to bear joint and several liability for investor losses.

3. Literature review and hypothesis development

3.1. Impact of state ownership on the job-fulfillment risks of independent directors

SOEs are important material and political foundations of China's socialist economy, playing "stabilizer" and "anchor" roles and facilitating the sustained and steady operations of the national economy. Guided by regulations such as the *Comprehensive Risk Management Guideline for Central Enterprises*, the *Compliance Management Methods for Central Enterprises*, the *Opinions on Strengthening the Debt Risk Management and Control of Local State-Owned Enterprises* and the *Implementation Opinions on Strengthening the Construction and Supervision of Internal Control System of Central Enterprises*, SOEs have established and improved their risk control systems, risk prevention capabilities and internal governance. Specifically, SOEs have the governance mechanisms outlined in the paragraphs below.

First, the *ex-ante* discussion procedure issued by the Party Committee ensures appropriate political decision-making. In June 2015, the Central Committee of the Communist Party of China issued the *Regulations on the Work of Party Organizations of the Communist Party of China*, establishing an *ex-ante* discussion

mechanism for "Three Key Decisions and One Significant Matter" for central SOEs.[5] In October 2016, the Central Committee issued the *Notice on Printing and Distributing the Key Tasks for Implementing the National Conference on Party Building Work in State-Owned Enterprises*, extending the *ex-ante* discussion mechanism to local SOEs. This mechanism embeds the party organization into the corporate governance structure of SOEs, requiring proposals to be discussed and approved by the Party Committee before submission to the board of directors. It strengthens the party organization's supervisory role and optimizes the decision-making process and outcomes for major issues in SOEs. By "guiding the direction, managing the overall situation, and ensuring implementation,"[6] the *ex-ante* discussion procedure aims to prevent major decision-making mistakes and ensure that SOEs follow the correct path of development. The party organization's participation in corporate governance improves SOEs' governance and economic performance (Xie et al., 2022).

Second, governments provide implicit guarantees and political resources to SOEs. The majority of SOEs' controlling shareholders are local governments, the State-owned Assets Supervision and Administration Commission of the State Council (SASAC) and other government agencies. Due to the "paternalism" of the socialist government (Kornai, 1986), government and state-owned banks are more willing to provide support and preferential policies to SOEs, reducing their business risks. Furthermore, the government's invisible guarantee behind SOEs can alleviate creditors' concerns about default risk (Brandt and Li, 2003). Both aspects make it easier for SOEs to obtain credit from banks (Khwaja and Mian, 2005), with lower collateral requirements (Charumilind et al., 2006) and longer loan terms (Lin et al., 2020). Therefore, SOEs enjoy an unparalleled advantage over non-SOEs in accessing bank credit. When faced with crises, SOEs can leverage their resources to minimize the negative impacts (Dai et al., 2014).

In summary, the *ex-ante* procedure in SOEs serves to avoid risks through early warnings, ensuring the correctness of the company's direction of development. Governments and banks offer preferential support to SOEs, insulating capital shortfall risks. During major crises, SOEs can leverage their political connections to diminish adverse effects. For these reasons, the overall governance risks and job-fulfillment risks are lower for independent directors in SOEs than for those in non-SOEs.

3.2. Purchase of D&O insurance under enhanced regulatory compliance risk

D&O insurance serves as a job security tool, aiming to safeguard top management from personal liability for economic losses due to dereliction of duty (including negligent or careless actions leading to false records, misleading statements and significant omissions, but excluding intentional acts or non-professional conduct). After firms purchase D&O insurance, any incurred costs and compensation losses are borne by the insurance company, separating litigation compensation from directors' personal property. Research proves that the purchase of D&O insurance can enhance the risk-bearing capacity of independent directors, reduce their risks in performing duties, contribute to their retention and improve their performance (Core, 1997; Boyer and Tennyson, 2015; Li et al., 2022a, 2022b).

The issuance of the new *Securities Law* significantly increases the regulatory compliance risk for independent directors. To alleviate the pressure faced by independent directors in performing their duties, listed firms may purchase D&O insurance, transferring the risk of personal property loss from independent directors to insurance companies and providing safeguards for their job-fulfillment duties. The *Listed Company D&O Insurance Market Report (2023)* shows that the purchase of D&O insurance in China's A-share market has been on an upward trend year by year since 2019. However, there may be differences in D&O insurance purchases between SOEs and non-SOEs.

The political nature of SOEs requires them to be highly responsive to national policies. With changes in the external regulatory environment in recent years, the regulatory compliance costs for independent directors

[5] Major issues, important appointments and removals, major projects and the use of large amounts of money must be addressed through collective discussion.

[6] Article 33 of the Constitution of the Communist Party of China (2017) stipulates that the party committees (party organizations) of state-owned enterprises shall play a leading role, guide the direction, manage the overall situation, ensure implementation, and discuss and decide on major matters of the enterprise in accordance with the regulations. Therefore, "guiding the direction, managing the overall situation, and ensuring implementation" becomes a summary of the primary roles of party organizations in SOEs.

have increased, and the state has placed greater emphasis on the protection of independent directors. In 2019, the SASAC issued the *Work Plan for Strengthening the Support and Service for the Performance of Duties by External Directors of Central Enterprises*, which requires the provision of necessary support and guarantees for external directors to promote the standardized operation of SOEs and to enhance the corporate governance system. On 4 August 2023, the CSRC issued the *Administrative Measures for Independent Directors of Listed Companies*, explicitly stating that listed companies can purchase D&O insurance for independent directors to provide them with job-fulfillment security. SOEs are naturally expected to be the first to cater to the policy and purchase D&O insurance.

Second, SOE independent directors' salaries are significantly lower than those of non-SOE independent directors. From 2016 to 2022, the average annual salary of SOE independent directors was 75,300 yuan, while that of non-SOE independent directors was 110,800 yuan.[7] Under the "salary cap" policy, SOEs are more inclined to provide compensation to directors through the purchase of D&O insurance, thereby alleviating the insufficient salary incentive problem for independent directors and retaining outstanding management talent (Zhang, 2021).

Finally, the core goal of SOE reform is to enhance the modern corporate governance structure and foster standardized operations. Purchasing D&O insurance mitigates independent directors' compliance risks and protects their personal property, thereby bolstering their enthusiasm to fulfill their duties. At the same time, by introducing active external supervisors, D&O insurance helps improve corporate governance and promote the high-quality development of SOEs.

Therefore, under the multiple goals of actively responding to national policy calls, strengthening the standardized operation of the board and providing support for independent directors, SOEs are more inclined to purchase D&O insurance.

The revised *Securities Law* also has a significant impact on the decision-making behavior of non-SOEs due to its anchoring effects. The anchoring effect, first proposed by Tversky and Kahneman (1974), refers to the tendency of individuals to adjust their estimates of events in uncertain environments based on the initial data. The initial data used in the decision-making process are referred to as the "anchor value" and include intrinsic anchors (i.e., anchors generated by one's own past decisions) and extrinsic anchors (i.e., anchors provided by other decision-makers; Epley and Gilovich, 2001). Initial anchors have a significant impact on the business decisions of individuals and firms, as evidenced by auditing judgments (Kinney and Uecker, 1982; Biggs and Wild, 1985), real estate pricing (Northcraft and Neale, 1987), stock market trading (Andersen, 2007) and corporate mergers and acquisitions (Malhotra et al., 2015).

The external regulatory environment faced by firms and independent directors has changed since the revision of the *Securities Law*. In an uncertain environment, firms' decision-making will adjust according to their intrinsic initial anchors. In this study, the initial anchor value corresponds to the annual salaries paid to independent directors by listed companies. Specifically, non-SOEs spend an average of 412,730 yuan annually on independent directors' salaries.[8] Faced with stricter judicial penalties, strengthened enforcement and special representative litigation following the revision of the *Securities Law*, non-SOEs have two choices, using their previous annual expenditure on independent directors' salaries as an anchor. The first choice is to purchase D&O insurance. The average premium for a firm to purchase D&O insurance was 460,000 yuan in 2022,[9] with the premium increasing year by year. This amount is twice the initial anchor value. The second choice is to increase the salaries of independent directors. A small increase in salary can serve as a risk compensation mechanism, and the cost will be far less than that of purchasing D&O insurance.

Given that non-SOEs have fewer political goals and are less directly affected by calls of national policy, they place greater emphasis on the economic interests of business decisions. Non-SOEs are more likely to increase the salaries of independent directors than to purchase D&O insurance. Based on the above analysis, we propose the following hypothesis:

[7] Based on the data collected in this study.

[8] It is calculated based on descriptive statistics, with an average of 3.725 independent directors on private enterprise boards (which have an average size of 9.478 and a proportion of independent directors of 0.393) and an average annual salary of 110,800 yuan for independent directors in private enterprises.

[9] It is calculated based on data from publicly listed companies that purchased D&O insurance in 2022.

H1a. SOEs are more likely than non-SOEs to purchase D&O insurance under the new *Securities Law*.

The regulatory compliance risk varies by stage around the issuance of the new *Securities Law*. In the legislative stage, the intent to increase the severity of penalties is signaled to relevant responsible parties, including independent directors. In the enforcement stage, rulings on representative cases serve as references for independent directors, allowing them to gauge liabilities, administrative penalties and litigation compensation. The adjustment stage specifies the specific grounds for exemption from liability for independent directors. Due to stronger risk prevention awareness and higher sensitivity to national policies, SOEs are more likely to purchase D&O insurance starting from the legislative stage of the new *Securities Law*. This phenomenon persists in the three stages around the new *Securities Law*, providing safeguards for independent directors and promoting the standardized operation of the board. Based on the above analysis, we propose the following hypothesis:

H1b. SOEs are more likely than non-SOEs to purchase D&O insurance during all three stages around the issuance of the new *Securities Law*.

3.3. Impacts of regulatory compliance risk and the governance premium of SOEs on independent directors' salaries

Salary, the primary incentive for independent directors (Yermack, 2004), is a crucial factor affecting their fulfillment performance (Perry, 2000). The literature suggests that increasing independent directors' salaries can enhance their supervisory effectiveness and improve corporate governance (Adams and Ferreira, 2008). The revision of the *Securities Law* in 2019 reflects an increase in penalty standards, and the Kangmei Pharmaceutical lawsuit reinforces litigation compensation. Before the revision of the *Securities Law*, independent directors' salaries were insufficient to motivate them to devote substantial time and effort to executing their duties and assuming potential risks (Salmon, 1993; Pound, 1995). Therefore, listed companies dynamically adjust salaries in response to changes in the external regulatory environment (Zhu and Fang, 2021; Donelson et al., 2022) to compensate for increased regulatory compliance risk.

The governance risk in SOEs is generally lower. In response to the increased regulatory compliance risk for independent directors, SOEs tend to transfer risk by purchasing D&O insurance, further widening the gap in job-fulfillment risk between SOE and non-SOE independent directors.

Following the revision of the *Securities Law*, non-SOEs are likely to use the previous year's average annual salaries of independent directors (i.e., 412,730 yuan) as the initial anchor for adjusting their decisions. If they choose to purchase D&O insurance, the average annual premium expenditure becomes approximately 460,000 yuan, and this amount will increase annually, leading to subsequent annual costs that are more than double the initial anchor. However, a modest increase in salary can also compensate for the risks taken by independent directors and provide an incentive. Comparatively, the cost incurred by non-SOEs via increasing independent directors' salaries is lower. According to the cost–benefit analysis, non-SOEs are more inclined to increase independent directors' salaries.

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

H2a. Non-SOEs are more likely than SOEs to increase their independent directors' salaries to compensate for the increased regulatory compliance risk associated with the new *Securities Law*.

In the legislative stage of the *Securities Law* (2019–2020), the signal of enhanced penalties lacked relevant judicial cases as references and the enforcement strength was uncertain. Non-SOEs and their independent directors did not give it adequate attention. Since 2021, with the new *Securities Law* entering the enforcement stage, independent directors have faced the prospect of fines exceeding their entire income during their tenure. The Kangmei Pharmaceutical lawsuit has highlighted the potential for independent directors to bear joint and several liabilities amounting to tens of millions of yuan, further reinforcing the deterrent effect of strict enforcement under the new *Securities Law*. During this period, perceiving the surge in regulatory compliance risk, non-SOEs subsequently increased salaries to offset the risks associated with independent directors' duty fulfillment. Based on the above analysis, we propose the following hypothesis:

H2b. The higher likelihood of non-SOEs than SOEs to increase their independent directors' salaries is more evident in the enforcement and adjustment stages of the new *Securities Law*.

3.4. Impacts of regulatory compliance risk and the governance premium of SOEs on the abnormal resignation of independent directors

Non-SOEs may increase the salaries of their independent directors in an attempt to strike a balance between job-fulfillment risk and reward. However, if the salary increases do not sufficiently compensate for the increased risk, independent directors may consider resignation. Independent directors' decision to remain in their position is contingent upon the total of the monetary costs, opportunity costs and risk costs associated with serving as an independent director, set against the salary they receive (Tan et al., 2006). According to prospect theory, individuals are more attuned to losses than gains in uncertain environments (Kahneman and Tversky, 1979). Therefore, following an increase in job-fulfillment risks, independent directors are more likely to resign prematurely.

Furthermore, independent directors typically hold a high social status and reputation in their primary occupations and obtain a respectable income. Serving as an independent director is typically a part-time job that complements their primary occupation. The salary from this role is not a primary source of income for them and thus is not a dependency (Tan et al., 2003). Independent directors are more concerned with their potential reputation loss and regulatory compliance risks than with the fixed salary.

Following the 2019 revision of the *Securities Law*, the regulatory compliance risk faced by independent directors increased. In the absence of D&O insurance to provide job security, the imbalance between risk and reward motivated independent directors to favor immediate resignation. Consequently, we propose the following hypothesis:

H3a. The abnormal resignation of independent directors in non-SOEs, rather than SOEs, increases significantly following the 2019 revision of the *Securities Law*.

The period from 2019 to 2020 was the legislative stage of the new *Securities Law*, signaling a shift toward stricter penalties. Non-SOE independent directors tried to assess their risks compared with the previous *Securities Law*. It was not until 2021, with the implementation of the first cases under the new *Securities Law* and the Kangmei Pharmaceutical lawsuit, that independent directors fully grasped the severity of the penalties and the magnitude of the litigation compensation pressure. In the case of Kangmei Pharmaceutical, for instance, an independent director earning only 80,000 yuan annually was compelled to assume compensation liabilities of 123 million or 246 million yuan, resulting in a substantial imbalance between risk and reward. In 2022, the Supreme People's Court issued the *Provisions*, delineating specific defenses for independent directors; no new class action cases were lodged, alleviating the regulatory compliance risk faced by independent directors compared with that in 2021.

Under the changing regulatory environment, the governance risk of non-SOEs was greater than that of SOEs, which was compounded by insufficient D&O insurance, leading to a sharp increase in regulatory compliance risk for independent directors in 2021. The shifts in the external regulatory environment and regulatory compliance risk captured the attention of independent directors (Donelson et al., 2022). During this period, the perceived risks borne by independent directors in non-SOEs far exceeded the rewards received, prompting them to be more inclined to resign promptly to mitigate risks. Based on this analysis, we propose the following hypothesis:

H3b. The higher resignation rate of non-SOE independent directors compared with SOE independent directors is more evident in the enforcement stage of the new *Securities Law*.

The research framework summarizing the above analysis is shown in Fig. 1.

4. Research design

4.1. Research sample

China's A-share listed companies from 2016 to 2022 serve as the study sample. Data on independent director resignations from 2016 to 2022 are initially manually extracted from the Wind database by reviewing announcements related to such resignations. Specifically, we utilize 12 keyword combinations, including "independent director," "independent non-executive director," "external director," "resignation," "step down," "departure" and "leave office," to search for the relevant announcements. Referring to the classification of

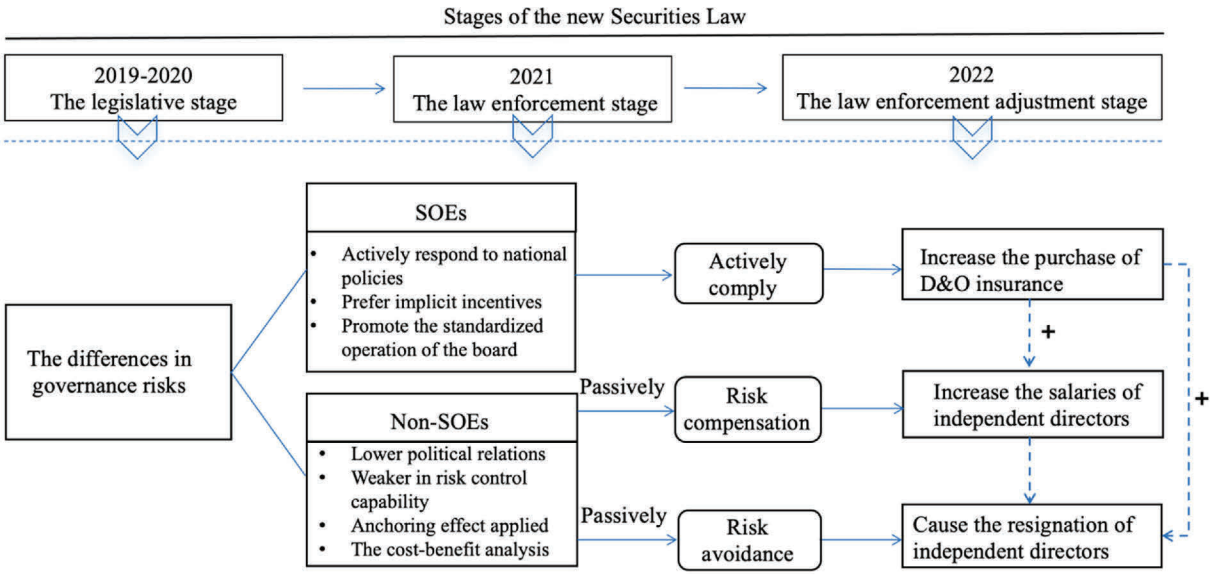

Fig. 1. Research framework.

reasons for independent director resignation by Dai et al. (2014) and Zhang and Zeng (2010), we attribute independent director resignations to either normal or abnormal reasons, as shown in Table 3.[10] This initial search yields 3,526 resignations,[11] with 2,679 attributed to abnormal reasons and 847 to normal reasons. For the sample of independent directors who resigned for abnormal reasons, we exclude firms in the financial sector, firms with "special treatment" status, firms with changes in ownership nature and firms with missing data. All of the continuous variables and the core variable, *Resign_num*, are winsorized at the 1 % and 99 % percentiles to mitigate the potential problem of outliers.[12] Including companies that did not have any independent director resignations between 2016 and 2022, the final dataset results in 20,216 firm-year observations. To test the independent directors' salaries, observations with a salary value of 0 are excluded, yielding a dataset of 20,080 firm-year observations.

4.2. Empirical design

To test the impact of regulatory compliance risks in the legislative, law enforcement and law enforcement adjustment stages of the new *Securities Law* on SOEs, non-SOEs and their independent directors, we refer to the research design of Lemmon and Roberts (2010) and construct the following model:

$$Outcomes = \alpha 0 + \alpha 1 Treat * Post1 + \alpha 2 Treat * Post2 + \alpha 3 Treat * Post3 + \alpha 4 Controls + Year\ Fixed\ Effects + Firm\ Fixed\ Effects + \varepsilon \quad (1)$$

The dependent variables (*Outcomes*) are *Insurance* (whether the company purchases D&O insurance in the current year), *Salary* (independent directors' salaries) and *Resign_num* (the number of abnormal independent director resignations in the current year), alternatively.

[10] A normal resignation is a passive action taken by listed companies and independent directors to meet regulatory requirements, such as resignation requests from independent directors after their term expires or they reach retirement age, or at the request of authorities such as the Central Commission for Discipline Inspection, the Ministry of Finance and the Ministry of Education. Resignations for reasons other than these are considered abnormal.

[11] Without any data filtering, these are the raw data obtained from keyword searches in the Wind database.

[12] Before winsorization, the maximum of *Resign_num* is 6, indicating a significant range of values. To avoid the influence of outliers, the variable is also winsorized at the top and bottom 1%.

Table 3
Independent director resignation reasons and classification.

Classification	Reasons
Resignation for normal reasons	① Reaching the maximum tenure requirement According to the announcement by CSRC ([2022]14), independent directors cannot serve consecutive terms exceeding six years. ② Independent director at retirement age ③ According to relevant regulations, concurrent positions are not allowed. Such as the *Notice on the Clean-up and Standardization of Part-time (Employment) Positions Held by Party and Government Leaders in Enterprises*, the *Opinions on Further Standardizing the Part-time (Employment) Positions of Party and Government Leaders in Enterprises*, and the regulations of schools, accounting firms, law firms, etc.
Resignation for abnormal reasons	④ Personal reasons ⑤ Age, physical, or health reasons ⑥ Work-related reasons ⑦ Changes in the company's ownership structure, actual controllers, management; adjustments to the size of the board of directors, etc. ⑧ Independent directors are unable to timely access the company's financial information; there are suspicions of fraud within the company; the company is engaged in illegal or non-compliant activities. ⑨ Not mentioned

On 20 April 2019, the third draft of the revised *Securities Law* was submitted for review at the 10th Session of the 13th National People's Congress Standing Committee. According to China's legislative process, amendments to laws generally go through three deliberations; after the third deliberation is passed, the new law is enacted within the same year. As expected, after the third deliberation of the *Securities Law*, the new *Securities Law* was revised and passed on 28 December 2019, officially taking effect on 1 March 2020. In 2021, the first few cases applying the new *Securities Law* were adjudicated, and on 12 November of the same year, China's first class action was pronounced. In view of this, we define the period from 2019 to 2022 as the stage after the revision of the *Securities Law* (*Post*), with a value of 1 during this period. Furthermore, 2019 to 2020 is defined as the legislative stage (*Post1*), 2021 as the law enforcement stage (*Post2*) and 2022 as the law enforcement adjustment stage (*Post3*).

SOEs enjoy inherent political connections with the government, which afford them preferential treatment and support in terms of government policies and bank credit. In times of severe crisis, local government officials are often more inclined and motivated to assist SOEs in resolving these crises and eliminate negative impacts, due to the significant tax contributions made by these enterprises and the impact on their political promotion (Dai et al., 2014). However, the private nature of non-SOEs and their weaker government relationships place them at a disadvantage in terms of policy support and crisis resolution. Therefore, the independent directors of SOEs have lower job-fulfillment risks than those of non-SOEs. As such, the *Treat* variable is identified according to ownership type in 2019, with a value of 1 for non-SOEs and 0 for SOEs.

Three groups of control variables are included: corporate financial variables, corporate governance variables and independent directors' personal characteristic variables. The corporate financial variables include company size (*Size*), profitability (*Roa*), leverage (*Lev*) and growth (*Growth*). The corporate governance variables include firm age (*Fage*), whether the chairman and CEO positions are filled by the same person (*Dual*), board size (*Board*), the proportion of independent directors (*Outdir*), ownership balance (*Eb*) and ownership concentration (*Top1*). The variables on independent directors' personal characteristics include age (*Age*) and gender (*Sex*). The regression model also controls for fixed effects at the firm level (*Firm*) and at the year level (*Year*). The variable definitions and measurement methods are presented in Table 4.

5. Empirical results

5.1. Descriptive statistics

The descriptive statistics of the main variables are reported in Table 5. The mean value of D&O insurance (*Insurance*) is 0.108, indicating that the proportion of D&O insurance in the Chinese capital market is cur-

Table 4
Definitions of variables.

Variable	Name	Definition
D&O insurance	*Insurance*	A dummy variable that equals 1 if the firm purchases D&O insurance in the current year, and 0 otherwise
Independent directors' salaries	*Salary*	Pay = Ln (the salaries received by independent directors in the current year)
Number of abnormal resignations	*Resign_num*	The number of independent directors resigned for abnormal reasons in the current year
Ownership types of enterprises	*Treat*	A dummy variable based on the ownership type in 2019 takes a value of 1 if the firm is not controlled by the state, and 0 otherwise.
Before and after the revision of the new *Securities Law*	*Post*	A dummy variable referring to the entire stage after the revision of the new *Securities Law*, with a value of 1 in the years 2019–2022, and 0 otherwise
The legislative stage of the new *Securities Law*	*Post1*	A dummy variable that takes a value of 1 when the new *Securities Law* is in its legislative stage between 2019 and 2020, and 0 otherwise
The law enforcement stage of the new *Securities Law*	*Post2*	A dummy variable that takes a value of 1 when the new *Securities Law* is in its law enforcement stage in 2021, and 0 otherwise
The law enforcement adjustment stage of the new *Securities Law*	*Post3*	A dummy variable that takes a value of 1 when the new *Securities Law* is in its law enforcement adjustment stage in 2022, and 0 otherwise
Firm size	*Size*	The natural logarithm of the total assets
Profitability	*Roa*	The ratio of net profit to average assets
Leverage ratio	*Lev*	The ratio of total liabilities to total assets
Growth rate	*Growth*	Growth rate of the firm's operating revenue
Firm age	*Fage*	Ln (1 + the number of years since the firm's establishment)
Chair-CEO duality	*Dual*	A dummy variable that takes 1 when the chairman also serves as the CEO, and 0 otherwise
Proportion of independent directors	*Outdir*	Number of independent directors to the total number of board members
Board size	*Board*	The total number of directors on the board
Largest shareholder	*Top1*	The shareholding ratio of the largest shareholder
Equity balance	*Eb*	The shareholding ratio of the second to tenth largest shareholders to the shareholding ratio of the largest shareholder in listed companies
Age of independent directors	*Age*	Ln (the average age of independent directors)
Gender of independent directors	*Sex*	The average gender of independent directors, with a value of 1 assigned to male directors and 0 to female directors
Firm fixed effects	*Firm*	Control for firm fixed effects
Time fixed effects	*Year*	Control for year fixed effects

rently low and still in the early stage of development, with a significant gap compared with a mature capital market such as the U.S. The natural logarithm of independent director salary (*Salary*) has a mean of 11.106, with a minimum of 9.980 and a maximum of 12.301, suggesting substantial variability in salaries among independent directors. The mean number of abnormal resignations of independent directors (*Resign_num*) is 0.073, with a minimum of 0 and a maximum of 1. The average board size (*Board*) is 10.013, with a maximum of 19 and a minimum of 5, indicating significant variation in the number of board members across companies. The average proportion of independent directors (*Outdir*) is 0.384, which is slightly higher than the one-third threshold required by the *Regulations on Independent Directors of Listed Companies*. This finding is consistent with the results reported by Jiang and Kim (2015). The descriptive statistics of the other variables are similar to those in previous studies.

The number and proportion of SOEs and non-SOEs that purchase D&O insurance during the sample period are reported in Table 6. The results indicate that both SOEs and non-SOEs have shown an upward trend in purchasing D&O insurance year by year, with a substantial increase after the 2019 revision of the *Securities Law*. However, the proportion of SOEs purchasing D&O insurance has consistently been higher than that of non-SOEs, which partially supports our predictions regarding D&O insurance.

5.2. Regression analysis

The baseline regression results are reported in Table 7. Columns (1), (3) and (5) report the results for independent director liability insurance, salary and the number of abnormal resignations as the dependent vari-

Table 5
Descriptive statistics results.

Varibles	Obs	Min	P25	P50	P75	Max	SD	Mean
Insurance	20,216	0.000	0.000	0.000	0.000	1.000	0.311	0.108
Salary	20,080	9.980	10.820	11.056	11.408	12.301	0.451	11.106
Resign_num	20,216	0.000	0.000	0.000	0.000	1.000	0.259	0.073
Treat	20,216	0.000	0.000	1.000	1.000	1.000	0.465	0.685
Post	20,216	0.000	0.000	0.000	1.000	1.000	0.498	0.451
Post1	20,216	0.000	0.000	0.000	1.000	1.000	0.460	0.303
Post2	20,216	0.000	0.000	0.000	0.000	1.000	0.357	0.150
Post3	20,216	0.000	0.000	0.000	0.000	1.000	0.356	0.149
*Treat*Post*	20,216	0.000	0.000	0.000	1.000	1.000	0.465	0.316
*Treat*Post1*	20,216	0.000	0.000	0.000	0.000	1.000	0.409	0.212
*Treat*Post2*	20,216	0.000	0.000	0.000	0.000	1.000	0.307	0.105
*Treat*Post3*	20,216	0.000	0.000	0.000	0.000	1.000	0.306	0.104
Top1	20,216	8.920	22.685	31.570	43.166	72.720	14.410	33.774
Eb	20,216	0.060	0.388	0.760	1.323	3.934	0.786	0.971
Dual	20,216	0.000	0.000	0.000	1.000	1.000	0.463	0.312
Size	20,216	19.790	21.410	22.170	23.100	26.210	1.301	22.334
Lev	20,216	0.064	0.261	0.410	0.559	0.971	0.201	0.420
Fage	20,216	2.197	2.833	3.045	3.219	3.555	0.284	3.009
Board	20,216	5.000	8.500	10.000	11.000	19.000	2.615	10.013
Outdir	20,216	0.250	0.333	0.375	0.429	0.600	0.075	0.384
Roa	20,216	−0.347	0.014	0.040	0.075	0.231	0.074	0.040
Growth	20,216	−0.648	−0.019	0.109	0.268	2.795	0.420	0.172
Sex	20,216	0.250	0.667	0.800	1.000	1.000	0.207	0.807
Age	20,216	3.761	3.932	3.994	4.055	4.202	0.092	3.991

able, respectively, with *Post* representing stages following the revision of the *Securities Law*. Columns (2), (4) and (6) present the regression results for the same variables in the legislative, law enforcement and law enforcement adjustment stages after the revision of the *Securities Law*, respectively.

As shown in Table 7, the coefficient of *Treat*Post* in column (1) for the independent director liability insurance regression is negative and significant (–0.048, at less than 1 % significance level), indicating that SOEs are more likely to purchase D&O insurance than non-SOEs after the revision of the *Securities Law*. Furthermore, the regression coefficients of *Treat*Post1*, *Treat*Post2* and *Treat*Post3* in column (2) are all negative and significant. These results suggest that SOEs have a strong sense of risk prevention and control. They begin to increase their purchase of D&O insurance in the legislative stage of the new *Securities Law*, closely following the guidance of relevant documents and providing job-fulfillment security for independent directors. Both H1a and H1b are thus supported. Under the premise that SOEs have lower governance risks, the purchase of D&O insurance exacerbates the imbalance in the risks faced by independent directors between SOEs and non-SOEs.

In column (3), the coefficient of *Treat*Post* for the independent director salary regression is positive and significant (0.019, at less than 5 % significance level), indicating that non-SOEs are more likely to increase independent directors' salaries than SOEs following the revision of the *Securities Law*. In column (4), the regression coefficient of *Treat*Post1* is not significant, whereas the regression coefficients of *Treat*Post2* and *Treat*Post3* are positive and significant, suggesting that non-SOEs begin to increase the salaries of independent directors in the law enforcement stage of the new *Securities Law* in 2021 to compensate for the regulatory compliance risks faced by independent directors. Both H2a and H2b are thus supported.

In column (5), the coefficient of *Treat*Post* for the number of abnormal independent director resignations regression is positive and significant (0.016, at less than 5 % significance level), indicating that non-SOEs see an increase in the number of abnormal resignations of independent directors compared with SOEs following the revision of the *Securities Law*. In column (6), the coefficients of *Treat*Post1* and *Treat*Post3* are not significant, whereas the coefficient of *Treat*Post2* is positive and significant, suggesting that only in the law enforcement stage of 2021, non-SOEs' independent directors are more likely to resign to avoid regulatory compliance

Table 6
The number and proportion of SOEs and non-SOEs purchasing D&O insurance.

Year	State-owned enterprises			Non-state-owned enterprises		
	No. of firms purchasing D&O insurance	Total number of firms	Proportion	No. of firms purchasing D&O insurance	Total number of firms	Proportion
2016	92	883	10.42 %	35	1490	2.35 %
2017	107	906	11.81 %	47	1879	2.50 %
2018	114	911	12.51 %	67	1963	3.41 %
2019	133	928	14.33 %	82	2135	3.84 %
2020	186	925	20.11 %	160	2145	7.46 %
2021	247	913	27.05 %	251	2126	11.81 %
2022	311	901	34.52 %	358	2111	16.96 %

Table 7
The effects of increased regulatory compliance risk of the new Securities Law.

VARIABLES	(1) *Insurance*	(2) *Insurance*	(3) *Salary*	(4) *Salary*	(5) *Resign_num*	(6) *Resign_num*
*Treat*Post*	−0.048***		0.019**		0.016**	
	(−4.374)		(1.983)		(1.994)	
*Treat*Post1*		−0.022***		0.014		0.009
		(−3.012)		(1.548)		(0.978)
*Treat*Post2*		−0.056***		0.023*		0.027**
		(−4.115)		(1.917)		(2.224)
*Treat*Post3*		−0.078***		0.027*		0.015
		(−4.778)		(1.919)		(1.298)
Top1	−0.000	−0.000	0.002***	0.002***	0.001	0.001
	(−0.258)	(−0.460)	(2.610)	(2.664)	(0.844)	(0.893)
Eb	−0.012	−0.013	0.016	0.016	0.003	0.003
	(−1.118)	(−1.230)	(1.545)	(1.583)	(0.320)	(0.341)
Dual	0.001	0.000	0.002	0.002	−0.013*	−0.013*
	(0.083)	(0.019)	(0.259)	(0.288)	(−1.777)	(−1.760)
Size	0.038***	0.039***	0.084***	0.084***	−0.010	−0.010
	(3.870)	(3.901)	(9.397)	(9.392)	(−1.329)	(−1.330)
Lev	−0.035	−0.033	−0.102***	−0.104***	0.065**	0.065**
	(−1.145)	(−1.061)	(−3.656)	(−3.699)	(2.381)	(2.348)
Fage	−0.095	−0.074	−0.049	−0.056	0.013	0.009
	(−1.068)	(−0.825)	(−0.618)	(−0.702)	(0.186)	(0.129)
Board	0.000	0.000	−0.077***	−0.077***	0.009***	0.009***
	(0.463)	(0.435)	(−71.077)	(−71.096)	(8.117)	(8.104)
Outdir	−0.036	−0.033	−2.290***	−2.290***	0.763***	0.764***
	(−1.175)	(−1.104)	(−72.311)	(−72.301)	(20.351)	(20.354)
Roa	−0.050	−0.053	−0.055	−0.054	−0.047	−0.046
	(−1.410)	(−1.501)	(−1.482)	(−1.458)	(−0.983)	(−0.973)
Growth	−0.013***	−0.013***	−0.021***	−0.021***	−0.004	−0.004
	(−3.011)	(−3.082)	(−4.052)	(−4.019)	(−0.722)	(−0.707)
Sex	0.020	0.020	0.024	0.024	0.014	0.014
	(1.050)	(1.054)	(1.319)	(1.320)	(0.948)	(0.945)
Age	−0.039	−0.038	0.015	0.015	−0.209***	−0.209***
	(−0.832)	(−0.808)	(0.330)	(0.333)	(−5.354)	(−5.354)
_cons	−0.344	−0.411	10.769***	10.788***	0.673**	0.683**
	(−0.924)	(−1.098)	(32.467)	(32.391)	(2.327)	(2.354)
Firm	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	20,216	20,216	20,080	20,080	20,216	20,216
Adj.R^2	0.120	0.121	0.602	0.602	0.044	0.044

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

risks. Both H3a and H3b are thus supported. Overall, the empirical results are consistent with the assumptions of this study.

5.3. Robustness tests

5.3.1. Parallel trend test

The prerequisite for using the DID method is the satisfaction of the parallel trend test. We use 2018 as the base year to construct period dummy variables and conduct the parallel trend test. The results are illustrated in Fig. 2 for independent director liability insurance, independent director salary and the number of independent directors who resigned for abnormal reasons, respectively. As shown in the figure, during the period before the revision of the *Securities Law* (2016–2018), the treatment group and the control group maintain a similar trend of change, but differences arise after 2019, indicating that the parallel trend test has been passed.

5.3.2. Placebo test

To exclude the influence of missing variables and unobservable factors on the conclusions, we conduct placebo tests. The samples are randomly assigned to either the treatment or control group, and the sample assignments are then used as a basis for conducting the DID regressions. We repeat this process 1,000 times to obtain 1,000 estimated coefficients and *t*-values. Their distributions are reported in Figs. 3–5. As shown, the *t*-values of the coefficients in the randomized placebo tests are mostly distributed around 0. That is, the regression coefficients are not statistically significant.

5.3.3. Utilizing annual new purchases of D&O insurance data

Once a listed firm purchases D&O insurance, it tends to continue purchasing it. The annual D&O insurance purchase data used in the previous regression is influenced by the decisions made in lagged years. In the robustness test, we use the annual new D&O insurance purchases by listed companies.[13] The results, presented in Table 8, remain consistent.

5.3.4. Excluding independent directors serving less than 1 year in their current position

Currently, databases provide data on the salaries of independent directors during their tenure. However, in practice, there may be instances where an independent director resigns early or a new director takes office during the transition, resulting in some directors having a tenure of less than a year. As the salaries of independent directors are directly proportional to their tenure, the inclusion of these samples would lower the overall average salary, potentially biasing our conclusions. To ensure the reliability of our findings, we exclude samples with independent directors who have served less than 1 year in their current position in the robustness test. The regression results are reported in Table 9.

As shown in column (1) of Table 9, the coefficient of *Treat*Post* remains positive and significant. In column (2), the coefficients of *Treat*Post1*, *Treat*Post2* and *Treat*Post3* are all positive and significant, and the significance of *Treat*Post2* and *Treat*Post3* is enhanced. The regression results are consistent with the original findings that non-SOEs attach a higher importance to salary for compensating the risks assumed by independent directors. As a result, non-SOEs begin to increase salaries in the legislative stage.

5.3.5. Alternative measure of abnormal independent director resignations

To ensure the robustness of our conclusions, we use the *Resign_ratio* (which represents the number of abnormal independent director resignations divided by the average number of board members at the beginning and end of the year) as an alternative indicator for resignations. The regression results presented in Table 10 indicate that our findings remain robust.

[13] For example, if company A announces its first purchase of D&O insurance in 2021, then the indicator for company A's annual new purchase of D&O insurance is set to 0 from 2016 to 2020 and to 1 in 2021. Subsequent years of continuous purchase are not included in the sample.

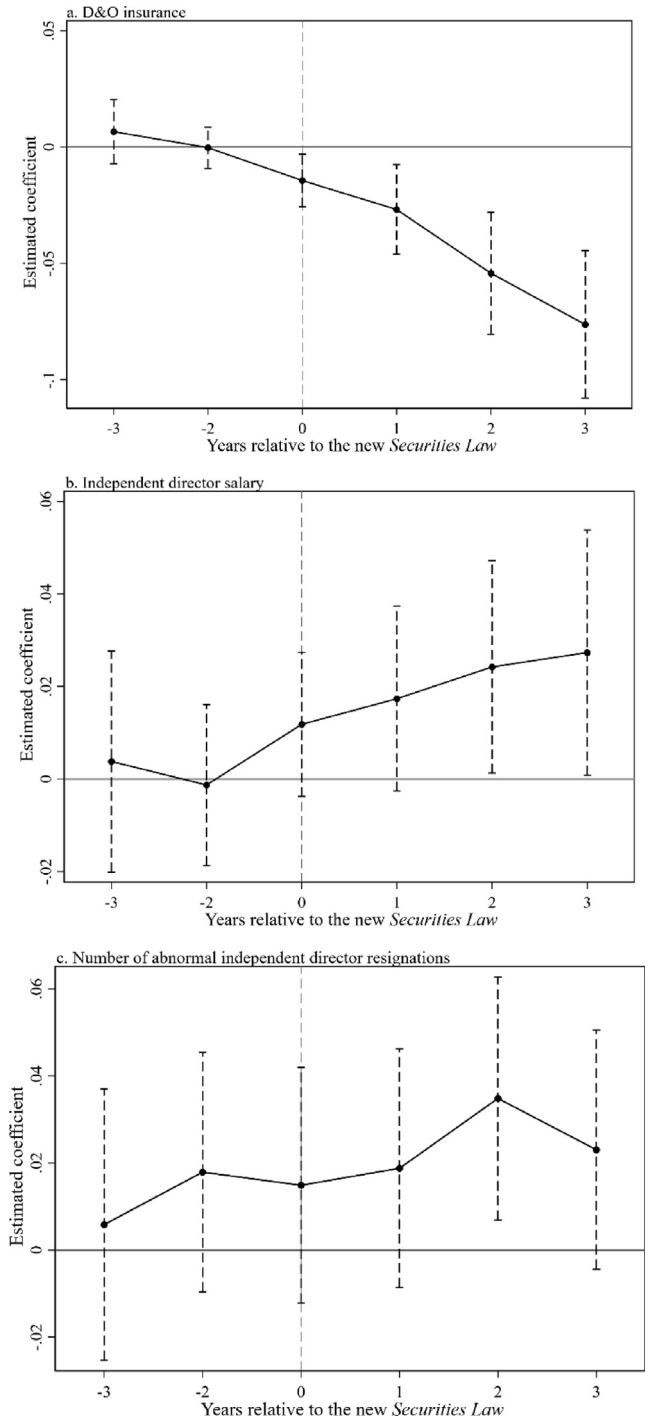

Fig. 2. Parallel trend test (Note: 95% confidence interval).

5.3.6. Propensity score matching with DID

To reduce measurement error in the model, we further apply propensity score matching (PSM), using all of the control variables as covariates for 1:2 nearest neighbor matching and excluding observations with a maximum distance exceeding 0.05. Drawing on the approach of Li and Xiao (2020), we select samples that satisfy

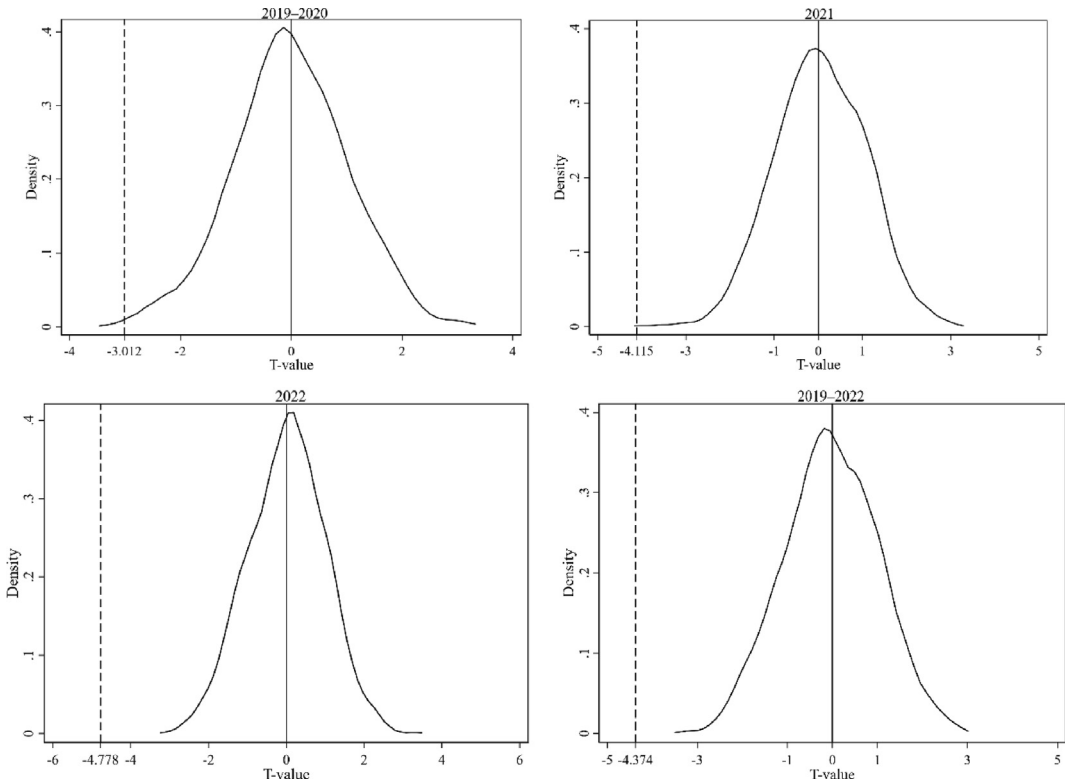

Fig. 3. Placebo tests for independent director liability insurance.

the common support assumption to substitute for the original sample in the main regression model. The regression results, shown in Table 11, remain robust.

6. Further analysis

6.1. Effects of firm-level governance risks

As discussed in previous sections, the purchase of D&O insurance, the increase in independent directors' salaries and resignation for abnormal reasons are responses to changes in regulatory compliance risks that occur with the promulgation of the new *Securities Law*. Additionally, firm-level governance risk, as an important factor affecting the regulatory compliance risks faced by independent directors, also influences the risk management behaviors of companies and independent directors.

Companies with higher governance risk are more likely to purchase D&O insurance, thereby transferring independent directors' risk of personal property loss to the insurance firms. This not only compensates directors for their risk-taking but also helps attract and retain outstanding management talent for the company (Priest, 1987). In instances where listed companies fail to offer adequate job security to independent directors and encounter risks, such as deteriorating business performance (Asthana and Balsam, 2007), financial restatements (Srinivasan, 2005; Arthaud-Day et al., 2006) and board conflicts (Hooghiemstra and van Manen, 2002), independent directors may opt to resign based on their risk assessment.

We explore the impact of company-level risk characteristics on D&O insurance, independent director salary and abnormal independent director resignations at the legislation, enforcement and enforcement adjustment stages of the new *Securities Law*. Specifically, firm-level risk indicators include the number of regulatory decision letters received from the CSRC (*Violate*), the number of regulatory inquiry letters received from the

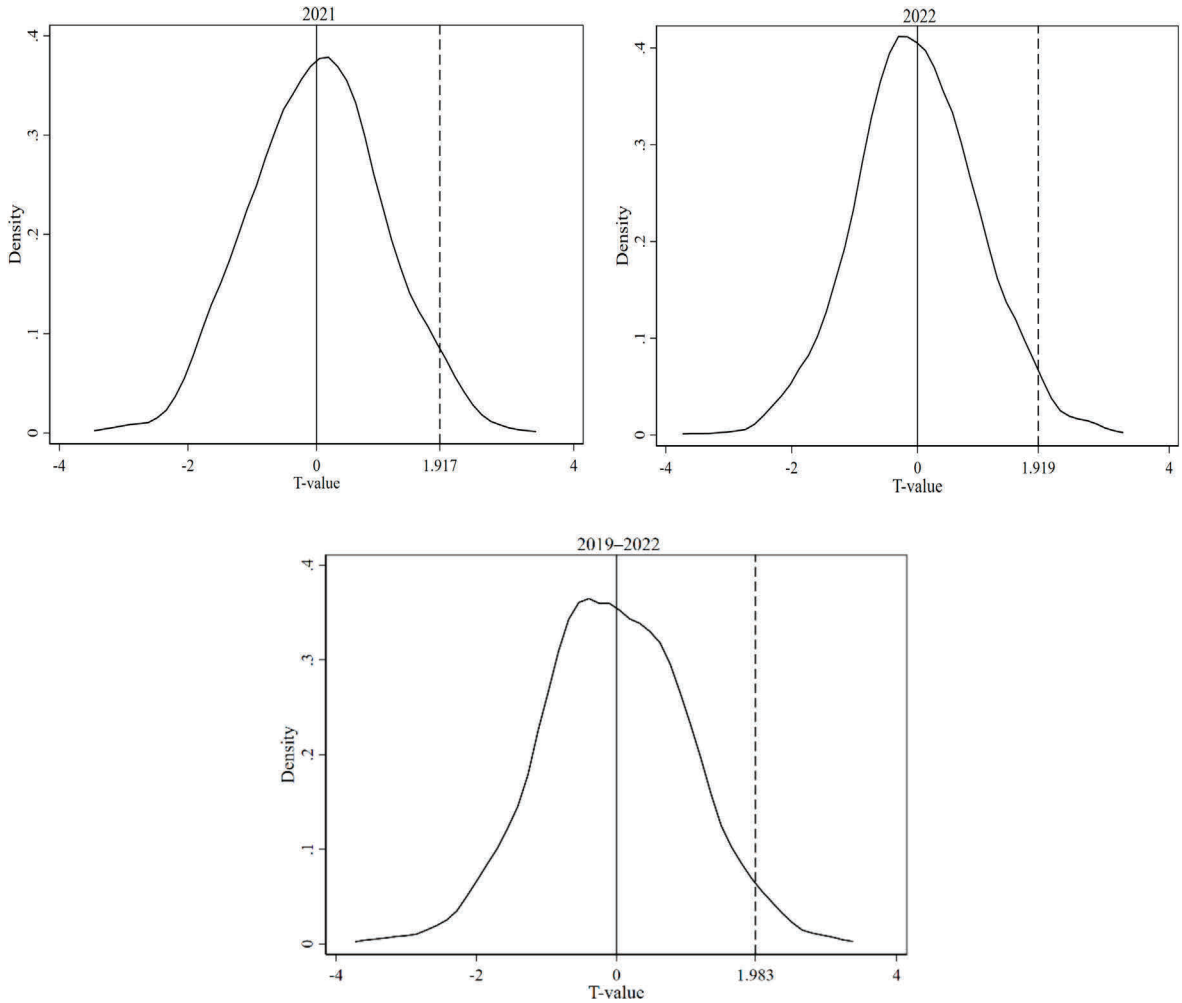

Fig. 4. Placebo tests for independent director salaries.

CSRC (*Inquiry*), the severity of audit opinions (*Audit*) and the number of financial restatements (*Restate*), with variable definitions and measurements presented in Table 12.

We introduce the following model to test the impact of firm-level and individual-level governance risk characteristics:

$$\begin{aligned} Outcomes = {} & \alpha 0 + \alpha 1 Treat * Post1 + \alpha 2 Treat * Post2 + \alpha 3 Treat * Post3 + \alpha 4 Treat * Post1 * M \\ & + \alpha 5 Treat * Post2 * M + \alpha 6 Treat * Post3 * M + \alpha 7 M + \alpha 8 Controls + Year\ Fixed\ Effects \\ & + Firm\ Fixed\ Effects + \varepsilon \end{aligned} \tag{2}$$

In this model, *M* represents the risk characteristic variables at the company or individual level, and the control variables are consistent with those in the main model. The regression results are presented in Tables 13–18.

The results in Table 13 indicate that compared with SOEs, non-SOEs with high-risk profiles are more likely to purchase D&O insurance. Furthermore, the motivations to purchase D&O insurance vary for SOEs and non-SOEs. SOEs mainly purchase liability insurance to proactively comply with relevant policy documents and achieve the goal of promoting the standardized operation of the board. Non-SOEs purchase liability insurance to reduce the job-fulfillment risks associated with independent directors. Therefore, non-SOEs are more sensitive than SOEs to firm-level risk characteristics.

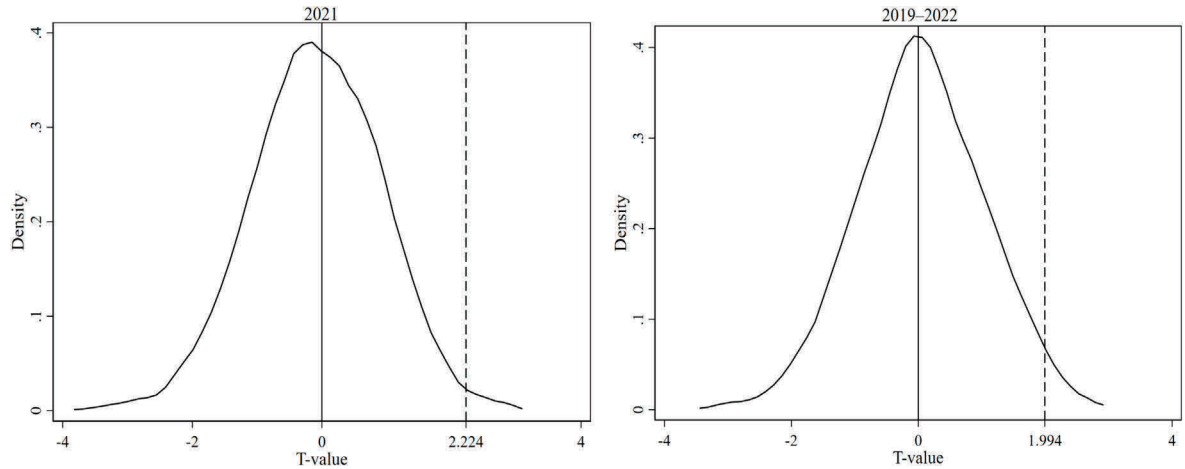

Fig. 5. Placebo tests for abnormal independent director resignations.

As shown in Table 14, non-SOE independent directors are more sensitive to corporate risk and require higher salaries than those in SOEs. As discussed in previous sections, non-SOEs face higher governance risks and have less comprehensive D&O insurance coverage. Consequently, as the regulatory compliance risks for independent directors increase, non-SOEs and their independent directors become more attuned to company-level governance risks. Independent directors in non-SOEs are more likely to request higher salaries to compensate for these risks.

The results in Table 15 reveal that in the legislative and enforcement stages of the new *Securities Law*, there is no significant difference in the effect of firm-level risk characteristics on the number of abnormal resignations of independent directors between SOEs and non-SOEs. However, in the enforcement adjustment stage, non-SOEs show a decrease in independent director resignations compared with SOEs if firms receive an inquiry letter. Overall, the firm-level governance risk plays little role in independent directors' resignation decisions.

In the enforcement stage of the new *Securities Law*, independent directors of Kangmei Pharmaceutical faced compensation obligations amounting to hundreds of millions of yuan. This dramatically disrupted the original risk–reward balance for independent directors, leading to a severe imbalance of rewards and responsibilities. Furthermore, due to their high sensitivity to negative events (Cianci and Falsetta, 2008), the strong signaling event of Kangmei Pharmaceutical likely caused independent directors to overestimate their regulatory compliance risks (Kahneman and Tversky, 1979). As a result, in 2021, many non-SOE independent directors chose to resign. Given that those independent directors had already resigned by 2022, the number of resignations of non-SOE independent directors with higher governance risks was relatively low in that year.

Overall, following the 2019 revision of the *Securities Law*, non-SOEs with higher corporate governance risks are more likely to purchase D&O insurance and increase their independent directors' salaries in response to the enhanced regulatory compliance risks. However, no significant differences are observed in the impact of corporate governance risks on the abnormal resignations of independent directors between SOEs and non-SOEs.

6.2. Effects of independent directors' individual-level characteristics

Independent directors are not homogenous. The risk-bearing capacity of independent directors depends on their individual-level characteristics, which may influence their risk response behaviors upon the revision of the *Securities Law*. We select indicators, such as independent directors' adverse opinions, whether they have directorships in other listed companies, the number of such directorships and the degree of independent directors' information advantage, to explore whether these factors affect the purchase of D&O insurance, independent directors' salaries and their resignation choices.

Table 8
Utilize the data on annual new purchases of D&O insurance.

VARIABLES	(1) *Insurance*	(2) *Insurance*
*Treat*Post*	−0.033***	
	(−4.254)	
*Treat*Post1*		−0.018***
		(−2.948)
*Treat*Post2*		−0.042***
		(−3.505)
*Treat*Post3*		−0.053***
		(−3.834)
_cons	−0.288	−0.335
	(−1.241)	(−1.442)
Controls	YES	YES
Firm	YES	YES
Year	YES	YES
N	18,590	18,590
Adj.R^2	0.059	0.059

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 9
Exclude independent directors serving less than one year in current position.

VARIABLES	(1) *Salary*	(2) *Salary*
*Treat*Post*	0.019**	
	(2.321)	
*Treat*Post1*		0.015*
		(1.873)
*Treat*Post2*		0.023**
		(2.096)
*Treat*Post3*		0.031***
		(2.592)
_cons	9.513***	9.541***
	(30.370)	(30.355)
Controls	YES	YES
Firm	YES	YES
Year	YES	YES
N	18,497	18,497
Adj.R^2	0.253	0.253

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

6.2.1. Independent directors expressing adverse opinions

In China, the selection and appointment of independent directors are largely controlled by major shareholders. When independent directors exercise their supervisory role by publicly expressing adverse opinions based on their independent and professional judgment, they may fail to be reelected in the subsequent term (Zheng et al., 2016). Furthermore, the number of directorships they can obtain in other companies will be reduced after leaving their current role (Chen et al., 2015). Considering the potential directorship reduction and loss of wealth, independent directors who express adverse opinions are under dual pressure from management and the market; not only may the current management be displeased with them, but the future market may be reluctant to appoint them. This makes independent directors more inclined to request that their companies purchase D&O insurance and for their salary to be increased as compensation for the risk they take in expressing adverse opinions.

Table 10
Alternative measure of independent director abnormal resignations.

VARIABLES	(1) *Resign_ratio*	(2) *Resign_ratio*
*Treat*Post*	0.001*	
	(1.845)	
*Treat*Post1*		0.001
		(0.820)
*Treat*Post2*		0.003**
		(2.118)
*Treat*Post3*		0.001
		(0.974)
_cons	0.075**	0.076**
	(2.392)	(2.399)
Controls	YES	YES
Firm	YES	YES
Year	YES	YES
N	20,216	20,216
Adj.R^2	0.042	0.042

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

6.2.2. Concurrent directorships in other firms and the number of such directorships

In 2001, the CSRC introduced a rule limiting independent directors to no more than five concurrent positions in listed companies, ensuring that they could dedicate sufficient time and energy to their duties. In August 2023, the CSRC further tightened this regulation, reducing the number of concurrent positions to three for independent directors in domestic listed companies.

Managerial talent is a precious resource, and the time and energy that independent directors allocate to multiple roles can compromise their performance in their primary full-time positions or other part-time engagements (Conyon and Read, 2006; Masulis and Mobbs, 2014). Excessive part-time work can undermine the supervisory function of independent directors, thereby diminishing corporate governance and business performance (Fich and Shivdasani, 2007; Jiraporn et al., 2009; Cashman et al., 2012). As a result of the *Securities Law* revision, independent directors with more positions may encounter more administrative penalties

Table 11
PSM-DID.

VARIABLES	(1) *Insurance*	(2) *Insurance*	(3) *Salary*	(4) *Salary*	(5) *Resign_mun*	(6) *Resign_mun*
*Treat*Post*	−0.046***		0.019**		0.013*	
	(−4.140)		(2.002)		(1.650)	
*Treat*Post1*		−0.023***		0.014		0.005
		(−3.037)		(1.600)		(0.550)
*Treat*Post2*		−0.051***		0.022*		0.024**
		(−3.752)		(1.800)		(1.971)
*Treat*Post3*		−0.074***		0.025*		0.011
		(−4.530)		(1.798)		(0.944)
_cons	−0.492	−0.553	10.899***	10.902***	0.585*	0.593*
	(−1.235)	(−1.385)	(30.705)	(30.614)	(1.914)	(1.932)
Controls	YES	YES	YES	YES	YES	YES
Firm	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	19,201	19,201	19,056	19,056	19,201	19,201
Adj.R^2	0.122	0.123	0.603	0.603	0.044	0.044

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 12
Variable definitions.

	Variable	Name	Definition
Firm-level Risk variables	Number of CSRC penalties	*Violate*	The number of regulatory decision letters received by firms from the CSRC
	Number of regulatory inquiry letters	*Inquiry*	The number of regulatory inquiry letters received by firms from the CSRC
	Audit opinions	*Audit*	According to the severity of audit opinions, "Unqualified", "Unqualified with explanatory Paragraph", "Qualified", "Qualified with Explanatory Paragraph", "Adverse", and "Disclaimer of Opinion" are assigned values of 1 to 5, respectively
	Financial restatements	*Restate*	The number of financial restatements
Individual-level Risk variables	Adverse opinion	*Objection*	The average annual number of times independent directors express adverse opinions
	Hold other directorship	*Idj*	Whether the independent director holds positions in other listed companies. Those who also serve as independent directors in other listed companies are assigned a value of 1, and 0 otherwise
	Number of directorships	*Idj_num*	The average number of positions as independent directors that one hold in other listed companies
	The degree of information advantage	*Structural holes*	The average degree of information advantage of independent directors. The number of structural holes occupied by directors calculated using *Pajek* software, where a higher value indicates that the director has greater information advantage

Table 13
The impact of firm-level governance risk characteristics on D&O insurance.

VARIABLES	*Insurance*			
	(1) *Violate*	(2) *Inquiry*	(3) *Audit*	(4) *Restate*
*Treat*Post1*	−0.023***	−0.024***	−0.024***	−0.024***
	(−2.899)	(−3.052)	(−3.026)	(−2.929)
*Treat*Post2*	−0.058***	−0.056***	−0.058***	−0.055***
	(−4.168)	(−4.061)	(−4.167)	(−3.940)
*Treat*Post3*	−0.085***	−0.083***	−0.078***	−0.084***
	(−5.056)	(−4.945)	(−4.681)	(−4.809)
*Treat*Post1*Moderator*	0.008**	0.012*	0.003	0.002
	(2.149)	(1.847)	(0.161)	(0.625)
*Treat*Post2*Moderator*	0.012**	0.035***	0.031	0.009
	(2.233)	(2.804)	(0.963)	(1.200)
*Treat*Post3*Moderator*	0.020***	0.034**	−0.000	0.010
	(2.999)	(2.040)	(−0.001)	(1.127)
Moderator	−0.002	0.003	0.022*	0.003
	(−0.732)	(0.817)	(1.725)	(1.192)
_cons	−0.422	−0.443	−0.386	−0.357
	(−1.038)	(−1.079)	(−0.940)	(−0.876)
Controls	YES	YES	YES	YES
Firm	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	18,981	18,981	18,981	18,981
Adj.R2	0.122	0.122	0.121	0.121

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The *Moderator* specifically corresponds to the *Violate*, *Inquiry*, *Audit* and *Restate* variables.

and heightened litigation risks due to a dereliction of duty. This could lead to substantial compensation claims and potential harm to their reputation. Consequently, independent directors with an excessive number of concurrent positions face heightened regulatory compliance risks. This may prompt them to advocate for their companies to obtain D&O insurance and increase their salaries or even to request early resignation to mitigate these risks.

6.2.3. Independent directors' relationship networks

Social relationship networks, as informal institutions, can supplement formal institutions and significantly influence corporate governance and resource allocation (Battiston et al., 2003; Farina, 2008; Schonlau and Singh, 2009). Individuals who occupy structural hole positions within the network enjoy informational and control advantages, which allow them to access and manage a greater variety of heterogeneous information and knowledge resources (Chang and Wu, 2021). In this study, we use the number of structural holes controlled by independent directors in the relationship network as a proxy for their information advantage. Independent directors with a higher number of structural holes can access inside information more quickly, thoroughly and accurately, thereby enhancing their ability to monitor and control company risks. Even after the revision of the *Securities Law*, these directors, leveraging their informational edge, can better understand a company's governance and financial information, exercise effective supervision and make informed decisions. Consequently, independent directors with an information advantage face relatively lower regulatory compliance risks, have lower demands for D&O insurance and salary and demonstrate relatively low levels of resignation for abnormal reasons.

We use model (2) to test the impact of the personal characteristics of independent directors on the main regression results. *M* refers to the variables at the individual independent director level. The specific variables are defined in Table 12. The regression results are reported in Tables 16–18.

The results reported in Table 16 indicate that independent directors who publicly voice objections and serve in non-SOEs are more likely than others to prompt their companies to purchase D&O insurance. Independent directors in non-SOEs who occupy multiple structural holes within the director relationship network enjoy an informational advantage. Consequently, they face lower litigation risks and, as a result, exhibit a reduced urgency for the listed company to purchase D&O insurance on their behalf.

The results reported in Table 17 suggest that independent directors in non-SOEs who publicly voice objections are more likely to advocate salary increases from the companies they serve, aiming to mitigate potential financial loss and the risk of losing their directorships.

The regression results in Table 18 indicate that independent directors in non-SOEs who hold concurrent positions in other listed companies, as well as those holding multiple such roles, are more likely to resign swiftly following the 2021 Kangmei Pharmaceutical lawsuit. This swift resignation is intended to evade the cumulative litigation compensation pressures associated with multiple directorships in listed companies. In contrast, independent directors in non-SOEs who have publicly expressed dissenting opinions are less likely to resign prematurely. Dissenting opinions indicate active fulfillment of supervisory responsibilities and thus reduce independent directors' litigation risk. Finally, independent directors in non-SOEs who occupy a greater number of structural holes can leverage their informational advantage and are also less likely to resign prematurely.

The differing risk sensitivity among independent directors in SOEs and non-SOEs arises from the higher governance risks inherent in the latter. The heightened regulatory compliance risks associated with the revision of the *Securities Law* have made independent directors in non-SOEs more cognizant of job-fulfillment risks. Consequently, non-SOE independent directors are more likely to advocate that non-SOEs enhance D&O insurance coverage and increase their salaries. They may opt to resign early if the necessary incentives for duty fulfillment are lacking or if the risks associated with their positions become excessively burdensome.

6.3. Characteristics of successors before and after the Securities Law revision

The new *Securities Law* reenforces the regulatory compliance risk of independent directors, creating a demand for talent with high capability to assume supervisory, advisory and decision-making duties. To evaluate the characteristics of successors before and after the revision of the *Securities Law*, we analyze a range of

Table 14
The impact of firm-level governance risk characteristics on independent directors' salaries.

VARIABLES	*Salary*			
	(1) *Violate*	(2) *Inquiry*	(3) *Audit*	(4) *Restate*
*Treat*Post1*	0.014	0.014	0.014	0.013
	(1.513)	(1.469)	(1.534)	(1.384)
*Treat*Post2*	0.021	0.023*	0.022*	0.023*
	(1.643)	(1.869)	(1.741)	(1.799)
*Treat*Post3*	0.019	0.018	0.022	0.017
	(1.330)	(1.231)	(1.532)	(1.113)
*Treat*Post1*Moderator*	0.008*	0.007	0.077**	0.003
	(1.759)	(0.923)	(2.556)	(0.905)
*Treat*Post2*Moderator*	0.016***	0.046***	0.123***	0.002
	(2.711)	(3.382)	(2.817)	(0.285)
*Treat*Post3*Moderator*	0.017***	0.049***	0.128***	0.016**
	(3.164)	(3.092)	(3.017)	(2.007)
Moderator	0.000	0.003	−0.010	−0.001
	(0.058)	(0.735)	(−0.598)	(−0.582)
_cons	10.888***	10.833***	10.861***	10.954***
	(30.193)	(30.122)	(30.043)	(30.417)
Controls	YES	YES	YES	YES
Firm	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	18,859	18,859	18,859	18,859
Adj.R^2	0.609	0.609	0.609	0.609

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The *Moderator* specifically corresponds to the *Violate*, *Inquiry*, *Audit* and *Restate* variables.

Table 15
The impact of firm-level governance risk characteristics on the abnormal resignations.

VARIABLES	*Resign_num*			
	(1) *Violate*	(2) *Inquiry*	(3) *Audit*	(4) *Restate*
*Treat*Post1*	0.008	0.009	0.008	0.008
	(0.790)	(0.926)	(0.806)	(0.788)
*Treat*Post2*	0.026**	0.028**	0.027**	0.028**
	(2.098)	(2.223)	(2.147)	(2.158)
*Treat*Post3*	0.014	0.018	0.013	0.017
	(1.122)	(1.471)	(1.097)	(1.332)
*Treat*Post1*Moderator*	−0.006	0.002	0.015	0.001
	(−0.801)	(0.189)	(0.372)	(0.139)
*Treat*Post2*Moderator*	−0.005	−0.011	0.024	−0.000
	(−0.524)	(−0.585)	(0.460)	(−0.030)
*Treat*Post3*Moderator*	−0.008	−0.031*	−0.043	−0.008
	(−0.985)	(−1.694)	(−0.818)	(−0.910)
Moderator	0.011***	0.002	0.050***	0.004
	(2.991)	(0.320)	(2.614)	(1.446)
_cons	0.455	0.518*	0.419	0.472
	(1.454)	(1.647)	(1.334)	(1.513)
Controls	YES	YES	YES	YES
Firm	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	18,981	18,981	18,981	18,981
Adj.R^2	0.043	0.042	0.043	0.042

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The *Moderator* specifically corresponds to the *Violate*, *Inquiry*, *Audit* and *Restate* variables.

Table 16
The impact of individual-level characteristics on D&O insurance.

VARIABLES	*D&O insurance*			
	(1) *Objection*	(2) *Idj*	(3) *Idj_num*	(4) *Structral holes*
*Treat*Post1*	−0.023***	−0.023***	−0.023***	−0.023***
	(−3.110)	(−3.058)	(−3.082)	(−3.125)
*Treat*Post2*	−0.058***	−0.057***	−0.057***	−0.057***
	(−4.243)	(−4.207)	(−4.200)	(−4.163)
*Treat*Post3*	−0.091***	−0.089***	−0.089***	−0.089***
	(−5.090)	(−4.954)	(−4.927)	(−4.976)
*Treat*Post1*Moderator*	0.013	0.006	0.003	−0.052*
	(1.269)	(0.538)	(0.643)	(−1.794)
*Treat*Post2*Moderator*	0.013	−0.008	−0.001	−0.110**
	(1.007)	(−0.382)	(−0.122)	(−2.480)
*Treat*Post3*Moderator*	0.034***	−0.004	0.000	−0.082
	(2.716)	(−0.129)	(0.014)	(−1.235)
Moderator	−0.001	−0.013	−0.005	0.064**
	(−0.088)	(−1.297)	(−1.140)	(2.559)
_cons	−0.404	−0.379	−0.371	−0.420
	(−1.059)	(−0.988)	(−0.968)	(−1.096)
Controls	YES	YES	YES	YES
Firm	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	19,148	19,060	19,060	19,079
Adj.R^2	0.111	0.110	0.110	0.111

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The *Moderator* specifically corresponds to the variables *Objection*, *Idj*, *Idj_num* and *Structural holes*.

Table 17
The impact of individual-level characteristics on independent directors' salaries.

VARIABLES	*Salary*			
	(1) *Objection*	(2) *Idj*	(3) *Idj_num*	(4) *Structral holes*
*Treat*Post1*	0.016*	0.017*	0.016*	0.017*
	(1.735)	(1.851)	(1.822)	(1.850)
*Treat*Post2*	0.025**	0.026**	0.026**	0.027**
	(2.003)	(2.134)	(2.135)	(2.152)
*Treat*Post3*	0.031**	0.026*	0.026*	0.032**
	(1.997)	(1.745)	(1.721)	(2.101)
*Treat*Post1*Moderator*	0.013	0.007	0.006	−0.046
	(1.167)	(0.497)	(1.106)	(−1.275)
*Treat*Post2*Moderator*	0.018*	−0.004	0.005	−0.055
	(1.759)	(−0.211)	(0.702)	(−1.181)
*Treat*Post3*Moderator*	0.041***	−0.038	−0.010	−0.008
	(3.435)	(−1.501)	(−1.067)	(−0.123)
Moderator	0.004	0.025**	0.007*	−0.007
	(0.535)	(2.296)	(1.669)	(−0.257)
_cons	10.880***	10.890***	10.882***	10.914***
	(31.213)	(31.193)	(31.191)	(31.164)
Controls	YES	YES	YES	YES
Firm	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	19,063	18,975	18,975	18,994
Adj.R^2	0.607	0.608	0.608	0.606

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The *Moderator* specifically corresponds to the variables *Objection*, *Idj*, *Idj_num* and *Structural holes*.

Table 18
The impact of individual-level characteristics on the abnormal resignations.

VARIABLES	*Resign_num*			
	(1) *Objection*	(2) *Idj*	(3) *Idj_num*	(4) *Structral holes*
*Treat*Post1*	0.009	0.009	0.009	0.010
	(1.013)	(1.004)	(0.995)	(1.087)
*Treat*Post2*	0.027**	0.027**	0.028**	0.029**
	(2.159)	(2.207)	(2.229)	(2.308)
*Treat*Post3*	0.008	0.004	0.003	0.007
	(0.559)	(0.285)	(0.229)	(0.550)
*Treat*Post1*Moderator*	0.034	0.029*	0.007	−0.008
	(1.243)	(1.725)	(1.054)	(−0.214)
*Treat*Post2*Moderator*	−0.039*	0.063***	0.021**	−0.130**
	(−1.780)	(2.873)	(2.501)	(−2.556)
*Treat*Post3*Moderator*	−0.049*	−0.003	−0.005	0.015
	(−1.662)	(−0.104)	(−0.613)	(0.265)
Moderator	0.042***	−0.004	0.001	−0.075***
	(3.060)	(−0.376)	(0.237)	(−2.787)
_cons	0.629**	0.660**	0.663**	0.722**
	(2.037)	(2.123)	(2.133)	(2.321)
Controls	YES	YES	YES	YES
Firm	YES	YES	YES	YES
Year	YES	YES	YES	YES
N	19,148	19,060	19,060	19,079
Adj.R^2	0.046	0.045	0.045	0.045

Note: T-statistics in parentheses are based on standard errors adjusted for firm-level clustering. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. The *Moderator* corresponds to the variables *Objection*, *Idj*, *Idj_num* and *Structural holes*.

Table 19
Comparison of the characteristics of successors before and after the revision of Securities Law.

Panel A:	Successor in non-state-owned enterprises				
	2016–2018		2019–2022		
VARIBLIES	N	Mean	N	Mean	Mean Diff
Age	3386	50.868	5301	52.800	−1.932***
Educational background	2614	4.143	4278	4.215	−0.072***
Number of directorships	2608	1.801	5259	1.533	0.268***
Legal qualifications	2608	0.169	5259	0.215	−0.045***
Industry expertise	2608	0.138	5259	0.178	−0.040***
Non-local	2309	0.599	4846	0.450	0.149***
Panel B:	Successor in state-owned enterprises				
	2016–2018		2019–2022		
VARIBLIES	N	Mean	N	Mean	Mean Diff
Age	1574	52.132	2459	54.336	−2.204***
Educational background	916	4.317	1541	4.385	−0.069**
Number of directorships	1305	1.845	2430	1.645	0.200***
Legal qualifications	1305	0.183	2430	0.227	−0.044***
Industry expertise	1305	0.162	2430	0.214	−0.052***
Non-local	1130	0.553	2203	0.408	0.145***

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

indicators, including age, educational background, the number of concurrent directorships, industry expertise, legal qualifications and whether they are non-local independent directors. The results are reported in Table 19, and they reveal that successors in both SOEs and non-SOEs share similar traits. In comparison to successors from 2016 to 2018, those appointed from 2019 to 2022 exhibit more senior qualifications, broader working experience, higher educational levels and improved capabilities in knowledge acquisition, application and transfer. They also have fewer concurrent directorships, which allows them to dedicate more time to a single firm, aligning with the CSRC's regulations on the number of concurrent positions. Additionally, they possess stronger legal backgrounds and industry expertise. The proportion of non-local independent directors has decreased, which facilitates job fulfillment. In conclusion, in the post-revision period, the successors are more capable and better prepared to fulfill their supervisory and advisory roles.

7. Conclusions and implications

The revised *Securities Law* increases the penalties for misconduct and establishes a representative litigation system with Chinese characteristics. Its aim is to protect the legitimate rights and interests of investors and ensure the high-quality development of the capital market. An unresolved question, however, is how firms of different ownership type and their independent directors respond to this dynamic regulatory environment and compliance risks following the revision of the *Securities Law*. In this study, we use the revision of the *Securities Law* in 2019 as a quasi-natural experiment and divide the post-2019 period according to the implementation process. The period from 2019 to 2020 is the legislative stage, 2021 is the enforcement stage and 2022 is the enforcement adjustment stage. Using ownership type to divide the sample, we design a DID model to test the changes in the purchase of D&O insurance, independent director salary and the number of abnormal resignations at each stage following the revision of the *Securities Law*.

We find that given the systematic differences in the governance risks between SOEs and non-SOEs, the two types of firms behave differently after the enactment of the new *Securities Law*. SOEs are more likely to purchase D&O insurance due to their higher political sensitivity, stronger risk prevention awareness and inclination to provide implicit incentives for their independent directors. This helps reduce the litigation risks that independent directors face and provides them with job security. It also further exacerbates the differences between independent directors' job-fulfillment risk in SOEs and non-SOEs. As the new *Securities Law* enters the enforcement stage, non-SOEs with higher governance risks and less protection from D&O insurance are more likely to increase their independent directors' salaries to compensate for the regulatory compliance risks they face. The 2021 Kangmei Pharmaceutical lawsuit disrupted the established equilibrium of rights, responsibilities and interests for independent directors in non-SOEs. This imbalance increases the likelihood of independent directors in non-SOEs resigning to avoid risk.

Firm-level governance risks and director-level characteristics also influence risk-coping strategies after the revision of the *Securities Law*. Non-SOEs with higher governance risks are more likely to increase the purchase of D&O insurance and increase their independent directors' salaries, thus preventing their resignation. The individual-level characteristics of non-SOE independent directors lead to greater purchases of D&O insurance, higher salaries and abnormal resignation. Finally, a comparison of the personal characteristics of successors before and after the *Securities Law* revision reveals that the new *Securities Law* has improved the competency of successive independent directors, enabling them to better fulfill their supervisory, advisory and decision-making roles.

The findings of this study enrich research on the behavior of companies and independent directors around the revision of the *Securities Law*. The empirical results also help elucidate the real effect of each stage of the new *Securities Law* and how to promote reform of the independent director system in the future.

The results of this study have three policy implications. First, legislation and law enforcement are equally important. Law enforcement fulfills the legislative intent. The deterrent effect of the new *Securities Law* on independent directors varies across the legislative and enforcement stages. Once regulations are legislated, strict enforcement becomes crucial. A coordinated effort across legislation, enforcement and the judicial system is essential to ensure strict implementation, safeguarding the legitimate rights and interests of minority shareholders. The new *Securities Law* has legislatively toughened penalties, but it is in the enforcement stage

that non-SOEs and their independent directors truly feel its deterrent effect. Only through rigorous, systematic and fair law enforcement can the original intent and objectives of the legislation be realized.

Second, legislation and law enforcement should form a two-way cycle, with law enforcement enhancing legislative principles. Under the participation principle of the special representative litigation system, namely the opt-out mechanism, independent directors may face heavy fines if they fail to diligently fulfill their duties. This imbalance between risk and reward has created a sense of panic among independent directors. However, this is not the intended outcome of the revised *Securities Law*. New issues arising during law enforcement should be promptly addressed to promote more systematic legislation and enhance the legislative system overall. In response to the imbalance in the rights, responsibilities and interests of independent directors, the Supreme People's Court specified grounds for exemption to alleviate their concerns about potential liability in 2022. In 2023, the State Council explicitly declared that independent and non-independent directors should bear different legal responsibilities jointly and separately, reflecting the principles of proportional punishment and targeted accountability. This approach not only deters independent directors' misconduct but also considers their unique roles and identities, achieving a harmony of legal and social effects.

Third, it is crucial to acknowledge the diverse governance risks faced by independent directors under different ownership types. SOEs generally encounter lower governance risks and are more inclined to increase their D&O insurance purchases following the revision of the *Securities Law*. Comparatively, independent directors in non-SOEs are more acutely aware of the need for enhanced job security to address regulatory compliance risks. However, salary increases alone are insufficient to alleviate the concerns of independent directors in non-SOEs. For instance, in the case of the Kangmei Pharmaceutical lawsuit, salary was inadequate to mitigate independent directors' litigation risk, resulting in an increase in abnormal resignations and a severe negative market reaction, which is detrimental to the healthy growth of the capital market. Under the higher compliance risk environment faced by independent directors in non-SOEs, how to implement the *ex-ante* protective measures and *ex-post* punitive measures is a topic that deserves further exploration.

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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How does digital transformation affect corporate accounting employees?

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ABSTRACT

The rapid pace of digitalization has given rise to concerns about its influence on job roles. Our findings reveal a substitution effect on accounting employees. This effect is more evident in private firms, firms with higher levels of digital transformation in their accounting departments, firms in the information technology industry, firms with overconfident managers and firms with a higher-level network infrastructure. Digitalization also has a positive effect on technically skilled and highly educated employees, leading to a decline in the proportion of entry-level employees. We also document that digitalization contributes to more efficient labor investment. Our study therefore offers insights into how digital transformation can change the labor market for accounting employees.

1. Introduction

The race between man and machine has been a subject of debate, particularly in terms of the restructuring and reorganization of the workplace (e.g., Frey and Osborne, 2017; Acemoglu and Restrepo, 2018; Jarrahi, 2018; Acemoglu et al., 2022; Fotoh and Lorentzon, 2023). The development of digital technologies such as big data, artificial intelligence, cloud computing, the internet of things and blockchain has led to the emergence and expansion of the digital economy. This is gradually changing the way business operates and has the potential to drive productivity, facilitate ongoing innovation and thus become a new engine of economic growth (Brynjolfsson and Collis, 2019). Firms have embraced or are embracing the potential of the digital economy in various business aspects, i.e., they are going through what is referred to as digital transformation.

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Will large-scale digitalization cause unemployment? Historical examples of job losses due to technological development can be identified, but many new jobs are also created in the unprecedented wave of technological advancement. Some recent studies of digital transformation stress the magnitude of the disruption and suggest that it will replace humans in the workplace (Frey and Osborne, 2017). However, others regard digitalization as a tool that augments human contribution (e.g., Jarrahi, 2018; Furr and Shipilov, 2019; Cao et al., 2021). These arguments are not entirely new and suggest that there is a need to assess how digital transformation will affect the human workplace, particularly considering the rapid growth and widespread use of digital technology in business.

Numerous studies assess whether and how the digital revolution involving computers, automation and robots will affect business processes and reshape the labor market (Geerts et al., 2013; Acemoglu and Restrepo, 2018; Kim et al., 2018; Hjort and Poulsen, 2019; Acemoglu and Restrepo, 2020; Ashraf et al., 2020). However, research into the effects of digital transformation on the labor market is limited. Many studies lack support from empirical data (e.g., Jarrahi, 2018; Chiu and Koeppl, 2019; Moll and Yigitbasioglu, 2019; Kaplan and Haenlein, 2020). We extend the debate regarding digital transformation and its possible link to mass unemployment by using novel, hand-collected digitalization data from Chinese listed firms to explore the impact of digitalization on corporate accounting employees. Our findings offer further insights into how digital transformation may change the labor market for accounting employees.

Empirical studies of the economic consequences of digital transformation are relatively rare in the accounting domain. This is surprising, considering that accounting involves new technology. The BBC reports that accountants had the third highest (97.6 %) future "probability of being eliminated". Some studies demonstrate that firms with a high-quality workforce exhibit higher financial reporting quality and enjoy lower audit fees (Call et al., 2017; Liu et al., 2017; Li et al., 2020; Gul et al., 2023). High-quality accounting employees can provide superior information, which is helpful when making financial reporting choices. Investigating the effects of digital transformation on accounting employees is therefore important, and we acknowledge the challenges that digital technology pose to the accounting profession (Borthick and Pennington, 2017; Moll and Yigitbasioglu, 2019; Taib et al., 2022). Accounting employees may face the threat that well-defined, routine, or even knowledge-based tasks will no longer be the exclusive domain of humans (e.g., Goos et al., 2014; Autor, 2015; Jarrahi, 2018). These tasks could be performed more efficiently through digital technology, and at a lower cost. Thus, it initially appears that digital transformation will lead to the laying off of accounting employees. However, such transformation may instead increase the demand for accounting employees, as it enables large volumes of data from non-accounting departments to be processed in a much shorter time and then quickly evaluated and restructured, so various specifications and information can be identified (Fülöp et al., 2023). This will result in a greater workload for accounting departments. The revolutionary and complex nature of digital transformation (Yermack, 2017; Bonyuet, 2020) thus suggests that the demand for accounting employees may increase.

To examine our assumptions, we use hand-collected digital transformation data from China and provide evidence for the impact of digitalization on accounting employees. Specifically, we determine the proportion of firms' accounting employees subject to its substitution effect. Our results hold across different measures of digital transformation and different sub-samples, and are robust to mitigating the self-selection concern and the placebo test. We also provide evidence for the moderating effects of the digital transformation level of accounting departments, management characteristics, industry characteristics, property rights and network infrastructure.

We then conduct various supplementary analyses. First, we find that digitalization also affects the proportions of technical employees, highly educated employees and entry-level employees in firms, which we interpret as the biased effect of digital transformation in the labor market. Technological advancements appear to have a stronger substitution effect on routine tasks and promote the demand for highly skilled and highly educated employees. Second, we demonstrate that digital transformation improves labor investment efficiency, indicating that firms can take advantage of digitalization to reallocate and optimize their labor resources. In summary, we provide evidence that digital transformation influences corporate employment decisions.

This study makes two main contributions. First, the rapid development of the digital economy has attracted the attention of firms, regulators and other parties, who have come to recognize its potential. This has led to increased research into how digital technology is incorporated into functional departments and the economic

consequences of digital transformation (e.g., Cao et al., 2018; Jarrahi; 2018; Chiu and Koeppl, 2019; Cong and He, 2019; Furr and Shipilov, 2019; Kaplan and Haenlein, 2019; Moll and Yigitbasioglu, 2019; Zhu, 2019; An and Rau, 2021; Chen et al., 2022). However, few studies address the influence of digital transformation on corporate accounting employment decisions. We explore this issue using data from China, the world's largest developing country.[1] Although some studies demonstrate the challenges that digital technology pose to the accounting profession (Borthick and Pennington, 2017; Moll and Yigitbasioglu, 2019; Taib et al., 2022), evidence on how digital transformation affects accounting employees needs to be provided. Our archival study reveals how changes in corporate accounting employee structure are driven by digitalization, thus providing further insights on the issue. Second, our study expands the body of evidence on the association between technical revolution and labor redundancy. Numerous studies investigate how computerization, information technology (IT) and robots will reshape the labor market (Autor, 2015; Frey and Osborne, 2017; Acemoglu and Restrepo, 2018; Hjort and Poulsen, 2019; Acemoglu and Restrepo, 2020). The digital economy has unique features that differentiate it from traditional economies: data collection and analysis become highly efficient, automation is facilitating, digitized information can be widely integrated into economic activities. Thus, the effects of technologically driven change are expected to be significant and widespread. We offer new insights into this domain by providing further evidence of the effects of digital transformation and reconfirm the notion that the technology revolution plays an important role in the evolution of the labor market.

The remainder of this paper proceeds as follows. In the second section, we discuss the institutional background and the development of testable hypothesis. In the third section, we describe the data and sample. The fourth section presents our main findings. In the fifth section, we discuss the moderating effects of the level of digital transformation in accounting departments, management characteristics, industry characteristics, property rights and network infrastructure. The sixth section explores further economic consequences, and the seventh section concludes the paper.

2. Institutional background and hypothesis development

2.1. Institutional background

The emergence and advancement of digital technology enables firms to engage in new and innovative ways of doing business. This not only brings about technological transformation but also transforms the business culture. By completely reconstructing the business model, digital transformation provides new ways for firms to create value and improve efficiency. In the process of digitalizing the economy, China has emphasized the need to develop core technologies, enhance technical innovation capabilities, accelerate the construction of technological innovation systems and support the expansion of digital transformation. The report of the Supreme People's Court regarding the Fourth Session of the Thirteenth National People's Congress on 8 March 2021 expresses China's commitment to "promote the digital and intelligent transformation" and "accelerate digital technology development and create new advantages in the digital economy".

This strong support from the government has led China's digital economy to a dramatic breakthrough: digital capabilities are continuously increasing, and the scale of digitalization is growing fast. China's digital economy also has a leading global position, ranking second to the U.S. in terms of total output.[2] Thus, China is selected as the study locale for exploring the economic consequences of digital transformation. Anecdotal evidence confirms that digitalization has become an important booster of economic growth. However, few studies examine its economic consequences at the micro-level, particularly its impact on the ability of an enterprise to absorb labor. Thus, the question of whether digitalization induces labor redundancy should be addressed. We aim to provide supplementary evidence on the association between the technical revolution and the labor market by linking digital transformation to firms' employment decisions.

[1] See "Purchasing Power Parities and the Size of World Economies: Results from the 2017 International Comparison Program" from the World Bank.

[2] See the "White Paper on the Global Digital Economy-A New Dawn of Recovery under the Shock of COVID-19" published by the China Academy of Information and Communications Technology.

2.2. Hypothesis development

2.2.1. The effect of digital transformation on accounting employees

As the trend of digitalization continues, firms are faced with the challenge of assessing its influence in the workplace, such as how it will reshape corporate employee structure. Some studies argue that the technical revolution will change business processes entirely (e.g., Fulop and Magdas, 2022), and the accounting domain is no exception (Nixon, 2015). With the widespread application of digital technology, the future role of accounting employees has been questioned. The nature of human accounting work can lead to unintentional errors or intentional manipulation. In comparison, automation made possible by the advance of technology appears to be more trustworthy and less costly. Thus, machines are gradually replacing accounting employees in the time-consuming, defined and unskilled routine tasks they have traditionally performed. For example, new technology offers real-time access to accounting data, and documents can be uploaded to accounting systems automatically and simultaneously with little interference from employees. Data recording can now be automated, thus resulting in layoffs of employees with these skills. Nevertheless, tasks such as decision-making and performance management are not easily automatable (Richins et al., 2017). Thus, digital transformation is changing the role of accounting employees through new types of automated accounting services (Vasarhelyi et al., 2015; Warren et al., 2015; Moll and Yigitbasioglu, 2019; Rindasu, 2021).

However, digital transformation may also increase the demand for accounting employees. Digital transformation is expected to revolutionize traditional business by offering potential benefits in terms of efficiency, providing valuable services to customers and managing potential risks (Wang et al., 2023). The revolutionary and complex nature of digital transformation (Yermack, 2017; Bonyuet, 2020) may lead to an increase in the demand for accounting employees. Digital transformation means that large volumes of data from non-accounting departments can be processed in a much shorter time and then quickly evaluated and restructured, so various information can be obtained (Fülöp et al., 2023). This can result in a greater workload for accounting departments. More employees will then be required to cope with the complex financial data created by other departments, especially those equipped with the necessary knowledge and skill sets to effectively operate in a digitalized environment. The processing and evaluating of information cannot currently be fully automated, as AI cannot as yet make decisions based on professional judgment. Thus, the demand for accounting employees may increase.

Drawing on these analyses, we propose the following hypothesis:

H1: Digital transformation has no effect on firms' accounting employees.

3. Research design

3.1. Data and sample selection

In this subsection, we outline the sample selection procedure and describe the data acquisition process. We obtain corporate accounting employee data from the RESSET Financial Database, which provides detailed information on the number of employees in various categories. To establish whether a firm goes through digital transformation, we manually read the MD&A sections of firms' annual reports using a dictionary approach. Other data we consider in this paper are from the China Stock Market and Accounting Research database (CSMAR). We include all A-share firms listed on the Shanghai and Shenzhen stock exchanges in our initial sample. Firms belonging to the financial industry, those that are specially treated (ST), observations with missing data on corporate employee structure and observations with missing financial data are excluded. Our final sample consists of 13,943 firm-year observations during the 2014–2019 period. We select 2014 as the starting point of our sample period because digitalization was first observed to gradually appear after that year. The sample selection process is summarized in Table 1.

3.2. Variable definitions and model specification

Firms disclose their future development plans and strategies in the MD&A sections of their annual reports, so we determine a firm's digital transformation status according to these sections. Our approach consists of

Table 1
Sample Selection and Distribution.

Sample of Chinese listed firms from 2014 to 2019	19,757
Drop: Firms belonging to the financial industry	(558)
ST firms	(1,250)
Observations with missing data	(4,006)
Final sample	**13,943**

This table outlines the sample selection procedure used in this paper. The initial sample consists of 19,757 firm-year observations during the 2014–2019 period. Firms belonging to the financial industry, ST firms, observations with missing accounting data from CSMAR and observations with missing corporate employee structure data from RESSET are dropped.

two steps. First, we conduct a search of the MD&A sections of annual reports using the keyword search method. We search for digitalization-related terms, such as "Digital Transformation", "Digitalization", "Big Data", "Artificial Intelligence", "AI", "Internet of Things", "Cloud Computing", "Cloud" and "Blockchain".[3] However, even if these terms appear in a firm's MD&A section, it may not necessarily be undergoing digital transformation. These digitalization-related terms may simply be included in a statement on the industry background or indicate that the firm is planning to go digital in the future, which will lead to measurement bias. To eliminate such interference, in the second stage we manually read the selected MD&A section to determine a firm's digitalization status.[4]

To assess the effect of digital transformation on corporate accounting employees, we specify the following model:

$$ACC\_PER_{i,t} = b_0 + b_1 DT_{i,t} + CONTROL_{i,t} + INDUSTRY + YEAR + e_{i,t} \quad (1)$$

where i indicates the firm and t indicates the year. The independent variable is ACC_PER, defined as the proportion of accounting employees among the firm's total employees. The test variable DT is an indicator variable that equals one after a year from the base year a firm begins its digital transformation, and zero otherwise. A set of firm- and region-level control variables are included, i.e., firm age (AGE), firm size ($SIZE$), leverage ratio (LEV), return on assets (ROA), sales growth rate ($GROWTH$), the market–book ratio (MB), equity shares of the largest shareholder ($TOP1$), equity shares of management ($MANHO$), the proportion of independent board members ($INDEPB$), the equity nature (SOE) and the level of regional development (GDP). We also include industry fixed effects to control for unobserved industry-invariant heterogeneity and year fixed effects to control for time variations. We cluster the standard errors at the firm level. Detailed definitions of the above variables are given in the Appendix.

4. Main model estimation

4.1. Summary statistics

Panel A of Table 2 reports the summary statistics for the 13,943 observations in our sample over the 2014–2019 period. The variable DT has a mean value of 0.548, suggesting that approximately half of the sample is undergoing digital transformation. We also observe that accounting employees account for 3.1 % of the workforce. Panels B and C show the sample distributions by year and by industry, respectively. The annual distribution indicates that the number of firms going digital has increased rapidly over the years, especially in 2018

[3] We also used two alternative measures of digital transformation in the robustness checks. The results remain unchanged.

[4] For example, the term "Big Data" appears in the MD&A section of GGEC's (stock code: 002045) 2018 annual report, as follows: "The interconnection between different platforms and devices has formed a seamless audio-visual entertainment environment. The four-screen, one-cloud environment (TV, computer, mobile phone, pad, and big data cloud) deployed by the home entertainment center will generate more demand for electric devices". Despite this reference, the firm has not actually gone digital.

Table 2
Descriptive Statistics.

Panel A: Descriptive statistics of main variables

Variable	N	Mean	Std	Min	P25	Median	P75	Max
ACC_PER	13,943	0.031	0.024	0.004	0.016	0.024	0.038	0.141
DT	13,943	0.548	0.498	0.000	0.000	1.000	1.000	1.000
GROWTH	13,943	0.183	0.439	−0.544	−0.016	0.106	0.266	2.856
AGE	13,943	2.193	0.787	0.000	1.609	2.303	2.890	3.296
SIZE	13,943	22.253	1.142	20.487	21.386	22.119	23.000	24.634
LEV	13,943	0.422	0.200	0.060	0.262	0.413	0.570	0.879
ROA	13,943	0.040	0.041	−0.049	0.014	0.035	0.065	0.123
MB	13,943	2.101	1.349	0.866	1.261	1.668	2.409	8.733
TOP1	13,943	0.340	0.145	0.090	0.227	0.319	0.436	0.740
MANHO	13,943	0.138	0.195	0.000	0.000	0.009	0.260	0.677
INDEPB	13,943	0.376	0.054	0.333	0.333	0.364	0.429	0.571
SOE	13,943	0.348	0.476	0.000	0.000	0.000	1.000	1.000
GDP	13,943	28.994	0.707	26.482	28.574	28.970	29.592	30.008

Panel B: Annual distribution of digitalization

Year	Observations
2014	330
2015	707
2016	1,082
2017	1,472
2018	1,876
2019	2,179
Total	7,646

Panel C: Industry distribution of digitalization

Industry	Observations
Manufacturing	4,773
Information Technology	931
Wholesale and retail	321
Real estate	210
Transportation, warehousing and post	208
Others	1,203
Total	7,646

This table presents summary statistics of the variables of the main model used in this paper (Panel A) during the 2014–2019 period and the annual and industry distributions of digital transformation, respectively, in Panels B and C.

and 2019. As reported in the industry distribution, digital transformation varies across industries, with manufacturing and IT as the top two industries going digital. These insights from the data are not surprising.

4.2. Validity test

To test the validity of our measure of digital transformation, we conduct the following tests. Digital transformation is accompanied by substantial tangible and intangible investments, such as in importing technology and in research and development (R&D), so we focus on the association between digital transformation and digital investment. We use two measures of digital investment: digital-related fixed and intangible assets and R&D expenditure. We search the details of firms' investments and define "computer", "software", "internet", "smart platform" and "management system" as digital-related investments. *DIGITAL_ASSETS* is the natural logarithm of firms' digital-related investments. Digital transformation is strongly associated with digital-related investment and R&D expenditure and has a *P* value of less than 1 %, as shown in Table 3, indicating the validity of our measure of digitalization.

Table 3
Validity Test.

Dependent variable =	(1) *DIGITAL_ASSETS*	(2) *R&D*
DT	1.547***	0.003***
	(8.54)	(6.82)
GROWTH	0.495***	–0.000
	(3.88)	(–1.59)
AGE	–0.489***	–0.003***
	(–3.27)	(–6.14)
SIZE	1.452***	0.000
	(11.42)	(0.23)
LEV	1.146**	–0.001
	(2.01)	(–0.65)
ROA	5.875***	0.025***
	(2.75)	(6.88)
MB	–0.039	0.002***
	(–0.53)	(7.13)
TOP1	1.210*	–0.004**
	(1.73)	(–2.42)
MANHO	0.770	0.005***
	(1.47)	(2.83)
INDEPB	–0.516	0.004
	(–0.32)	(0.89)
SOE	–0.361	0.001**
	(–1.42)	(2.15)
GDP	0.020	0.002***
	(0.15)	(6.73)
Constant	0.034***	–0.065***
	(49.49)	(–5.18)
Ind/Year FE	Yes	Yes
N	13,930	13,943
Adj.R^2	0.17	0.39

This table presents the results of the validity test of our measurement of digital transformation. The dependent variables are the natural logarithm of the digital assets in Column (1) and R&D expenditure deflated by total assets in Column (2). The independent variable, *DT*, is an indicator variable that equals to one after the year a firm started to go digital, and zero otherwise. Control variables are shown in the Appendix. T-statistics are reported at the 1%, 5% and 10% significance levels, denoted by ***, ** and *, respectively, and are based on robust standard errors clustered at the firm level.

4.3. The effect of digital transformation on corporate accounting employees

The results of our model estimation are presented in Table 4. In Column (1), no controls are included. Consistent with our expectation, as shown in Column (2), the negative and significant coefficient using the model specification that includes all of the control variables and the fixed effects suggests that digitalization has brought about a decrease in the proportion of accounting employees. The substitution effect is therefore currently dominant.

4.4. Robustness tests

4.4.1. Alternative measures of the test variable

In this subsection, we alter the measure of *DT,* our test variable. We code *DT* as one only if digital transformation is mentioned in the MD&A section that year, which is a narrower criterion than that used in the main regression. The results shown in Column (1) of Table 5 are similar to those reported in Table 4.

Table 4
The Effect of Digital Transformation on Corporate Accounting Employees.

Dependent variable = *ACC_PER*	(1)	(2)
DT	–0.005***	–0.002***
	(–6.30)	(–3.07)
GROWTH		0.002***
		(2.77)
AGE		0.004***
		(5.93)
SIZE		–0.003***
		(–8.09)
LEV		–0.001
		(–0.38)
ROA		–0.051***
		(–6.48)
MB		0.001**
		(2.18)
TOP1		–0.003
		(–1.01)
MANHO		–0.003*
		(–1.88)
INDEPB		0.015***
		(2.72)
SOE		–0.005***
		(–4.91)
GDP		–0.002***
		(–4.26)
Constant	0.034***	0.177***
	(49.49)	(8.76)
Ind/Year FE	No	Yes
N	13,943	13,943
Adj.R^2	0.01	0.32

This table presents the results of analysis of the effect of digital transformation on corporate accounting employees. The dependent variable is the proportion of accounting employees. The independent variable, *DT*, is an indicator variable that equals to one after the year a firm started to go digital, and zero otherwise. Control variables are shown in the Appendix. T-statistics are reported at the 1%, 5% and 10% significance levels, denoted by ***, ** and *, respectively, and are based on robust standard errors clustered at the firm level.

In Column (2), we include mobile internet in digital technology,[5] although we exclude it from the scope of digital technology in the main regression as it is widely applied and fairly well established. The coefficient of *DT_INTERNET* is significant and has the same signs as in Table 4, thus strongly confirming the robustness of our findings.

4.4.2. The propensity score matching approach

We carefully control for differences in firms that are going digital and those that are not by generating a matched sample using the propensity score matching (PSM) method; we then rerun the models accordingly. For each firm going digital, we perform a one-to-one PSM and match each treatment group observation with the control group observation that has the closest propensity score. The results are reported in Column (1) of Table 6 and indicate that we can draw the same implications after using the matched sample.

[5] That is, "mobile internet" is included as a keyword when implementing the keyword search method.

Table 5
Robustness Tests Based on Alternative Measurements.

Dependent Variable = *ACC_PER*	(1)	(2)
DT	–0.001**	
	(–2.34)	
DT_INTERNET		–0.002***
		(–2.72)
GROWTH	0.002***	0.002***
	(2.81)	(2.78)
AGE	0.004***	0.004***
	(5.93)	(5.95)
SIZE	–0.003***	–0.003***
	(–8.27)	(–8.13)
LEV	–0.001	–0.001
	(–0.37)	(–0.39)
ROA	–0.051***	–0.051***
	(–6.50)	(–6.50)
MB	0.001**	0.001**
	(2.18)	(2.18)
TOP1	–0.002	–0.003
	(–0.99)	(–1.01)
MANHO	–0.003*	–0.003*
	(–1.94)	(–1.91)
INDEPB	0.015***	0.015***
	(2.72)	(2.73)
SOE	–0.005***	–0.005***
	(–4.85)	(–4.90)
GDP	–0.003***	–0.002***
	(–4.33)	(–4.27)
Constant	0.179***	0.177***
	(8.94)	(8.81)
Ind/Year FE	Yes	Yes
N	13,943	13,943
Adj.R^2	0.32	0.32

This table reports the results for alternative measures of our test variable. First, *DT* is coded as one only if digital transformation is mentioned in a certain year in Column (1). Second, we add mobile internet to digital technology in Column (2). Control variables are shown in the Appendix. T-statistics are reported at the 1%, 5% and 10% significance levels, denoted by ***, ** and *, respectively, and are based on robust standard errors clustered at the firm level.

4.4.3. Mitigating self-selection bias: Heckman two-stage estimation

Firms voluntarily choose whether to undergo digital transformation. The same unobserved factors may then motivate adjustments to the corporate employee structure in addition to digitalization. To address self-selection bias, we conduct a Heckman two-stage estimation. In the first stage, we run a probit model in which the dependent variable is *DT* and the independent variables are factors that can influence the decision to embark on digital transformation, such as the basic characteristics of the firm, financial conditions and the proportion of executives with an IT background. Executives with an IT background are likely to be enthusiastic about implementing new technology (Bassellier et al., 2003). Compared with other executives, those with IT expertise can also better monitor value creation through IT, evaluate threats, provide advice and aid in the formulation of IT strategies (Parent and Reich, 2009). In addition to the basic characteristics of a firm (*AGE*, *SIZE*, *LEV*), its financial conditions such as *ROA*, *GROWTH* and *MB* may affect the decision to embark on digital transformation, as sufficient financial support will be required. We include *MANHO*, a management characteristic variable, as management teams play an important role in promoting digitalization (Singh and Hess, 2017). We also include *SOE,* as public and private firms may have different attitudes toward digital transformation. We also add *GDP* to control for region-level factors that may influence the choice of digitalization. In the second stage, we re-estimate the main regression including the inverse Mills ratio (*INV-*

Table 6
Robustness Tests Based on the Propensity Score Matching Approach.

Dependent Variable = *ACC_PER*	(1)
DT	–0.002*
	(–1.73)
GROWTH	0.001*
	(1.93)
AGE	0.003***
	(3.23)
SIZE	–0.003***
	(–5.89)
LEV	–0.003
	(–0.83)
ROA	–0.051***
	(–4.93)
MB	0.000
	(0.95)
TOP1	–0.004
	(–1.18)
MANHO	–0.002
	(–0.88)
INDEPB	0.019***
	(2.60)
SOE	–0.005***
	(–3.58)
GDP	–0.003***
	(–3.51)
Constant	0.183***
	(6.78)
Ind/Year FE	Yes
N	8,762
Adj.R^2	0.33

This table shows the results for robustness tests based on the propensity score matching approach. Column (1) presents the results using the propensity score matched sample. Control variables are shown in the Appendix. T-statistics are reported and ***, ** and * reflect statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are based on robust standard errors clustered at the firm level.

MILLS), as calculated from the first stage, as a control variable. The results remain constant, as shown in Column (2) of Table 7.

4.4.4. Placebo test

One concern is that the results in Table 4 may be induced by random effects. To demonstrate that the decrease in the proportion of accounting employees is caused by digital transformation, we conduct a placebo test. Our test variable *DT* is randomly assigned 500 times and 1,000 times to each firm-year observation, and the respective regression results are recorded. If the change in the proportion of accounting employees is due to random effects, then we should observe results similar to those reported in Table 4 when artificially assigning the test variable. Fig. 1 shows the probability density function of the coefficients in each placebo test, which are near normally distributed with a mean zero, suggesting that the effect of digitalization on accounting employees disappears. Thus, we demonstrate that our findings are caused by digital transformation.

5. Analysis of the moderating effects

5.1. Does the digital transformation of the accounting department matter?

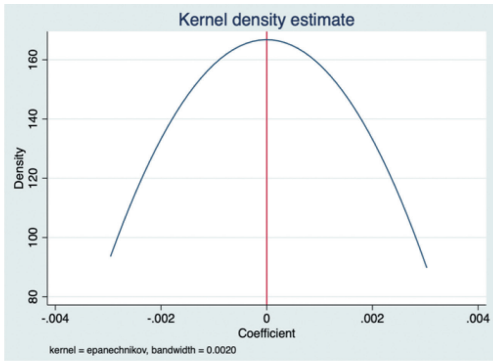
We aim to distinguish the digital transformation of the accounting department from that of other non-accounting departments in a firm by reading the MD&A section of the firm's annual report and conducting

Table 7
Mitigating Self-selection Bias: Heckman Two-stage Estimation.

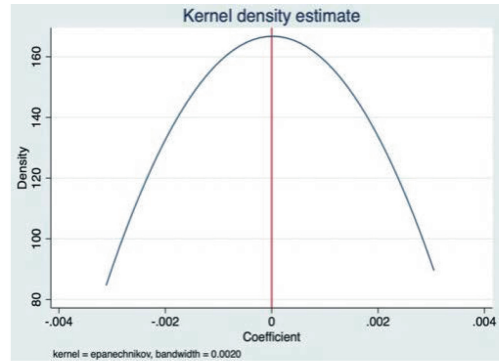
Dependent Variable =	(1) *First Stage* *DT*	(2) *Second Stage* *ACC_PER*
DT		–0.002***
		(–3.15)
GROWTH	–0.060**	0.002***
	(–2.18)	(2.95)
AGE	–0.043**	0.004***
	(–2.09)	(6.13)
SIZE	0.222***	–0.004***
	(14.30)	(–7.47)
LEV	–0.175**	–0.000
	(–2.26)	(–0.13)
ROA	0.458**	–0.052***
	(1.98)	(–6.67)
MB	–0.002	0.001**
	(–0.19)	(2.18)
TOP1		–0.003
		(–1.00)
MANHO	0.217***	–0.004**
	(2.77)	(–2.21)
INDEPB		0.015***
		(2.74)
IT_PER	0.865***	
	(9.65)	
SOE	–0.173***	–0.004***
	(–5.66)	(–4.41)
GDP	0.104***	–0.003***
	(5.84)	(–4.58)
INVMILLS		–0.004*
		(–1.65)
Constant	–8.804***	0.204***
	(–14.37)	(8.07)
Ind/Year FE	Yes	Yes
N	13,943	13,943
Pseudo.R^2/Adj.R^2	0.18	0.32

This table shows the results of Heckman two-stage estimation, with the results for the first stage in Column (1) and the results for the second stage in Column (2). *ACC_PER* is the fraction of accounting employees. *DT* is an indicator variable that equals to one after the year a firm started to go digital, and zero otherwise. Control variables are shown in the Appendix. Z-statistics or T-statistics are reported, and ***, ** and * reflect statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are based on robust standard errors clustered at the firm level.

a keyword search of this section. The search terms related to the digitalization of accounting department include "Accounting Information System", "Intelligent Finance", "Intelligent Accounting", "Big Data and Accounting", "Big Data and Finance", "Accounting Digitalization", "Data-driven Accounting", "Data-driven Finance", "AI and Accounting" and "AI and Finance". We then manually read the selected MD&A section to determine the digitalization status of the firm's accounting department. We construct an indicator variable, *DT_ACC*, which takes the value of one if the accounting department goes digital, and zero otherwise. We then construct another indicator variable, *DT_NACC*, which equals one if the firm goes digital but the accounting department does not, and zero otherwise. We incorporate these two variables into the regression to more clearly distinguish the impact of digital transformation in the accounting department on accounting employees. Column (1) of Table 8 shows that the coefficient of *DT_ACC* is negative and significant



a: Placebo test repeated 500 times with the dependent variable *ACC_PER*



b: Placebo test repeated 1,000 times with the dependent variable *ACC_PER*

Fig. 1. Placebo Test. These figures report the results for the distribution of coefficients of *DT* in the placebo test with 500 repeats (Fig. 1a) and 1,000 repeats (Fig. 1b).

at the 1 % level, while the coefficient of *DT_NACC* is not significant. The results indicate that digital transformation has a more significant impact on accounting employees when digitalization occurs in the accounting department.

To provide further insights into how digital transformation affects accounting employees, we decompose *DT_ACC* into two components: digital transformation solely related to the accounting department (*DT_ACC_SOLELY*) and related to both accounting and non-accounting departments (*DT_ACC_BOTH*). We then incorporate *DT_ACC_SOLELY*, *DT_ACC_BOTH* and *DT_NACC* into the regression. As Column (2) of Table 8 shows, the coefficient of *DT_ACC_SOLELY* is negative and significant at the 1 % level, and the coefficient of *DT_ACC_BOTH* is negative and significant at the 10 % level. However, the coefficient of *DT_NACC* is not significant. These results suggest that the decrease in accounting employees is mainly driven by the digitalization of accounting departments. The impact of digitalization on accounting employees is weakened for firms in which the accounting department and other functional departments go digital together, possibly because the accounting departments of these firms may have to deal with complex financial data from other departments.

5.2. Will an overconfident executive fire more accountants?

Managers typically play an important role in firms' digital transformation, as they decide when and how to go digital. They are also central to employment decisions. Therefore, the role of managers in the association between digitalization and corporate employee structure should be considered. Upper echelons theory suggests that managers' decision-making will be affected by their personal characteristics, such as age, gender and experience. In this subsection, we explore the role of management characteristics in terms of the impact of digitalization on corporate employee structure. We investigate this issue from the perspective of management overconfidence (*OVERCONF*), as this is a vital determinant when making risky and challenging decisions (Campbell et al., 2011; Hirshleifer et al., 2012). Overconfident managers tend to overestimate their abilities and judgment (Malmendier and Tate, 2005; Malmendier et al., 2011). We therefore expect that they will be more enthusiastic about the prospect of digital transformation and more likely to actively explore its potential in substituting for employees in unskilled tasks than less confident managers. A decline in the proportion of accounting employees is then likely.

We measure overconfidence based on managerial stock sales (Malmendier and Tate, 2005). If managers increase their stock holdings, they are likely to be confident in their capabilities and in the firms' prospects. *OVERCONF* equals one when net buying behaviors are observed, and zero otherwise. We divide the full sam-

Table 8
Moderating Effect of the Digitalization of the Accounting Department.

Dependent Variable = *ACC_PER*	(1)	(2)
DT_ACC	–0.002***	
	(–2.95)	
DT_ACC_SOLELY		–0.002***
		(–2.97)
DT_ACC_BOTH		–0.002*
		(–1.68)
DT_NACC	–0.001	0.000
	(–1.50)	(0.17)
GROWTH	0.001***	0.001***
	(2.88)	(2.87)
AGE	0.003***	0.003***
	(5.79)	(5.77)
SIZE	–0.003***	–0.003***
	(–8.10)	(–8.07)
LEV	–0.000	–0.000
	(–0.17)	(–0.17)
ROA	–0.048***	–0.047***
	(–6.61)	(–6.56)
MB	0.001*	0.001*
	(1.95)	(1.94)
TOP1	–0.002	–0.002
	(–1.05)	(–1.06)
MANHO	–0.003	–0.003
	(–1.61)	(–1.64)
INDEPB	0.014***	0.014***
	(2.77)	(2.76)
SOE	–0.004***	–0.004***
	(–4.71)	(–4.73)
GDP	–0.002***	–0.002***
	(–4.39)	(–4.40)
Constant	0.168***	0.167***
	(9.32)	(9.34)
Ind/Year FE	Yes	Yes
N	13,943	13,943
Adj.R^2	0.33	0.33

This table presents the results of analysis of the effect of digital transformation on corporate accounting employees, conditional on the digitalization of the accounting department. In Column (1), *DT_ACC* is an indicator variable that equals to one if the accounting department of the firm goes digital, and zero otherwise. *DT_NACC* is an indicator variable that equals to one if the firm goes digital but the accounting department does not, and zero otherwise. In Column (2), we decompose *DT_ACC* into two components, digital transformation solely related to the accounting department (*DT_ACC_SOLELY*) and digital transformation related to both the accounting department and non-accounting departments (*DT_ACC_BOTH*). Control variables are shown in the Appendix. T-statistics are reported, and ***, ** and * reflect statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are based on robust standard errors clustered at the firm level.

ple into two subsamples according to the level of management overconfidence and rerun model (1) for both subsamples. The results are shown in Columns (1) and (2) of Table 9. The coefficient of *DT* is only significant and negative in Column (1), and the coefficient estimate between the two subsamples is statistically different at the 1 % level, implying that the negative impact of digital transformation on the proportion of accounting employees is more salient in firms with overconfident managers.

5.3. The moderating effect of industry characteristics

As the IT industry is close to the technological frontier, it is likely to engage more deeply in digitalization than other industries. Firms in this industry can better monitor the value created through digitalization, evaluate the problems with digital transformation and help formulate digitalization strategies (Parent and Reich, 2009). They can more easily comprehend how a specific technology functions, judge the adequacy of validation controls and identify potential governance loopholes. Thus, we propose that the effect of digitalization on accounting employees will be more salient in the IT industry. We divide the full sample into two subsamples, *INTERNET* group and *Non INTERNET* group, based on whether the firm belongs to the IT industry. The results reported in Columns (3) and (4) of Table 9 are consistent with our conjecture.

5.4. The moderating effect of property rights

State-owned enterprises (SOEs) are best able to consistently fulfill social objectives and responsibilities regarding socially desirable goods and services (Lee et al., 2017; Gong et al., 2021). Private enterprises face

Table 9
Moderating Effects of Management and Industry Characteristics.

Dependent Variable = *ACC_PER*	(1) *OVERCONF*	(2) *Non OVERCONF*	(3) *INTERNET*	(4) *Non INTERNET*
DT	–0.003***	–0.001	–0.009***	–0.002***
	(–5.72)	(–1.14)	(–3.50)	(–2.79)
GROWTH	0.002***	0.001	0.002	0.002**
	(3.75)	(1.61)	(1.06)	(2.56)
AGE	0.004***	0.003***	0.005***	0.003***
	(9.21)	(5.34)	(4.00)	(5.46)
SIZE	–0.003***	–0.003***	–0.005***	–0.003***
	(–10.18)	(–9.50)	(–4.15)	(–7.52)
LEV	–0.003**	0.002	0.005	–0.001
	(–2.03)	(1.05)	(1.19)	(–0.50)
ROA	–0.044***	–0.060***	–0.073***	–0.048***
	(–6.26)	(–8.48)	(–3.91)	(–5.90)
MB	0.001***	0.000	–0.001	0.001**
	(4.33)	(1.18)	(–1.46)	(2.54)
TOP1	–0.003*	–0.003	0.011*	–0.003
	(–1.78)	(–1.50)	(1.70)	(–1.25)
MANHO	–0.004**	–0.002	–0.018***	–0.002
	(–2.55)	(–1.16)	(–4.13)	(–1.08)
INDEPB	0.010**	0.020***	0.007	0.015***
	(2.13)	(4.53)	(0.51)	(2.77)
SOE	–0.005***	–0.004***	–0.010***	–0.005***
	(–8.88)	(–5.36)	(–4.30)	(–4.39)
GDP	–0.003***	–0.002***	–0.002**	–0.003***
	(–7.64)	(–5.51)	(–2.19)	(–4.32)
Constant	0.180***	0.161***	–0.009***	0.175***
	(14.73)	(12.00)	(–3.50)	(8.55)
P value for the test of the difference	0.01		0.08	
Ind/Year FE	Yes	Yes	Yes	Yes
N	7,625	6,318	1,012	12,931
Adj.R^2	0.35	0.28	0.10	0.35

This table reports the results of analysis of the moderating effects of management and industry characteristics on the association between digital transformation and corporate accounting employees. In Column (1) and Column (2), firms in the sample are separated into two subsamples based on management overconfidence: *OVERCONF* and *Non OVERCONF*. In Column (3) and Column (4), firms in the sample are separated into two subsamples based on whether they belong to the IT industry or not: *INTERNET* and *Non INTERNET*. Control variables are shown in the Appendix. T-statistics are reported, and ***, ** and * reflect statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are based on robust standard errors clustered at the firm level.

greater ongoing pressure regarding social production than SOEs and will therefore be more enthusiastic about implementing digital technology (Li and Zhang, 2010). SOEs may also be reluctant to reduce the hiring headcount due to their social responsibility objectives. We thus expect that the substitution effect of digitalization for accounting employees will be more significant in private firms.

To test this conjecture, we divide the overall sample into the two sub-samples of SOEs and non-SOEs according to their property rights. The estimated results in Table 10 show that the coefficient of *DT* in Column (2) is –0.004 and statistically significant at the 1 % level. In contrast, the coefficient sign of *DT* in Column (1) is negative but not statistically significant. These findings indicate that the substitution effect of digitalization on accounting employees is more pronounced in private enterprises, which is consistent with our expectations.

5.5. The moderating effect of network infrastructure

In this subsection, we investigate whether the effect of digital transformation on accounting employees varies according to the network infrastructure. We measure network infrastructure based on the ''Broadband China" strategy, which aims to accelerate broadband implementation in the country. This strategy is likely to popularize and optimize broadband in its pilot cities, thus providing the prerequisites for improved network infrastructure. Firms within these cities will therefore be more likely to choose to go digital and lay off accounting employees than firms located elsewhere. We split the full sample into *High INFRAS* and *Low*

Table 10
Moderating Effects of Property Rights and Network Infrastructure.

Dependent Variable = *ACC_PER*	(1) *SOE*	(2) *Non SOE*	(3) *High INFRAS*	(4) *Low INFRAS*
DT	–0.001	–0.004***	–0.003***	–0.001
	(–1.34)	(–3.58)	(–5.84)	(–1.55)
GROWTH	0.001**	0.003***	0.002***	0.001**
	(2.20)	(2.60)	(3.44)	(2.27)
AGE	0.001	0.006***	0.004***	0.003***
	(1.12)	(8.10)	(9.52)	(6.64)
SIZE	–0.002***	–0.005***	–0.004***	–0.003***
	(–8.45)	(–6.96)	(–12.35)	(–9.57)
LEV	–0.000	0.005	–0.001	0.000
	(–0.13)	(1.48)	(–0.44)	(0.06)
ROA	–0.004	–0.062***	–0.053***	–0.040***
	(–0.47)	(–4.99)	(–8.05)	(–6.28)
MB	0.000	0.001*	0.000	0.001***
	(0.62)	(1.75)	(1.57)	(3.52)
TOP1	–0.002	–0.001	–0.005***	0.001
	(–1.06)	(–0.42)	(–2.87)	(0.67)
MANHO	0.007	0.001	–0.005***	–0.002
	(0.81)	(0.32)	(–3.14)	(–1.29)
INDEPB	0.012***	0.026***	0.014***	0.010**
	(2.83)	(3.07)	(3.58)	(2.37)
GDP	–0.002***	–0.003***	–0.006***	–0.004***
	(–5.22)	(–4.62)	(–9.30)	(–6.46)
Constant	0.140***	0.208***	0.167***	0.175***
	(11.80)	(8.54)	(14.22)	(15.41)
P value for the test of the difference	0.06		0.07	
Ind/Year FE	Yes	Yes	Yes	Yes
N	4,849	9,094	9,062	4,881
Adj.R^2	0.38	0.10	0.33	0.31

This table reports the results of analysis of the moderating effects of property rights and network infrastructure on the association between digital transformation and corporate accounting employees. Firms in the sample are separated into two subsamples based on their property rights (*SOE* and *Non SOE*) or their network infrastructure level (*High INFRAS* and *Low INFRAS*). Control variables are shown in the Appendix. T-statistics are reported, and ***, ** * reflect statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are based on robust standard errors clustered at the firm level.

INFRAS groups according to whether the registered city of the firm is included in the "Broadband China" pilot program. As presented in Columns (3) and (4) of Table 10, the coefficient of *DT* is negative and significant at a 1 % level in the *High INFRAS* group, which is consistent with our expectation.

6. Further analysis

6.1. The impact of digitalization on the skills and education levels of accounting employees

To provide further insights into the impact of digital transformation on accounting employees, we examine whether their education and skill levels will change after digital transformation. Although we cannot obtain the detailed characteristics of these employees, we can obtain the total numbers of accounting employees from the recruitment data of the accounting departments. We do this by manually identifying the specific recruitment of accounting employees. We only consider recruitment data from 2014 and 2015, due to the huge costs and time required to collect the data. Through reading the detailed recruitment requirements, we obtain information on the work experience required, which is often used to measure the skill levels of employees. We also identify the education level of the accounting employees through this approach. *EDUCATION* is an indicator variable equals to one if the firm requires accounting employees to have a bachelor's degree or above, and zero

Table 11
Impact of Digital Transformation on the Skill and Education Levels of Accounting Employees.

Dependent Variable =	(1) *SKILL*	(2) *EDUCATION*
DT	0.224**	0.108*
	(1.99)	(1.74)
GROWTH	–0.033	0.023
	(–0.50)	(0.38)
AGE	–0.210**	0.007
	(–2.22)	(0.18)
SIZE	–0.043	0.071**
	(–0.89)	(2.15)
LEV	0.236	0.100
	(0.85)	(0.67)
ROA	1.451	0.390
	(1.30)	(0.69)
MB	–0.035	0.021
	(–1.18)	(1.19)
TOP1	0.140	–0.289*
	(0.54)	(–1.68)
MANHO	–0.016	–0.103
	(–0.05)	(–0.79)
INDEPB	0.631	0.425
	(0.95)	(0.93)
SOE	–0.076	0.062
	(–0.88)	(1.08)
GDP	0.064	0.105***
	(1.05)	(2.77)
Constant	–0.064	–4.278***
	(–0.03)	(–3.12)
Ind/Year FE	Yes	Yes
N	995	995
Adj.R^2	0.02	0.06

This table presents the results of analysis of the impact of digital transformation on the skill and education levels of accounting employees. T-statistics are reported, and ***, ** and * reflect statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are based on robust standard errors clustered at the firm level.

otherwise. We then investigate the effect of digitalization on the skills and education levels of accounting employees. The regression results are shown in Columns (1) and (2) of Table 11. The positive and significant coefficients of *DT* are consistent with our conjecture. These results indicate that the impact of technological advancements on labor demand is not neutral, and they appear to increase the demand for highly skilled and educated employees, due to the revolutionary and complex nature of digital transformation (Acemoglu and Restrepo, 2018; Hjort and Poulsen, 2019). These employees are also better equipped with the knowledge and skill sets necessary to effectively operate in the digitalization environment.

6.2. The impact of digital transformation on technical, highly educated and entry-level employees

To better inform our research narrative, we examine in more detail whether digital transformation can affect other kinds of employees such as those who are technical, highly educated or entry-level. Column (1) of Table 12 repeats Model (1), with the additional dependent variable *TECH_PER* providing evidence for the impact of digitalization on technical employees. Digital transformation increases the demands on employ-

Table 12
Impact of Digital Transformation on Technical, Highly Educated and Entry-level Employees.

Dependent Variable =	(1) *TECH_PER*	(2) *HE_PER*	(3) *ENTRY_PER*
DT	0.022***	0.023***	–0.020***
	(5.53)	(4.30)	(–4.59)
GROWTH	0.004	0.015***	–0.004
	(1.20)	(4.32)	(–1.09)
AGE	–0.007*	–0.012***	0.008**
	(–1.88)	(–2.68)	(2.23)
SIZE	0.001	0.023***	0.003
	(0.36)	(6.56)	(0.95)
LEV	–0.058***	–0.071***	0.070***
	(–3.80)	(–4.00)	(4.49)
ROA	–0.036	–0.043	0.080
	(–0.70)	(–0.69)	(1.47)
MB	0.009***	0.021***	–0.011***
	(4.12)	(8.16)	(–5.25)
TOP1	–0.059***	–0.060***	0.065***
	(–3.64)	(–2.90)	(3.96)
MANHO	0.037***	0.054***	–0.035**
	(2.67)	(3.28)	(–2.41)
INDEPB	0.085**	0.102**	–0.094**
	(2.07)	(2.22)	(–2.27)
SOE	0.023***	0.048***	–0.024***
	(3.82)	(6.49)	(–3.93)
GDP	0.001	–0.021***	0.001
	(0.26)	(–5.17)	(0.39)
Constant	0.047	0.215	0.784***
	(0.44)	(1.51)	(7.11)
Ind/Year FE	Yes	Yes	Yes
N	13,943	13,943	13,943
Adj.R^2	0.36	0.33	0.37

This table presents the results of analysis of the impact of digital transformation on technical, highly educated and entry-level employees. The dependent variable in Column (1) is *TECH_PER*, defined as the proportion of technical employees to total employees. The dependent variable in Column (2) is *HE_PER*, defined as the proportion of highly educated employees to total employees. The dependent variable in Column (3) is *ENTRY_PER*, defined as the percentage of entry-level employees to total employees. Control variables are shown in the Appendix. T-statistics are reported, and ***, ** and * reflect statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are based on robust standard errors clustered at the firm level.

ees with professional knowledge and technical skills to explore and facilitate the effective embedding of digital processes and technologies into businesses, which is consistent with the notion that the technology revolution is biased (e.g., Acemoglu, 2002; Goos et al, 2014; Autor, 2015). Therefore, we predict that the proportion of technical employees will increase with digitalization.

The impact of the technological revolution on labor demand is not neutral: it substitutes for less-educated workers and complements highly educated workers (Acemoglu, 2002; Acemoglu and Restrepo, 2018; Hjort and Poulsen, 2019). The demand for less-educated employees is likely to decline because they lack the necessary specialist knowledge and digital skills. Demand for highly educated employees will increase as they have the skills required for applying the latest technology (Richins et al., 2017). Emerging technologies such as big data, cloud computing and blockchain are complex and involve specialist knowledge such as advanced mathematics, leading to high technical barriers when integrating them into current business models. Successful integration requires a deep understanding of the potentials and risks that accompany digital technology. Thus, we expect that digital transformation will have a positive effect on firms' highly educated employees. The results in Column (2) of Table 12 are consistent with this conjecture.

In terms of entry-level employees, compared with complex tasks that require flexible decision-making and judgments, those conducting routine tasks are found to be more easily replaced by machines (Cortes, 2016; Acemoglu and Restrepo, 2018). We expect similar results concerning the impact of digitalization. To test this prediction, we define employees other than executives and technical employees as entry-level. The negative and salient coefficient of *DT* in Column (3) of Table 12 indicates that digital transformation does bring about a greater shock to routine work, causing a decline in the demand for such employees.

Table 13
Impact of Digital Transformation on Labor Investment Efficiency.

Dependent Variable = *AB_NETHIRE*	(1)
DT	–0.014**
	(–2.02)
GROWTH	0.246***
	(16.31)
AGE	–0.003
	(–0.51)
SIZE	0.003
	(0.64)
LEV	–0.044*
	(–1.94)
ROA	–0.569***
	(–5.87)
MB	0.009***
	(2.95)
TOP1	0.019
	(0.80)
MANHO	0.013
	(0.70)
INDEPB	0.034
	(0.62)
GDP	–0.011**
	(–2.23)
Constant	0.441***
	(2.76)
Ind/Year FE	Yes
N	12,745
Adj.R^2	0.15

This table shows the results of analysis of the economic consequences of digital transformation on labor investment efficiency (*AB_NETHIRE*). Control variables are shown in the Appendix. T-statistics are reported, and ***, ** and * reflect statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are based on robust standard errors clustered at the firm level.

6.3. The impact of digital transformation on labor investment efficiency

Thus far, we have provided evidence that digital transformation has a substitution effect for regular and routine tasks. This gives rise to the question of whether labor investment efficiency will increase. The applications and promotion of digitalization are often accompanied by the re-allocation and optimization of firms' labor resources, causing them to make better labor investment decisions, which will eventually lead to improved labor investment efficiency. Following Jung et al. (2013), we measure labor investment efficiency using the absolute deviation of actual net hiring from its expected level. As Column (1) of Table 13 shows, the coefficient of *DT* is –0.014 and is significant at the 5 % level. This implies that digital transformation facilitates more efficient investment in labor.

7. Conclusion

The rapid advance of digital transformation has intensified concerns that it will make labor redundant, and especially accounting employees. Accountants may feel challenged by ongoing technical changes and find it hard to compete with them. Although the debate on the race between humans and technology is longstanding, few studies evaluate the impact of digitalization on the accounting profession. This study provides a further understanding of this issue in the digital age and contributes to the small but growing body of literature concerning the economic consequences of digital transformation by using a manually collected dataset from China on digital transformation.

We provide evidence regarding the specific impact of digital transformation on corporate accounting employees. This study documents a substitution effect of digitalization to accounting employees. Our findings are both statistically and economically significant and remain unchanged after an extensive set of robustness checks, such as alternative measures of the test variable, different subsamples and placebo tests. We further consider the moderating effects of the level of digital transformation in accounting departments, management characteristics, industry characteristics, property rights and network infrastructure. We show that the effect of digitalization on accounting employees is more evident in private firms, those with a higher level of digital transformation in their accounting departments and those in the IT industry. The effect on accounting employees also varies according to the level of management overconfidence and the network infrastructure. Based on these results, we further investigate the economic consequences of digital transformation.

Our findings show that digitalization induces a decline in the share of entry-level employees but increases the demand for technical and highly educated employees. It also facilitates more efficient investment in labor. Our study provides evidence to open research questions that previous studies have not sufficiently considered. These suggest opportunities for future studies and have wide-ranging implications for practitioners. Our findings can further the understanding of how the accounting profession is transforming in the digital age. The quality of labor must be considered together with issues of technology in the unprecedented rise of the digital economy.

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. Variable definitions

This table details the main variables used in this paper and their definitions.

Variable	Definition
ACC_PER	The proportion of accounting employees to total employees.
HE_PER	The fraction of highly educated employees to total employees. An employee is considered as highly educated when they have a bachelor's degree or above.
DT	An indicator variable that equals one after the year a firm starts to go digital, and zero otherwise.
TECH_PER	The proportion of technical employees to total employees.
ENTRY_PER	The fraction of entry-level employees to total employees. Employees other than technical employees and executives are considered as entry-level employees.
AB_NETHIRE	Labor investment efficiency, based on Jung et al. (2013).
DIGITAL_ASSETS	The natural logarithm of digital-related tangible and intangible investments.
IT_PER	The proportion of executives with an information technology (IT) background to the total number of executives. An executive is considered to have an IT background when their previous study and work experience includes "IT", "information technology", "computer" or "communication".
GROWTH	Sales growth rate.
AGE	The natural logarithm of the number of years a firm has been listed plus one.
SIZE	The natural logarithm of total assets.
LEV	Total liabilities deflated by total assets.
CFO	Net operating cash flow deflated by total assets.
ROA	Net income divided by total assets.
MB	The market–book ratio.
TOP1	Equity shares of the largest shareholder.
MANHO	Equity shares of the management.
INDEPB	The proportion of independent board members to the total number of board members.
SOE	An indicator variable that equals one if the ultimate controlling owner is the government, and zero otherwise.
GDP	The natural logarithm of the total GDP of the firm's registered province.

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ESG performance and cost of debt

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ABSTRACT

We analyze China Securities Index Co., Ltd. (CSI) environmental, social and governance (ESG) scoring data, which incorporate Chinese characteristics, to assess the impact of ESG performance on corporate debt financing costs. Our findings indicate that better CSI ESG scores are correlated with lower debt financing costs. Additionally, improvements in local environmental execution enhance the effect of CSI ESG scores on debt financing costs. However, this effect diminishes with increased internal control quality and marketization. Governance has the greatest impact on reducing debt financing costs, followed by social and environmental factors. Superior CSI ESG scores reduce corporate debt financing costs by enhancing debt repayment capacity and reducing information asymmetry. Economic consequence analysis confirms that lower financing costs, driven by improved ESG performance, significantly enhance total factor productivity and firm value. CSI ESG scores also significantly impact bank loans but not corporate bond financing.

1. Introduction

Environmental, social and governance (ESG) aspects reflect micro-level sustainable development within an enterprise (Friede et al., 2015). These aspects not only enhance green and responsible investment but also serve as key standards within the international community for measuring corporate green and sustainable development. The evolution of ESG investment concepts has progressed from socially responsible investment to

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responsible investment, then to sustainable investment and, ultimately, to ESG investment (Gillan et al., 2021). In their pursuit of sustainability, producers often forgo some profits to invest in environmental protection technologies and labor protection, achieving reduced pollution and increased efficiency (Mao and Wang, 2023). Similarly, with the expansion of cross-border investments, financial institutions, especially commercial banks, now recognize that the costs associated with labor protection and community development not only impact project returns but also play a crucial role in determining corporate solvency (Fang and Hu, 2023). Additionally, the market recognizes that factors such as board structure, compensation systems and corporate reputation influence the long-term stability of corporate financing more significantly than do short-term financial positions (Goldstein et al., 2022). Consequently, environmental stewardship, social responsibility and corporate governance are increasingly acknowledged as the three pivotal dimensions of corporate sustainability.

Debt financing constitutes the primary financial conduit for corporations (Yu et al., 2019a, 2019b). For instance, in 2022, the total social financing of Chinese corporations amounted to 32.01 trillion yuan, marking an increase of 0.67 trillion yuan over the previous year. Specifically, 65.3 % of this financing comprised RMB loans, while 22.3 % was sourced from government bonds and 6.4 % from corporate bonds. Conversely, domestic equity financing only accounted for 1.18 trillion yuan. Within the context of economic activities, banks and financial institutions integrate enterprises' performance in environmental protection, social responsibility and corporate governance into their credit assessments. Consequently, a company's ESG performance substantially influences its financing conditions. In this paper, the strengths of the China Securities Index Co., Ltd. (CSI) ESG metrics are leveraged to investigate their impact on corporate financing costs.

Research primarily examines the impact of a single dimension of ESG performance on the cost of debt financing. For instance, corporations demonstrating robust environmental performance typically incur lower default and reputational risks than their peers (Zhou et al., 2018), which reduces their debt-related expenses (Menz, 2010; Oikonomou et al., 2014). However, high levels of environmental disclosure do not always result in decreased financing costs, as companies may allocate excessive resources to sustainability initiatives (Martin and Moser, 2016). Similarly, superior corporate social responsibility (CSR) performance can facilitate companies' access to more affordable financing options with longer maturities and reduced interest rates, thereby diminishing their overall financing costs (Naughton et al., 2019). Conversely, some critics argue that significant investments in CSR are inefficient and divert valuable resources (Friedman and Friedman, 1962; Barnea and Rubin, 2010). In the realm of corporate governance, Sengupta (1998) finds that effective governance mechanisms can alleviate agency issues and information asymmetry, thus lowering debt financing costs. In conclusion, although substantial evidence links individual aspects of ESG performance to debt financing costs, scholarly consensus remains elusive.

China, as the world's second-largest economy with a robust industrial chain, plays a crucial role in global economic stability. From 2018 to 2020, China's regulations required that listed companies issue periodic reports and make immediate disclosures concerning significant environmental issues that detail the causes, impacts on corporate performance and corrective measures taken. Between 2006 and 2008, the Shanghai and Shenzhen stock exchanges issued directives emphasizing the social responsibilities of listed companies. In 2018, the China Securities Regulatory Commission (CSRC) introduced revised Governance Guidelines for Listed Companies, mandating a commitment to innovative, coordinated, green and inclusive development. These guidelines also encourage an entrepreneurial spirit and an increased focus on ESG responsibilities. Furthermore, in 2020, the China Banking and Insurance Regulatory Commission (CBIRC) released the Guiding Opinions on Promoting the High-quality Development of the Banking and Insurance Industry. This document recommends the integration of ESG criteria throughout the credit process to mitigate financial risks and enhance corporate excellence. Consequently, China's capital market has emerged as an exemplary setting for examining the economic impacts of ESG investments.

In contrast to previous research, we investigate the influence of overall CSI ESG performance on corporate debt financing costs within China's distinctive systemic context. Differing from studies on the economic effects of ESG, we use data on the ESG scores formulated by CSI, which assesses firms' comprehensive performance in environmental protection, social responsibility and corporate governance. CSI then produces ESG scores for listed companies, with higher scores indicating superior ESG performance. The advantages of the CSI ESG evaluation over other systems are manifold. First, the CSI ESG evaluation incorporates both China's specific national circumstances and international practices such as the United Nations' sustainable investment

principles, selecting indicators relevant to poverty alleviation and corporate social contributions. Second, the evaluation system offers clear and investment-worthy indicators of risk and return; thus, it reflects corporate quality through metrics such as stock pledges and illegal guarantees, alongside innovative measures such as green income and the social contribution value per share. Third, the CSI ESG evaluation balances ESG risk factors with opportunities, emphasizing investments that address risks and sectors, such as new energy, with substantial growth potential. Lastly, the Shanghai and Shenzhen stock exchanges are investors in CSI, and CSI manages their stock custody operations; accordingly, the CSI ESG evaluation is likely to surpass other evaluations in terms of information accessibility due to its proximity to these exchanges.

In this paper, we investigate the impact of CSI ESG performance on corporate debt financing costs by analyzing constituent stocks from the HS 300 and CSI 500 indices between 2018 and 2020. Our findings indicate that better CSI ESG scores significantly reduce corporate debt financing costs. Additionally, after disaggregating ESG into its environmental, social and governance components and conducting separate regressions, we observe that all three factors negatively influence debt financing costs, with governance factors having the most substantial impact, followed by social and environmental factors. We further categorize corporations based on their levels of environmental implementation, social responsibility and governance. Our results show that improvements in local environmental execution enhance the reducing effect of ESG on debt costs, whereas advancements in internal control quality and marketization weaken this effect. Analysis of the underlying mechanisms reveals that the CSI ESG evaluation lowers debt costs by improving companies' debt repayment capacity and reducing informational asymmetry. Economic outcome analysis further demonstrates that reductions in financing costs through superior ESG performance contribute to enhanced total factor productivity and firm value. Additionally, while our findings show no significant impact of CSI ESG scores on corporate bond financing, we observe a significant positive effect of the scores on bank loan financing. We also conduct baseline regressions using instrumental variables to address potential endogeneity and use alternative indices, measures and data to confirm the robustness of our results.

To the best of our knowledge, our study's contributions to the literature are substantial. First, we examine the relationship between the ESG performance of enterprises within China's capital market and their cost of debt financing using CSI ESG score data. The CSI ESG evaluation benefits from its alignment with China's national conditions and thus offers advantages in data reliability and validity over other ESG ratings.

Similar to our study, Houqe et al. (2020) and Ratajczak and Mikołajewicz (2021) examine the associations of the Bloomberg ESG and Corporate Knights ESG metrics with the costs of debt financing. However, a potential issue in their research is international evaluators' lack of understanding of the specific Chinese context, which leads to a mismatch in the assessment criteria. For instance, social initiatives such as targeted poverty alleviation and rural revitalization, along with governance practices such as party building and anti-corruption measures, increase objectivity and enable a fair reflection of Chinese enterprises' ESG performance. Yet, these factors are often overlooked in ESG assessments, particularly for Chinese state-owned enterprises. Conversely, the CSI ESG scoring system, as described by Shi and Wang (2023), is rooted in the United Nations' Sustainable Development Goals, and its indicators are tailored to better suit local market demands and the distinct characteristics of Chinese firms.

Xie and Lv (2022) utilize the Sino-Securities ESG index to explore the link between ESG and China's outbound foreign direct investment (OFDI). However, the Sino-Securities ESG index, being rating-based, tends to cluster results around the medium level, making it challenging to differentiate between companies' ESG performance (Shi and Wang, 2023). In contrast, we use ESG scoring data that not only enhance data reliability and validity but also allow for an effective comparison of ESG levels across different companies. Our findings, which are supported by an information value test, confirm that the CSI ESG score index provides more precise and comprehensive data than other measures.

Second, our analysis reveals that corporate governance factors in the CSI ESG framework significantly contribute to reducing debt financing costs. These findings are in marked contrast to those of Ratajczak and Mikołajewicz (2021), who argue that heightened involvement in corporate governance is correlated with increased debt costs and posit that expenditures on corporate governance are perceived as squandering company resources and opportunities. However, our study indicates that a one standard deviation increase in governance performance leads to a 10.09 % decrease in corporate debt financing costs.

Third, the literature scarcely examines the influence of ESG performance on enterprises' financing methods. Our research, however, demonstrates that robust ESG performance can alleviate enterprises' financing constraints and thus facilitate increased access to bank loans. Nevertheless, ESG performance appears to have no effect on corporate bond issuance. This distinction offers a practical avenue for enterprises seeking to mitigate financing constraints.

The remainder of this paper is organized as follows. Section 2 provides an overview of the literature and develops the hypotheses. Section 3 introduces the sample, variables and model settings. Section 4 reports the research results. Section 5 examines the robustness of the results. We perform further analysis in Section 6. Section 7 provides an overall conclusion of the study.

2. Literature review and hypothesis development

2.1. Literature review

2.1.1. Economic consequences of ESG

Our study is related to the literature on the economic consequences of ESG. Extant research on the evaluation of ESG performance predominantly explores the correlation between corporate ESG ratings and financial outcomes.

Various studies indicate a negative correlation between corporate ESG evaluation and financial performance. Drawing on neoclassical theory, researchers such as Vance (1975), Alexander and Buchholz (1978) and Wright and Ferris (1997) support the stakeholder expense view, initially proposed by Friedman (1970), which posits that high corporate ESG ratings detrimentally affect firms' financial outcomes. Furthermore, some managers reportedly increase ESG investments to enhance their reputation, which, according to Krueger (2015), undermines shareholder value and the advancement of core technologies and products. Hariom and Rajgopal (2017) also affirm this negative impact of ESG investment. Additionally, Di Giuli and Kostovetsky (2014) demonstrate a significant inverse relationship between fluctuations in firms' ESG scores and their return on assets (ROA) or stock returns. Similarly, Duque-Grisales and Aguilera-Caracuel (2021) observe negative correlations between ESG sub-factors and corporate financial performance.

Other studies find a positive correlation between corporate ESG evaluation and financial performance. This correlation is supported by several studies advocating for stakeholder maximization (e.g., Freeman, 1984; Deng et al., 2013). For example, Freeman (1984) argues that CSR serves as an effective strategy for minimizing transaction costs and resolving stakeholder conflicts. Additionally, ESG performance reduces agency costs (Bernanke and Gertler, 1989; Bernanke and Gertler, 1990) and information asymmetry (Cormier et al., 2011) and decreases firm-level risk (Diamond, 1989; Datta et al., 1999). From their analysis of over 2,000 studies, Friede et al. (2015) report that for nearly 90 %, there is a nonnegative correlation between ESG and corporate financial performance, with increasing evidence over time of a significant and positive relationship. For instance, Velte (2017) investigates German listed companies from 2012 to 2014 and concludes that superior ESG performance positively influences ROA, although it does not affect Tobin's Q.

2.1.2. Influencing factors of debt financing costs

Our research is also related to the literature on factors, especially individual ESG factors, affecting the cost of debt financing. The literature primarily examines the impact of accounting conservatism (Gigler et al., 2009), disclosure of accounting information (Watts and Zimmerman, 1990), corporate social responsibility (Goss and Roberts, 2011; Stellner et al., 2015; Jung et al., 2018), ownership structure (Lin et al., 2011) and corporate governance (Ashbaugh-Skaife et al., 2006). In this section, we systematically review studies pertaining to debt financing costs across three aspects: environmental, social and governance.

In terms of environmental performance, several studies confirm that debt financing costs correlate with corporate environmental risk management (Aintablian et al., 2007) and environmental performance (Fonseka et al., 2019). For corporations exhibiting strong environmental performance, comprehensive environmental information disclosure can reduce information asymmetry between creditors and corporations (Goss and Roberts, 2011), thereby lowering debt costs (Menz, 2010; Oikonomou et al., 2014). However, imperfect capital market systems and regulatory mechanisms may enable corporations to occasionally overinvest in green

initiatives (Martin and Moser, 2016); in other words, high levels of environmental disclosure do not always lead to reduced debt financing costs.

In terms of social performance, superior CSR performance, characterized by activities such as engaging in CSR initiatives (Oware and Mallikarjunappa, 2021) and enhancing transparency through social information disclosures (Hadlock and Pierce, 2010), is deemed to be creditworthy. Such efforts can reduce information asymmetry, ease financing constraints, facilitate access to cost-effective financing with extended maturities and lower interest rates and positively affect investor sentiment, without necessarily boosting financial performance (Naughton et al., 2019). Additionally, CSR initiatives can lower overall corporate financing costs. Conversely, CSR investments are considered to be resource wastage from the overinvestment perspective. From an agency standpoint, excessive spending on CSR initiatives is seen as a misallocation of resources and managers' potential prioritization of personal benefits over shareholder wealth maximization (Friedman and Friedman, 1962; Barnea and Rubin, 2010). From this perspective, robust ESG performance could detrimentally impact both debtholders and shareholders.

In the context of corporate governance, creditors' loan decision-making processes encompass not only financial assessments but also evaluations of corporate governance structures (Boubakri and Ghouma, 2010). Foreseeing potential issues with poor governance and opportunistic behavior by corporate insiders, creditors typically require an increase in the risk premium to offset the increased investment risk (Jensen and Meckling, 1976; John and John, 1993; Kabir et al., 2013). Sengupta (1998) demonstrates that effective corporate governance mechanisms can alleviate agency problems and reduce information asymmetry, thereby decreasing the costs associated with debt financing.

We find that Houqe et al. (2020) is the most pertinent literature for our study: the authors demonstrate that both aggregate and individual ESG performance are significantly and negatively correlated with the cost of corporate debt across samples from 41 countries. Additionally, Ratajczak and Mikołajewicz (2021) confirm that environmental and social factors tend to increase the costs of short-term and long-term debt, whereas governance factors may decrease these costs. Their research encompasses 300 companies globally that were recognized in 2017 by Corporate Knights as the most sustainable. In general, while the Bloomberg ESG and Corporate Knights ESG datasets include Chinese companies, the ratings are derived from international evaluations and may not fully account for aspects specific to the Chinese context, such as targeted poverty alleviation and rural revitalization. Consequently, the applicability of their findings to China requires empirical validation.

In conclusion, while the literature provides a solid foundation for research and theoretical analysis, it also has several limitations. First, prior studies predominantly concentrate on individual aspects of ESG performance and explore their impact on debt financing costs. However, consensus on the correlations of the E, S and G dimensions with debt financing costs remains elusive. Second, little research on the relationship between ESG performance and debt financing costs uses Chinese ESG evaluation samples. Consequently, we posit that the current understanding of the link between ESG performance and debt financing costs is incomplete and warrants further investigation, particularly within the Chinese context, especially given the emergence of ESG as a concept and practice in China.

2.2. Hypothesis development

We propose that corporate ESG performance can influence debt financing costs in the following ways.

First, improved ESG performance can indirectly enhance a firm's debt repayment capabilities. This improvement is reflected in lower default risks and higher credit ratings, which are critical indicators of a firm's financial health. Specifically, firms with superior ESG performance exhibit robust ESG practices, which enhances their market reputation and, potentially, their long-term financial stability. Consequently, these firms may benefit from reduced default risks, which can lower their debt financing costs. Additionally, credit ratings—an essential metric for investors and financial institutions—are factored into a company's comprehensive ESG performance. Better ESG scores often result in higher credit ratings and, in turn, reduce the cost of debt when issuing bonds or obtaining loans (Oware and Mallikarjunappa, 2021).

Second, improved ESG performance can mitigate information asymmetry between enterprises. Firms typically possess more accurate and abundant information than creditors, placing them in a superior position.

Consequently, creditors often require higher risk premiums for financing due to having less financial information, which increases corporate debt financing costs (Jaffee and Russell, 1976; Stiglitz and Weiss, 1981). Enhanced ESG performance indicates robust corporate information disclosure and reduced information asymmetry, which can enhance stock market liquidity (Roy et al., 2022), decrease the default risk and lower the cost of debt financing (Xu et al., 2019). Conversely, poorer ESG performance, characterized by lower disclosure quality and greater information asymmetry (Hong and Kacperczyk, 2009; Hsu et al., 2019), can lead to diminished profitability (Chen et al., 2018), which adversely affects debt financing costs. Therefore, to pursue risk mitigation during financing decisions, creditors favor firms with strong CSI ESG performance and offer them good financial terms, such as reduced bond yield spreads and extended maturities, resulting in reduced debt financing costs for these firms (Hamrouni et al., 2019).

We propose the following hypothesis:

H1-A. A better CSI ESG evaluation is associated with lower corporate debt financing costs.

CSI ESG evaluations may lead to increased debt financing costs for several reasons, as follows.

First, the practice of greenwashing at the product level, a prevalent marketing strategy, often involves overstating or misrepresenting the environmental benefits of specific products, services and business activities to boost sales (Parguel et al., 2011). Companies may selectively share positive information regarding their environmental or social initiatives on platforms such as official websites, annual reports and sustainability reports, while simultaneously omitting negative details. Such selective disclosure can create a misleading perception of commendable overall environmental or social performance (Lyon and Maxwell, 2011). Ultimately, greenwashing represents a disconnect between firms' symbolic gestures and substantive environmental actions (Guo et al., 2017; Siano et al., 2017). Such practices, aimed at minimizing or concealing firms' negative impacts on the environment and society by promoting an eco-friendly image, are likely to elevate their financing costs.

Second, banks and other financial institutions prioritize financial risks and profitability when extending credit to firms. Firms' allocation of these funds to environmental and social initiatives and simultaneous diversion of resources from core business activities can disrupt production and operational plans, decrease efficiency, elevate corporate financial risks and increase debt financing costs (Becchetti et al., 2015).

Third, corporate executives often engage in socially responsible activities to enhance their own reputations and social impact (Zhang et al., 2021), or to mask unethical corporate management practices (Hemingway and Maclagan, 2004). Such actions, which are primarily driven by self-interest (Gillan et al., 2021), overlook the value and competitiveness of the corporation and lead to increased debt financing costs (Cespa and Cestone, 2007; Barnea and Rubin, 2010).

We propose the following hypothesis:

H1-B. A better CSI ESG evaluation is associated with higher corporate debt financing costs.

3. Research design

3.1. Sample selection and data sources

We use HS 300 and CSI 500 index constituent stocks from 2018 to 2020 as our initial research sample. Unlike ESG ratings data from other institutions,[1] the CSI ESG index primarily adheres to the framework of international consensus, exemplified by the United Nations' Sustainable Development Goals, and selects indicators that align with China's specific conditions and corporate characteristics. Indicators reflecting Chinese distinctiveness, such as common prosperity, state-owned enterprises' equity concentration and involve-

[1] Currently, approximately 50 ESG rating systems are utilized in China, including the FTSE Russell, Harvest, Sino-Securities, CASVI, SynTao Green and OWL indices. These indices predominantly feature ratings clustered at the median level and thus lack sufficient differentiation. Specific indices, like Sino-Securities, rely primarily on financial data to formulate ESG ratings, resulting in incomplete coverage. Moreover, international bodies often fail to grasp the unique context of China, leading to evaluations that do not adequately reflect local practices. It is imperative for both domestic and international ESG frameworks to broaden their assessment criteria to include social initiatives such as poverty alleviation and rural revitalization, as well as governance factors like party-building and anti-corruption efforts, particularly within state-owned enterprises. The variability in ESG evaluation outcomes is largely due to the differing perspectives, standards and aggregation methods employed by various institutions, along with their distinct backgrounds and objectives, which introduce notable discrepancies and biases in the results.

ment of the party organization in corporate governance, provide a more objective and equitable representation of ESG levels. Crucially, while most ESG index data comprise ratings, these typically cluster around the median and offer little differentiation of companies' ESG performance.

We subsequently exclude financial corporations and samples lacking critical financial data. We apply winsorization to all continuous variables at the 1st and 99th percentiles, yielding 2,058 valid samples.

The CSI ESG data are sourced from the third-party rating agency CSI, and corporate financial data are obtained from the WIND database, China Stock Market & Accounting Research database and China Research Data Service Platform.

3.2. Variable measurement and empirical models

To test H1-A and H1-B, which examine the relationship between corporate ESG performance and the cost of debt financing, we employ a multivariate linear regression model, designated as model (1):

$$DebtCost_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (1)$$

The dependent variable in model (1) is debt financing costs (*DebtCost*), measured using the ratio of financial expenses to total liabilities. This study also evaluates CSI ESG performance (*ESG*), grading corporations on their ESG efforts using a system developed by CSI. This system assigns scores ranging from 0 to 1, with higher scores indicating superior ESG performance. The control variables, based on Jin et al. (2022), include corporate size (*Size*), asset–liability ratio (*Lev*), age (*Age*), profitability (*Roe*), nature of property rights (*Soe*), the fixed assets ratio (*Fa*) and annual (*Year FE*), industry (*Ind FE*) and province (*Pro FE*) fixed effects. To address potential endogeneity issues, all dependent variables are lagged by one period to reduce the impact of possible reverse causality. Detailed descriptions of the variables are available in Table 1.

The focus of this analysis is on β_1, the coefficient of *ESG*. A significant and negative β_1 confirms H1-A, whereas a significant and positive β_1 confirms H1-B.

4. Empirical results

4.1. Descriptive statistics

Table 2 presents the comprehensive descriptive statistics for the primary variables. For *DebtCost*, the mean is 1.155 %, the median is 1.330 % and the standard deviation is 2.080 %, indicating significant variability in

Table 1
Descriptions of the variables.

Type	Symbol	Name	Descriptions
Independent variable	*DebtCost*	Debt financial costs	Financial expenses divided by total liabilities
Dependent variable	*ESG*	CSI ESG performance	Index calculated according to data from CSI; score ranges from 0 to 1
	E	E of CSI ESG	Environmental component of CSI ESG; score ranges from 0 to 1
	S	S of CSI ESG	Social component of CSI ESG; score ranges from 0 to 1
	G	G of CSI ESG	Governance component of CSI ESG; score ranges from 0 to 1
Control variables	*Size*	Corporate size	Natural logarithm of total assets
	Lev	Corporate leverage	Total liabilities divided by total assets
	Roe	Profitability	Net profit divided by total assets
	Soe	Nature of property rights	Equal to 1 for state-owned enterprises, and 0 otherwise
	Age	Corporate age	Sample year minus inception year
	Fa	Fixed assets ratio	Net value of fixed assets divided by total assets
	Ind FE	Industry fixed effects	Dummy variables for industry codes; manufacturing requires two industry codes
	Year FE	Year fixed effects	Year dummy variable
	Pro FE	Province fixed effects	Province dummy variable

Table 2
Descriptive statistics of the main variables.

Variable	N	Mean	Standard Deviation	Minimum	Median	Maximum
DebtCost	2,058	1.155	2.080	–6.557	1.330	5.715
ESG	2,058	0.519	0.286	0.018	0.524	1.000
E	2,058	0.552	0.268	0.020	0.566	1.000
S	2,058	0.519	0.285	0.018	0.522	1.000
G	2,058	0.523	0.287	0.018	0.525	1.000
Size	2,058	23.867	1.217	21.464	23.694	27.424
Roe	2,058	7.787	6.485	–7.777	6.188	31.673
Age	2,058	21.772	5.332	9.118	21.541	36.274
Lev	2,058	48.159	18.660	9.071	49.764	86.225
Soe	2,058	0.467	0.499	0.000	0.000	1.000
Fa	2,058	20.702	17.557	0.159	15.489	73.227

debt financing costs across corporations. *ESG* ranges from a minimum of 0.018 to a maximum of 1, with a standard deviation of 0.286, suggesting considerable variation in ESG assessments across the sample corporations. The distribution profiles for *E*, *S* and *G* mirror those of the overall *ESG*, highlighting the diverse evaluations within these categories. The descriptive statistics for other variables align closely with the findings of Lin et al. (2011) and Christensen et al. (2021).

4.2. Baseline regression

Table 3 presents the regression results for model (1). Column (1) analyzes the impact of *ESG* on debt financing costs, yielding a negative coefficient of –1.184, which is significant at the 1 % level. Incorporating

Table 3
Analysis of the relationship between CSI ESG performance and corporate debt financing costs.

	(1) *DebtCost*	(2) *DebtCost*	(3) *DebtCost*
ESG	–1.184***	–0.604***	–0.726***
	(0.156)	(0.137)	(0.138)
Size		–0.273***	–0.212***
		(0.041)	(0.043)
Roe		–0.036***	–0.039***
		(0.008)	(0.008)
Age		–0.012*	–0.009
		(0.007)	(0.008)
Lev		0.058***	0.062***
		(0.004)	(0.004)
Soe		–0.667***	–0.705***
		(0.079)	(0.084)
Fa		0.037***	0.025***
		(0.002)	(0.003)
Cons	1.770***	5.274***	4.524***
	(0.093)	(0.862)	(1.055)
Ind FE	No	No	Yes
Pro FE	No	No	Yes
Year FE	No	No	Yes
N	2,058	2,058	2,058
Adj.R^2	0.027	0.344	0.413

Note: This table displays the results of a regression exploring the relationship between CSI ESG performance and corporate debt financing costs across the entire sample. Parentheses denote robust standard errors. *Ind* represents industry fixed effects, *Year* represents annual fixed effects and *Pro* represents provincial fixed effects. Definitions of the variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

corporate variables such as *Roe*, *Lev*, *Size*, *Soe* and *Age* into the regression yields a coefficient of –0.604 on *ESG* in column (2), which is significant at the 1 % level. When annual, provincial and industry fixed effects are added in column (3), the coefficient on *ESG* is –0.726, which is also significant at the 1 % level. This suggests that a one standard deviation increase in *ESG* is associated with a 9.98 % decrease in corporate debt financing costs (–0.726*0.286/2.080), supporting H1-A.

The regression of control variables, also reported in Table 3, includes the ownership coefficient, which is negative and significant at the 1 % level, indicating lower debt financing costs for state-owned corporations due to implicit guarantees and a reduced default risk. Similarly, the coefficients for corporate size and profitability are negative and significant at the 1 % level, reflecting the lower default risks of larger and more profitable firms (Hahn and Kühnen, 2013). The coefficient on *Lev* is positive and significant, suggesting that a higher *Lev* corresponds to an increased default risk and thus higher financing costs. Other control variables such as *Age* and *Fa* are aligned with the findings of Lin et al. (2011) and Christensen et al. (2021) and are not detailed further.

4.3. Information value test of the CSI ESG score index

As noted earlier, ESG ratings data are predominantly clustered around the median, making it challenging to discern differences between companies. Consequently, we evaluate the ability of the CSI ESG score to deliver more precise and comprehensive insights, aiming to address the limitations of existing ESG ratings. For comparison, we employ widely recognized ESG benchmarks, including the Sino-Securities ESG, SynTao Green ESG and Wind ESG indicators.

Table 4 presents the results of a regression assessing the informational value of various indicators. Column (1) incorporates both the CSI ESG and Sino-Securities ESG indicators as explanatory variables. The analysis yields a coefficient of –0.657 on *ESG*, which is statistically significant at the 1 % level, and a coefficient of –0.067 on *H_ESG*, which is statistically significant at the 10 % level. The F-test indicates a statistically

Table 4
Results of regression to test the informational value of the CSI ESG score index.

	(1) *DebtCost*	(2) *DebtCost*	(3) *DebtCost*	(4) *DebtCost*
ESG	–0.657***	–0.692***	–0.742***	–0.684***
	(0.143)	(0.139)	(0.147)	(0.149)
H_ESG	–0.067*			–0.059
	(0.034)			(0.038)
S_ESG		–0.082**		–0.081*
		(0.039)		(0.048)
W_ESG			–0.069	–0.013
			(0.049)	(0.056)
Cons	4.430***	4.574***	4.680***	4.620***
	(1.057)	(1.062)	(1.106)	(1.111)
Ind FE	Yes	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F-tests on coefficient differences	*ESG* = *H_ESG*; $F = 14.59$, $p = 0.0001$	*ESG* = *S_ESG*; $F = 17.24$, $p = 0.0000$	*ESG* = *W_ESG*; $F = 17.08$, $p = 0.0000$	*ESG* = *H_ESG*; $F = 15.22$, $p = 0.0001$ *ESG* = *S_ESG*; $F = 15.48$, $p = 0.0001$ *ESG* = *W_ESG*; $F = 16.31$, $p = 0.0001$
N	2,053	2,050	1,856	1,856
Adj. R^2	0.416	0.415	0.419	0.421

Note: This table displays the results of a regression to test the informational value of the CSI ESG score index. Robust standard errors are presented in parentheses. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. Definitions of these variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

significant disparity, demonstrating that the CSI ESG index provides more valuable information than the Sino-Securities ESG indicator. Subsequent columns compare the CSI ESG indicator with the SynTao Green ESG (column 2) and Wind ESG (column 3) indicators, as well as a model that incorporates all of the indicators (column 4). Each test confirms significant disparities between the indicators, highlighting the superior informational content of the CSI ESG score relative to other ESG ratings.

5. Robustness tests

5.1. Alternative measurement

To assess the robustness and reliability of our findings, we apply several methodological adjustments to the variable metrics. First, we redefine the independent variable: we refer to the research method of Houqe et al. (2020) and recalculate debt financing costs as the ratio of a corporation's interest expense to interest-bearing liabilities, then rerun model (1). Second, CSI EGS evaluates the dependent variables every six months; accordingly, we use the annual means of these evaluations as an alternative index and rerun model (1). The specific regression results are detailed in Table 5 and confirm that H1-A is supported.

5.2. Alternative estimation method

To enhance the robustness and reliability of the findings, we modify the estimation approach of model (1) as follows. First, acknowledging self-correlation at individual levels, we use a clustering method to adjust the standard errors at the corporate level and then rerun model (1). Second, to mitigate the impact of unobservable, time-varying industry-level factors, we incorporate *Industry* × *Year* fixed effects at a higher order. Third, to address potential reverse causality, whereby the cost of debt in the prior period might influence the ESG score in the current period, we adopt the approach of El Ghoul et al. (2011) and include the lagged cost of debt (*L.DebtCost*) as an independent variable. This dynamic panel model uses the system generalized method of moments (GMM) technique for estimation. The results, presented in Table 6, indicate that the regression coefficients on *ESG* are negative and significant at the 1 % level, suggesting that improved CSI ESG performance notably reduces a firm's debt financing costs, thereby supporting H1-A.

Table 5
Results of regression using alternative measures.

	(1) *DebtCost*	(2) *DebtCost*
ESG	–0.530***	
	(0.105)	
ESG1		–1.224***
		(0.185)
Cons	3.040***	4.036***
	(0.758)	(1.072)
Ind FE	Yes	Yes
Pro FE	Yes	Yes
Year FE	Yes	Yes
N	2,058	2,058
Adj.R^2	0.376	0.418

Note: This table displays the results of a regression exploring the relationship between CSI ESG performance and corporate debt financing costs in which alternative variable measures are used. Robust standard errors are presented in parentheses. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. Definitions of these variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

Table 6
Results of regression using an alternative estimation method.

	(1) *DebtCost*	(2) *DebtCost*	(3) *DebtCost*
ESG	–0.730***	–0.726***	–0.283***
	(0.140)	(0.166)	(0.074)
L.DebtCost			0.353***
			(0.056)
Cons	5.323***	4.524***	2.021***
	(1.123)	(1.465)	(0.510)
Ind FE	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Ind FE × *Year FE*	No	Yes	No
Cluster	Yes	No	No
N	2,058	2,058	1,216
Adj.R^2	0.420	0.413	–

Note: This table displays the results of a regression examining the relationship between CSI ESG performance and corporate debt financing costs. The analysis uses the system GMM technique and includes clustered standard errors at the corporate level and higher-order controls for *Industry* × *Year* fixed effects. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. Definitions of the variables are provided in Table 1. ***, ** and * correspond to significance levels of 1 %, 5 % and 10 %, respectively.

5.3. Alternative sample period and sample size

To validate the robustness of our conclusions, we apply several modifications to the sample period and size. We first change the number of samples and use semi-annual data to replicate model (1). Next, to mitigate the influence of the COVID-19 pandemic on sample companies, we exclude data from 2020. Furthermore, given the substantial proportion of companies in the manufacturing sector among all listed companies and the relevance of this industry to high-quality economic development, we rerun model (1) using only samples from this sector. Table 7 presents the results of the adjusted regressions. The coefficient on *ESG* remains negative and significant, confirming that H1-A remains supported even after these changes.

Table 7
Results of regression using an alternate sample period and sample size.

	(1) *DebtCost*	*(2)* *DebtCost*	*(3)* *DebtCost*
ESG	–0.182***	–0.916***	–0.500***
	(0.032)	(0.161)	(0.184)
Cons	1.387***	4.644***	3.920***
	(0.242)	(1.195)	(1.319)
Ind FE	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	4,747	1,366	1,151
Adj.R^2	0.281	0.450	0.450

Note: This table displays the results of a regression exploring the correlation between CSI ESG performance and corporate debt financing costs, using semi-annual data. We also exclude the samples from 2020 and focus solely on the manufacturing sector. Robust standard errors are shown in parentheses. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. Definitions of the variables are given in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

5.4. Placebo test

The influence of CSI ESG performance on debt financing costs may stem from omitted variables. To mitigate the impact of these variables on our findings, we apply a placebo test. Following the methodology of Cornaggia and Li (2019), we randomly exchange the CSI ESG variables among the listed companies and perform a regression analysis using these shuffled samples. If the observed negative correlation between CSI ESG performance and the cost of debt financing is due to omitted variables, the regression coefficient on *ESG* should remain negative and significant after the exchange. However, as shown in column (1) of Table 8, this regression coefficient is not significant, suggesting that the reduction in debt financing costs is attributable to superior CSI ESG performance. This conclusion is further supported by the results of the placebo test.

To further enhance the robustness of the placebo test results, we randomly assign *ESG* to each listed company and repeat the model 500 times. Fig. 1 presents the kernel density estimation of the coefficients post-regression. As shown, most of the coefficients cluster around zero, indicating that the impact of CSI ESG performance on the cost of debt financing remains unaffected by other unobserved factors. This finding reaffirms the robustness of the baseline regression conclusions of our study.

5.5. Endogeneity issues

5.5.1. Instrumental variable method

Unobserved confounding variables may influence both the independent and dependent variables or lead to reverse causality between variables. To address potential endogeneity problems, we employ the instrumental variable method. Following the approach of Xie and Lv (2022), three instrumental variables are selected to mitigate endogeneity issues: whether the enterprise is held by "pan-ESG funds," the logarithm of the number of holdings by pan-ESG funds and the logarithm of the market value of these holdings. Initially, these instrumental variables meet the relevance criterion. Dyck et al. (2019) argue that public funds typically manifest their preference for enhanced ESG performance through direct engagement. Interviews with Chinese fund managers indicate that they proactively engage with the management of listed companies to encourage a focus on and improvement of ESG practices, thus establishing a positive correlation between pan-ESG fund holdings and corporate ESG metrics. Furthermore, these variables meet the exogeneity criterion. The establishment and size of these pan-ESG funds are determined by fund companies; thus, they are exogenous variables that are unrelated to the debt financing costs of listed companies. Similarly, decisions regarding pan-ESG fund shareholdings are made by fund managers and do not directly affect the debt financing costs of the listed companies. We apply the two-stage least squares method to test for endogeneity in this context.

Table 9 displays the results of a regression using an instrumental variable. Columns (1), (3) and (5) reveal that the instrumental variable positively influences CSI ESG evaluation, with coefficients that are statistically

Table 8
Regression results of a placebo test.

	(1) *DebtCost*
ESG	–0.132
	(0.125)
Cons	5.294***
	(1.052)
Ind FE	Yes
Pro FE	Yes
Year FE	Yes
N	2,058
Adj.R^2	0.406

Note: This table displays the results of a regression illustrating the correlation between CSI ESG performance and corporate debt financing costs, assessed via a placebo test. Robust standard errors are presented in parentheses. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. Definitions of the variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

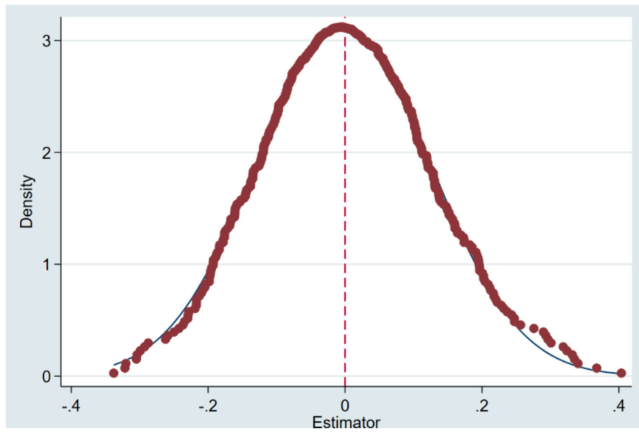

Fig. 1. Density plot of coefficient kernel estimates.

Table 9
Results of regression using the instrumental variable method.

	(1) *ESG*	(2) *DebtCost*	(3) *ESG*	(4) *DebtCost*	(5) *ESG*	(6) *DebtCost*
ESG		–3.602***		–3.461***		–3.430***
		(1.463)		(1.368)		(1.290)
IFfundhold	0.065***					
	(0.013)					
Fundholdnum			0.004***			
			(0.001)			
Fundholdmv					0.004***	
					(0.001)	
Cons	–0.836***	1.668	–0.785***	1.808	–0.781***	1.839
	(0.168)	(1.917)	(0.170)	(1.839)	(0.169)	(1.775)
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,058	2,058	2,058	2,058	2,058	2,058
Adj.R^2	0.178	0.287	0.180	0.299	0.181	0.302
Weak Instrumental Variable F value	24.421			27.469		31.250

Note: This table displays the results of a regression exploring the impact of CSI ESG performance on corporate debt financing costs via instrumental variables. Robust standard errors are shown in parentheses. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. Definitions of the variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

significant at the 1 % level. This result confirms a strong positive correlation between the instrumental variable and CSI ESG evaluation. Additionally, the F-values for the weak instrument variable test are 24.421, 27.469 and 31.250, respectively, which substantially exceed the threshold of 10 and thereby robustly validate the instrument's relevance. In columns (2), (4) and (6), the second-stage regression results indicate that CSI ESG evaluation negatively affects corporate debt financing costs, and this relationship is significant at the 1 % level. These findings further confirm H1-A, even after adjusting for potential endogeneity.

5.5.2. Propensity score matching and entropy balancing

To mitigate selection bias, we use propensity score matching (PSM) and entropy balancing and thus address a potential endogeneity problem. Consequently, we find no systematic differences between the treatment and control groups. The study categorizes ESG scores based on annual and industry medians: scores above the median form the experimental group, while those below form the control group.

Table 10
Results of regression involving propensity score matching.

	(1) *DebtCost*	(2) *DebtCost*	(3) *DebtCost*
ESG	–0.701***	–0.727***	–0.806***
	(0.148)	(0.139)	(0.152)
Cons	5.319***	4.478***	5.049***
	(1.131)	(1.056)	(1.192)
Ind FE	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1,660	2,036	2,058
Adj.R^2	0.416	0.413	0.409

Note: This table displays the results of a regression examining the correlation between CSI ESG performance and corporate debt financing costs, using propensity score matching and entropy balancing. Robust standard errors are enclosed in parentheses. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. Definitions of the variables are included in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

Table 10 displays the results of regressions using these methods. Column (1) illustrates outcomes from 1-to-3 nearest neighbor matching, column (2) presents kernel matching results and column (3) provides the findings from entropy balancing. Despite addressing potential endogeneity, H1-A remains supported.

6. Additional analyses

6.1. Analysis of ESG components

Thus far, the findings indicate that improved CSI ESG performance reduces corporate debt financing costs. This performance encompasses the factors *E*, *S* and *G*. We explore whether each of these components influences debt financing costs in CSI ESG. The analysis is presented in model (2).

$$DebtCost_{i,t} = \beta_0 + \beta_1 E/S/G_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (2)$$

In model (2), the independent variable is *DebtCost*, as previously defined. The dependent variables are the sub-indicators of CSI ESG performance, namely *E*, *S* and *G*. The control variables follow the specifications in model (1).

Table 11 details the regression results for *E*, *S* and *G*. For *E*, column (1) reports a coefficient of –0.297, which is significant at the 5 % level. This result suggests that a one standard deviation increase in environmental performance decreases corporate debt financing costs by approximately 3.83 % (–0.297*0.268/2.080). Creditors are likely to consider a corporation's environmental consciousness in their financing decisions, offering lower rates to those demonstrating stronger environmental commitments (Jung et al., 2018). For *S*, as shown in column (2), the coefficient is –0.464 and significant at the 1 % level, indicating that a similar increase in social responsibility performance leads to a 6.36 % (–0.464*0.285/2.080) reduction in debt financing costs. Corporations with robust social responsibility practices, which cultivate a positive social image and attract investor favor, tend to secure financing at reduced costs (Naughton et al., 2019). For *G*, the coefficient in column (3) is –0.731 and significant at the 1 % level, corresponding to a 10.09 % (–0.731*0.287/2.080) decrease in financing costs for each one standard deviation increase in governance performance. Effective governance thus significantly lowers debt financing costs. Social performance creates a lasting public impression more readily than environmental performance, while governance issues garner extensive external attention and thus directly influence potential investors. Consequently, both social and governance performances significantly aid in lowering financing costs. Furthermore, compared with social performance, enhancing corporate governance not only strengthens stakeholder consensus but also mitigates risks such as moral hazards and adverse selection due to principal–agent conflicts, thereby exerting a more substantial direct influence on financing conditions and enterprise value.

Table 11
Results of regression conducted separately on *E*, *S* and *G*.

	(1) *DebtCost*	(2) *DebtCost*	(3) *DebtCost*	(4) *DebtCost*
E	–0.297**			–0.243*
	(0.136)			(0.136)
S		–0.464***		–0.387***
		(0.148)		(0.149)
G			–0.731***	–0.691***
			(0.145)	(0.145)
Cons	5.429***	4.553***	4.180***	3.810***
	(1.053)	(1.083)	(1.077)	(1.108)
Ind FE	Yes	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2,058	2,058	2,058	2,058
Adj. R^2	0.407	0.408	0.413	0.416

Note: This table displays the results of a regression examining the association between CSI ESG performance and corporate debt financing costs, segmented by E, S and G performance metrics. Robust standard errors are presented in parentheses. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. Definitions of the variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

In column (4), *E*, *S* and *G* are controlled simultaneously, and all coefficients are negative and significant, confirming that CSI ESG metrics indeed cover the environmental, social and governance dimensions. Financial institutions, including banks, focus on these performance areas during the financing process.

6.2. Heterogeneity analysis

6.2.1. Local environmental execution

The strength of environmental execution in a company's location influences the utility of its ESG information. Strong local execution often garners increased attention from regulatory authorities (Shen and Zhou, 2017; Tang et al., 2019). In such contexts, robust ESG performance by a company sends a positive signal to the market. Consequently, in regions with stringent environmental execution, the reducing impact of the CSI ESG evaluation on corporate debt financing costs should be more pronounced. To test this prediction, we divide the sample based on the Eleventh Five-Year Plan for National Environmental Protection by the State Council into cities with either strong or weak environmental execution. We apply model (1) to each group and use model (3) specifically to test this prediction.

$$DebtCost_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 ESG \times City_{i,t-1} + \beta_3 City_{i,t-1} + \beta_4 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (3)$$

In model (3), the independent variable is *DebtCost*, defined as described in previous sections. The dependent variable is *ESG*. *City* is assigned a value of 1 for cities in regions with robust environmental execution, and 0 otherwise. The control variables are defined in Table 1.

Table 12 displays the outcomes of analysis across varying levels of environmental execution. In column (1), the regression analysis of cities with lax environmental execution reveals that the coefficient on *ESG* is –0.223, which is statistically nonsignificant. This indicates that in cities with lenient environmental execution, CSI ESG performance does not influence debt financing costs. In contrast, column (2) shows that in cities with stringent environmental execution, the coefficient on *ESG* performance is –0.852 and significant at the 1 % level. This finding suggests that in cities with rigorous environmental regulations, better CSI ESG performance substantially lowers corporate debt financing costs. Furthermore, column (3) displays a coefficient of –0.611 on the interaction of *ESG* × *City*, which is significant at the 1 % level, underscoring the pronounced reducing effect of CSI ESG performance on debt financing costs in cities with strict environmental execution. As local

Table 12
Results of heterogeneity analysis regression of local environmental execution.

	Weak environmental execution	Strong environmental execution	
	(1) *DebtCost*	(2) *DebtCost*	(3) *DebtCost*
ESG	–0.223	–0.852***	–0.246
	(0.299)	(0.157)	(0.275)
City			0.090
			(0.178)
ESG × City			–0.611**
			(0.310)
Cons	–37.421	–36.791***	–41.052***
	(41.578)	(12.092)	(11.526)
Ind FE	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	344	1,714	2,058
Adj.R²	0.588	0.421	0.421

Note: This table displays the results of a regression examining the association between CSI ESG performance and corporate debt financing costs, incorporating local environmental execution in model (3). Parentheses denote robust standard errors. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. Definitions of the variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

environmental execution strengthens, the reducing impact of CSI ESG performance on debt financing costs intensifies.

6.2.2. Internal control quality

Poor internal control quality exacerbates earnings management by managers and increases information asymmetry between a company and the capital market (Fang and Jin, 2011; Fan et al., 2013). In such situations, ESG performance actively transmits signals; accordingly, the reducing impact of CSI ESG evaluation on corporate debt financing costs should become more pronounced in companies with weaker internal controls. Drawing on the findings of Ji et al. (2021), we employ the internal control index to assess companies' internal control quality. To test our prediction, we categorize the sample into two groups based on the industry's annual median—those with high and low internal control quality—and rerun model (1). We then use model (4) to test this prediction.

$$DebtCost_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 ESG \times HIC_{i,t-1} + \beta_3 HIC_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (4)$$

The dependent variable in model (4) is *DebtCost*, as previously defined. The independent variable is *ESG*, and a dummy variable (*HIC*) is assigned a value of 1 for corporations with high internal control quality, and 0 otherwise. The control variables correspond to those outlined in Table 1.

The regression results are given in Table 13. Columns (1) and (2) present the results for corporations with low and high internal control quality, respectively. In both cases, the coefficient on *ESG* is negative and significantly, with the absolute value of the coefficient in column (1) being larger than that in column (2). Furthermore, the coefficient on the interaction term *ESG* × *HIC*, presented in column (3), is positive and significant. These results suggest that CSI ESG performance more significantly reduces debt financing costs in corporations with lower internal control quality. As internal control quality improves, the reducing influence of CSI ESG performance on debt financing costs diminishes, indicating a substitution effect between internal control quality and CSI ESG performance on debt financing costs.

6.2.3. Marketization degree

Lower marketization levels are correlated with diminished efficiency in enterprise resource allocation and with increased difficulty in obtaining bank credit funding (Yang et al., 2023). Nonetheless, ESG can serve

Table 13
Results of heterogeneity analysis regression of corporate internal control quality.

	Low internal control quality	High internal control quality	
	(1) *DebtCost*	(2) *DebtCost*	(3) *DebtCost*
ESG	–0.779***	–0.680***	–0.292***
	(0.218)	(0.181)	(0.853)
HIC			–0.001**
			(0.001)
ESG × *HIC*			0.002*
			(0.001)
Cons	–96.290***	–17.748*	–40.415***
	(24.740)	(12.634)	(11.653)
Ind FE	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	992	1,031	2,023
Adj.R^2	0.428	0.455	0.419

Note: This table displays the results of a regression examining the association between CSI ESG performance and corporate debt financing costs, with the inclusion of internal control quality in model (4). Robust standard errors are presented in parentheses. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. The variables are defined in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

as a signaling mechanism that communicates an enterprise's robust performance to financial institutions, thereby alleviating financing constraints (Hu et al., 2023). In regions with lower marketization levels, the influence of the CSI ESG evaluation on reducing corporate debt financing costs should be more pronounced. We employ corporations' marketization index, following the methodology of Wang et al. (2021), to gauge marketization levels. To test our prediction, we categorize the sample into two groups—high and low marketization—based on the marketization index and rerun model (1). We use model (5) to further examine our prediction.

$$DebtCost_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 ESG \times MD_{i,t-1} + \beta_3 MD_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (5)$$

The dependent variable in model (5) is *DebtCost*, defined as previously described. The independent variable is *ESG*, and the variable *MD* is assigned a value of 1 for corporations in regions with high marketization, and 0 otherwise. The control variables are as listed in Table 1.

Table 14 displays the results segmented by marketization degree. Column (1) presents the regression outcomes for areas with low marketization, while column (2) does so for areas with high marketization. In both categories, the coefficients on *ESG* are negative and significant, indicating a robust impact on reducing debt financing costs. The absolute value of *ESG* in column (1) is greater than that in column (2). Moreover, the positive coefficient on the interaction term *ESG* × *MD* in column (3) signifies that the influence of CSI ESG performance on reducing debt financing costs is more pronounced in areas with lower marketization. As marketization increases, the efficacy of CSI ESG performance in diminishing debt financing costs diminishes.

6.3. Analysis of influencing mechanisms

6.3.1. Debt repayment ability

Debt repayment capacity is a crucial metric of a company's overall operational and managerial health. Accordingly, we predict that superior CSI ESG performance is correlated with an enhanced corporate debt repayment capacity and reduced debt financing costs. To examine the underlying mechanisms, we use models (6) and (7), detailed below:

Table 14
Results of heterogeneity analysis regression of marketization degree.

	Low marketization degree	High marketization degree	
	(1) *DebtCost*	(2) *DebtCost*	(3) *DebtCost*
ESG	–0.807***	–0.509**	–2.790***
	(0.180)	(0.223)	(1.022)
MD			–0.113**
			(0.045)
ESG × MD			0.149**
			(0.074)
Cons	6.573***	3.899**	6.092***
	(1.352)	(1.981)	(1.191)
Ind FE	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1,216	839	2,055
Adj.R²	0.452	0.427	0.416

Note: This table displays the results of a regression examining the impact of CSI ESG performance on corporate debt financing costs, incorporating the degree of marketization in model (5). Robust standard errors are shown in parentheses. *Ind*, *Year* and *Pro* represent controls for industry, annual and provincial fixed effects, respectively. The variables are defined in Table 1. ***, ** and * denote significance levels of 1%, 5% and 10%, respectively.

$$ZSCORE_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (6)$$

$$Rate_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (7)$$

ZSCORE measures corporate financial and default risks, adopting the modified Z score based on Hu et al. (2020). *Rate* signifies corporate credit ratings, translated into a multi-value ordered discrete variable based on the model by Barnea and Rubin (2010). The ratings are quantified as follows: AAA equals 21, AAA– equals 20 and so forth, continuing to C and below, which equals 0. Consequently, a lower value corresponds to a poorer credit rating. *DebtCost* denotes corporate debt financing costs, defined as detailed previously. *ESG* represents CSI ESG evaluation and is also as defined earlier. The control variables are specified in Table 1.

Table 15 presents the results of a regression concerning the impact of corporate debt repayment capacity. The positive coefficients on *ESG* suggest that a high ESG score enhances a company's debt repayment capacity, supporting the hypothesis that improved debt repayment capacity is a mechanism through which CSI ESG can reduce debt financing costs.

Table 15
Results of influence mechanism analysis regression of debt repayment ability.

	(1) *ZSCORE*	(2) *Rate*
ESG	0.730*	0.331***
	(0.402)	(0.104)
Cons	18.346***	1.766**
	(3.200)	(0.889)
Ind FE	Yes	Yes
Pro FE	Yes	Yes
Year FE	Yes	Yes
N	2,058	709
Adj.R²	0.471	0.709

Note: This table displays the results of a regression examining the relationship between CSI ESG performance and corporate debt repayment capacity, measured using the Z-score and *Rate*. Robust standard errors are presented in parentheses. *Ind*, *Year* and *Pro* control for industry, annual and provincial fixed effects, respectively. Definitions of the variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

6.3.2. Information asymmetry

To ascertain whether the mechanism through which CSI ESG performance reduces corporate debt financing costs by mitigating corporate information asymmetry is operational, we establish model (8).

$$Asy_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (8)$$

Information asymmetry (*Asy*) is the extent of corporate information discrepancies, based on research by Dhaliwal et al. (2011). We use the analyst equity earnings forecast error (*ERR*), the liquidity ratio (*LR*) from Amihud et al. (1997), the illiquidity ratio (*ILL*) from Amihud, 2002 and the yield inversion indicator (*GAM*) from Pastor and Stambaugh (2003) as indicators. Higher values of *ERR*, *LR*, *ILL* and *GAM* suggest greater information asymmetry. *DebtCost* denotes the corporate debt financing costs, as previously defined. The control variables are outlined in Table 1.

Table 16 displays the results of regression analysis, demonstrating how information asymmetry acts as a mechanism of influence. The coefficient on *ESG* is negative and significant, suggesting that a higher CSI ESG score is correlated with lower information asymmetry. This finding confirms our hypothesis that a high CSI ESG score reduces corporate debt financing costs by reducing information asymmetry.

6.4. Analysis of economic consequences

Thus far, the results indicate that CSI ESG evaluations negatively and significantly impact debt financing costs. Subsequently, we explore whether robust ESG performance yields economic benefits for firms. This involves assessing whether superior ESG performance enhances total factor productivity and overall firm value.

First, corporate productive efficiency reflects a company's resource development and utilization effectiveness. Enhanced ESG performance not only leads to reduced energy consumption and resource conservation, thereby lowering production costs (Russo and Fotus, 1997; Aras and Crowther, 2008), but also attracts higher quality employees, which boosts labor productivity (Greening and Turban, 2000; Bhattacharya et al., 2008). Consequently, we predict that improved CSI ESG performance is correlated with increased corporate productive efficiency.

Second, corporate value is demonstrated by financial data, which reflect operational capabilities. Superior CSI ESG performance, exemplified by exemplary ESG practices, is associated with increased corporate value (Shi and Wang, 2023). To further examine these economic impacts, we formulate models (9) through (12).

$$Sc_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (9)$$

$$Sc_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 DebtCost_{i,t-1} + \beta_3 Controls_{i,t-1} + Year\,FE + Ind\,FE + Pro\,FE + \varepsilon_{i,t} \quad (10)$$

Table 16
Results of influence mechanism analysis regression of information asymmetry.

	(1) *ERR*	(2) *LR*	(3) *ILL*	(4) *GAM*
ESG	–0.655***	–0.336***	–0.193***	–0.048***
	(0.090)	(0.057)	(0.028)	(0.010)
Cons	13.572***	6.480***	5.455***	0.987***
	(0.702)	(0.488)	(0.207)	(0.082)
Ind FE	Yes	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2,057	2,057	2,057	2,057
Adj.R^2	0.367	0.401	0.433	0.188

Note: This table displays the results of a regression illustrating the relationship between CSI ESG performance and corporate information asymmetry, which is measured using *ERR*, *LR*, *ILL* and *GAM*. Robust standard errors are enclosed in parentheses. *Ind*, *Year* and *Pro* control for industry, annual and provincial fixed effects, respectively. Definitions of these variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

$$TobinQ_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (11)$$

$$TobinQ_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 DebtCost_{i,t-1} + \beta_3 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (12)$$

Sc denotes corporate productive efficiency, with references to seminal works by Olley and Pakes (1996) (OP), Levinsohn and Petrin (2003) (LP) and Ackerberg et al. (2015). We employ the OP and LP metrics to gauge total corporate productive efficiency. *TobinQ* signifies corporate value, as defined by Rountree et al. (2008) and Tsang et al. (2021); we use the corporate TobinQ metric for measurement. *DebtCost* indicates the costs associated with corporate debt financing, as previously defined. *ESG* refers to CSI ESG assessment, as defined earlier. The control variables are as listed in Table 1.

Table 17 presents the results of the economic consequence analysis regression. Column (1) illustrates the influence of CSI ESG performance on total factor productivity, as measured using the OP method, where the coefficient on *ESG* is 0.161 and significant at the 1 % level. Incorporating *DebtCost* in column (2), the coefficient is –0.019, which is significant at the 5 % level, demonstrating that a superior CSI ESG assessment is correlated with reduced corporate debt financing costs and enhanced total factor productivity. Extending this analysis, column (3) explores the impact of ESG performance on productivity using the LP method. Column (4) integrates *DebtCost* as an explanatory factor. Column (5) examines the relationship between CSI ESG performance and firm value via *TobinQ*, and column (6) further includes *DebtCost*. The findings consistently indicate that higher CSI ESG assessments are associated with lower debt costs and, consequently, with increased total factor productivity and firm value.

6.5. Analysis of financing manner

Higher financing costs indicate greater financial constraints on enterprises (Yu et al., 2019a, 2019b). Improved ESG performance can somewhat mitigate these constraints. Thus, the question arises: How can enterprises reduce their financial constraints?

Corporate debt financing primarily comprises bond financing and bank loans. Bond financing targets dispersed investors, who typically seek profit maximization. In contrast, banks and other financial institutions not only aim for profit maximization but also evaluate ESG performance comprehensively, adhering to policy requirements for sustainable development (Aintablian et al., 2007). Consequently, corporations with superior CSI ESG performance secure loans from banks and other financial institutions more readily and at lower costs than other firms, although this does not affect corporate bond issuance. We predict that enhanced CSI ESG performance is correlated with easier access to loans from financial institutions like banks, resulting in a nota-

Table 17
Results of economic consequence analysis regression.

	(1) *OP*	(2) *OP*	(3) *LP*	(4) *LP*	(5) *Tobin Q*	(6) *Tobin Q*
ESG	0.161***	0.147***	0.161***	0.150***	0.434***	0.387***
	(0.050)	(0.051)	(0.050)	(0.050)	(0.095)	(0.097)
DebtCost		–0.019**		–0.013*		–0.065***
		(0.007)		(0.007)		(0.022)
Cons	5.494***	5.555***	5.446***	5.489***	8.837***	9.129***
	(0.307)	(0.305)	(0.300)	(0.299)	(0.819)	(0.808)
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,058	2,058	2,058	2,058	2,057	2,057
Adj.R^2	0.528	0.530	0.563	0.564	0.435	0.440

Note: This table displays the results of a regression exploring the relationship between CSI ESG performance, total factor productivity and firm value. Robust standard errors are presented in parentheses. *Ind*, *Year* and *Pro* represent industry, annual and provincial fixed effects, respectively. Definitions of the variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

Table 18
Results of financing manner analysis regression.

	(1) *Bond*	(2) *Bank*
ESG	1.189	0.233**
	(0.959)	(0.117)
Cons	–4.175	0.571
	(9.036)	(0.941)
Ind FE	Yes	Yes
Pro FE	Yes	Yes
Year FE	Yes	Yes
N	275	1,845
Adj. R^2	0.413	0.098

Note: This table displays the results of a regression on financing methods. *Bond* denotes the proportion of total annual financing derived from bond issuance, while *Bank* refers to the proportion from bank loans and other financial institution borrowings. Robust standard errors are presented in parentheses. *Ind*, *Year* and *Pro* control for industry, annual and provincial fixed effects, respectively. The definitions of these variables are provided in Table 1. ***, ** and * correspond to significance levels of 1%, 5% and 10%, respectively.

ble increase in the scale of corporate bank loans, while the scale of corporate bond financing remains relatively unchanged. Models (13) and (14) are developed to test these predictions.

$$Bond_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (13)$$

$$Bank_{i,t} = \beta_0 + \beta_1 ESG_{i,t-1} + \beta_2 Controls_{i,t-1} + YearFE + IndFE + ProFE + \varepsilon_{i,t} \quad (14)$$

Bond refers to the proportion of total annual financing represented by bond issuance, while *Bank* denotes the proportion of loans from banks and other financial institutions relative to total annual financing. *ESG* refers to the CSI ESG assessment. The control variables are as defined in Table 1.

Table 18 presents the regression results for financing methods. The coefficient on *ESG* in column (1) is positive but not statistically significant, while that in column (2) is positive and significant at the 5 % level. These results indicate that CSI ESG evaluations do not significantly affect corporate bond financing but do have a positive and significant influence on corporate bank loans. This supports our prediction that banks and other financial institutions consider ESG factors. Consequently, CSI ESG evaluations significantly impact the external financing of corporations, thereby influencing corporate micro-behaviors.

7. Conclusion

Using the constituent stocks of the HS 300 and CSI 500 indices from 2018 to 2020 as our sample, we explore the impact of CSI ESG performance on debt financing costs. We investigate heterogeneity effects in different sections of this paper, delineate the mechanisms through which ESG performance may reduce debt financing costs and assess its influence on external financing. Our research yields several conclusions. First, superior CSI ESG performance is correlated with reduced corporate debt financing costs. Second, among the ESG components, corporate governance has the greatest effect on lowering debt financing costs, followed by social responsibility, while environmental factors have the smallest effect. As local environmental execution intensifies, the reducing influence of ESG on debt financing costs strengthens. Conversely, this effect is weakened as the internal control quality and marketization level improve. Third, CSI ESG performance lowers debt financing costs by enhancing corporate debt repayment capacity and reducing information asymmetry. Fourth, improved ESG performance, which lowers financing costs, also enhances total factor productivity and firm value. Lastly, although CSI ESG assessments do not significantly impact corporate bond financing, they positively affect corporate bank loans. These findings are confirmed following endogeneity and robustness checks.

Based on the research described above, we propose the following policy recommendations. First, at the policy level, China should expedite the enhancement of ESG information disclosure standards, refine the assessment system for ESG indicators and promote the implementation of ESG principles among enterprises.

Relevant authorities should develop mechanisms to incentivize businesses to engage in environmental protection, reduce carbon emissions, pursue green and low-carbon transformation and actively undertake social responsibilities, thereby fostering better corporate governance and a more transparent information milieu. Second, at the corporate level, embracing ESG can bolster a company's total factor productivity and corporate value, alleviate its financing constraints and facilitate sustainable development. Consequently, companies should prioritize ESG integration across all operational aspects, reinforce their commitment to these practices and ensure precise and proactive ESG information disclosure to support high-quality corporate growth.

However, the availability of CSI ESG score data limits this research, as our samples extends only to 2020. As CSI updated the CSI ESG scores semi-annually in 2021 and has done so monthly since 2022, future studies could regularly update the sample and employ more frequent data to reassess the validity of our conclusions and address the issue of an inadequate sample duration.

Authorship Contribution Statement

All authors contributed equally to the paper.

Conflict of Interest Statement

We declare that we have no financial or personal relationships with other people or organizations that could inappropriately influence our work. We have no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled "ESG Performance and Cost of Debt."

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Economic policy uncertainty and firms' investments in venture capital funds: Evidence from China

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ABSTRACT

The latest business practice in the Chinese venture capital (VC) market involves the active participation of non-financial firms, as limited partners, in VC funds. Exploiting a unique hand-collected dataset from China, we find that economic policy uncertainty is positively related to the propensity of firms to participate in VC funds. Cross-sectional tests show that the positive effect of policy uncertainty on the likelihood of participating in VC funds is enhanced by industrial growth opportunities. Furthermore, economic consequence tests show that participating in VC funds is conducive to improving investment efficiency, increasing innovation performance and promoting product diversification. This study advances our understanding of firms' investment decisions and the VC industry development amid economic policy uncertainty.

1. Introduction

Intensified uncertainty around government economic policies pervades the world and is attracting widespread interest from scholars. Policy implementation and adjustment play a critical role in optimizing industrial structures and improving economic growth quality. However, frequent changes also exacerbate the uncertainty faced by firms, as they cannot perfectly predict the timing, contents and potential impacts of government policy decisions. In response to the negative effect of economic policy uncertainty, a stream of literature argues that the optimal decision for a firm is to postpone investments and maintain flexibility due to the increased value of waiting options (Julio and Yook, 2012; Gulen and Ion, 2016; Bonaime et al., 2018; Liu

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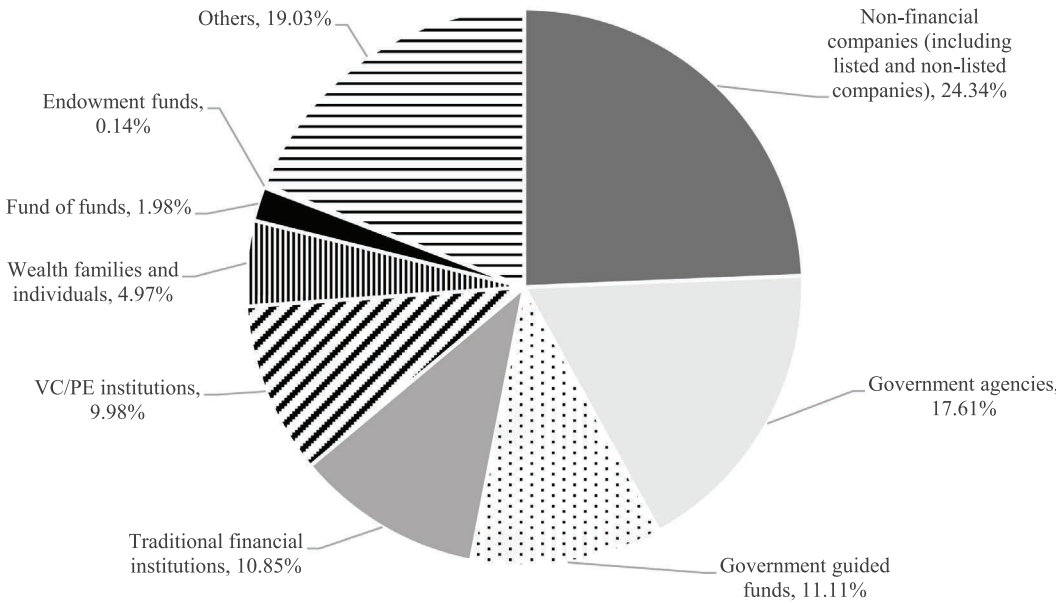

Fig. 1. The investment amounts of different types of LP in China. . Source: *China LP Market Development Report 2020*, issued by PEdata

et al., 2021). However, uncertainty represents not only danger but also potential development opportunities (Kulatilaka and Perotti, 1998). For example, economic policy uncertainty may be related to changes in the existing industrial structure. In this case, some firms may worry that their existing business models cannot adapt to the new industrial environment, in which case they need to seek new development opportunities embedded in policy adjustment. Not investing, but instead continuing to wait, may lead to loss of first-mover advantages, allowing competitors to seize these opportunities and thus create value.

An important question is how firms make strategic decisions to fully grasp and exploit "good" uncertainties to create advantages. Answering this question will contribute to providing a more complete picture of firms' micro-behavior under macroeconomic policy changes. From an opportunity expectation view, firms may devise an active strategic response in the face of economic policy uncertainty, rather than exclusively engaging in investment reduction. Identifying, capturing and capitalizing on the development opportunities contained in future uncertainties is of the utmost importance for firms' sustainable growth (Zhang et al., 2021). Prior literature suggests that firms may adopt precautionary financial policies to hedge the risk of policy uncertainty, such as increasing cash holdings (Phan et al., 2019; Duong et al., 2020) and purchasing bank wealth management products (WMPs) (Huang et al., 2023). However, these studies do not answer the question of how firms proactively seize growth opportunities amid uncertainty.

The new business practice in the Chinese venture capital (VC) market provides a window to explore firms' investment choices under economic policy uncertainty.[1] A surge in the Chinese VC market has transformed it into the second-largest in the world, behind that of the US (Chen, 2022). The latest data show that non-financial established firms, as limited partners (LPs), actively participate in VC funds in the Chinese market in the hope of achieving their financial and strategic objectives (Lin, 2021). Firms are now among the most

[1] In the US, venture capital is merely a subset of private equity that mainly focuses on early-stage equity investments (Kaplan and Sensoy, 2015). However, the usage of the term *venture capital* may differ in other countries (Gompers and Lerner, 2001). The boundary between *venture capital* and *private equity* is blurred in China because some venture capital or private equity firms have mixed investment portfolios that range from early to later stages (Jia and Wang, 2017; Huang and Tian, 2020). Due to these overlapping investment strategies, the two terms are often used interchangeably in China (Ahlstrom et al., 2007; Huang and Tian, 2020). Given these considerations, in the context of China, *venture capital* is a broad term for describing venture capital funds that engage in equity investments from early to later stages.

significant capital providers in the Chinese VC market (see Fig. 1). VC funds are typically managed by professional general partners (GPs) and mainly invest in young and innovative start-ups that are disrupters and sources of new ideas. Thus, the special advantages of VC funds may attract firms that wish to seize potential opportunities amid this period of high policy uncertainty. First, firms have the option to be involved in subsequent rounds, allowing them to target more promising and profitable projects in advance. Second, firms can gain access to a wider range of targets and are more likely to discover promising projects. Third, firms have access to valuable information about external technological and business environments through formal or informal interactions via VC funds. Despite the benefits stemming from participating in VC funds, the VC market is also fraught with risk (Huang et al., 2022). Firms may avoid undertaking high-risk behaviors due to the potential investment losses. Although participating in VC funds is a potentially good investment choice amid economic policy uncertainty, it depends on how firms weigh the acquisition of opportunities and the aversion to risks.

Based on business practice and theoretical analysis, we empirically test the relationship between economic policy uncertainty and the likelihood of firms participating in VC funds. We place our study context in China for several reasons. First, over the past four decades, the Chinese economy has achieved remarkable growth. The high-speed economic growth of the early period has seen the emergence of a series of structural problems, such as high leverage ratios and insufficient allocation efficiency of production factors (Liu et al., 2021). China is an economy in transition, in which government intervention plays an important role. To address these problems, the Chinese government has introduced a package of economic policies, such as Mass Entrepreneurship and Innovation, the Belt and Road Initiative and Supply-side Reform (Liu et al., 2022). Thus, economic policy uncertainty confronted by firms is the most salient type of environmental uncertainty shaping their decision-making in the context of China. Second, firms' investments in VC funds continue to increase in China, which boasts the second-largest VC market in the world. This provides a representative and appropriate scenario for studying our conjecture. Finally, Chinese listed companies are mandated by securities regulations to disclose detailed information about their investments in any VC fund. This regulation allows us to directly observe firms' investments in VC funds. Overall, the Chinese market provides an ideal setting to shed light on the relationship between economic policy uncertainty and firms' propensity to participate in VC funds.

Taking advantage of the disclosure requirements for Chinese listed companies, we obtain a unique hand-collected dataset on the Chinese VC market. Our empirical results suggest that the greater the economic policy uncertainty, the more likely firms are to participate in VC funds. We also provide additional analysis to further clarify this relationship. Our cross-sectional tests show that the positive relationship is enhanced by industrial growth opportunities. Furthermore, economic consequence tests show that VC funds serve as an important mechanism for firms to improve investment efficiency, increase innovation performance and promote product diversification.

Our research contributes to the literature in the following ways. First, our study contributes to the literature on corporate investment decisions under economic policy uncertainty. Extant literature generally finds that economic policy uncertainty can depress corporate investments (e.g., Wang et al., 2014; Gulen and Ion, 2016; Liu et al., 2021). There are few studies on how firms hedge the negative effect of economic policy uncertainty, such as through cash holdings (Phan et al., 2019; Duong et al., 2020), bank WMP purchasing (Huang et al., 2023), and corporate social responsibility (CSR) engagement (Yuan et al., 2022). In our paper, we emphasize that firms are actively responding to policy uncertainty by allocating part of their internal capital to VC funds. These strategic investments are conducive to seizing potential growth opportunities embedded in economic policy uncertainty. Our study provides a new understanding of how firms respond to economic policy uncertainty from an opportunity expectation perspective.

Second, our study enriches research on the decisions of potential LPs to invest in VC funds. One main area of study in VC research is the determinants of fundraising by VC funds. Existing literature mainly focuses on how GPs' or VC firms' characteristics (e.g., Cumming et al., 2005; Kaplan and Schoar, 2005; Hochberg et al., 2014; Barber and Yasuda, 2017) or VC firms' investment types (e.g., Lahr and Trombley, 2020) affect fundraising. However, we know little about the motivations of LPs participating in VC funds. Our paper shows that firms may view VC funds as strategic tools to respond to policy uncertainty. The results provide additional evidence on the fundraising by VC funds amid high policy uncertainty from the LP perspective.

Finally, this study enriches the literature on the VC industry under economic policy uncertainty. Prior literature investigates how economic policy uncertainty affects investment staging decisions and exit outcomes in VC markets, drawing on real options theory (Litov et al., 2021; Huang et al., 2022; Tian et al., 2023). However, these studies mainly focus on investment decisions under economic policy uncertainty from the GP or fund standpoints, while less is known from the LP standpoint. Our study finds that firms respond to policy uncertainty by allocating internal capital to VC funds. Our paper provides new insights for the VC industry under economic policy uncertainty by shifting our research horizon from GPs to LPs.

The remainder of this paper proceeds as follows. Section 2 presents the background, literature review and hypothesis development. Section 3 describes our sample and methodology. Section 4 presents the empirical results. Section 5 presents the additional tests, and Section 6 concludes this paper.

2. Background, literature and hypothesis development

2.1. Background: LPs in China

The history of the VC industry in China can be traced back to the mid-1980s, after which it experienced a dramatic evolution. The rapid expansion of the overall VC market does not necessarily mean that the market is mature, but generates some unique features that are worth exploring (Huang and Tian, 2020). Rather than simply restating the history of the Chinese VC industry, which has been discussed in previous work (e.g., Ahlstrom et al., 2007; Jia and Wang, 2017; Huang and Tian, 2020), we primarily highlight some specific observations by comparing Chinese and US LPs to better establish the context of our study.

2.1.1. The composition of LPs

In the US, LPs in VC funds are primarily pension plans, endowments, funds of funds or other institutional investors (Lerner et al., 2007). Unlike the current US market, the Chinese VC industry has undergone increased expansion during the transition from a centrally planned to a market-oriented economy. In the 1980s and 1990s, VC funds were almost entirely backed by the Chinese government (Huang and Tian, 2020). Lacking the necessary experience in the VC industry, regulators in China recognized the importance of institutional investors as a source of capital and made efforts to encourage capital supply from them (Lin, 2021). The most iconic reformation emerged in June 2007 when the Chinese government enacted the amended Partnership Enterprise Law (PEL), which stipulated that the liabilities of LPs were confined solely to the capital they contribute to the limited partnership (Jia and Wang, 2017). This amendment greatly incentivized various investors, such as corporate investors, to participate in the VC industry. The latest data on the composition of LPs show that non-financial corporate investors (including listed and non-listed companies) have developed into important capital providers in the Chinese VC market in 2019 (see Fig. 1).

2.1.2. The objectives of LPs

Financial returns have always been the core focus of LPs in the US and Chinese VC markets. Beyond this shared feature, listed companies in the Chinese VC market also view VC funds as new avenues to achieve strategic business development (Lin, 2021), as VC funds mainly invest in promising and innovative start-ups that are important sources of new ideas. Across all cases of listed companies engaging in VC funds, we can identify four primary objectives of LPs: (a) pursuing financial returns; (b) searching for new technologies and markets; (c) identifying new commercial opportunities; and (d) building relationships with venture capitalists and learning from them. Moreover, a listed company often simultaneously embraces multiple objectives within one VC fund.[2]

[2] For the sake of rigor, we suggest that listed companies, rather than all LP types, expect to achieve strategic gains through VC funds, because we can only obtain detailed information about listed companies. Our information sources include disclosure announcements, LPAs and news media. Listed companies often state why they are investing in VC funds in announcements. Under Chinese disclosure requirements, we can obtain such information and explicitly learn why they participate in VC funds as LPs.

2.1.3. The status of LPs

In the view of legal scholarship, in the US, the rights LPs have in the governance of VC funds are typically rigorously circumscribed by the limited partnership law and agreement (Gilson, 2003; Magnuson, 2018). However, the PEL of China is ambiguous about whether LPs will lose limited liability if they participate in activities considered as taking part in the business of the fund, thus leaving space for them to engage in these activities (Lin, 2013; 2021).[3] In addition, Chinese LPs often have considerable access to the operation of the VC fund according to the limited partnership agreement (LPA). A well-known route is through the investment strategy committee, which generally comprises LPs, the GP and external advisers, and is formed to review and approve investment proposals. This internal governance model enables listed companies to acquire information and directly communicate with GPs, other LPs and start-ups.

2.2. Literature review

"Economic policy uncertainty" refers to uncertainty about macroeconomic policies, including fiscal, regulatory and monetary policies (Baker et al., 2016). Firms facing such uncertainty cannot perfectly predict these policy-related decisions in terms of their timing, content and potential economic consequences (Wellman, 2017). Recent literature pays growing attention to how economic policy uncertainty affects corporate investment decisions (Wang et al., 2014; Gulen and Ion, 2016; Bonaime et al., 2018; Duong et al., 2020; Liu et al., 2021). Real options theory offers an approach to investigate how firms make investment decisions under economic policy uncertainty. This theory traces its intellectual roots to Myers's (1977) initial insight of viewing a firm's discretionary future investment opportunities as growth options, or call options on real assets, in that the firm has the discretion to decide in the future whether to exercise the option to undertake these investments (Tong et al., 2008). With higher economic policy uncertainty, the best decision is to postpone current investments and wait for the resolution of the uncertainty and the disclosure of more information (Gulen and Ion, 2016). This allows a firm to maintain flexibility in preparation for growth opportunities in the next business cycle (Huang et al., 2023). Prior work confirms the critical role of real options and provides empirical evidence on the relationship between economic policy uncertainty and firms' investment decisions, such as capital investment levels (Gulen and Ion, 2016) and mergers and acquisitions (Nguyen and Phan, 2017; Bonaime et al., 2018).

Despite the various negative effects of uncertainty, prior literature emphasizes that uncertainty represents not only danger but also potential growth opportunities (Kulatilaka and Perotti, 1998; Zhang et al., 2021). From this perspective, the literature also argues that firms may devise a proactive response to deal with economic policy uncertainty. During periods of high economic policy uncertainty, firms often suffer severe financial constraints and higher operational risk, thus being forced to rely more on internally generated resources (Almeida et al., 2004; Chen et al., 2012; Bordo et al., 2016; Duong et al., 2020). In response to economic policy uncertainty, firms have incentives to increase their internal financing ability and improve the utilization efficiency of internal resources in a variety of ways (Huang et al., 2023). For example, Phan et al. (2019) and Duong et al. (2020) find that firms tend to increase their cash holdings under policy uncertainty, mitigating the negative impact of such uncertainty on capital investments and innovation outcomes. Despite the role of precautionary reserves in hedging the risk of policy uncertainty, due to the presence of cash holding costs (Almeida et al., 2004), the increase in cash holdings may also result in the inefficient allocation of capital and subsequent welfare loss (Liu et al., 2021). Another strand of literature argues that firms may undertake other precautionary strategies to manage risk caused by policy uncertainty, such as purchasing bank WMPs (Huang et al., 2023) or adopting more CSR engagement (Yuan et al., 2022). Zhang et al. (2021) also point out that a rise in economic policy uncertainty increases the level of corporate risk-taking from an opportunity expectation view.

[3] Article 68 of the PEL states that "a limited partner shall neither carry out partnership affairs nor represent the limited partnership when dealing with other parties." However, the PEL is silent on whether personal liability is attributable to LPs in the event that they contravene Article 68.

2.3. Hypothesis development

A firm's decision on whether to participate in VC funds depends on the trade-off between the acquisition of opportunities and the aversion of risks under economic policy uncertainty. When firms weight growth opportunities higher than risks, they are more likely to invest in VC funds amid economic policy uncertainty. In contrast, firms are less likely to participate in VC funds when they weight risks higher than growth opportunities amid economic policy uncertainty.

Firms have incentives to grasp potential opportunities contained in economic policy uncertainty by participating in VC funds. Higher uncertainty also implies more development opportunities rather than merely larger risks (Kulatilaka and Perotti, 1998). Firms need to identify these opportunities embedded in economic policy uncertainty and capture them to create value. The opportunity expectation view emphasizes that economic policy may encourage firms to seek future development by increasing the level of firm risk-taking (Zhang et al., 2021). Thus, strategic investments under uncertainty can be viewed as a commitment to a more aggressive future strategy (Kulatilaka and Perotti, 1998). Given that VC investments have some features that differ from other investments, firms can seize potential opportunities in advance by investing in VC funds.

First, a prominent feature of VC investments is the staged financing of portfolio companies by VC firms (Sahlman, 1990; Tian, 2011). Firms acting as LPs have the option to be involved in subsequent rounds, allowing them to target more promising and profitable projects in advance. LPAs give firms the following options: (1) expand investments (e.g., increase the capital allocation to funds, purchase stake from other LPs, acquire equity of targets from funds, directly invest in potential targets), (2) abandon investments (e.g., withdraw partial capital from funds, sell the stake to other LPs, excise veto power over certain projects, completely withdraw from funds) or (3) defer any definitive decision concerning whether to expand or abandon (i.e., wait and see). This enables firms to promptly grasp promising investment opportunities and be prepared when a positive signal about uncertainty emerges.

Second, another feature of VC investments is that a VC fund will create a portfolio of many targets by utilizing the capital raised from LPs. Moreover, VCs mainly finance entrepreneurship, especially high-tech and high-growth entrepreneurship (Chen, 2022). Entrepreneurship is typically an important source of new ideas, such as frontier technologies, emerging markets and new business modes (Dushnitsky and Yu, 2022). Once an initial investment is undertaken by the VC fund, the firm has access to a wider range of targets, especially those that are far away in industry or geography. Discovering and valuing each investment opportunity may be costly for a firm that faces many investment opportunities simultaneously, due to limited time and attention. Participating in VC funds helps firms have a greater likelihood of discovering the most promising opportunities amid economic policy uncertainty.

Third, informal and formal interactions in VC funds grant firms access to valuable information about external technological and business environments. Firms acting as LPs may have access to new knowledge through various mechanisms, such as the investment strategy committee in which they serve, the quarterly investment reports they receive from GPs, official meetings of LPs and GPs, and direct communications with GPs, other LPs and start-ups (Ozmel et al., 2019; Lin, 2021). Not only are start-ups a source of new knowledge, but GPs have comparative advantages in sharing industry-wide best practices and managing asset portfolios at the industry level (Brav et al., 2015; Buchner et al., 2017). Thus, these mechanisms are conducive to acquiring critical information, thereby providing firms with an advantage in not only identifying profitable investment opportunities (Ozmel et al., 2020) but also being alerted to potential threats in external environments (Maula et al., 2013) during the waiting period of high policy uncertainty. High-quality information is critical for firms to predict business prospects and create value.

In contrast to the above arguments, however, firms facing economic policy uncertainty may behave conservatively and avoid engaging in VC funds. Under high economic policy uncertainty, the consumption and supply levels of the market are continually disrupted and reset, resulting in great changes in income and higher operational risk for firms (Si et al., 2022; Zhao and Su, 2022). Due to financing constraints and operational risks, firms' investment decisions and behavior patterns may be more conservative and less likely to support high-risk investment projects (Zhang et al., 2021). Given that VCs invest primarily in entrepreneurship, there is a potential concern that VCs may bring high returns while carrying tremendous risk (Chen, 2022). There-

fore, when facing high economic policy uncertainty, firms are more likely to engage in stable investment projects or hold more cash and avoid undertaking high-risk behaviors, such as participating in VC funds.

In summary, we propose hypotheses 1a and 1b:

Hypothesis 1a (H1a). The greater the economic policy uncertainty, the more likely firms are to participate in VC funds.

Hypothesis 1b (H1b). The greater the economic policy uncertainty, the less likely firms are to participate in VC funds.

3. Data and methodology

3.1. Sample

Our sample consists of all Chinese A-shared listed companies (non-financial) in the Shanghai and Shenzhen stock markets from 2010 to 2019. Specifically, the independent and control variables span from 2010 to 2018, and the dependent variable spans from 2011 to 2019. We focus on the dependent variable from 2011 onwards because that year is widely regarded as the beginning of a period of firms' vibrant participation in VC funds in China (Lu and Song, 2022). To exclude the effect of the COVID-19 pandemic that emerged in 2020, we set 2019 as the end year of the dependent variable. Our sample selection process is as follows: (1) excluding firms in special treatment (ST, suspended and delisted firms); (2) excluding observations with missing values of variables; (3) excluding firms in the real estate and financial sectors.

A common challenge in VC research is the scarcity of publicly available data. Research on LPs of VC funds in the US market often exploits multiple data sources, such as Thomson Reuters's Venture Economics, Private Equity Intelligence, VentureOne, Capital IQ and Securities Data Company Platinum. However, none of these commercial databases provide complete coverage of any given LP's investments or LPs in any given fund, a drawback noted by numerous studies (Lerner et al., 2007; Hochberg and Rauh, 2013; Ozmel et al., 2019; Braun et al., 2020; Ozmel et al., 2020). Chinese listed companies are mandated by securities regulations to disclose detailed information about investments in any given fund. This regulation allows us to observe LPs' investments in VC funds, with less reliance on other commercial databases. Therefore, the initial data of listed companies investing in VC funds can be collected manually by looking up their announcements. To revise and complement the initial data, we also cross-check the initial data with other databases, namely Wind, CSMAR, PEdata[4] and Asset Management Association of China. Finally, we obtain a clean and complete dataset on VC funds invested in by listed companies from 2011 to 2019.

We obtain accounting data from the Wind and CSMAR databases. To mitigate the influence of outliers, we winsorize continuous variables at the 1 % and 99 % levels.

3.2. Variables

3.2.1. Independent variable

Following prior research (Gulen and Ion, 2016; Liu et al., 2021), we measure China's economic policy uncertainty (*EPU*) using an aggregate index developed by Baker et al. (2016). Through textual analysis, Baker et al. (2016) provide a new index related to newspaper coverage frequency. Specifically, their economic policy uncertainty index is based on the South China Morning Post, a leading English language newspaper in Hong Kong. They first obtain a monthly count of articles that contain a trio of terms about the economy (E), policy (P) and uncertainty (U). Then, they scale the raw counts, standardize each newspaper's variation, average across papers in a country by month, and normalize.[5] By tracking the changes in index values following major events, the uncertainty brought about by the adjustment of economic policies by Chinese governments can be estimated (Liu et al., 2021). To obtain an index that matches firm-level data from the monthly series, we

[4] Wind and CSMAR contain all listed companies' information in the Chinese stock market. PEdata is a leading database containing Chinese VC market information. These databases have been widely used for research on the Chinese capital market.

[5] For more information about the economic policy uncertainty index developed by Baker et al. (2016), see https://www.policyuncertainty.com/index.html.

calculate *EPU* by taking the average of the monthly economic policy uncertainty index at the end of each quarter (March, June, September and December) over a given year and dividing it by 100. We also use alternative measures of economic policy uncertainty in robustness checks.

3.2.2. Dependent variable

We define the propensity of a firm to participate in VC funds in terms of whether the firm newly participates in VC funds as the LP in year $t + 1$. The dummy variable *VCFund* takes the value of one if a firm newly participates in at least one VC fund and zero otherwise. Because this variable setting reflects the incremental number of VC funds, it is conducive to observing whether a firm responds to policy uncertainty by participating in VC funds.

3.2.3. Control variables

Following prior literature (Gulen and Ion, 2016; Bonaime et al., 2018; Duong et al., 2020), we use the following control variables: firm size (*Size*), leverage (*Lev*), intangible assets (*IA*), return on assets (*ROA*), cash flows (*CF*), firm age (*Age*), state-owned enterprises (*SOE*), executive shareholding (*ES*), largest shareholding (*Top1*) and institutional shareholding (*IS*). Detailed definitions of the variables are shown in Table 1.

3.3. Methodology

We estimate the impact of economic policy uncertainty on the propensity of firms to participate in VC funds by running the following logit regression:

$$VCFund_{i,t+1} = \beta_0 + \beta_1 EPU_t + \beta_2 Control_{i,t} + Industry + \varepsilon_{i,t} \quad (1)$$

where i and t denote firm and time, respectively; the dependent variable *VCFund* represents the propensity of firms to participate in VC funds; the independent variable *EPU* refers to economic policy uncertainty; *Control* represents all control variables in the previous section; and *Industry* denotes industry fixed effects. Because economic policy uncertainty is calculated as a time series at the national level and does not vary across firms, year fixed effects would absorb all the explanatory power of economic policy uncertainty (Duong et al., 2020). Thus, we do not include year fixed effects in the model. Lastly, we cluster standard errors at the firm level.

4. Economic results

4.1. Descriptive statistics and analysis

Table 2 presents the sample distribution at the year level. We find that the number of firms participating in VC funds and the number of VC funds both grow from 2011 to 2017, finally reaching their highest values in 2017. Table 3 reports the descriptive statistics of variables used in the primary analysis. The average value of

Table 1
Variable definitions.

Variable	Description	Definition
VCFund	Propensity to invest in VC funds	One if a firm newly participates in at least one VC fund in a given year, zero otherwise
EPU	Economic policy uncertainty	An index developed by Baker et al. (2016)
Size	Firm's size	Natural logarithm of total assets
Lev	Leverage	Total liabilities/total assets
IA	Intangible assets	Intangible assets/total assets
ROA	Return on assets	Net profits/total assets
CF	Cash flows	Operating cash flows/total assets
Age	Firm's age	Natural logarithm of time since the establishment of a firm
SOE	State-owned enterprise	One if a firm is state-owned, zero otherwise
ES	Executive shareholdings	Shareholdings of executives/total shares
Top1	Largest shareholdings	Shareholdings of the largest shareholder/total shares
IS	Institutional shareholdings	Shareholdings of institutional investors/total shares

Table 2
Sample distribution.

Year	Number of firms	Number of VC funds
2011	36	50
2012	37	44
2013	29	31
2014	100	110
2015	224	287
2016	299	416
2017	341	478
2018	294	374
2019	264	326

Table 3
Descriptive statistics.

Variables	N	Mean	S.D.	Min	P25	Median	P75	Max
VCFund	19,794	0.082	0.274	0	0	0	0	1
EPU	19,794	2.591	1.288	0.989	1.236	2.445	3.648	4.604
Size	19,794	22.066	1.238	19.796	21.172	21.899	22.764	25.985
Lev	19,794	0.419	0.206	0.050	0.252	0.412	0.576	0.892
IA	19,794	0.048	0.051	0.000	0.019	0.035	0.059	0.330
ROA	19,794	0.038	0.056	–0.215	0.014	0.037	0.065	0.188
CF	19,794	0.051	0.085	–0.209	0.006	0.048	0.096	0.330
Age	19,794	2.783	0.357	1.609	2.565	2.833	3.045	3.434
SOE	19,794	0.381	0.486	0	0	0	1	1
ES	19,794	0.071	0.140	0.000	0.000	0.001	0.060	0.615
Top1	19,794	0.346	0.147	0.088	0.231	0.328	0.447	0.737
IS	19,794	0.064	0.069	0.000	0.011	0.040	0.094	0.328

This table reports the descriptive statistics for the main variables in our study. Mean represents the average value of the variable. S.D. represents the standard deviation of the variable. Min represents the minimum value. Max represents the maximum value. P25, Median and P75 represent the numerical values of the 25%, 50% and 75% quantiles of the variable, respectively.

VCFund is 0.082, suggesting that a large majority of firms have not participated in VC funds. The average yearly *EPU* in China is 2.591, which is relatively high, consistent with the notion that China, as an emerging country, has experienced high economic policy uncertainty over a long period. The distributions of the other variables are generally consistent with those reported in prior studies.

4.2. Baseline results

Table 4 reports the baseline results of the effect of economic policy uncertainty on the propensity of firms to invest in VC funds. In Column (1), we include the independent variable but exclude the control variables. The coefficient of *EPU* is 0.131 and is significant at the 1 % level. In Column (2), all control variables are added to the regression model. The coefficient of *EPU* remains positive and significant at the 1 % level. These results support Hypothesis 1a and indicate that the greater the economic policy uncertainty, the more likely firms are to invest in VC funds. In other words, given the role of VC funds in seizing opportunities, firms have incentives to participate in VC funds during a period of high economic policy uncertainty.

4.3. Endogeneity and robustness tests

4.3.1. Mitigating endogeneity

An essential challenge related to estimating the association between economic policy uncertainty and the likelihood of firms investing in VC funds is that the result may be subject to endogeneity concerns. First,

Table 4
Economic policy uncertainty and the propensity of firms to invest in VC funds.

	(1)	(2)
EPU	0.131***	0.055***
	(8.083)	(2.807)
Size		0.505***
		(13.430)
Lev		–1.147***
		(–5.409)
IA		0.730
		(1.043)
ROA		2.567***
		(3.879)
CF		0.558
		(1.438)
Age		0.206**
		(2.110)
SOE		–0.597***
		(–6.810)
ES		0.488**
		(2.183)
Top1		–0.910***
		(–3.317)
IS		0.695
		(1.549)
Constant	–3.694***	–14.271***
	(–6.544)	(–14.766)
Industry FE	Yes	Yes
N	19,794	19,794
Pseudo R^2	0.047	0.088

This table reports the baseline results for the effect of economic policy uncertainty on the propensity of firms to invest in VC funds, calculated using the logit model. Column (1) only includes the independent variable. Column (2) includes the independent variable and all control variables. All specifications include industry fixed effects, and standard errors are clustered at the firm level. *t* statistics are reported in parentheses below the coefficients. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

although economic policy uncertainty is rarely shaped by firms' actions, China's central government decides the current policy based on the observed formation rate of fixed assets across the country (Liu et al., 2021). Hence, a bidirectional causality may remain in the association between policy uncertainty and firms' investment actions. Second, besides the effect of policy-related uncertainty, the effect of general economic uncertainty may also be captured by the economic policy uncertainty index, resulting in a potential measurement error bias in this index (Gulen and Ion, 2016). To mitigate these concerns, we employ two approaches as follows.

First, the classical approach to addressing endogeneity concerns is instrumental variable regression. We use the global economic policy uncertainty (*GEPU*) developed by Baker et al. (2016) as an instrumental variable for Chinese economic policy uncertainty. In the context of globalization, shocks in other economies are closely associated with Chinese economic policy uncertainty, but there is no evident reason to argue that they directly impact firms' participation in VC funds. It is worth noting that both China's economic policy uncertainty variable and the corresponding instrument are cross-sectionally invariant; their values are identical for all firms within each period (Gulen and Ion, 2016; Liu et al., 2021). Hence, a strong collinearity problem may remain in the model. Furthermore, Gulen and Ion (2016) note that the usual two-stage least-squares methodology is inappropriate in this context because it would mechanically overstate the correlation between the endogenous variable and its instruments. As such, to bypass this problem, we follow the method developed by Gulen and

Table 5
Mitigating endogeneity.

	IV: First stage		IV: Second stage	Eliminating contaminating components
	(1)		(2)	(3)
GEPU	2.914***	*EPU_IV*	0.050**	
	(4.703)		(2.210)	
MSize	–2.374	*EPU_R*		0.170***
	(–0.613)			(6.804)
MLev	–7.998	*Size*	0.508***	0.482***
	(–0.543)		(13.530)	(12.748)
MIA	28.812	*Lev*	–1.158***	–1.058***
	(1.728)		(–5.463)	(–4.970)
MROA	–12.335	*IA*	0.729	0.730
	(–1.560)		(1.041)	(1.038)
MCF	11.210***	*ROA*	2.535***	2.874***
	(6.845)		(3.825)	(4.348)
MES	–9.910	*CF*	0.564	0.472
	(–0.271)		(1.455)	(1.210)
MTop1	–55.740	*Age*	0.223**	0.103
	(–0.943)		(2.299)	(1.052)
MIS	–21.654	*SOE*	–0.603***	–0.555***
	(–0.792)		(–6.876)	(–6.350)
Constant	74.213	*ES*	0.495**	0.441**
	(0.632)		(2.213)	(1.971)
N	108	*Top1*	–0.912***	–0.909***
Adjusted R^2	0.820		(–3.327)	(–3.302)
		IS	0.668	0.842*
			(1.487)	(1.877)
		Constant	–14.381***	–13.481***
			(–14.921)	(–13.732)
		N	19,794	19,794
		Pseudo R^2	0.088	0.092

This table reports the results of mitigating endogeneity. Column (1) presents the results of monthly first-stage regression by running Eq. (2). Column (2) presents the results of yearly second-stage regression by re-running Eq. (1). *GEPU* denotes the global economic policy uncertainty and *EPU_IV* is the yearly fitted values from Eq. (2). Column (3) presents the results of eliminating contaminating components in the EPU index. *EPU_R* is the residual from Eq. (3). Specifications in Columns (2) and (3) include industry fixed effects, and standard errors are clustered at the firm level. *t* statistics are reported in parentheses below the coefficients. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Ion (2016), which is to run a time-series regression in the first stage and a panel regression in the second stage. Specifically, the monthly first-stage regression takes the following form:

$$EPU_t = \alpha + \beta_1 GEPU_t + \beta_2 MCV_t + e_t \quad (2)$$

where *GEPU* denotes the global economic policy uncertainty and *MCV* represents the average levels of all control variables in the economy.[6] As shown in Column (1) of Table 5, the coefficient of *GEPU* is 2.914 at the 1 % significance level, suggesting that our instrument satisfies the relevance condition. Thereafter, we obtain the fitted values from Eq. (2) and take the yearly values (*EPU_IV*) as an instrumental variable for the Chinese *EPU* index. Then, we use *EPU_IV* as the independent variable to estimate the yearly second-stage regression (Eq. (1)). Column (2) of Table 5 shows that the results remain significantly positive after mitigating endogeneity.

Second, an appropriate approach to mitigating measurement errors is to eliminate the contaminating component (e.g., macroeconomic conditions) embedded in the *EPU* index, as suggested by Gulen and Ion (2016).

[6] In this part, we only employ averages of continuous variables, i.e., *Size*, *Lev*, *IA*, *ROA*, *CF*, *ES*, *Top1* and *IS*. Following Gulen and Ion (2016), these averages are calculated for each calendar year in our sample period and then assigned to all 12 months in that year.

Following prior literature that exploits this approach in the Chinese context (e.g., Huang et al., 2022; Liu and Wang, 2022; Yuan et al., 2022), we do this by estimating the following monthly time-series regression:

$$EPU_t = \alpha + \beta_1 USEPU_t + \beta_2 EC_t + \beta_3 MV_t + \beta_4 M2_t + \varepsilon_t \quad (3)$$

where *EPU* represents Chinese economic policy uncertainty and *USEPU* represents the US economic policy uncertainty index developed by Baker et al. (2016). The reason for adding *USEPU* is that China and the US are the world's largest two economies and have extensive international trade activity, creating a tight link between them (Huang et al., 2022). We also control other variables to reflect macroeconomic conditions: *EC* represents the monthly Macro-Economic Climate Index of China; *MV* represents the natural logarithm of the monthly total market value of the Chinese stock market; *M2* represents the monthly growth rate of the M2 of China. Upon running Eq. (3), the residuals represent an exogenous measure of Chinese economic policy uncertainty after eliminating the contaminating part stemming from macroeconomic shocks. We use the yearly value of the residuals (*EPU_R*) as an alternative measure of *EPU* to re-estimate Eq. (1). In Column (3) of Table 5, we find that the results remain significantly positive after eliminating contaminating components in the *EPU* index.

4.3.2. Robustness tests

A set of robustness tests is conducted to ensure the robustness of our results. First, we use other measures of economic policy uncertainty. (1) We take the arithmetic average of the monthly economic policy uncertainty index over a given year and divide it by 100 (*EPU2*). (2) We take the geometric average of the monthly economic policy uncertainty index over a given year and divide it by 100 (*EPU3*). (3) Goodell et al. (2021) find that the volatility of economic policy uncertainty is much more economically significant in determining firm cash holdings than is economic policy uncertainty itself. Following their study, we take the standard deviation of the monthly economic policy uncertainty index over 12 months to capture the volatility of policy uncertainty (*EPU_σ*). The corresponding results are presented in Columns (1), (2) and (3) of Table 6. Our findings remain robust to these alternative measures of economic policy uncertainty (*EPU2*, *EPU3* and *EPU_σ*).

We also construct other regression models to verify our results. (1) We estimate Eq. (1) by using the probit model. (2) We take the annual number of VC funds newly invested in by firms as the dependent variable and thus use the negative binomial regression. (3) We take the natural logarithm of the annual number of VC funds newly invested in by firms plus 1 as the dependent variable and thus use the tobit model. As shown in Columns (4), (5) and (6) of Table 6, economic policy uncertainty still has a positive and significant impact on the propensity of firms to invest in VC funds.

5. Additional analysis

5.1. Cross-sectional tests

Our basic results show that firms have incentives to seize potential growth opportunities embedded in economic policy uncertainty by investing in VC funds. If that is the case, firms' motivations may be strengthened when they face more industrial growth opportunities. Seizing and capitalizing on these opportunities embedded in economic policy uncertainty is significant for firms to create value and competitive advantage in the future. Access to start-ups by investing in VC funds can help firms capture these opportunities because start-ups are often disrupters and sources of new ideas under economic policy uncertainty (Zhang et al., 2021). Moreover, participating in VC funds allows firms to acquire new information from GPs and other LPs through informal and formal communications. Delaying investment despite the presence of more growth opportunities may incur an opportunity cost of waiting (Tong and Li, 2011). Therefore, a greater level of growth opportunities may encourage firms to engage in VC funds amid economic policy uncertainty.

To test this conjecture, we use the median market-to-book ratio at the industry level to measure industrial growth opportunities. This is because, in general, industries with higher average market-to-book ratios should present higher levels of growth opportunities (Tong and Li, 2011). Next, we divide the sample into two groups based on the year median value: industries with more growth opportunities and industries with fewer growth opportunities. Table 7 presents the results of cross-sectional tests. The coefficient of *EPU* is positive and sig-

Table 6
Robustness tests.

	Independent variable: *EPU2*	Independent variable: *EPU3*	Independent variable: *EPU_σ*	Probit model	Negative binomial regression	Tobit model
	(1)	(2)	(3)	(4)	(5)	(6)
EPU2	0.045*					
	(1.817)					
EPU3		0.001**				
		(2.296)				
EPU_σ			0.001*			
			(1.812)			
EPU				0.032***	0.051**	0.003**
				(3.264)	(2.509)	(2.559)
Size	0.511***	0.507***	0.513***	0.256***	0.545***	0.032***
	(13.565)	(13.453)	(13.660)	(13.380)	(12.402)	(18.586)
Lev	–1.168***	–1.154***	–1.176***	–0.590***	–1.220***	–0.059***
	(–5.508)	(–5.445)	(–5.539)	(–5.616)	(–4.996)	(–5.560)
IA	0.727	0.728	0.728	0.441	0.430	0.025
	(1.039)	(1.040)	(1.040)	(1.254)	(0.575)	(0.724)
ROA	2.510***	2.537***	2.497***	1.280***	2.665***	0.131***
	(3.786)	(3.828)	(3.771)	(3.896)	(4.015)	(3.730)
CF	0.569	0.567	0.575	0.263	0.513	0.044**
	(1.468)	(1.460)	(1.481)	(1.376)	(1.360)	(2.092)
Age	0.233**	0.218**	0.238**	0.111**	0.244**	0.012**
	(2.386)	(2.235)	(2.444)	(2.262)	(2.311)	(2.414)
SOE	–0.607***	–0.601***	–0.610***	–0.313***	–0.576***	–0.030***
	(–6.907)	(–6.838)	(–6.958)	(–7.354)	(–5.886)	(–7.264)
ES	0.500**	0.493**	0.501**	0.243**	0.549**	0.030**
	(2.232)	(2.205)	(2.239)	(2.151)	(2.428)	(2.390)
Top1	–0.914***	–0.911***	–0.915***	–0.473***	–0.807***	–0.058***
	(–3.333)	(–3.322)	(–3.340)	(–3.545)	(–2.814)	(–4.905)
IS	0.656	0.678	0.652	0.363	0.235	0.029
	(1.459)	(1.508)	(1.453)	(1.578)	(0.503)	(1.171)
Constant	–14.430***	–14.351***	–14.450***	–7.400***	–15.277***	–0.666***
	(–14.944)	(–14.861)	(–14.975)	(–15.706)	(–14.625)	(–15.701)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	19,794	19,794	19,794	19,794	19,794	19,794
Pseudo R^2	0.088	0.088	0.088	0.089	0.079	–0.572

This table presents the results of robustness tests. In Column (1), *EPU2* is measured by taking the average of the monthly economic policy uncertainty index over a given year and dividing it by 100. In Column (2), *EPU3* is measured by taking the geometric average of the monthly economic policy uncertainty index over a given year and dividing it by 100. In Column (3), *EPU_σ* is measured by taking the standard deviation of the monthly economic policy uncertainty index over a given year. In Column (4), the probit model is employed. In Column (5), the negative binomial regression model is employed. In Column (6), the tobit model is employed. All specifications include industry fixed effects. *t* statistics are reported in parentheses below the coefficients. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 7
Additional analysis: Cross-sectional tests.

	More growth opportunities	Fewer growth opportunities
	(1)	(2)
EPU	0.123***	0.027
	(3.989)	(1.041)
Size	0.562***	0.448***
	(9.473)	(9.422)
Lev	–1.539***	–0.813***
	(–4.341)	(–3.169)
IA	0.799	0.248
	(0.777)	(0.265)
ROA	2.351**	3.049***
	(2.157)	(3.543)
CF	0.377	0.441
	(0.601)	(0.878)
Age	0.156	0.186
	(0.996)	(1.482)
SOE	–0.517***	–0.672***
	(–3.872)	(–5.974)
ES	0.384	0.581**
	(0.947)	(2.158)
Top1	–0.329	–1.417***
	(–0.834)	(–4.091)
IS	0.280	0.808
	(0.376)	(1.439)
Constant	–13.984***	–12.811***
	(–9.689)	(–11.829)
Difference p-value		0.013
Industry FE	Yes	Yes
N	8718	10,837
Pseudo R^2	0.102	0.093

This table reports the results of cross-sectional tests. All specifications include industry fixed effects, and standard errors are clustered at the firm level. *t* statistics are reported in parentheses below the coefficients. ***, ** and * denote significance at the 1%, 5% and 10% levels,

nificant for firms in industries with more growth opportunities, but nonsignificant for firms in industries with fewer growth opportunities. A SUEST test shows that there is a significant difference between the two groups. Our results indicate that firms operating in industries with more growth opportunities are more likely to invest in VC funds amid economic policy uncertainty.

5.2. Economic consequence tests

In this section, we test the economic consequences of participating in VC funds. Our basic results show that firms are more likely to participate in VC funds amid higher economic policy uncertainty. The rationale behind our prediction was that participating in VC funds allows firms to access a wider range of targets, target more promising projects in advance and obtain more valuable knowledge. To further validate our expectations, we test whether firms obtain more strategic benefits by participating in VC funds.

First, access to a wider range of start-ups through VC funds helps firms discover promising projects and promptly grasp them. This improves firms' investment plans and investment efficiency. Second, acquiring technological information through VC funds helps firms learn about frontier scientific domains and anticipate in advance which technologies are likely to dominate. This enables firms to improve their research and development activities and innovation performance. Third, acquiring business information through VC funds helps firms discover novel business practices and learn further application scenarios for current resources. Firms can thus better differentiate their products from those of their rivals and extend their market coverage.

To test these predictions, we investigate how participating in VC funds affects firms' investment efficiency, innovation outcomes and product diversification degrees. Following Lu and Song (2022), we estimate the following model:

$$Consequence_{i,t+1} = \beta_0 + \beta_1 VCFund\_Active_t + \beta_2 Control_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (4)$$

where *Consequence* denotes investment efficiency (*InvestEff*), innovation performance (*lnPatent*) and product diversification degree (*ProDiv*). Following the method of Richardson (2006), *InvestEff* is calculated using the deviation of the actual investment size from the predicted optimal investment size, which is the model residual. We take the absolute value of the residual to reflect inefficient firm investments. The larger the absolute value, the lower the investment efficiency and the higher the investment inefficiency. *lnPatent* is measured as the natural logarithm of the number of invention patent applications. Following prior literature (Jacquemin and Berry, 1979), *ProDiv* is calculated using an entropy measure. The explanatory variable is *VCFund_Active*, which equals one if there is at least one VC fund in a firm's existing fund portfolio in the year and zero otherwise.

Table 8 presents the results of the economic consequence tests. In Column (1), the coefficient of *EPU* is significantly negative, indicating that participating in VC funds suppresses firms' inefficient investments. The results in Columns (2) and (3) show that participating in VC funds significantly improves firms' innova-

Table 8
Additional analysis: Economic consequence tests.

	Investment efficiency	Innovation performance	Product diversification
	(1)	(2)	(3)
VCFund_Active	–0.002**	0.180***	0.035**
	(–2.318)	(4.102)	(2.069)
Size	–0.004***	0.550***	0.051***
	(–8.542)	(24.864)	(6.284)
Lev	0.000	–0.150	0.040
	(0.150)	(–1.511)	(0.982)
IA	0.021**	0.598*	0.441***
	(2.545)	(1.784)	(3.135)
ROA	–0.080***	2.417***	–0.106
	(–9.546)	(9.599)	(–1.169)
CF	0.036***	–0.054	–0.308***
	(8.306)	(–0.346)	(–5.642)
Age	–0.007***	–0.175***	0.085***
	(–5.414)	(–2.944)	(3.627)
SOE	–0.005***	0.242***	0.035*
	(–5.638)	(5.040)	(1.838)
ES	0.001	0.311**	–0.019
	(0.439)	(2.517)	(–0.397)
Top1	0.007***	–0.181	–0.130**
	(2.710)	(–1.332)	(–2.479)
IS	0.026***	1.489***	–0.205**
	(5.023)	(6.275)	(–2.528)
Constant	0.130***	–11.407***	–0.963***
	(12.794)	(–22.328)	(–4.887)
Year & Industry FEs	Yes	Yes	Yes
N	19,281	19,794	19,206
Adjusted R^2	0.053	0.437	0.117

This table presents the results of economic consequence tests. Column (1) shows the relationship between participating in VC funds and firms' investment efficiency. Column (2) shows the relationship between participating in VC funds and firms' innovation performance. Column (3) shows the relationship between participating in VC funds and firms' product diversification degrees. The sample size is reduced due to missing data. All specifications include year and industry fixed effects, and standard errors are clustered at the firm level. *t* statistics are reported in parentheses below the coefficients. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

tion performance and product diversification degrees. These findings indicate that participating in VC funds serves as a critical tool to help firms grasp promising opportunities and survive.

6. Conclusion

This study explores the relationship between economic policy uncertainty and the propensity of firms to participate in VC funds in the context of China. Our findings show that economic policy uncertainty is positively associated with the propensity of firms to participate in VC funds. We also provide additional analysis to further clarify this relationship. Our cross-sectional tests show that the positive relationship between economic policy uncertainty and the propensity to participate in VC funds is enhanced by industrial growth opportunities. Furthermore, economic consequence tests show that VC funds serve as an important mechanism for firms to improve investment efficiency, increase innovation performance and promote product diversification.

Our study suggests that economic policy uncertainty is an important antecedent of firms participating in VC funds. Firms may view VC funds as strategic tools to seize potential growth opportunities contained in economic policy uncertainty. These findings advance our understanding of how firms make investment decisions during periods of high policy uncertainty. Future research can explore how other types of uncertainty affect firms' decisions to participate in VC funds. We believe that this line of research on the motivations of firms to engage in VC funds in different situations can provide a more complete picture of the role of VC funds.

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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