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Green lending and stock price crash risk: Evidence from the green credit reform in China ☆

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ABSTRACT

Extant literature has under-theorized the equity market consequences of green credit reform. Our study addresses this gap by investigating the impact of green credit reform on stock price crash risk. Using the promulgation of the 2012 Green Credit Guidelines (GCGs) as a quasi-natural experimental setting, our results show that green lending significantly reduces high-polluting firms' stock price crash risk; and that the enhanced bank monitoring which green credit brings, both of accounting information quality and of corporate capital structure, serves as the mechanism underlying this causal effect. Cross-sectional analyses reveal that the reduction is more pronounced when banks face greater competition, and for firms without bank-client relationships or political connections. Overall, our study contributes to a finer-grained understanding of the equity market consequences of green lending and sheds new light on the determinants of stock price crash risk.

1. Introduction

Stock price crash risk refers to a collapse in stock prices that severely damages the welfare of shareholders. The frequency of these crashes has increased significantly over the past two decades, thus reinforcing the importance of identifying what drives the crash risk and how to reduce it effectively. Scholars have suggested that these crashes stem from the opportunistic withholding of bad news from outsiders by self-interested managers (Chen et al., 2001; Hutton et al., 2009; Jin and Myers, 2006) Kothari et al., 2009). When the accumulated bad news is released unexpectedly, the market reacts by correcting stock prices sharply downward, which leads to a collapse in stock prices (Jin and Myers, 2006; Kim et al., 2011a, 2011b).

Both theory and empirical evidence suggest that the attributes of corporate governance significantly affect this concealment of unfavorable information and, in turn, the future stock price crash risk of firms (Habib et al., 2018). For example, institutional ownership (An and Zhang, 2013; Callen and Fang, 2013), analyst coverage (Li and Zeng, 2019), media reporting

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(Dyck et al., 2008), short selling (Li and Zhang, 2015), accounting standards (DeFond et al., 2014), religion (Callen and Fang, 2015a), auditing services (Habib and Hasan, 2016), and tax enforcement (Bauer et al., 2021) have been documented as determinants of stock price crash risk. Among these corporate governance attributes, the corporate governance role of banks regarding the behavior of borrowers has been largely overlooked. Though emerging literature has documented the effect of bank monitoring on this behavior in the U.S. (Chen and Vashishtha, 2017; Dang et al., 2022), little is known about the corporate governance role of banks in reducing stock price crash risk, especially through green lending, in developing countries such as China. This study uses the promulgation of the 2012 Green Credit Guidelines (GCGs) in China as a quasi-natural experimental setting and explores the relationship between green credit[1] and stock price crash risk.

Screening and monitoring by banks are important attributes of corporate governance and, to some extent, are considered as substitutes for other attributes (Freixas and Rochet, 2008; Ahn and Choi, 2009; Lu et al., 2022). In China, the use of screening and monitoring to discipline managers is common since the important governance mechanisms of stock option plans and takeovers are still underdeveloped. Moreover, due to the lack of an efficient corporate bond market, most Chinese firms obtain a substantial amount of their debt financing from commercial banks. Therefore, banks have an information advantage in monitoring the behavior of borrowing firms and an edge in adjusting their lending decisions. As firms rely heavily on bank financing, the corporate governance role of bank screening and monitoring is significant (Kim et al., 2019).

As a new form of debt financing, green lending refers to the activities of financial institutions that are required to consider environmental and social factors and to give preferential credit to firms involved in sustainable development (An et al., 2021; Wen et al., 2021). The promulgation of the GCGs in China is regarded as a milestone in green credit policy, which was launched by the government in response to the growing demand for environmental, social, and governance (ESG) considerations. The green credit policy may influence high-polluting firms' stock price crash risk in two entirely different ways. On the one hand, from the perspective of the corporate governance role of banks, green lending may limit high-polluting firms' crash risk through strengthening bank screening and monitoring. In addition to the collecting of financial information, banks may require non-financial information to assess the environmental and social risks of clients, especially in regard to firms that are heavy polluters. Such enhanced pre-loan screening and post-loan monitoring is likely to constrain high-polluting firms from withholding cumulative bad news, thus decreasing firm-specific crash risks. On the other hand, such bank monitoring may be not effective because of information asymmetry between firms and banks, since managers of high-polluting firms may leverage their information advantage to deceive banks. Particularly, they may provide banks with dressed-up information or hoard negative news that may make them less likely to obtain bank loans. Following this reasoning, green lending may increase high-polluting firms' crash risk. These conflicting predictions mean that more research is needed to understand how green lending influences high-polluting firms' stock price crash risk.

To examine this, we use a sample of Chinese listed firms, comprising 13,114 firm-year observations from 2008 to 2015. Using high-polluting firms as the treatment group, we apply the difference-in-differences (DID) approach and find that the stock price crash risk has been significantly reduced for high-polluting firms compared with low-polluting firms since the introduction of the GCGs. The results show that GCGs-induced bank monitoring reduces the average crash risk of high-polluting firms by approximately 29 %. The results hold after a series of robustness tests. Mechanism analyses reveal that the GCGs play a significant role in reducing high-polluting firms' crash risk through closer bank monitoring of accounting information quality and corporate capital structures. Furthermore, the focal relationship is stronger when banks face greater competition, and for firms without bank-client relationships and political connections.

Our work contributes to the literature in several ways. First, this study explores the economic consequences of green credit policies. Previous research has documented that green credit reform influences credit allocations by financial institutions (Manderson and Kneller, 2012; Cai et al., 2016; Liu et al., 2019) and shapes corporate financing and investing behavior (An et al., 2021; Wen et al., 2021; Zhang, 2021; Zhang et al., 2021). This study, however, provides new insight into the consequences of green credit reform by being the first to investigate whether and how green lending affects the wealth of shareholders, through its impact on stock prices. Our findings show that green lending generates a positive externality on the share market by curbing the activities of managers hoarding bad news. Therefore, green lending reduces stock price crash risk and provides a beneficial spillover for shareholders.

Second, we enrich the growing stream of literature on the determinants of stock price crash risk. Examples of some known determinants are financial reporting and corporate disclosures (Cohen et al., 2008; Francis et al., 2016; Hutton et al., 2009), managerial characteristics (Kim et al., 2011a; Kim and Zhang, 2016), corporate governance (Andreou et al., 2016; Boubaker et al., 2014; Xu et al., 2014), informal institutions (Callen and Fang, 2015a); Lee and Wang, 2017; Li et al., 2017; Piotroski et al., 2015), and capital market transactions (Chang et al., 2017; Chen et al., 2001). Our research adds to this line of studies by providing evidence that green credit reform can influence future crash risk. It also adds to the existing literature by showing that creditors, like shareholders, play a valuable role in corporate governance and can significantly influence stock price crash risk through their capacity to screen and monitor firms' behavior. These findings are consistent with Jin and Myers' (2006) theory on the importance of governance in reducing the frequency of crashes.

Third, this study contributes to the literature regarding financial intermediation. The seminal work of Triantis and Daniels (1995) proposed an interactive theory of corporate governance, postulating that bank monitoring might generally benefit a firm's claimants. They argue that the divergence in the interests of lenders and shareholders reduces the benefits from

[1] This study uses green credit and green lending interchangeably.

governance. This study provides empirical evidence that some financial policies, such as green credit policies, could be effective mechanisms in directing the efforts of banks toward the common goal of restricting the behavior of managers, which would result in a reduction in stock price crash risk. Moreover, earlier research typically examines the role of banks in monitoring borrowers under narrow distress contexts, such as debt default and covenant violations (Diamond, 1984; Gustafson et al., 2021; (Vashishtha, 2014); (Wang et al., 2020a). Our work complements prior studies by indicating that banks can monitor borrowers through green lending policies. Notably, the exogenous research setting enables this study to better evaluate the consequences of bank monitoring, by largely avoiding the endogeneity concerns of previous studies. Furthermore, this work provides additional insight into understanding bank monitoring by showing that the effectiveness of green lending and the related bank monitoring depends on the extent of banking competition, bank–client connections, and political connections.

The remainder of this paper is structured as follows. Section 2 discusses the institutional background and presents hypotheses. Section 3 specifies the research design, followed by empirical results and robustness tests in Section 4. Mechanism analyses and cross-sectional analyses are discussed in Section 5 and Section 6, respectively. Section 7 concludes the paper.

2. Institutional background and hypothesis development

2.1. Green lending

With growing awareness of climate change and appeals for a better ecological environment, there is an urgent need to accelerate the transformation to a low-carbon, climate-resilient economy, i.e., a green economy. To achieve this, green lending becomes an important financial mechanism for governing corporate environmental behaviors in developing countries. Green lending is defined as debt financing provided by commercial banks to environmentally friendly projects or firms. This type of funding limits the access of polluting firms to credit resources by imposing restrictions on lending institutions and by demanding that such institutions incorporate an evaluation of environmental and social risks into their assessments of creditworthiness (An et al., 2021; Wen et al., 2021).

As a developing country, China still has a significant number of industries with a propensity for high energy consumption and pollution. To overcome these environmental problems and improve industrial structures, on February 24, 2012, the China Banking Regulatory Commission (CBRC) issued the GCGs, which applies to domestic policy banks, joint-stock commercial banks, financial assets management companies, provincial rural credit unions, as well as trusts, financial leasing companies, and enterprise group finance companies.[2] The issuance of the GCGs signifies a green credit reform in China. Generally, it encourages banks to increase lending to climate-friendly projects and to reduce lending to highly polluting ones.

The GCGs are designed to aid banks in allocating capital toward firms with better environmental and social risk management. In particular, it requires that banks identify clients "with major environmental and social risks" and establish separate credit approval guidelines "for restricted industries under state regulation and industries with major environmental and social risks." in addition to a conventional creditworthiness assessment. According to the GCGs, banks should incorporate environmental and social analyses into their pre-loan screening and post-loan monitoring for high-polluting corporations that present major environmental and social risks. Financial institutions may, however, lack the capability to effectively evaluate and monitor these types of risk. The GCGs therefore also give banks the option to outsource the auditing of clients' environmental and social risk to professional third parties. Key articles of the GCGs are summarized and displayed in the appendix.

Since the promulgation of the GCGs, scholars have examined the impacts of green lending on firms' financing and investing behaviors. For example, some studies find that heavily polluting firms have experienced a significant decline in debt financing capacity and debt maturity since the enactment of the GCGs (Liu et al., 2019; Wang et al., 2020b). Furthermore, high-polluting firms, such as energy-intensive companies, have significantly decreased their capital investments following the introduction of the GCGs. This has had a negative impact on the research and development intensity and total factor productivity of these companies (An et al., 2021; Wen et al., 2021; Zhang, 2021; Zhang et al., 2021).

The initiation of green credit reform was to promote industrial upgrades by guiding the credit allocation of financial institutions towards climate-friendly projects. The green credit reform, therefore, inevitably impacts the loan market. However, it remains unanswered whether such reform will exert a spillover effect on the equity market. The promulgation of the GCGs in 2012 provides an appropriate setting for this study to explore this question. Specifically, the study investigates how the GCGs-induced bank screening and monitoring influences stock price crash risk.

2.2. Stock price crash risk

Jin and Myers (2006) develop a theoretical framework and suggest that self-interested managers have incentives to hide bad news due to the presence of asymmetric information. Once this hoarded negative information reaches a certain

[2] See more on https://www.chinalawinsight.com/2012/03/articles/finance/the-green-credit-guideline/.

threshold, when revealed, the revelation of such information causes extreme downward stock price corrections that manifest as crashes. Subsequent studies provide empirical evidence showing bad news hoarding by managers, and find a battery of factors that influence stock price crash risk, such as financial reporting models (Cohen et al., 2008; Francis et al., 2016; Hutton et al., 2009), managerial characteristics (Kim et al., 2011a; Kim and Zhang, 2016), corporate governance (Andreou et al., 2016; Boubaker et al., 2014; Xu et al., 2014), informal institutions (Callen and Fang, 2015a; Lee and Wang, 2017; Li et al., 2017; Piotroski et al., 2015), and capital market transactions (Chang et al., 2017; Chen et al., 2001). However, few studies examine how lending policy affects stock price crash risks. The lack of literature in this field motivates this study to explore the association between lending policy and stock price crash risk, specifically green lending.

Banks, as loan providers, perform corporate governance functions for the borrower by screening loan applications and monitoring the fulfillment of obligations after a bank loan is made. Compared with loan application screening, monitoring is considered to play a dominant role in disciplining the managers of the borrowing firms. Effective monitoring can constrain these firms from withholding cumulative bad news, which is a major driver of firm-specific crash risk. The literature is limited in exploring the role of bank monitoring in determining stock price crash risk. This study therefore enriches the literature in this research field by investigating how China's green credit reform strengthens bank screening and monitoring, and thus affects stock price crash risk.

2.3. Hypothesis development

Green credit reform is intended to encourage financial institutions to fully integrate environmental and social considerations into their lending decisions and post-loan monitoring. We develop competing hypotheses, based on the corporate governance role of banks, regarding the impact of green lending on high-polluting firms' stock price crash risk.

On the one hand, prior literature shows that banks have an incentive to demand higher-quality accounting information from high-polluting clients ((Ball and Shivakumar, 2008a); Shivakumar, 2013; Sunder et al., 2018; Ryan and Tiller, 2022). The GCGs further intensify monitoring by banks of high-polluting borrowers by requesting a regular flow of information.[3] Prior research indicates that intensive monitoring constrains the ability of a manager to manage abnormal accruals opportunistically and hence improve firms' earnings quality (Ahn and Choi, 2009). Therefore, this research expects that the GCGs discourage bad news withholding behavior and reduces stock price crash risk.

In addition, GCGs also give banks the option to outsource the auditing of their clients' environmental and social risk to professional third parties. This allows the bank to benefit from the comparative advantage of being able to collect and process information at a lower cost – especially for those highly polluting companies with more processing required – which may, in turn, improve the effectiveness of monitoring.

Given that the main driver of stock price crash risk is the hoarding of negative information for an extended period (Hutton et al., 2009; (Jin and Myers, 2006); Kim and Zhang, 2016), the promulgation of GCGs is likely to limit the capacity of managers to be able to do this by strengthening screening and monitoring requirements in highly polluting companies. We therefore propose the following hypothesis:

> ***H1a****: After the promulgation of Green Credit Guidelines (GCGs), stock price crash risk is significantly reduced for high-polluting firms compared with low-polluting firms.*

On the other hand, bank screening and monitoring are not necessarily effective, because of the information asymmetry between banks and firms. Managers of high-polluting firms have an information advantage over banks, which they can exploit (Sufi, 2007; (Ivashina and Scharfstein, 2010)). Extant literature has documented that high-polluting firms have gone through greater difficulty in obtaining and maintaining bank loans (Liu et al., 2019; Wang et al., 2020a)). For example, article 17 of the GCGs has prohibited banking institutions from providing bank loans to high-polluting clients whose environmental and social performance are not in compliance. Additionally, article 19 has clearly stated that the allocation of credit funds can be suspended or terminated in cases of major potential environmental and social risks. Such requirements of the GCGs have imposed higher financing restrictions on high-polluting firms, putting these firms into a difficult financing situation.

The GCGs-induced financing difficulties, together with the information advantage possessed by managers of high-polluting firms, may lead to managerial opportunism (Andreou et al., 2021; Reichmann et al., 2022). With the purpose of securing bank loans, these firms may speculatively exploit their information advantage to deceive banks by providing "dressed-up" information or camouflaging negative information. Both behaviors could cause the corporate governance role of banks to become dysfunctional, and drive high-polluting firms' stock price crash risk to rise (Hutton et al., 2009; Jin and Myers, 2006; Kim and Zhang, 2016; Xu et al., 2013). Following this line of reasoning, we put forth the following hypothesis:

> ***H1b****: After the promulgation of Green Credit Guidelines (GCGs), stock price crash risk is significantly raised for high-polluting firms compared with low-polluting firms.*

[3] For example, Article 18 of the GCGs explicitly directs banks to use contractual covenants to strengthen clients' environmental and social risk management.

3. Data and methodology

3.1. Sample selection

The promulgation of GCGs in China offers a quasi-natural experiment that allows this study to alleviate endogeneity concerns when examining the impact of screening and monitoring by banks on reducing stock price crash risk. Moreover, the Chinese stock market is characterized by severe information asymmetry, weak governance, and frequent price crashes (Xu et al., 2014), which makes our research questions especially important. Findings based on the Chinese market could enhance an understanding of stock price crash risk and could be applied generally to other emerging economies.

Data for this study are obtained from the China Stock Market and Accounting Research (CSMAR) database. The initial sample contains all firms listed either on the Shanghai Stock Exchange or the Shenzhen Stock Exchange for the period 2008–2015. Following prior studies (Hutton et al., 2009; Kim and Zhang, 2016), this study employs the following filtering procedures: (1) remove financial firms, as their accounting data are not comparable to those of non-financial firms; (2) exclude ST, ST*, and PT firms, i.e., firms with special treatment; (3) remove firms with year-end share prices below 1 Chinese Yuan; (4) drop firms with fewer than 26 weeks of stock return data in each fiscal year; (5) eliminate companies with negative total assets or negative book values of equity; (6) delete firms with missing data; and (7) exclude firms that went public after 2012 to keep the sample consistent before and after the promulgation of the GCGs. Our final sample comprises 13,114 firm-year observations. All continuous variables at the 1 % and 99 % levels are winsorized to minimize the effects of outliers.

3.2. Measures of stock price crash risk

Following extant literature (Chen et al., 2001; Hutton et al., 2009; Kim et al., 2011b), two measures of stock price crash risk are employed in this study: negative conditional return skewness (*NCSKEW*) and the down-to-up volatility (*DUVOL*).

Specifically, the starting point is to run the following expanded market model:

$$r_{i,t} = \alpha_i + \beta_1 r_{m,t-2} + \beta_2 r_{m,t-1} + \beta_3 r_{m,t} + \beta_4 r_{m,t+1} + \beta_5 r_{m,t+2} + \varepsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the return on stock *i* in week *t*, and $r_{m,t}$ is the value-weighted market return in week *t*. The two-weeks lead and lag terms of the market returns are included to correct for non-synchronous trading (Dimson, 1979).

Taking the residual return ($\varepsilon_{i,t}$) from Eq. (1), the firm-specific weekly return ($W_{i,t}$) is defined as the natural logarithm of one plus the residual return.

Then $NCSKEW_{i,t}$ for a given firm *i* in year *t* is defined as follows:

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

where $W_{i,t}$ is the firm-specific weekly return, defined as above, and *n* is the number of weekly returns of firm *i* in year *t*. A higher value of *NCSKEW* corresponds to a high crash risk.

To calculate $DUVOL_{i,t}$, for firm *i* in year *t*, all weeks are divided into down weeks and up weeks, depending on whether the return of that particular week is below or above the annual average. Then $DUVOL_{i,t}$ is calculated as follows:

$$DUVOL_{i,t} = ln\left\{\frac{(n_u-1)\sum_{DOWN}W_{i,t}^2}{(n_d-1)\sum_{UP}W_{i,t}^2}\right\} \tag{3}$$

where n_u and n_d indicate the number of up and down weeks in year *t*, respectively. A higher *DUVOL* value indicates a greater likelihood of stock price crashes. This alternative measure is less likely to be excessively affected by the number of extreme returns, as it does not involve the third moment.

3.3. Model specification

To investigate the relationship between green lending and the stock price crash risk of firms, the following difference-in-differences (DID) model was constructed upon the promulgation of the GCGs in 2012:

$$CrashRisk_{i,t+1} = \beta_0 + \beta_1 TREAT_i + \beta_2 POST_t + \beta_3 TREAT_i * POST_t + \gamma Control_{i,t} + Industry + Year + \varepsilon_{i,t} \tag{4}$$

where $TREAT_i$ is an indicator equal to 1 if firm *i* is classified as a high-polluting firm (i.e., the treatment group) at the beginning of our sample period, and 0 otherwise (i.e., the control group). Specifically, high-polluting firms are those belonging to the 14 pollution-intensive industries (e.g., thermal power, steel, cement, electrolytic aluminum, and coal) classified by the Ministry of Environmental Protection in 2008. The control group includes all other listed firms. $POST_t$ is defined as 1 if time *t* was equal to or later than 2012 and 0 otherwise, as the GCGs were introduced in 2012. The coefficient of the interaction term reflects the incremental change in stock price crash risk of the treatment group relative to the control group from the pre- to post-GCGs periods. Specifically, a statistically significant negative coefficient would suggest that crash risk is significantly reduced for high-polluting firms compared with non-high-polluting firms.

In accordance with the literature (Chen et al., 2001; Hutton et al., 2009; Jin and Myers, 2006; Kim and Zhang, 2016), the following control variables are included in the analysis: stock return volatility (*SIGMA*), stock turnover (*DTURN*), firm-specific weekly returns (*RET*), firm size (*SIZE*), firm leverage (*LEV*), return on assets (*ROA*), market-to-book ratio (*MB*), largest shareholder ownership ratio (*FIRST*), CEO duality (*DUAL*), and firm opacity (*ABACC*). The appendix provides the definitions of all variables used in this study. We also control for industry and year fixed effects, with robust standard errors clustered at the firm level.

4. Empirical results

4.1. Descriptive statistics

The summary statistics of the variables are presented in Table 1. The mean values of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ are −0.26 and −0.17, with standard deviations of 0.66 and 0.46, respectively. The distribution of the stock price crash risk of the sample, measured with either *NCSKEW* or *DUVOL*, is similar to those reported in prior studies (Callen and Fang, 2015b; Xu et al., 2014). The mean of $TREAT_i$ is 0.33, indicating that approximately 33 % of firms in the sample were high polluters. This figure is also consistent with the number reported by Liu et al. (2019) for a similar sample, in which 35 % of firms are identified as high polluting. The statistics of the control variables are in line with prior work.

4.2. Main results

Table 2 reports the regression results of Eq. (4) using the full sample. The first column presents the results when $NCSKEW_{t+1}$ is used as the dependent variable, while the second column contains results when $DUVOL_{t+1}$ is used as the dependent variable. For both measures of stock price crash risk, the higher the value of the measure, the higher the associated crash risk. The statistically significant negative coefficients of *POST* provide preliminary evidence that the overall stock price crash risk was reduced after the promulgation of the GCGs.

Our major interest lies in the coefficient of the interaction term *TREAT_POST*, which captures the incremental change in the stock price crash risk of high-polluting firms before and after the GCGs. The coefficient of *TREAT_POST* is −0.076 using *NCSKEW* as the dependent variable, which is statistically significant with *t*-statistics −3.32. From an economic point of view, given the mean and standard deviation of *NCSKEW*, these numbers suggest that the average crash risk of high-polluting firms declined by 29 % after the promulgation of the GCGs. Comparable results hold if *DUVOL* is used instead. The associated coefficients of *TREAT_POST* is −0.056 and is negatively statistically significant with *t*-statistics −3.47, which corresponds to approximately a 33 % reduction in stock price crash risk. The results, therefore, are both statistically significant and economically meaningful.

These findings support *H1a* and suggest that high-polluting firms engage in less bad-news-hoarding activities as a result of the strengthened bank screening and monitoring on them. Consequently, high-polluting firms exhibit a lower crash risk after the promulgation of the GCGs in 2012. Turning to the control variables, our results generally align with prior work (Chen et al., 2001; Hutton et al., 2009; Jin and Myers, 2006); Kim and Zhang, 2016).

Table 1
Descriptive Statistics.

VarName	N	Mean	SD	P25	Median	P75
NCSKEW	13,114	−0.26	0.66	−0.62	−0.22	0.14
DUVOL	13,114	−0.17	0.46	−0.47	−0.17	0.14
TREAT	13,114	0.33	0.47	0.00	0.00	1.00
SIGMA	13,114	0.07	0.03	0.05	0.06	0.08
DTURN	13,114	−0.25	0.87	−0.63	−0.01	0.39
RET	13,114	0.01	0.01	−0.00	0.00	0.01
SIZE	13,114	21.93	1.25	21.04	21.75	22.62
LEV	13,114	0.44	0.21	0.28	0.45	0.61
ROA	13,114	0.04	0.05	0.01	0.04	0.07
MB	13,114	2.13	1.37	1.27	1.67	2.43
FIRST	13,114	35.97	15.22	23.76	34.12	46.86
DUAL	13,114	0.22	0.42	0.00	0.00	0.00
ABACC	13,114	0.09	0.09	0.03	0.06	0.12

Table 1 reports the descriptive statistics for the variables used in our empirical analyses. The definitions of these variables can be found in Appendix. The sample consists of 13,114 firm-years observations for firms listed either on Shanghai Stock Exchange or Shenzhen Stock Exchange for the period 2008–2015. All continuous variables are winsorized at the 1% and 99% levels.

Table 2
Green lending and stock price crash risk.

	(1) NCSKEW	(2) DUVOL
TREAT	0.011	0.016
	(0.56)	(1.08)
POST	−0.408***	−0.209***
	(−10.16)	(−7.52)
TREAT_POST	−0.076***	−0.056***
	(−3.32)	(−3.47)
SIGMA	−8.724***	−5.188***
	(−17.83)	(−16.17)
DTURN	−0.036***	−0.036***
	(−4.56)	(−6.49)
RET	−5.944***	−5.793***
	(−5.69)	(−7.93)
SIZE	−0.070***	−0.057***
	(−9.64)	(−11.46)
LEV	−0.001	−0.010
	(−0.03)	(−0.39)
ROA	0.376***	0.210**
	(2.85)	(2.24)
MB	0.022***	0.011***
	(3.67)	(2.69)
FIRST	−0.001***	−0.001**
	(−3.27)	(−2.42)
DUAL	0.064***	0.048***
	(4.36)	(4.63)
ABACC	0.218***	0.101**
	(3.30)	(2.21)
Constant	2.090***	1.519***
	(12.11)	(12.73)
INDUSTRY	Yes	Yes
YEAR	Yes	Yes
N	13,114	13,114
Adjusted R^2	0.13	0.13

Table 2 presents the regression results of our baseline model as following:
$CrashRisk_{i,t+1} = \beta_0 + \beta_1 TREAT_i + \beta_2 POST_t + \beta_3 TREAT\_POST_{i,t} + \gamma Control_{i,t} + Industry + Year + \varepsilon_{i,t}$
where $TREAT_i$ is an indicative variable equal to 1 if firm i is classified as a high-polluting firm and 0 otherwise; $POST_t$ is taken 1 if time t was equal to or later than 2012 and 0 otherwise. The interaction term $Treat\_Post_{i,t}$ is defined as $TREAT_i \times POST_t$. SIGMA, DTURN, RET, SIZE, LEV, ROA, MB, FIRST, DUAL, ABACC are control variables. The dependent variable, crash risk, is measured by negative conditional skewness (NCSKEW) in column (1) and down-to-up volatility (DUVOL) in column (2). All variables are defined in the Appendix. The industry fixed and year fixed effects are included in the regression. The numbers reported in parentheses are t-statistics based on standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

4.3. Robustness tests

Several diagnostic tests are conducted to ensure the robustness of the results. We begin with three standard tests to validate our DID model and enhance its reliability. Then we change the definition of the dependent variable and alter the testing period to further make sure that our results are robust.

First, a parallel trend analysis is conducted to address the issue of DID model identification. The validity of the DID model depends on the parallel trend assumption. In this research setting, the assumption requires the trend in stock price crash risk to be parallel for the treatment and control groups during the pre-GCGs period. To examine the parallel trend assumption, the study follows Cornaggia et al. (2015) and estimates the following model:

$$CrashRisk_{i,t+1} = \beta_0 + \beta_1 Before^{3+}_{i,t} + \beta_2 Before^{2}_{i,t} + \beta_3 Before^{1}_{i,t} + \beta_4 Current_{i,t} + \beta_5 After^{1}_{i,t} + +\beta_6 After^{2}_{i,t} + \beta_7 After^{3}_{i,t} + \beta_8 TREAT_i + \gamma Control_{i,t} + Industry + Year + \varepsilon_{i,t} \quad (5)$$

A set of new dummy variables are defined: $Before^{3+}$, which is equal to 1 if time t is 2009 or earlier for the treatment group and 0 otherwise; $Before^{2}$, equal to 1 if time t is 2010 for the treatment group and 0 otherwise; $Before^{1}$, equal to 1 if time t is 2011 for the treatment group and 0 otherwise; $Current$, equal to 1 if time t is 2012 for the treatment group and 0 otherwise; $After^{1}$, equal to 1 if time t is 2013 for the treatment group and 0 otherwise; $After^{2}$, equal to 1 if time t is 2014 for the treatment group and 0 otherwise; and $After^{3}$, equal to 1 if time t is 2015 for the treatment group and 0 otherwise. The results in Panel A of Table 3, together with Figs. 1 and 2, indicate that the parallel trend assumption is satisfied in this DID model.

Table 3
Robustness test.

Panel A: Parallel trend test		
	(1) NCSKEW	(2) DUVOL
TREAT	−0.012	0.005
	(−0.38)	(0.20)
Before^{3+}	0.083**	0.048
	(2.00)	(1.53)
Before^{2}	−0.024	−0.053
	(−0.54)	(−1.60)
Before^{1}	0.030	0.038
	(0.71)	(1.25)
Current	−0.081*	−0.057*
	(−1.86)	(−1.83)
After^{1}	−0.041	−0.063**
	(−0.97)	(−2.00)
After^{2}	−0.078*	−0.057*
	(−1.72)	(−1.74)
After^{3}	−0.010	−0.002
	(−0.23)	(−0.07)
Controls	Yes	Yes
INDUSTRY	Yes	Yes
YEAR	Yes	Yes
N	13,114	13,114
Adjusted R^2	0.13	0.13

Panel B: Placebo tests				
	(1) NCSKEW	(2) DUVOL	(3) NCSKEW	(4) DUVOL
TREAT	−0.034*	−0.019	−0.019	0.007
	(−1.72)	(−1.29)	(−0.94)	(0.43)
POST	0.163***	0.094***	−0.133***	−0.095***
	(5.37)	(4.31)	(−4.07)	(−4.05)
TREAT_POST	−0.029	−0.017	−0.023	−0.029
	(−1.26)	(−1.06)	(−0.94)	(−1.63)
Controls	Yes	Yes	Yes	Yes
INDUSTRY	Yes	Yes	Yes	Yes
YEAR	Yes	Yes	Yes	Yes
N	12,502	12,502	11,153	11,153
Adjusted R^2	0.12	0.11	0.11	0.11

Panel C: Regression with the propensity-score-matched samples		
	(1) NCSKEW	(2) DUVOL
TREAT	0.005	0.015
	(0.24)	(0.88)
POST	0.224***	0.195***
	(4.83)	(5.84)
TREAT_POST	−0.058**	−0.043**
	(−2.22)	(−2.34)
Controls	Yes	Yes
INDUSTRY	Yes	Yes
YEAR	Yes	Yes
N	8,728	8,728
Adjusted R^2	0.12	0.12

Panel D: Alternative measure of stock price crash risk	
	(1) CRASH
TREAT	−0.024***
	(−2.63)
POST	0.102***
	(5.68)
TREAT_POST	−0.030***
	(−3.05)
Controls	Yes
INDUSTRY	Yes
YEAR	Yes

Table 3 (*continued*)

Panel C: Regression with the propensity-score-matched samples		
	(1) NCSKEW	(2) DUVOL
N	13,114	
Adjusted R^2	0.04	

Panel E: Alter testing period		
	(1) NCSKEW	(2) DUVOL
TREAT	0.011	0.016
	(0.49)	(1.01)
POST	−0.090***	−0.038*
	(−3.09)	(−1.86)
TREAT_POST	−0.111***	−0.081***
	(−4.23)	(−4.50)
Controls	Yes	Yes
INDUSTRY	Yes	Yes
YEAR	Yes	Yes
N	10,047	10,047
Adjusted R^2	0.15	0.15

Table 3 presents robustness tests for our main results. Panel A lists the estimation results of parallel trend test. We replace *POST* and *TREAT_POST* with a set of indicator variables, i.e., $Before^1$, $Before^2$, $Before^{3+}$, *Current*, $After^1$, $After^2$, and $After^3$. Panel B gives results for Placebo tests. The GCGs enactment is artificially assigned to a hypothetical year earlier than 2012 (2009 or 2010) and re-estimates the baseline model using the new sample. Columns (1) and (2) present the results when the artificial event year is 2010 and Columns (3) and (4) show the results when assigning 2009 as the event year. Panel C reports the results using the propensity-score-matched sample. Panel D uses an alternative measure of stock price crash risk. This measure is an indicator variable $Crash_{i,t}$, which is equal to 1 if firm *i* experiences one or more crash weeks in year *t* and 0 otherwise. A crash week for firm *i* in year *t* is defined as a week when firm *i* experiences a weekly return that is 3.09 standard deviations below the mean of year *t*. Panel E presents the results when the testing period is changed to a six-year period from 2009 to 2014. For all regressions, all control variables, industry fixed and year fixed effects are included in the regression. The numbers reported in parentheses are *t*-statistics based on standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

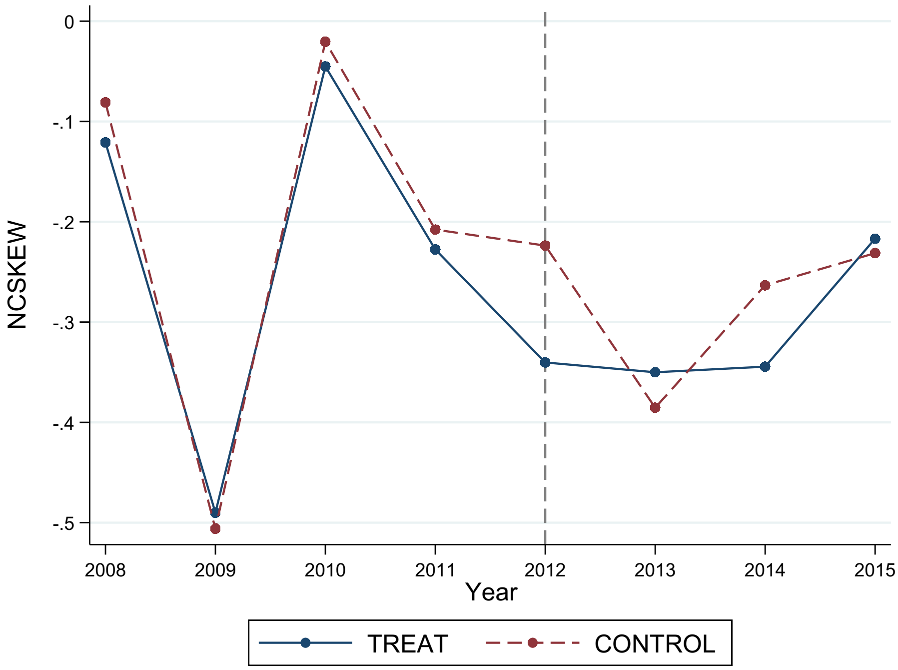

Fig. 1. Parallel Trend Test (Dependent variable = NCSKEW).

Second, to ensure that other unobservable events do not drive the results, placebo tests are conducted by artificially assigning a pseudo-year to the promulgation of the GCGs. In line with previous research (Obaydin et al., 2021), the GCGs enactment is artificially assigned to a hypothetical year earlier than 2012 (2009 or 2010), and the tests re-estimate the base-

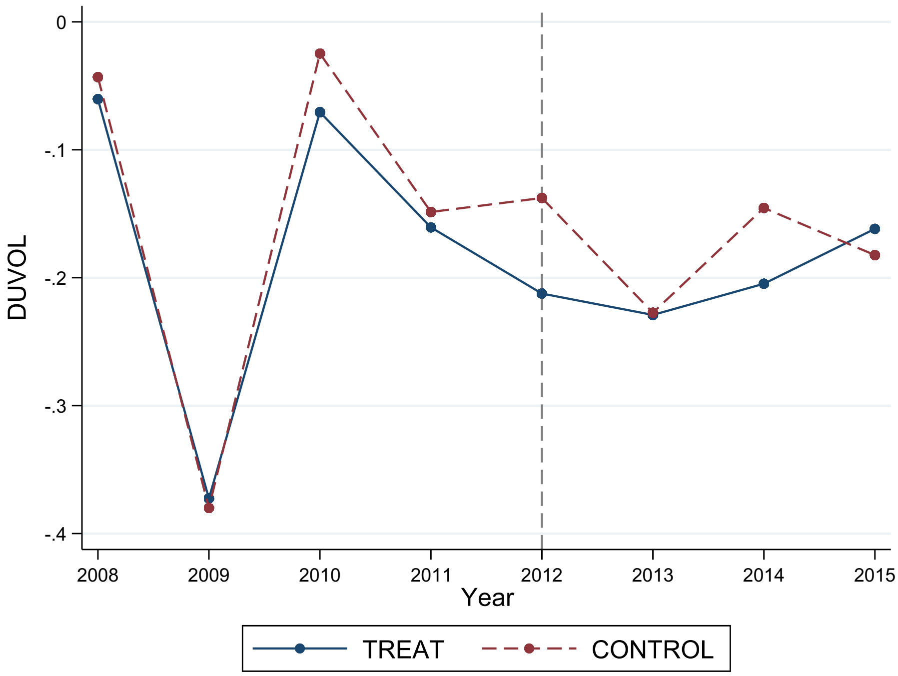

Fig. 2. Parallel Trend Test (Dependent variable = DUVOL).

line model using the new sample. Theoretically, the new regression should yield an insignificant coefficient for *TREAT_POST*. Panel B of Table 3 reports the results of the placebo tests. Columns (1) and (2) present the results when the artificially assigned pseudo-year is 2010 and Columns (3) and (4) show the results when assigning 2009 as the pseudo-year. The coefficients of *TREAT_POST* are consistently insignificant, providing no evidence that the baseline results can be generated by a random draw.

Third, a more comparable control group for high-polluting firms is constructed using the propensity score matching (PSM) approach. The DID model assumes that the treatment and control groups are identical. If the assumption of sample homogeneity is not satisfied, the reliability of regression results will be compromised due to endogenous issues. To address this concern, this study follows Obaydin et al. (2021) in selecting firm size, financial leverage, ROA ratio, MB ratio, state-owned enterprises, largest shareholder ownership ratio, percentage of independent directors, and CEO duality as covariates. Logistic regression is applied with nearest-neighbor matching within caliper to estimate a propensity score. Consequently, we build a balanced and matched sample and then repeat the regressions analysis. The results are shown in Panel C of Table 3. As demonstrated, the results are qualitatively identical to the results presented in Table 2, providing further support for our findings. We also carry out balancing tests to ensure the performance of our PSM procedure. The untabulated results suggest that our PSM procedure has significantly reduced the bias between the treatment and control groups.[4]

Fourth, an alternative measure of stock price crash risk is adopted and the study re-estimates the model to check whether the findings are sensitive to different definitions of stock price crash risk. Following Kim and Zhang (2016), $Crash_{i,t}$, an indicator variable of firm *i* in year *t*, is employed as an alternative measure of stock price crash risk. This variable is equal to 1 if firm *i* in year *t* experiences one or more crash weeks and 0 otherwise. A crash week for firm *i* in year *t* is defined as a week when firm *i* experiences a weekly return that is 3.09 standard deviations below the mean over the entire year *t*. With the assumption that weekly returns are normally distributed, there is only a 0.1 % chance that a firm has such a weekly return. The choice of 0.1 % serves as a reasonable benchmark for the rare event of a stock price crash. Panel D of Table 3 lists the regression results using *Crash*, and these results are qualitatively identical to the previous results when *NCSKEW* and *DUVOL* are used as measures of stock price crash risk, indicating that our findings hold under different measures of stock price crash risk.

Finally, the testing period is changed to a six-year period from 2009 to 2014, including three years before the GCGs and three years after. Panel E of Table 3 shows that the results are identical, implying that our findings are not sensitive to the testing period.

[4] Related results are available upon request.

5. Mechanism analyses

The baseline findings of this study are consistent with the hypothesis that green lending encourages banks to strengthen monitoring on high-polluting firms, and that such enhanced monitoring curbs these firms' bad-news-hoarding activities. As a result, high-polluting firms' stock price crash risk has significantly reduced since the introduction of the GCGs. This section continues to examine the underlying mechanisms through which green lending influences crash risk. It is argued that green lending reduces the stock price crash risk of high-polluting firms by intensifying bank screening and monitoring of both accounting information quality and corporate capital structures. To evaluate these channels, we conduct the following tests.

5.1. Accounting information quality

From the inception of the GCGs, banks have had to impose more stringent debt covenants on high-polluting firms. Since most debt covenants are based on accounting information (Tung et al., 2008), higher-quality accounting information is needed to ensure proper management of these covenants. Banks may require high-polluting firms to adopt more conservative accounting practices and may incline to review their financial reports more closely to deter unfavorable accrual management (Fama, 1985; Frankel et al., 2020; Rajan and Winton, 1995). Therefore, we use both earnings quality and accounting conservatism to measure the quality of accounting information.

5.1.1. Earnings quality

Earnings management is a way to manipulate accounting information via discretionary accrual choices (Dechow et al., 1995; Jiang et al., 2016). The GCGs require banks to improve their pre-loan screening and post-loan monitoring of high-polluting firms, leading to more stringent governance of financial reporting by borrowers, and greater attention to unfavorable earnings manipulation. The ability of high-polluting firms to manipulate accruals is, therefore, significantly constrained by stricter bank monitoring. Since firms with more opaque financial reporting are more prone to stock price crash risk (Hutton el al. 2009), we expect that the stringent bank screening and monitoring after the introduction of the GCGs will significantly improve the earnings quality of high-polluting firms and, consequently, reduce their stock price crash risk. More specifically, referencing firms' existing status of earnings quality before the GCGs, we expect that the GCGs-induced stringent bank screening and monitoring can only offer a marginal improvement on earnings quality for those firms that already had high earnings quality before the promulgation of the GCGs. If earnings quality is an underlying channel for the effectiveness of bank screening and monitoring, the GCGs are more likely to reduce the price crash risk of those high-polluting firms that had low earnings quality before the promulgation of the GCGs.

Earnings quality in our work was measured by the level of discretionary accruals. The discretionary accruals are estimated on the modified Jones model (Dechow et al., 1995). The sample is then divided into high- and low-quality groups. If the improvement of earnings quality as the underlying mechanism is valid, it would be expected that the GCGs should have a significant impact on the crash risk of high-polluting firms in the low-quality group. Table 4 reports the regression results. We find that the coefficients of *TREAT_POST* are significantly negative only in the low-quality sub-sample, which supports the argument that bank monitoring of earnings manipulation serves as a channel through which the GCGs reduce future price crashes for high-polluting firms.

Table 4
Earnings quality, green lending and stock price crash risk.

Earnings Quality	(1) NCSKEW Low	(2) NCSKEW High	(3) DUVOL Low	(4) DUVOL High
TREAT	0.010	0.014	0.015	0.018
	(0.36)	(0.48)	(0.75)	(0.89)
POST	0.304***	0.204***	0.255***	0.154***
	(5.48)	(3.96)	(6.52)	(4.17)
TREAT_POST	−0.124***	−0.035	−0.085***	−0.029
	(−3.80)	(−1.07)	(−3.75)	(−1.29)
Controls	Yes	Yes	Yes	Yes
INDUSTRY	Yes	Yes	Yes	Yes
YEAR	Yes	Yes	Yes	Yes
N	6,557	6,557	6,557	6,557
Adjusted R^2	0.12	0.14	0.12	0.14

Table 4 presents the regression results of exploring the earning quality as an underlying channel for the effect of green lending on reducing high-polluting firms' stock price crash risk. The earnings quality is measured by the level of discretionary accruals. Based on the cross-sectional median of this measure before the promulgation of the GCGs, we partition all firms into two groups, low earning-quality and high earning-quality groups. We then run the baseline model Eq. (4) on the two group separately. The "Low" and "High" in the titles of columns represent regression results for the low earning-quality and high earning-quality groups, respectively. The dependent variable, crash risk, is measured by negative conditional skewness (*NCSKEW*) in column (1) and (2) and down-to-up volatility (*DUVOL*) in column (3) and (4). All variables are defined in the Appendix. The industry fixed and year fixed effects are included in the regression. The numbers reported in parentheses are *t*-statistics based on standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.1.2. Accounting conservatism

Accounting conservatism is generally defined as accounting policies or principles that result in a downward bias in accounting net asset value relative to economic net asset value (Basu, 1997; Watts, 2003; Lu et al., 2020). Conservative accounting treatments limit managers' incentives and abilities to hide bad news, therefore reducing stock price crash risk. Kim and Zhang (2016) find that firms that exert more conservative accounting policies are less likely to have future stock price crashes. From a lender's perspective, accounting conservatism is preferred in debt contracting, especially in those with an elevated risk, because conservative accounting treatments result in lower distributions of resources to shareholders and management, and limit wealth transfers from debt holders to shareholders (Ahmed et al., 2002; Ball and Shivakumar, 2008b; Shivakumar, 2013; Watts and Zimmerman, 1986). Accounting conservatism also helps lenders evaluate the adequacy of borrowers' assets to repay loans, thus reducing the credit risk associated with lending. Accounting conservatism is, therefore, often regarded as an effective monitoring mechanism for lenders to reduce uncertainty, mitigate information asymmetry, and facilitate *ex post* monitoring (Ball and Shivakumar, 2008a; Shivakumar, 2013; Sunder et al., 2018).

The GCGs have imposed stringent bank screening and monitoring on high-polluting firms and may push these firms to adopt more conservative accounting policies. If the promulgation of the GCGs reduce the stock price crash risk for high-polluting firms by promoting accounting conservatism, we expect to observe no significant crash risk reduction in those high-polluting firms that have already adopted conservative accounting policies before the GCGs' inception.

To test this channel, accounting conservatism is measured using the C-score developed by Khan and Watts (2009). The sample is then split into more and less conservative firms, based on the median C-score of the whole sample before the GCGs implementation. We then run the same baseline analysis on the two sub-samples. According to the results in Table 5, green lending has significantly reduced stock price crash risk for those high-polluting firms which had not adopted conservative accounting policies before the promulgation of the GCGs. The results hold for both measures of crash risk, i.e., *NCSKEW* and *DUVOL*. On the contrary, those high-polluting firms which had already adopted conservative accounting policies experience a non-significant incremental reduction in their stock price crash risk when *NCSKEW* is used as the measure of crash risk. In the case of *DUVOL* used as the crash risk measure, while we do observe a marginally significant (at 10 % level) crash risk reduction in firms with conservative accounting policies, the economic significance of risk reduction is much weaker compared with those observed in firms without conservative accounting policies in place before the promulgation of the GCGs. In summary, the results presented in Table 5 suggest that the GCGs-induced bank screening and monitoring demand more conservative accounting information from high polluting borrowers, and in turn force these firms to adopt more conservative accounting policies. The results corroborate our conjecture that bank monitoring on accounting conservatism functions as an underlying mechanism through which the GCGs reduce future price crashes for high-polluting firms.

5.2. Corporate capital structure

In addition to enhancing bank screening and monitoring on accounting information quality, the GCGs may affect the stock price crash risk through active bank monitoring of the capital structure of high-polluting firms. Increased environmental and social risks may lead banks to control the loan size and shorten the length of debt maturity approved for high-polluting firms thanks to dictates contained within the GCGs (Liu et al., 2019). Bank monitoring of corporate capital structure may, therefore, take two forms to influence stock price crash risk: firm leverage and maturity structure.

Table 5
Accounting conservativism, green lending and stock price crash risk.

Accounting conservatism	(1) NCSKEW Less	(2) NCSKEW More	(3) DUVOL Less	(4) DUVOL More
TREAT	0.022	0.005	0.025	0.014
	(0.77)	(0.17)	(1.20)	(0.69)
POST	−0.594***	−0.209***	−0.368***	−0.034
	(−10.41)	(−3.62)	(−9.30)	(−0.84)
TREAT_POST	−0.115***	−0.043	−0.069***	−0.044*
	(−3.28)	(−1.33)	(−2.83)	(−1.96)
Controls	Yes	Yes	Yes	Yes
INDUSTRY	Yes	Yes	Yes	Yes
YEAR	Yes	Yes	Yes	Yes
N	6,184	6,248	6,184	6,248
Adjusted R^2	0.14	0.13	0.14	0.13

Table 5 presents the regression results of exploring the accounting conservatism as an underlying channel for the effect of green lending on reducing high-polluting firms' stock price crash risk. The accounting conservatism is measured by C-score developed by Khan and Watts (2009). Based on the cross-sectional median of this measure before the promulgation of the GCGs, we partition all firms into two groups, less- and more-conservative groups. We then run the baseline model Eq. (4) on the two groups separately. The "Less" and "More" in the titles of columns represent regression results for the less- and more-conservative groups, respectively. The dependent variable, crash risk, is measured by negative conditional skewness (*NCSKEW*) in column (1) and (2) and down-to-up volatility (*DUVOL*) in column (3) and (4). All variables are defined in the Appendix. The industry fixed and year fixed effects are included in the regression. The numbers reported in parentheses are *t*-statistics based on standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5.2.1. Firm leverage

The GCGs require banks to reduce lending to high-polluting firms. In response to that, banks have strengthened their credit controls on high-polluting firms and reduced the size of approved loans to these firms. As a result, the leverage of high-polluting firms has declined (Liu et al., 2019). Lower leverage reduces the financial risk associated with high-polluting companies, enhances their financial stability (Modigliani and Miller, 1958), mitigates the agency problem, and reduces the likelihood of them hiding bad news (Dang et al., 2017). Accordingly, this study argues that the GCGs reduce the crash risk of high-polluting firms through the impact that bank monitoring has on the leverage of firms. Specifically, we expect to observe a significant reduction in stock price crash risk for high-polluting firms if these firms had high leverage before the promulgation of the GCGs. Equally, if green lending does reduce stock price crash risk through enhanced bank monitoring on firm leverage, we might not be able to find a significant reduction in stock price crash risk in firms that already had a comparatively low firm leverage before the promulgation of the GCGs.

To investigate the role of firm leverage, we measure it using bank loans divided by total assets as the underlying mechanism. We divide the sample into high- and low-leverage groups, based on the median value of the firm leverage before the implementation of the GCGs. We then run the baseline model on the two sub-groups; and the results are contained in Table 6. If lowering firm leverage is indeed an effective mechanism underlying the inverse relation between the GCGs and stock price crash risk, we would expect to find a significant relationship in the high-leverage group. Consistent with this prediction, the results in Table 6 show that the coefficient of *TREAT_POST* is significant and negative in the high-leverage subsample, irrespective of whether the crash risk is measured by *NCSKEW* or *DUVOL*. In contrast, in the low-leverage subsample, the coefficient of *TREAT_POST* is insignificant. These results indicate that the reduction of crash risk after the promulgation of the GCGs could be explained by the intensified bank monitoring of firm leverage for high-polluting firms.

5.2.2. Maturity structure

Compared with long-term debts, short-term loans involve more frequent renewal or refinancing (Diamond, 1991; Myers, 1977), leading to closer monitoring by lenders of managerial behavior (Datta et al., 2005; Graham et al., 2008; Stulz, 2001). Lenders of short-term loans also require managers to provide timely and reliable information about firms' financial positions and future investments when negotiating the renewal of debt contracts (Dang et al., 2017). Furthermore, banks can use the threat of non-renewal of debt contracts to deter managers' *ex post* opportunistic behavior (Giannetti, 2003). Bank loans with shorter maturities could therefore enhance information disclosure, deter bad-news-hoarding, and reduce future stock price crash risk.

The promulgation of the GCGs may motivate banks to enhance their monitoring by shortening the debt maturities of loans approved to high-polluting firms, since the credit risk has increased considerably when it comes to high-polluting companies following the promulgation of the GCGs (Liu et al., 2019). The long-term nature of environmental risk also leads banks to prefer offering short-term loans to high-polluting firms (Wang et al., 2020b). Therefore, in order to mitigate both the possible failure of the GCGs abidance and credit risk, banks are likely to shorten high-polluting firms' debt maturities post the inception of the GCGs. The increased frequency of information updates associated with loan renewals can reduce information asymmetry, limit managers' capacity to hoard bad news, and thus reduce firms' stock price crash risk.

To assess this argument, we divide the sample into two groups (i.e., short- and long-maturity groups) based on the median value of the proportion of short-term loans to total bank loans in the pre-GCGs period. We then follow the baseline model

Table 6
Debt size, green lending and stock price crash risk.

Leverage	(1) NCSKEW High	(2) NCSKEW Low	(3) DUVOL High	(4) DUVOL Low
TREAT	0.002	0.001	0.018	−0.001
	(0.09)	(0.05)	(0.92)	(−0.05)
POST	0.238***	0.224***	0.214***	0.168***
	(4.48)	(4.32)	(5.73)	(4.42)
TREAT_POST	−0.089***	−0.039	−0.065***	−0.033
	(−2.78)	(−1.12)	(−2.99)	(−1.31)
Controls	Yes	Yes	Yes	Yes
INDUSTRY	Yes	Yes	Yes	Yes
YEAR	Yes	Yes	Yes	Yes
N	6,554	6,560	6,554	6,560
Adjusted R^2	0.13	0.13	0.13	0.12

Table 6 presents the regression results of exploring the firm leverage as an underlying channel for the effect of green lending on reducing high-polluting firms' stock price crash risk. The firm leverage is measured by ratio of bank loan to its total assets. The higher the ratio, the higher the leverage of a firm. Based on the cross-sectional median of this measure before the promulgation of the GCGs, we partition all firms into two groups: high-leverage firms and low-leverage firms. We then run the baseline model Eq. (4) on the two groups separately. The "High" and "Low" in the titles of columns represent regression results for the high- and low-leverage groups, respectively. The dependent variable, crash risk, is measured by negative conditional skewness (*NCSKEW*) in column (1) and (2) and down-to-up volatility (*DUVOL*) in column (3) and (4). All variables are defined in the Appendix. The industry fixed and year fixed effects are included in the regression. The numbers reported in parentheses are *t*-statistics based on standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Debt structure, green lending and stock price crash risk.

Maturity	(1) NCSKEW Short	(2) NCSKEW Long	(3) DUVOL Short	(4) DUVOL Long
TREAT	0.008	−0.004	0.008	0.016
	(0.30)	(−0.15)	(0.38)	(0.77)
POST	0.243***	0.223***	0.214***	0.171***
	(4.56)	(4.12)	(5.55)	(4.41)
TREAT_POST	−0.029	−0.091***	−0.018	−0.075***
	(−0.88)	(−2.69)	(−0.82)	(−3.16)
Controls	Yes	Yes	Yes	Yes
INDUSTRY	Yes	Yes	Yes	Yes
YEAR	Yes	Yes	Yes	Yes
N	6,557	6,557	6,557	6,557
Adjusted R^2	0.13	0.13	0.14	0.12

Table 7 presents the regression results of exploring the maturity structure as an underlying channel for the effect of green lending on reducing high-polluting firms' stock price crash risk. Based on the cross-sectional median of this ratio before the promulgation of the GCGs, we partition all firms into two groups, i.e., short- and long-maturity groups. We then run the baseline model Eq. (4) on the two groups separately. The "Short" and "Long" in the titles of columns represent regression results for the short- and long-maturity groups, respectively. The dependent variable, crash risk, is measured by negative conditional skewness (*NCSKEW*) in column (1) and (2) and down-to-up volatility (*DUVOL*) in column (3) and (4). All variables are defined in the Appendix. The industry fixed and year fixed effects are included in the regression. The numbers reported in parentheses are *t*-statistics based on standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

presented in Eq. (4) to do the regression on the two sub-samples. The results are presented in Table 7. If the GCGs-induced bank monitoring decreases high-polluting firms' stock price crash risk by shortening their debt maturities, the reduction in crash risk will presumably be insignificant among those high-polluting firms whose bank loans have already been dominated by short-term debt before the promulgation of the GCGs (i.e., the short-maturity sub-sample). Consistent with our prediction, Table 7 illustrates that the coefficient of *TREAT_POST* is insignificant in the short-maturity subsample but significant at the 1 % level in the long-maturity subsample for both measures of crash risk. These results support our conjecture that corporate debt maturity is another channel underlying the mitigating effect of the GCGs on high-polluting firms' crash risk.

6. Cross-sectional analyses

Thus far, we have established that green lending has significantly reduced high-polluting firms' stock price crash risk through enhanced bank monitoring of accounting information quality and corporate capital structure. The following question is whether the focal relationship is conditional on regional and firm heterogeneities. Prior studies suggest that the intensity and effectiveness of bank monitoring may be influenced by banking competition, bank-firm connections, and political connections (Brancati, 2015; Hörner, 2002; Houston et al., 2014). Given the literature and the research context, we address this question by considering the moderating roles of banking competition, bank-client connections, and political connections.

6.1. Banking competition

Banks can choose the intensity of their monitoring capacity, while effective monitoring provides borrowers with incentives to avoid withholding bad news which, in turn, reduces stock price crash risk. With the introduction of the GCGs, banks are obliged to enhance their information collection methods and the assessment of environmental and social risks for their borrowers. Therefore, the effect of the GCGs on stock price crash risk is expected to depend on the degree of monitoring by banks. Prior literature documents that banking competition affects the intensity of monitoring by banks. For example, it is documented that banks are more likely to increase monitoring activities when competition is low because banks can retain a larger share of the surplus created by monitoring activities (Diamond, 1984; Petersen and Rajan, 1995; Vashishtha, 2014). However, in the context of green lending, it is also possible for banks to increase monitoring activities when competition is high. With strong competition in the general loan market, banks are more eager to establish an environmentally responsible image to the public for long-term benefits by engaging in "green reputation building" behavior (Hörner, 2002). This type of behavior includes performing stricter screening and monitoring of high-polluting firms. In addition, the GCGs require banks to report annually to the China Banking and Insurance Regulatory Commission (CBIRC) on their GCGs implementation and the level of green credit lending provided. With increasing pressure from the public and greater inter-banking competition, the consequent reputational damage from failing to comply with the GCGs is higher. Therefore, banks under higher competition are more likely to tighten the screening and monitoring of high-polluting firms to comply with the GCGs in order to mitigate risks to their reputations. That is, higher banking competition is expected to drive banks to enforce the GCGs more stringently and to facilitate stricter monitoring of high-polluting borrowers. High-polluting firms, therefore, are less likely to hoard bad news. As explained above, we predict the focal relationship to be more significant and stronger when banks face higher competition.

To examine the moderating effect of banking competition, we measure banking competition in a given market as the market share of a bank in that particular market in terms of deposits, loans, or the number of branches (Bikker and Haaf, 2002; Degryse et al., 2009; Petersen and Rajan, 1995). Given the limitation and availability of financial data from banks for each city, the number of bank branches in each city is used to construct a measure to quantify the intensity of bank competition in a particular city. The data of bank branches can be obtained from the CBRC.

Specifically, the city-level Herfindahl–Hirschman Index (*HHI*) is calculated using the following equation (Chong et al., 2013; Degryse and Ongena, 2007; Zhang et al., 2019):

$$HHI_{j,t} = \sum\nolimits_{k=1}^{K_{j,t}} \left(\frac{Branch_{k,j,t}}{\sum\nolimits_{k=1}^{K_{j,t}} Branch_{k,j,t}} \right)^2 \tag{6}$$

where $HHI_{j,t}$ is the Herfindahl-Hirschman index at city j in year t, $K_{j,t}$ is the total number of commercial banks in the city j in year t, and $Branch_{k,j,t}$ is the total number of branches of bank k in the city j in year t. A higher value of *HHI* represents a lower level of banking competition.

Specifically, in each year, all cities are partitioned into two groups—high and low competition—based on the median level of the Herfindahl-Hirschman index, $HHI_{j,t}$ of city j in year t, for all cities. Accordingly, given that borrowing by firms in China is mainly restricted to their host cities (Cao et al., 2015; Degryse and Ongena, 2005; Zhang et al., 2018), for each year, we categorize all firms into two groups—firms with headquarters located in high-competition cities and those with headquarters in low-competition cities. We then run the regression of Eq. (4) separately on the two sub-samples. As shown in Table 8, the coefficient of *TREAT_POST* is only significantly negative in the high-competition group (i.e., Column (2) and (4)). The results indicate that compared with non-high-polluting firms, only high-polluting firms located in regions of high banking competition exhibit significant incremental reductions in stock price crash risk. These results thus support our prediction that banking competition could complement the GCGs to reinforce their effect on lowering the crash risk of high-polluting firms.

6.2. Bank-client connections

Bank-client connections may impact the effectiveness of bank screening and monitoring. However, no consensus is reached in the current literature. Some research suggests that connections with banks (i.e., through pre-existing relationships) can alleviate information asymmetry and reduce monitoring costs, thus enhancing the effectiveness of bank monitoring (Brancati, 2015; Engelberg et al., 2012). Other studies have found that bank connections play a completely different role in emerging markets by serving as a rent-seeking tool; and firms with bank connections tend to undertake more risk-taking projects (Cucculelli et al., 2019; (Zhai et al., 2021).

China is the largest emerging economy in the world, and firms in China have been found to purposefully develop relationships with banks to secure funds (Cao et al., 2021; Li et al., 2017; Liang et al., 2021; Zhai et al., 2021. Guo and Xiao (2021)) find that high-polluting firms with close ties to banks receive bank loans on more favorable terms and with less bank mon-

Table 8
Banking competition, green lending and stock price crash risk.

Bank Competition	(1) NCSKEW Low	(2) NCSKEW High	(3) DUVOL Low	(4) DUVOL High
TREAT	−0.077	0.016	−0.066	0.023
	(−1.35)	(0.72)	(−1.59)	(1.44)
POST	−0.446***	−0.409***	−0.274***	−0.203***
	(−3.24)	(−9.49)	(−2.75)	(−6.87)
TREAT_POST	0.037	−0.091***	0.050	−0.066***
	(0.55)	(−3.49)	(1.04)	(−3.64)
Controls	Yes	Yes	Yes	Yes
INDUSTRY	Yes	Yes	Yes	Yes
YEAR	Yes	Yes	Yes	Yes
N	1,429	11,047	1,429	11,047
Adjusted R^2	0.12	0.13	0.11	0.13

Table 8 presents the regression results of exploring the role of banking competition as a moderator. The banking competition for city j in year t is measured by Herfindahl-Hirschman index, $HHI_{j,t}$. Based on the cross-sectional median of this measure, we first partition all cities into two groups: high-competition and low-competition cities. Accordingly, in each year, based on firms' headquarters, we categorize all firms into two groups, firms in high-competition cities and those in low-competition cities. We then run the baseline model Eq. (4) on the two groups separately. The "Low" and "High" in the titles of columns represent regression results for firms in low-competition cities and those in high-competition cities, respectively. The dependent variable, crash risk, is measured by negative conditional skewness (*NCSKEW*) in column (1) and (2) and down-to-up volatility (*DUVOL*) in column (3) and (4). All variables are defined in the Appendix. The industry fixed and year fixed effects are included in the regression. The numbers reported in parentheses are *t*-statistics based on standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

itoring. In line with this, when close ties exist between banks and heavily polluting firms, these firms are more likely to form alliances with tied banks in response to the implementation of the GCGs. We thus assert that bank-client ties would weaken the effect of the GCGs on reducing high-polluting firms' stock price crash risk.

Two alternative ways are used to evaluate whether bank-client connections exist for a firm. Firstly, a firm is identified as having a bank connection if its top executives or directors are currently working or have previously worked in the banking sector (Booth and Deli, 1999; Sisli-Ciamarra, 2012). This type of connection is denoted by the variable $BC_{PRIVATEi,t}$ for firm i in year t. The value of $BC_{PRIVATEi,t}$ is set to 1 if any executive or director of firm i in year t has banking-related work experience and 0 otherwise. Alternatively, bank connections can be established through ownership, such as holding shares in banks. Once a firm holds a significant proportion of ownership of a bank, it has a high influence on the decision and practice of "related lending" of the bank manager (La Porta et al., 2003; Charumlind et al., 2006). Therefore, we define another variable of $BC_{OWNERSHIPi,t}$, which is equal to 1 if firm i holds shares in banks in year t and 0 otherwise.

We use either $BC_{PRIVATE}$ or $BC_{OWNERSHIP}$ to divide firms into two groups, i.e., firms with and without bank connections. Table 9 provides regression results for the different sub-groups. Across the columns of Table 9, only high-polluting firms without bank connections exhibit a significant incremental reduction in stock price crash risk. These findings confirm our conjecture that bank connections alleviate the impact of the GCGs in lowering high-polluting firms' stock price crash risk.

6.3. Political connections

Similarly to bank-client ties, political connections are also common in emerging economies such as China; and such connections could influence the extent of monitoring that banks impose on firms (Hillman et al., 2009; Wang et al., 2021). Although found to be a double-edged sword, political ties are documented to offer firms non-market advantages which are difficult for non-connected firms to acquire (Firth et al., 2009; Houston et al., 2014). China's commercial banks are mainly government-controlled, enabling the government to intervene in bank credit allocation (Firth et al., 2009; Xu, 2021). Politically connected firms are thus normally subject to reduced bank screening and monitoring, and have preferential access to bank loans in the credit market (Claessens et al., 2008; Morck et al., 2005).

Under the GCGs, banks may screen politically connected high-polluting firms less stringently, and impose lower post-loan monitoring on these firms. These well connected high-polluting firms may also enjoy easier access to bank credit and negotiate more favorable terms with banks, compared with non-connected counterparts. They therefore are more likely to withhold bad news, owing to the lowered screening and monitoring by banks. We thus conjecture that political connections would mitigate the effect of the GCGs on lowering high-polluting firms' stock price crash risk.

Consistent with Fan et al. (2007), we define political connections as whether firms' CEOs used to be or are currently officials of the central government, local government, or military, and denote the measure as *PC*. We partition our sample into subsamples based on *PC* and then re-estimate Eq. (4) separately in each subsample. As illustrated in Table 10, the coefficient of *TREAT_POST* is significantly negative in the subsample without political connections at the 1 % level, whilst the politically connected subsample produces an insignificant coefficient. These results are in line with our assertion that political connections would weaken the effect of the GCGs on abating high-polluting firms' crash risk.

Table 9
Bank connections, green lending and stock price crash risk.

Bank connections	(1) NCSKEW Private with	(2) NCSKEW Private without	(3) DUVOL Private with	(4) DUVOL Private without	(5) NCSKEW Owner with	(6) NCSKEW Owner without	(7) DUVOL Owner with	(8) DUVOL Owner without
TREAT	0.040	0.006	0.036	0.012	−0.018	0.021	0.004	0.020
	(0.55)	(0.28)	(0.66)	(0.83)	(−0.42)	(0.91)	(0.12)	(1.25)
POST	−0.605***	−0.396***	−0.379***	−0.199***	0.169	−0.382***	0.114	−0.202***
	(−4.29)	(−9.50)	(−3.78)	(−6.91)	(1.45)	(−8.64)	(1.37)	(−6.48)
TREAT_POST	−0.028	−0.077***	−0.030	−0.055***	0.034	−0.100***	0.003	−0.068***
	(−0.35)	(−3.23)	(−0.48)	(−3.35)	(0.67)	(−3.87)	(0.10)	(−3.76)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INDUSTRY	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YEAR	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,058	12,056	1,058	12,056	2,640	10,474	2,640	10,474
Adjusted R^2	0.15	0.13	0.16	0.13	0.15	0.13	0.15	0.13

Table 9 presents the regression results of exploring the role of bank connections as a moderator. We use two alternative ways to capture the existence of bank connections for a firm and then divide all firms into two groups: firms with bank connections and firms without bank connections. We then run the baseline model Eq. (4) on the two groups separately. In the first way, a firm is identified as having a bank connection if its top executives or directors have banking related working experience. Columns labeled with "Private with" and "Private without" contain regression results using subsamples with and without such bank connections. Alternatively, bank connections can be established through ownership, and we divide firms into two groups depending on whether a firm holds a significant stake in some commercial bank. Columns labeled with "Owner with" and "Owner without" contain regression results by using subsamples with and without bank connections established by ownership. The dependent variable, crash risk, is measured by negative conditional skewness (*NCSKEW*) in column (1), (2), (5) and (6) and down-to-up volatility (*DUVOL*) in column (3), (4), (7) and (8). All variables are defined in the Appendix. All control variables, industry fixed and year fixed effects are included in the regression. The numbers reported in parentheses are *t*-statistics based on standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10
Political connections, green lending and stock price crash risk.

Political connections	(1) NCSKEW With	(2) NCSKEW Without	(3) DUVOL With	(4) DUVOL Without
TREAT	0.000	0.019	0.001	0.025
	(0.01)	(0.75)	(0.06)	(1.37)
POST	−0.387***	0.233***	−0.215***	0.192***
	(−6.44)	(4.87)	(−5.12)	(5.59)
TREAT_POST	−0.042	−0.096***	−0.042	−0.064***
	(−1.16)	(−3.15)	(−1.60)	(−3.06)
Controls	Yes	Yes	Yes	Yes
INDUSTRY	Yes	Yes	Yes	Yes
YEAR	Yes	Yes	Yes	Yes
N	5,033	8,081	5,033	8,081
Adjusted R^2	0.13	0.13	0.13	0.13

Table 10 presents the regression results of exploring the role of political connections as a moderator. We measure political connections based on whether firms' CEOs used to be or are currently officials of the central government, local government, or military. We then divide all firms into two groups: firms with political connections and firms without political connections. We run the baseline model Eq. (4) on the two groups separately. Columns labeled with "With" and "Without" contain regression results by using subsamples with and without political connections. The dependent variable, crash risk, is measured by negative conditional skewness (*NCSKEW*) in column (1) and (2) and down-to-up volatility (*DUVOL*) in column (3) and (4). All variables are defined in the Appendix. All control variables, industry fixed and year fixed effects are included in the regression. The numbers reported in parentheses are *t*-statistics based on standard errors clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

7. Conclusion

This study explores the impact of green credit on stock price crash risk, and finds a positive spillover effect of green lending on reducing stock price crash risk. Mechanism analyses show that green credit reduces the crash risk of high-polluting firms through enhanced bank monitoring of both accounting information quality and corporate capital structures. Such a reduction appears more pronounced in situations where there is greater competition among banks, and for firms without bank connections or political connections. Our findings highlight the role of bank monitoring as an effective governance mechanism to curb managerial bad news hoarding, which in turn reduces future stock price crash risk.

This study contributes to the emerging literature on green credit and stock price crash risk, respectively. First, it provides novel evidence that green credit policies generate positive externalities for the share market by curbing bad news hoarding. Second, we extend the literature on stock price crash risk by showing that green credit and bank monitoring, in addition to other corporate governance factors, influence the crash risk. The evidence also contributes to classical research on conflicts of interest between shareholders and creditors by showing that creditor and shareholder preferences can converge to some extent. Last, this study contributes to the research on financial intermediation by providing more insights into the role of bank monitoring and how it is impacted by banking competition, bank-client relationships, and political connections.

Overall, this study shows that green credit reform compels banks to strengthen their monitoring on high-polluting corporations. This limits the ability of managers to withhold bad news and thus protects the interests of shareholders by alleviating stock price crash risk. These findings from the world's largest emerging economy can usefully be generalized to other emerging markets—particularly those planning on green credit reforms. Policymakers need to consider the potential spillover effects and the interaction between formal and informal institutions when formulating and implementing policies (Garg et al., 2020; Pinnuck and Stevenson, 2021). Financial institutions also need to strictly implement green credit policies and actively promote the development of ESG. In addition, regulators and investors should not overestimate the cost of green credit policies, such as it being more difficult to raise debt financing. Instead, they should recognize the positive externalities and support green credit reforms.

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

Key articles of the GCGs

Articles	Contents
Article 4	Banking institutions should effectively identify, measure, monitor, and control environmental and social risks in credit businesses, and establish an environmental and social risk management system.
Article 11	Banking institutions should formulate standards for clients' environmental and social risk assessment, conduct dynamic assessment and classification of clients' environmental and social risks. The relevant results should be used as an important basis for clients' rating, credit access, management, and exit.
Article 14	When necessary, banking institutions can obtain relevant professional services about the evaluation of environmental and social risks from qualified and independent third parties or other effective outsourcing methods.
Article 16	Banking institutions should carry out strict compliance review for clients that are to be granted credit, formulate the list of environmental and social compliance documents and the list of compliance risk review based on the characteristics of clients in different industries, ensure the compliance, effectiveness and integrity of the documents submitted by clients, and finally make sure that clients pay enough attention to the dynamic monitoring of relevant risk points.
Article 17	Banking institutions should strengthen the management of credit approval, and determine appropriate credit authority and approval process according to the nature and severity of environmental and social risks faced by clients. No credit shall be granted to clients whose environmental and social performance are not in compliance.
Article 18	Banking institutions should urge clients to strengthen environmental and social risk management by enhancing contract terms. For clients involved in major environmental and social risks, the contract should require the clients to submit environmental and social risk reports, establish guarantee terms for clients to strengthen environmental and social risk management, and set commitment terms for clients to accept the supervision of lenders.
Article 19	Banking institutions should strengthen the management of credit allocation and take clients' management of environmental and social risks as a key basis for determining credit allocation. Environmental and social risk assessment checkpoints should be set up in the design, preparation, construction, completion, operation, shutdown and other stages of credit projects, and the allocation of credit funds can be suspended or terminated in case of major potential risks.
Article 20	Banking institutions should strengthen post-loan management, especially for clients with potential major environmental and social risks, and improve the internal reporting system and accountability system for clients' major environmental and social risks.

Definitions of variables

Variable	Definition
NCSKEW	The negative coefficient of skewness, calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power. See Eq. (2) for more details.
DUVOL	The down-to-up volatility, calculated by taking the natural logarithm of the ratio of the standard deviation of the down weeks to the standard deviation of the up weeks. See Eq. (3) more for details.
TREAT	Defined as 1 if the firm is categorized as a high-polluting firm, and otherwise 0.
POST	Defined as 1 if time t equals or is later than 2012, and otherwise 0.
SIGMA	The standard deviation of firm-specific weekly returns over the fiscal year.
DTURN	Detrended average monthly stock turnover in a year, calculated as the average monthly share turnover in the year minus the average monthly share turnover in the previous year.
RET	The mean of firm-specific weekly returns over the fiscal year.
SIZE	The natural logarithm of the book value of total assets at the fiscal year end.
LEV	The ratio of total debts to total assets at the fiscal year end.
ROA	The ratio of net income to total assets at the fiscal year end.
MB	The ratio of market value of equity to book value of equity at the fiscal year end.

(*continued*)

Variable	Definition
FIRST	The percentage of outstanding shares held by the largest shareholder at the fiscal year end.
DUAL	Defined as 1 if a firm's CEO is also its chairman, and 0 otherwise.
ABACC	The absolute value of annual discretionary accruals estimated from the modified Jones model.

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