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Corporate environmental responsibility and default risk: Evidence from China

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ABSTRACT

We use a novel and comprehensive dataset to investigate the influence of corporate environmental responsibility on the default risk of listed firms in China. We document a significant and negative impact of environmental performance on a firm's default risk. We use instrumental variables regressions and placebo tests to address endogeneity concerns and document consistent results. Further, we conduct cross-sectional analysis and find a strong negative influence of environmental performance on default risk in firms with high systematic risk, weak fundamentals, severe pollution, and high energy consumption, supporting volatility and environmental regulation uncertainty channels. Our findings reveal the externality of corporate environmental responsibility on a firm's financial risk profile.

1. Introduction

Recent severe corporate environmental disasters (e.g., the Exxon Valdez oil spill, Chevron's environmental damage in the Lago Agrio oilfield, the Deepwater Horizon oil spill in 2010, and the Volkswagen emissions scandal) have proven the significant influence of environmental responsibility on corporate risk profiles. However, related literature in economics and finance presents mixed results on the relation between environmental responsibility and corporate default risk. On the one hand, there is abundant empirical evidence showing that environmental concerns are associated with lower credit ratings (Graham et al., 2001; Bauer and Hann, 2010; Attig et al., 2013; Oikonomou et al., 2014; Jiraporn et al., 2014).[1] On the other hand, Chava (2014) show that there is no significant relation between environmental concerns (e.g., hazardous chemical, substantial emissions, and climate change) and firm bankruptcies, covenant violations, and credit rating downgrades.[2] Rizwan et al. (2017) foundd no significant impact of engagement in secondary (institutional) corporate social responsibility (CSR) activities (environmental and community-related) on a firm's implied default probability. These mixed results raise the following questions. Does corporate environmental performance affect a firm's default risk? If

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[1] Specifically, Oikonomou et al. (2014) documented a positive relation between environmental strengths and bond rating. Graham et al. (2001) found that environmental liability information is negatively related to bond rating. Meanwhile, Bauer and Hann (2010) presented evidence that environmental concerns are associated with lower credit ratings. Attig et al. (2013) found that CSR scores are positively related to credit ratings.

[2] These results are shown in Tables 7, 8, and 9 on pages 2236–2238 of Chava's (2014) study. Chava (2014) argued that “at least the environmental profile of a firm is not simply proxying for an omitted component of its default risk.”

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so, what characteristics of a firm affect the relation between environmental performance and default risk?

This study uses a novel dataset of a corporate environmental profile in China to investigate the relation between corporate environmental responsibility and default risk. Listed firms in the Chinese market are selected to examine the impact of their environmental profile on their default risk for two major reasons. First, the Chinese economy is in a transitional phase toward sustainable development, with an emphasis on environmental awareness. In the early stage of development in China, economic growth was the priority and the lack of awareness regarding environmental protection caused serious environmental problems, such as the phenomenon of smog[3] and water contamination. However, since the release of the State Council's (2015) *Integrated Reform Plan for Promoting Ecological Progress*, the Chinese government has started to "green" the economic system, thus alleviating environmental damage. Further, capital markets are required to establish a mandatory environmental information disclosure system for listed companies. Building on this, seven ministerial agencies (including the People's Bank of China and the Ministry of Finance) released the *Guidelines for Establishing the Green Financial System*, which is the first systematic green finance policy framework in the world.[4] In 2017, the Securities and Futures Commission required mandatory disclosure of environmental information by key pollutant-discharging entities and required other listed companies to "disclose or explain." This transition in the dynamics of Chinese economy provides an ideal experimental field for examining the impact of environmental responsibility on a firm's default risk. Second, the Chinese government is in active collaboration with the United Nations to speed up the green transformation of the global economy. For instance, the G20 Green Finance Study Group was established under China's Presidency of the G20 in 2016 to prompt the development of a global green finance system. Third, although it has not yet been made mandatory, the Chinese government is working to encourage all listed companies to prepare and disclose CSR reports in accordance with GRI guidelines.[5] Thus, the empirical evidence that we have gathered from Chinese markets has significant implications for policymakers worldwide.

We use a novel and unique environmental information dataset from China. This dataset has three major advantages over well-known datasets for environmental information, such as Asset4, KLD, and Sustainalytic. First, the leading international datasets have limited coverage of Chinese firms because of the opaqueness with regard to firms' environmental information in China. Our dataset covers all the firms that are (or used to be) included in the Chinese Stock Index 300 (HS300) from 2012 to 2018. The component stocks of HS300 are the largest and most liquid stocks in the Chinese market. Moreover, the aggregated market capitalization of HS300 accounts for 67% of the total market capitalization in China.[6] The time length of our dataset spans the whole period of the green transformation of the Chinese economy. Second, the International Institute for Green Finance (IIGF) and the environmental, social, and governance (ESG) database integrates international standards and Chinese characteristics to achieve a "1 + 1" ESG rating system. The IIGF applications have special consideration of the development path and mode of Chinese listed firms, such as state-owned enterprises. By adapting the original system with Chinese characteristics, they measure the Chinese ESG performance accurately and equip international investors with new instruments to invest in the Chinese market. Besides, the IIGF considers negative behaviors and risk exposure to identify the potential ESG risks of firms effectively. Third, our dataset contains much-enriched information on firms' environmental profiles—such as green income, bad news associated with environmental issues,[7] and fines for violating environmental policy—that allows us to systematically study the impact of environment profiles on firms' default risk from various aspects.

We use the probability of default (PD), which is calculated based on the forward intensity model of Duan et al. (2012),[8] to proxy for a firm's default risk. A firm's PD accommodates the probability of bankruptcies and other types of corporate exits, such as mergers and acquisitions. In contrast to classic structural models (e.g., Merton, 1974; Leland and Toft, 1996), Duan et al.'s (2012) approach combines a reduced-form model and a structural model. Duan et al. (2012) used the forward probabilities of default (PDs) as building blocks to construct the PD term structure for prediction. In addition, Duan et al.'s (2012) approach employed 14 covariates, including market-based and accounting-based firm-specific attributes and macro-financial factors, to predict PDs. PDs calculated according to firm-specific and macro-financial information are more objective as measurements of default risk compared with bond ratings, loan spreads, and corporate bond spreads that reflect the viewpoints of rating agencies, banks, and public investors, respectively. Specifically, we use 1-year and 5-year forward PDs to proxy for the short-run and long-run default risks, respectively.

We present profound empirical evidence that better environmental profiles are negatively associated with the PD after controlling for other determinants of a firm's default risk and year and industry fixed effects, especially for long-term PDs. One standard deviation of increase in the environmental score is associated with a 9.5% and a 5.1% decrease in the 1-year and 5-year PDs,[9] respectively. We divided the environmental profile into three components: the amount of green income, the number of bad news events associated with

[3] https://www.nytimes.com/2013/04/23/world/asia/pollution-is-radically-changing-childhood-in-chinas-cities.html

[4] http://unepinquiry.org/wp-content/uploads/2017/11/China_Green_Finance_Progress_Report_2017_Summary.pdf

[5] The Shanghai Stock Exchange (SSE) mandates the disclosure of CSR reports for three categories of companies, including companies in the SSE Corporate Governance Panel, companies issuing overseas-listed foreign shares, and financial companies. Meanwhile, the Shenzhen Stock Exchange (SZSE) mandates the disclosure of CSR reports for the constituent companies of the SZSE 100 Index. In 2018, 851 A-share listed companies disclosed CSR reports, with 407 companies announcing reports on a regulatory basis and 444 companies disclosing them voluntarily.

[6] As of December 31, 2018, the total market capitalization of Chinese A-share market was about 434,924 billion RMB, whereas the aggregated market capitalization of the component stocks in CSI300 index was about 293,959 billion RMB.

[7] The IIGF collects the bad news with several keywords, including pollution, environmental event, environmental penalties, and environmental violations. For example, TISCO was fined 1.65 million yuan for environmental violations, and Sinitai was trapped in the pollution-gate controversy.

[8] The PD data is available at the Credit Research Initiative at National University of Singapore. (https://www.rmicri.org/en/home/)

[9] The details of the calculation are described in Section 3.

environmental risk, and the fine levied because of violation of environmental rules. We found a negative relation between a firm's green income and PDs, suggesting that the amount of green revenue of business lines could be a potential venue to alleviate firms' default risk. Also, the number of bad news events caused by environmental damage is positively related to default risk.

We employed two approaches to examine possible endogeneity concerns: instrumental variables and placebo tests. First, we used an industry's average environmental performance score excluding the score of the firm examined in this study as an instrumental variable. We selected this instrumental variable considering that other firms' corporate environmental scores are less likely to affect the default risk of the firm we are examining directly. However, a spillover effect of the adoption of CSR is a strategic response to competitive threat (Liu and Wu, 2016; Cao et al., 2018); therefore, firms are motivated to improve their environmental performance under the pressure of their peer firms' improved environmental performance. Consistent with this conjecture, the results indicate a significantly positive relation between the average environmental score of peer firms and the environmental score of the firm of our interest in the first-stage regression. The second-stage regression results provide strong support for the negative impact of environmental performance on default risk. Second, in placebo tests, we adopt the bootstrap-resampling approach to assign a "wrong" environmental score to each firm-year observation in our sample. Then, we conduct multivariate regressions using artificially "wrong" environmental scores and retain the *t*-statistics value for the coefficient of the environmental score. After repeating such simulated regressions 10,000 times, we determine the probabilities to generate significant and negative coefficients of environmental scores to be 0.7%, 4.7%, and 9.8% at the 1%, 5%, and 10% significance levels, respectively. Such a low probability of generating significantly negative relations between environmental performance and default risk using the wrong environmental score adds credence to the negative relation between corporate environmental responsibility and default risk.

Further, to investigate the possible channels through which environmental performance affects a firm's default risk, we conduct a subsample analysis and test the difference between the coefficients of the environmental score in each pair of the subsample. Specifically, we find a more pronounced negative impact of corporate environmental responsibility on default risk for firms with a high systematic risk and weak fundamentals, supporting the volatility channel. Further, the impact of an environmental score on default risk is relatively strong in high-polluting industry, but the difference is not significant at the conventional level, which is consistent with the uncertainty of the environmental regulation channel.

This study contributes to the literature in at least three respects. First, taking advantage of the enriched information of our novel dataset of environmental information, we examine the relation between a firm's green income and default risk. The significantly negative relation between the two highlights an internal channel through which a firm's environmental profile affects the PD. Literature in the area mostly focuses on the negative consequences of environmental issues, such as hazardous chemical infiltration, substantial emissions, climate change concerns (e.g., Bauer and Hann, 2010; Chava, 2014), and environmental liability (Graham et al., 2001). However, the present study shows the potential of green income as an alternative venue through which environmental performance mitigates a firm's default risk.

Second, the empirical evidence in this study contributes to the ongoing debates on the impact of environmental risk on a firm's default risk. Most past studies have used bond ratings (e.g., Graham et al., 2001; Attig et al., 2013; Oikonomou et al., 2014; Jiraporn et al., 2014) or cost of debt (e.g., Sharfman and Fernando, 2008; Schneider, 2011; Chava, 2014; Hoepner et al., 2016). The bond ratings reflect the rating agencies' viewpoint regarding firms, which might be problematic, such as rating shopping (e.g., Becker and Milbourn, 2011; Bolton et al., 2012) and poor prediction of the probability of survival (Manso, 2013). The cost of debt relies not only on the firm's default risk but also on other non-default components, such as illiquidity, debt covenants, and tax code (e.g., Huang and Huang, 2012). Chava (2014) also used firm bankruptcies and covenant violations to proxy for the actual default risk. The occurrence of these events reflects a dramatic, and not a gradual, change of default risk. Moreover, bankruptcies would be the last resort of corporate decision, which rarely occurs. Therefore, this study uses the PD, which is calculated by combining reduced and structural models using firm-specific and macro-financial information. The PD is relatively objective and purely reflects the default risk of a firm in contrast to bond ratings and bond spreads.

Third, this study extends the understanding of CSR on the default risk of a firm by providing a piece of novel empirical evidence from an emerging market with civil-law origin. Corporate environmental performance, a component of CSR activities, is becoming increasingly important nowadays in response to severe pollution and climate change crises. Investigating the impact of corporate environmental performance on default risk facilitates the understanding of the possible channels through which CSR activities affect corporate risk profile. Most literature has focused on examining the relation between CSR performance and default risk in the context of firms in the United States, which is a well-developed country that follows common law. For example, Jiraporn et al. (2014) found a positive relation between CSR performance and credit ratings, whereas Rizwan et al. (2017) documented a negative influence of CSR performance on the implied PD. Meanwhile, Liang and Luc (2017) showed the significant differences in CSR mechanisms and performance between civil-law and common-law countries. Using the U.S. sample, Rizwan et al. (2017) found no significant impact of engagement in secondary (institutional) CSR activities (environmental and community-related) on a firm's implied default probability. However, using a Chinese sample, we show a significantly negative influence of corporate environmental performance on a firm's implied default probability. Our findings contribute to the international empirical evidence on the real impacts of CSR performance and highlight the role of institutional characteristics.

The rest of this paper is organized as follows: Section 2 describes our sample data and variables. Section 3 presents our empirical design and the main empirical findings. Section 4 provides a comprehensive cross-sectional analysis examining the possible channels. Section 5 concludes the paper.

2. Hypothesis development

We discuss the potential channels through which corporate environmental responsibility affects a firm's default risk and then develop corresponding hypotheses to examine our conjecture. First, according to the classic structural model (Merton, 1974), the default risk of a firm is driven by the distance between asset value and the boundaries of default.[10] The fluctuation of asset value relies on a firm's fundamental performance, such as profitability and free cash flow, whereas the default boundary is usually associated with a firm's financial leverage (e.g., Merton, 1974; Leland, 1994; Leland and Toft, 1996; Perrakis and Zhong, 2015) or business strategies (Fan and Sundaresan, 2000). Improving corporate environmental performance could generate a twofold impact on default risk by altering asset value or default boundary. On the one hand, better environmental performance reduces the cost of capital (e.g., Graham et al., 2001; Sharfman and Fernando, 2008; Chava, 2014; El Ghoul et al., 2018), resulting in a higher asset value for the given future cash flows. Dowell et al. (2000) showed the positive association between the adoption of the stringent global corporate environmental standard and higher market values. Additionally, there is abundant literature showing a positive relation between CSR and firm value (e.g., Deng et al., 2013; Kruger, 2015). Given the default boundary, an increase in asset value amplifies the distance to default (DTD) and results in a lower likelihood of bankruptcy. Meanwhile, as a result of increasing awareness of environmental problems around the world, local governments are motivated to issue more regulations on environmental issues. Firms with high energy consumption and high pollution levels are exposed to uncertain environmental regulations. Better corporate environmental performance reduces the impact of environmental regulation uncertainty on these firms, resulting in a lower PD. Thus, we expect a negative relation between corporate environmental performance and a firm's default risk. To examine this conjecture, we posit the following hypothesis:

H1. . Corporate environmental performance is negatively associated with a firm's default risk.

Because corporate environmental performance is a key component of CSR, empirical findings based on CSR scores apply to corporate environmental responsibility to a certain extent. Literature in the area shows that CSR serves as a hedging tool by reducing a firm's risk factors, such as litigation risk (Koh et al., 2014); stock price crash risk (Kim et al., 2014); idiosyncratic risk (Boutin-Dufresne and Savaris, 2004; Lee and Faff, 2009); and systematic risk (Albuquerque et al., 2013). Also, Attig et al. (2013) found that high-CSR firms exhibit higher credit ratings. These risks are positively related to the fluctuation of a firm's asset value. According to structural models, corporate equity can be considered a long call option on a firm's unleveraged asset value (Merton, 1974), whereas corporate debt can be considered a short put option on a firm's asset value, with the default boundary as the strike price. Note that option value is more sensitive to the volatility of the underlying asset when the option is close to being “at the money.” Thus, when the asset value (underlying asset) is close to the default boundary (strike price), a firm's value should be more sensitive to firm risk. If corporate environmental performance affects default risk by altering the firm's risk profile, we expect to observe a stronger impact when asset value is close to the default boundary. To examine this conjecture, we posit the following hypothesis:

H2. . The negative impact of corporate environmental performance on a firm's default risk is more pronounced for a firm with high default risk.

Next, environmentally responsible firms could benefit from moral capital among stakeholders, similar to that of firms with high social responsibility (Williams and Barrett, 2000; Godfrey, 2005; Godfrey et al., 2009; Minor and Morgan, 2011; Lins et al., 2017). Because of the heterogeneity of business lines across industries, the benefits of moral capital vary. For instance, Chatterji et al. (2009) demonstrated that firms producing more pollution commit more regulatory compliance violations than other firms. Meanwhile, Hong and Kacperczyk (2009) found that sin stocks face higher litigation risk than other firms. Furthermore, environmental regulations have a greater impact on high-pollution firms than others. Thus, the uncertainty of environmental regulations poses a channel through which corporate environmental performance affects the default risk of a firm. For example, better environmental performance alleviates the impact of environmental regulation uncertainty, resulting in a lower default risk. Therefore, improvements in environmental performance would generate greater benefits to reducing firms' default risk in industries that have caused severe environmental damage than in others. To examine this conjecture, we posit the following hypothesis:

H3. . The negative impact of corporate environmental performance on a firm's default risk is more pronounced for firms that generate severe environmental damage.

[10] The default boundary could be either exogenous or endogenous. For instance, Merton (1974) used the total debt value as the boundary of default. KMV's model adopts the sum of short-term debt and half of long-term debt value as the boundary of default. Leland (1994), Leland and Toft (1996), and Perrakis and Zhong (2015) employ the endogenous default boundary.

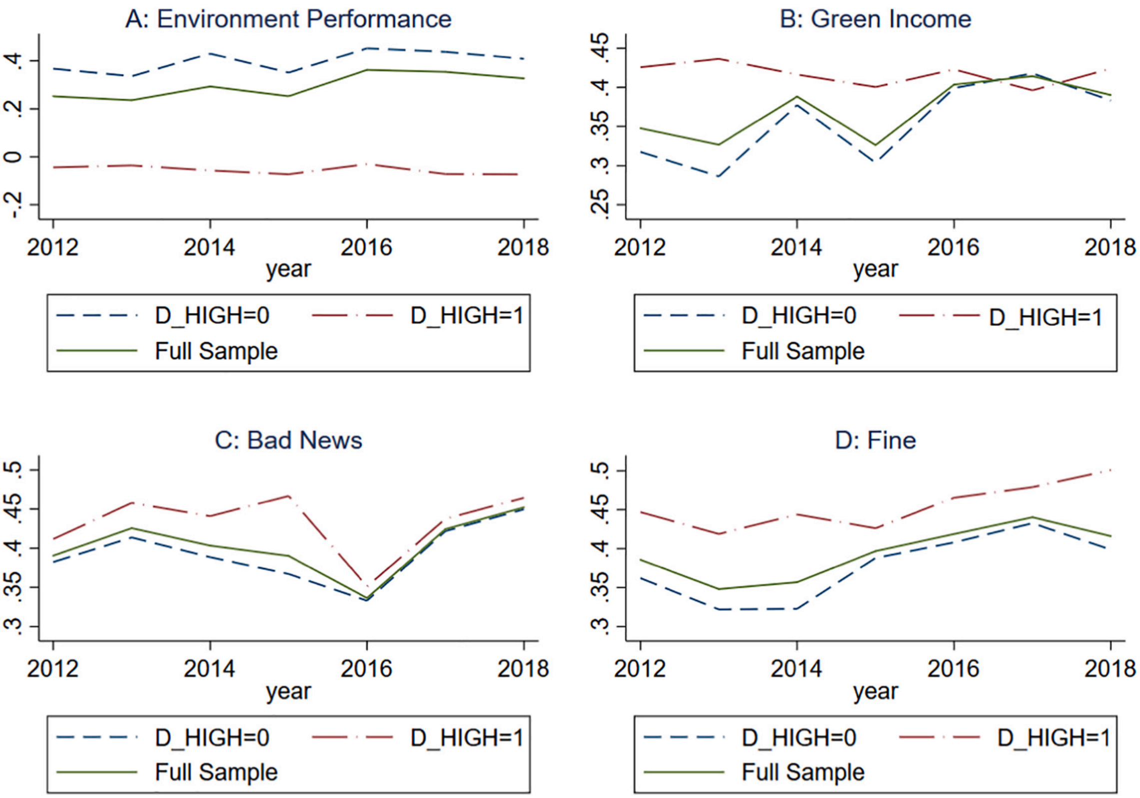

Fig. 1. Time series analysis of corporate environmental responsibility scores.
This figure shows the trend of the environmental performance of firms in the HS300 Index. Panels A and B are the time trend for the average value of environmental performance and green income performance, respectively. Meanwhile, Panels C and D are the time trend for the average value of bad news frequency and fine performance, respectively. Each graph has three lines: a solid line for the average value of the full sample, a dashed line for the average value of non-"two highs and one-overcapacity" industry ($D\_HIGH = 0$) firms, and a dash-dot line for the average value of "two highs and one-overcapacity" industry ($D\_HIGH = 1$) firms. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Data

3.1. Environmental performance

We use the novel environmental information dataset constructed by the IIGF at Central University of Finance and Economics (CUFE).[11] In 2016, IIGF developed a comprehensive evaluation system to measure the Green performance of Chinese listed companies and gradually formed the IIGF Green database. Based on the environmental information in this dataset, IIGF, China Securities Index Co., Ltd., and the Luxembourg Stock Exchange jointly released the CSI 300 Green Leading Index (Ticker: 931037.CSI); and IIGF and Shenzhen Securities Information Co., Ltd. jointly released the CUFE-CNI SZ-HK Connect Green Selection Index (Ticker: G10013. CNI).[12] The performance of both indices has surpassed the benchmark (HS300 Index) since they were released.

IIGF evaluates the environmental performance of a firm according to the results of a green scoring form, green income ratio, environmentally negative news, and environmental penalty. They developed a comprehensive green scoring form that includes both quantitative and quality indicators. To calculate green income, IIGF identifies a firm's green income according to the classification of

[11] IIGF is the first international research institute in China; the organization's goal is to promote the development of green finance. It works with the People's Bank of China, the Chinese Ministry of Finance, the National Development and Reform Commission, The Chinese Ministry of Environmental Projection, and many national, regional, and local government institutions, financial institutions, and research organization to promote green finance in China. Internationally, IIGF conducts many joint research projects on green finance with international organizations, such as UNEP, UN PRI, the European Investment Bank, Cambridge University, and the International Institute for Sustainable Development. More information on IIGF can be obtained from the following link: http://iigf.cufe.edu.cn/.

[12] The IIGF has compiled the CSI CUFE SH-SZ 100 ESG Leading Index, CSI 300 Green Leading Stock Index, CUFE-CNI SZ-HK Connect Green Selection Index, SINA Beautiful China ESG 100 Stock Index, JD Digital ESG Industry Series Index, CUFE-SZRCB Suzhou Green Development Index, and CUFE-Suzhou Yangtze River Delta Integrated Green Development Bond Index.

Table 1
Descriptive statistics.

Panel A: Full Sample						
Variables	*N*	Mean	STD	25%	Median	75%
Default prob 1y(%)	1482	0.276	0.297	0.0700	0.177	0.380
Default prob 5y(%)	1482	1.202	1.132	0.355	0.844	1.734
Environmental Score	1482	0.279	0.328	0.0214	0.275	0.479
Tangibility	1482	0.955	0.0812	0.962	0.990	0.998
Cash	1482	0.155	0.114	0.0753	0.124	0.199
Log Assets	1482	23.78	1.120	23.02	23.66	24.47
ROE(%)	1482	5.498	5.470	2.082	4.895	8.389
EBITDA	1482	0.244	0.220	0.0941	0.179	0.329
Leverage	1482	0.495	0.203	0.333	0.509	0.651
SOE	1482	0.609	0.488	0	1	1
GDP Growth (%)	1482	7.217	0.370	6.902	7.479	7.559
Index return(%)	1482	1.576	11.95	−1.994	0.273	6.098
Index vol(%)	1482	1.017	0.444	0.527	0.972	1.217
Risk free(%)	1482	4.167	0.847	3.233	4.078	4.750
Panel B: N-THOO Industries						
Variables	*N*	Mean	STD	25%	Median	75%
Default prob 1y (%)	1166	0.244	0.266	0.0576	0.157	0.344
Default prob 5y (%)	1166	1.090	1.058	0.270	0.745	1.621
Environmental Score	1166	0.370	0.295	0.178	0.345	0.528
Tangibility	1166	0.958	0.0823	0.970	0.993	0.998
Cash	1166	0.169	0.118	0.0870	0.136	0.220
Log Assets	1166	23.72	1.157	22.91	23.56	24.40
ROE (%)	1166	6.111	5.276	2.704	5.555	8.865
EBITDA	1166	0.264	0.232	0.104	0.195	0.361
Leverage	1166	0.477	0.208	0.308	0.484	0.639
SOE	1166	0.549	0.498	0	1	1
Panel C: THOO Industries						
Variables	*N*	Mean	STD	25%	Median	75%
Default prob 1y (%)	316	0.395	0.367	0.127	0.303	0.519
Default prob 5y (%)	316	1.615	1.291	0.618	1.327	2.188
Environmental Score	316	−0.0563	0.200	−0.197	−0.0948	0.0298
Tangibility	316	0.944	0.0763	0.922	0.980	0.995
Cash	316	0.103	0.0767	0.0553	0.0831	0.131
Log Assets	316	24.00	0.942	23.41	24.00	24.55
ROE (%)	316	3.233	5.587	0.664	2.594	6.463
EBITDA	316	0.171	0.145	0.0768	0.123	0.217
Leverage	316	0.558	0.168	0.460	0.577	0.688
SOE	316	0.832	0.374	1	1	1

This table is the data description of the main variables in the paper. The detailed definitions of the variables are shown in Appendix Table A1.

the FTSE Green Income Index, the classification of the "12th Five-Year Energy Conservation and Environmental Protection Industry Development Plan," and the classification of the *China Green Bond Classification Catalog*. The green income ratio is aggregated green income scaled by operating income, which measures the environmental performance according to final products from business lines. Further, IIGF's evaluation system introduces a negative information-filtering process to penalize the companies that are associated with several negative environmental events and illegal behaviors even while saving energy and engaging environmental protection. Finally, IIGF assigns optimal weights for each component to compose the environmental performance score.

Fig. 1 reports the average of the environmental score, green income, bad news, and environmental fines during our sample period. We observe a sharp increase in environmental performance, green income, and fines. A significant decrease in bad news in 2016 is also observed, which is in contrast to the previous year. This is possibly caused by the implementation of the Integrated Reform Plan for Promoting Ecological Progress in late 2015. Meanwhile, a series of guidelines and policies were published in 2016 to promote environmental protection and speed up the greening of the economic system. Considering the top-design framework of Chinese economic structure, such structural change indicates the effectiveness of government policy in improving the environmental performance of listed firms in China.

3.2. Default risk

We employ Duan et al.'s (2012) PD to measure the default risk of a firm. This approach combines both reduced-form and structural models. The structural models (e.g., Merton, 1974; Leland, 1994) consider a firm's equity (E) as a call option written on the firm's unleveraged asset (A) with the firm's liability (L) as the strike price. To improve the accuracy of the structural model's DTD measure, Duan et al. (2012) adopted a special treatment on its own DTD calculation to overcome several drawbacks identified in the literature. They added a fraction (δ) of other liability to the default point L and set $\mu = \frac{\sigma_A^2}{2}$ to improve the stability of DTD estimation. Then, Duan

Table 2
Corporate environmental responsibility and default risk: univariate analysis.

	G1	G2	G3	G4	G5	G5−G1
Panel A: Scoring by Environmental Performance						
Full Sample	0.3182	0.2711	0.2686	0.2784	0.2397	0.0784*** (0.0013)
Panel B: Scoring by Environmental Performance and Leverage						
L1	0.0490	0.0905	0.0530	0.0727	0.0620	−0.0123 (0.8944)
L2	0.1473	0.1592	0.1604	0.1458	0.1642	−0.0169 (0.7269)
L3	0.2545	0.2926	0.2780	0.2761	0.2475	0.0070 (0.4337)
L4	0.4451	0.3899	0.3210	0.4215	0.3018	0.1432*** (0.0028)
L5	0.7441	0.5149	0.5937	0.5043	0.5346	0.2095*** (0.0090)
Panel C: Sorting by Environmental Performance and Size						
S1	0.1526	0.1469	0.1312	0.1221	0.1205	0.0322 (0.1170)
S2	0.2575	0.2264	0.2242	0.2617	0.2009	0.0566** (0.0790)
S3	0.4130	0.3093	0.2717	0.3534	0.2559	0.1572*** (0.0044)
S4	0.4699	0.4297	0.3876	0.3469	0.4275	0.0425 (0.2831)
S5	0.3033	0.3959	0.4269	0.4030	0.2143	0.0890 (0.1593)
Panel D: Sorting by Environmental Performance and Market-to-Book Ratio						
P1	0.4578	0.4438	0.4513	0.4366	0.5104	−0.0525 (0.7165)
P2	0.4296	0.3690	0.3405	0.3595	0.2853	0.1444** (0.0124)
P3	0.3618	0.3049	0.2535	0.3365	0.2465	0.1122** (0.0373)
P4	0.2168	0.2222	0.2490	0.2198	0.2308	−0.0172 (0.6663)
P5	0.1159	0.1311	0.1145	0.1258	0.1259	−0.0114 (0.6827)

This table is the univariate analysis for default probability of a firm. *Default prob 1y* is the probability of default according to Duan et al.'s (2012) model. We divided the sample into five groups according to the value of *Environmental Score*. The level of environmental performance monotonically increases from group G1 to group G5. In Panels A, B, and C, we double sort the sample using *Leverage*, *Size*, and *M/B* ratio. First, we divide the sample into five groups according to the value of *Leverage*, *Size*, and *M/B* ratio. *Leverage* monotonically increases from group L1 to group L5. Meanwhile, *Size* monotonically increases from group S1 to group S5, whereas *M/B* ratio monotonically increases from group P1 to group P5. Then, we divide each subsample group into five groups according to the value of *Environmental Score*, and the level of environmental performance monotonically increases from group G1 to group G5.

et al. (2012) calculated the PD on the forward intensity model using the reduced-form DTD. This forward intensity model is governed by two independent doubly stochastic Poisson processes, which operate on forward time instead of spot time. It enables the model to produce forward-looking PD term structures of public firms based on dynamic learning from the macro-financial and firm-specific data. Besides, they accommodate the default risk and other types of risk of the corporate exits (i.e., mergers and acquisitions) together in the final default risk. All these characteristics make firms' PD under Duan et al.'s (2012) model to incorporate more information in contrast to the classic structural models (e.g., Merton, 1974). Merton's structural model can be considered a simpler version of Duan et al.'s (2012) approach. The probability of corporate default using Duan et al.'s (2012) approach is extracted from the database provided by the Credit Risk Initiative (*CRI*) at the National University of Singapore.

3.3. Other controls

To isolate the impact of environmental performance on default risk, we control for several well-known determinants of firm default risk based on previous research (e.g., Collin-Dufresne et al., 2001; Ericsson et al., 2009). Specifically, we control asset tangibility (*Tangibility*), asset liquidity ratio (*Cash*), firm size (*Log assets*), profitability (*ROE* and *EBITDA*), and financial leverage (*Leverage*). We also control the impact of macroeconomic factors on firms' default risk, such as economic development (*GDP growth*), equity market (*Index return*, *Index vol*), and the risk-free rate (*Risk free*). Moreover, we use the GDP growth rate to measure economic growth, the return of CSI 300 index to measure equity market performance, and the three-month Shanghai Interbank Offered Rate (SHIBOR) to proxy for the risk-free rate.

We extract a firm's fundamental information and macroeconomic indicators from the *WIND* database; the sample period is from June 2012 to 2017. The financial industry and the observations with missing information are excluded. Our final sample comprises 468 firms and 1482 observations. We winsorized all the variables at 1% and 99% quantile to mitigate the impact of extreme values. Table 1 presents the descriptive statistics of variables. The detailed definitions of the variables and matrix of the variable correlation coefficients are shown in Appendix Table A1 and Table A2.

Table 1 reports the descriptive statistics of all variables in our analysis. Further, we separate the whole sample according to industry classification: two-high-and-one-overcapacity industry (*THOO*) and none two-high-and-one-excess industry (*N-THOO*). Specifically, "two-high" refers to high-pollution, high-energy, resource-based industries and "one-overcapacity" refers to overcapacity industries. The environmental performance of *THOO* industries is poor compared with that of *N-THOO* industries (Fig. 1). As shown in Table 1, the default probabilities of firms belonging to *THOO* industries on average are greater than those of *N-THOO* industries.

Table 3
Corporate environmental responsibility and default risk: multivariate regressions.

Dependent variables	Default prob 1y	Default prob 1y	Default prob 1y	Default prob 1y	Default prob 1y
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	Tobit
Environmental Score	−0.0770**	−0.0890***	−0.0710*	−0.0338*	−0.0710**
	(0.0307)	(0.0268)	(0.0354)	(0.0170)	(0.0349)
Tangibility		0.0440	−0.0540	0.0471	−0.0540
		(0.0673)	(0.0732)	(0.2696)	(0.0721)
Cash		−0.1094**	−0.0459	0.0744	−0.0459
		(0.0499)	(0.0522)	(0.0769)	(0.0514)
Log Assets		−0.0340**	−0.0466***	−0.1222**	−0.0466***
		(0.0147)	(0.0165)	(0.0457)	(0.0162)
ROE		−0.0163***	−0.0158***	−0.0111***	−0.0158***
		(0.0023)	(0.0022)	(0.0036)	(0.0022)
EBITDA		0.1781***	0.0987*	0.2442*	0.0987**
		(0.0448)	(0.0496)	(0.1236)	(0.0489)
Leverage		0.9436***	0.9721***	0.8189***	0.9721***
		(0.0880)	(0.1032)	(0.1387)	(0.1017)
SOE		0.0266*	0.0358***		0.0358***
		(0.0150)	(0.0116)		(0.0114)
GDP Growth		−0.0925***	−0.3038***	−0.3121***	−0.3038***
		(0.0261)	(0.0659)	(0.0526)	(0.0649)
Index returns		−0.0052***	−0.0103***	−0.0047***	−0.0103***
		(0.0007)	(0.0018)	(0.0009)	(0.0018)
Index vol		−0.0143	0.2498***	0.0135	0.2498***
		(0.0117)	(0.0663)	(0.0107)	(0.0654)
Risk free		−0.0650***	−0.0200**	−0.0507***	−0.0200**
		(0.0110)	(0.0088)	(0.0121)	(0.0087)
Constant	0.2975***	1.6078***	3.2718***	5.1690***	3.2718***
	(0.0400)	(0.4450)	(0.6073)	(1.4106)	(0.5986)
Year FE	NO	NO	YES	YES	YES
Industry FE	NO	NO	YES	NO	YES
Firm FE	NO	NO	NO	YES	NO
N	1527	1482	1482	1482	1482
r2	0.0073	0.5152	0.5705	0.8451	2.071

This table reports the multivariate panel regression results for the default probability of a firm from 2012 to 2017 using various models. *Default prob 1y* is the 1-year default probability of enterprises in Duan et al.'s (2012) model, and *Environmental Score* is the environmental performance of firms. Definitions of other variables are given in Appendix Table A1. Regressions (1–4) are OLS regression models with different control variables. Regression (5) is the full control variable result of the Tobit model. The standard errors are robust and clustered at the industry level in models (1, 2, 3, 5) and at the firm level in model (4). *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

4. Environmental performance and default risk

4.1. Univariate analysis

In this section, we present a univariate analysis examining the relation between environmental performance and the default risk of a firm. We employ a 1-year PD to a proxy for a firm's default risk and use the scores of environmental responsibility to proxy for environmental performance. First, we sort observations according to environmental performance.[13] Specifically, we divide the sample into five groups according to the scores of environmental responsibility from low to high (G1–G5). The means of the 1-year PD are reported in Panel A of Table 2. We find that the mean of the PD in the group with the highest environmental performance, about 0.24%, is significantly lower than that in the group with the lowest environmental performance, about 0.32%, at the conventional level. This evidence suggests a negative relation between environmental performance and corporate default risk, which supports our baseline hypotheses.

Previous research shows that a firm's financial leverage and size are known determinants for corporate default risk (e.g., Collin-Dufresne et al., 2001; Ericsson et al., 2009; Liu and Zhong, 2017). To control the impact of financial leverage, firm size, and market-to-book ratio on default risk, we adopt a double-sorting approach accordingly.[14] In particular, we first sort the firm-year observations according to leverage (size or market-to-book ratio) and assign the sort outputs to five groups evenly. Next, in each group, we sort observations according to the scores for environmental performance and assign this output to five subgroups. Panel B (C or D) of Table 2 reports the means of default probability in each subgroup. The last column in Table 2 shows the differences between subgroups with the highest and lowest environmental performance for each group. We find both positive and negative differences between the

[13] Banz (1981) introduced the approach of sorting portfolio. He sorted the portfolio according to size and grouped equity returns.
[14] See Fama and French (1992, 2008) for the double sorting approach of analyzing risk factors in equity returns.

Table 4
Environmental performance and term structure of probability of default.

Dependent variables	Default Prob 1 m	Default Prob 3 m	Default prob 6 m	Default prob 2y	Default prob 3y	Default prob 5y	Slope
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Environmental Score	−0.0067**	−0.0197*	−0.0381*	−0.1249*	−0.1689**	−0.2452**	−0.1742**
	(0.0033)	(0.0097)	(0.0189)	(0.0614)	(0.0807)	(0.1088)	(0.0744)
Tangibility	−0.0024	−0.0087	−0.0210	−0.1429	−0.2475	−0.4850**	−0.4310**
	(0.0069)	(0.0203)	(0.0394)	(0.1264)	(0.1672)	(0.2350)	(0.1713)
Cash	−0.0036	−0.0110	−0.0227	−0.0802	−0.1022	−0.1252	−0.0793
	(0.0047)	(0.0140)	(0.0275)	(0.0934)	(0.1257)	(0.1794)	(0.1321)
Log Assets	−0.0046***	−0.0134***	−0.0259***	−0.0716**	−0.0799*	−0.0676	−0.0210
	(0.0015)	(0.0044)	(0.0087)	(0.0293)	(0.0391)	(0.0533)	(0.0373)
ROE	−0.0014***	−0.0042***	−0.0083***	−0.0283***	−0.0383***	−0.0539***	−0.0381***
	(0.0002)	(0.0006)	(0.0012)	(0.0039)	(0.0051)	(0.0069)	(0.0048)
EBITDA	0.0108**	0.0309**	0.0575**	0.1499	0.1773	0.2004	0.1016
	(0.0045)	(0.0133)	(0.0259)	(0.0914)	(0.1284)	(0.1983)	(0.1517)
Leverage	0.0834***	0.2507***	0.4990***	1.8048***	2.5078***	3.7136***	2.7416***
	(0.0094)	(0.0279)	(0.0545)	(0.1866)	(0.2554)	(0.3705)	(0.2688)
SOE	0.0031***	0.0092***	0.0183***	0.0659***	0.0894***	0.1218**	0.0860**
	(0.0010)	(0.0031)	(0.0060)	(0.0214)	(0.0299)	(0.0450)	(0.0340)
GDP Growth	−0.0269***	−0.0803***	−0.1583***	−0.5530***	−0.7536***	−1.0681***	−0.7644***
	(0.0060)	(0.0177)	(0.0348)	(0.1175)	(0.1590)	(0.2273)	(0.1638)
Index return	−0.0009***	−0.0026***	−0.0052***	−0.0201***	−0.0292***	−0.0457***	−0.0354***
	(0.0002)	(0.0005)	(0.0010)	(0.0033)	(0.0046)	(0.0067)	(0.0049)
Index vol	0.0209***	0.0631***	0.1264***	0.4768***	0.6729***	0.9984***	0.7485***
	(0.0059)	(0.0175)	(0.0346)	(0.1213)	(0.1672)	(0.2442)	(0.1793)
Risk free	−0.0012	−0.0037	−0.0083*	−0.0514***	−0.0898***	−0.1787***	−0.1587***
	(0.0008)	(0.0024)	(0.0047)	(0.0160)	(0.0226)	(0.0353)	(0.0282)
Constant	0.2962***	0.8822***	1.7307***	5.7225***	7.4899***	9.8384***	6.5666***
	(0.0555)	(0.1646)	(0.3219)	(1.0732)	(1.4361)	(2.0018)	(1.4096)
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES
N	1482	1482	1482	1482	1482	1482	1482
r2	0.5401	0.5459	0.5545	0.5939	0.6115	0.6363	0.6509

This table reports the multivariate panel regression results for default risk proxies with various maturities and the slope of the term structure of default risk from 2012 to 2017. *Default prob 1 m*, *Default prob 3 m*, *Default prob 6 m*, *Default prob 2y*, *Default prob 3y*, and *Default prob 5y* denote 1-month, 3-month, 6-month, 2-year, 3-year, and 5-year probability of default, respectively. *Slope* denotes the slope of the term structure of default risk, which is calculated as the difference between the 5-year and 1-year probability of default. *Environmental Score* denotes firms' environmental performance. The definitions of other variables are given in Appendix Table A1. The standard errors are robust and clustered at the industry level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

subgroups with the highest and lowest environmental scores, but only the negative differences are statistically different from zero in all cases, according to the *p*-value reported in parentheses. Specifically, the negative relation between environmental performance and default risk is significant at the conventional level for firms with relatively high financial leverage, medium size, and market-to-book ratios. Such heterogeneity of the relation between environmental performance and corporate default risk among various scenarios indicates the necessity of conducting cross-section analysis to explore the possible channels through which corporate environmental responsibility affects a firm's default risk.

4.2. Multivariate regression model

Univariate analysis, in the previous section, shows the relation between corporate environmental performance and default risk vaguely. To investigate the impact of a firm's environmental performance on default risk rigorously, we conduct multivariate regressions as follows:

$$DFR_{i,t} = \alpha + \beta_1 env_{i,t-1} + \sum \gamma_i x_{j,i,t-1} + \eta_{t-1} + \eta_i + \varepsilon_{i,t} \tag{6}$$

where $DFR_{i,\,t}$ denotes the default risk of firm *i* in year *t*, $env_{i,\,t-1}$ denotes the environmental performance for firm *i* in year $t-1$, and $x_{j,\,i,\,t-1}$ represents control variables. We use the PD calculated by CRI according to Duan et al.'s (2012) model to measure the default risk of a firm. The control variables include a firm's tangibility (*Tangibility*), cash and cash equivalent ratio (*Cash*), total assets (*Log Assets*), return on equity (*ROE*), the ratio of *EBITDA* and sales (*EBITDA*), financial leverage (*Leverage)*, GDP growth rate (*GDP Growth*), return of CSI 300 index (*Index return*), the volatility of CSI300 index return (*Index vol*), and the risk-free rate (*Risk free*). We also control for the year- and industry- fixed effect, denoted by η_t and η_i, respectively, and ε_{it} denotes the error term.

The results of multivariate regression (6) are reported in Table 3. We find significant negative coefficients for *Environmental score* in both the restricted and unrestricted models after controlling for industry and time fixed effects. This suggests a negative relation between environmental score and a firm's default risk, which is consistent with the findings of past studies (e.g., Graham et al., 2001;

Table 5
The components of corporate environmental responsibility.

Panel A: Subcomponent of Environmental Performance and Short−run Default Risk			
Dependent variables	Default prob 1y	Default prob 1y	Default prob 1y
	(1)	(2)	(3)
Green income	−0.0909***		
	(0.0318)		
Bad news		0.0124	
		(0.0246)	
Fine			−0.0355*
			(0.0202)
Constant	3.3564***	3.2182***	3.1844***
	(0.6243)	(0.6033)	(0.6086)
Other Controls	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
N	1482	1482	1482
R2	0.5700	0.5661	0.5667
Panel B: Subcomponent of Environmental Performance and Long − run Default Risk			
Dependent variables	*Default prob 5y*	*Default prob 5y*	*Default prob 5y*
	(1)	(2)	(3)
Green income	−0.3126***		
	(0.1074)		
Bad news		0.0173	
		(0.0908)	
Fine			−0.1315*
			(0.0716)
Constant	10.1285***	9.6486***	9.5288***
	(2.0518)	(2.0015)	(2.0089)
Other Controls	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
N	1482	1482	1482
R2	0.6359	0.6326	0.6333

Panels A and B report the multivariate panel regression results for *Default prob 1y* and *Default prob 5y* for the period 2012–2017 using various models, respectively. *Default prob 1y* and *Default prob 5y* denote the 1- and 5-year default probability of enterprises, respectively, according to Duan et al.'s (2012) model. The company's environmental score consists of three parts: green income (*Green income*), bad news (*Bad news*), and environmental punishment (*Fine*). The definitions of other variables are given in Appendix Table A1. The standard errors are robust and clustered at the industry level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Bauer and Hann, 2010; Attig et al., 2013; Oikonomou et al., 2014). We also control for firm fixed effects and observe a consistently negative relation between environmental score and the default risk of a firm, as reported in model (4) in Table 3. The distribution of the PD is truncated to be non-negative; hence, we use Tobit regression with a truncated distribution to check the robustness and find consistent results. For the economic significance, the one-standard-deviation increase in economics score is associated with about a 9.5% decrease in default probability relative to the mean.[15]

Regarding the control variables, in terms of firm characteristics, the cash ratio (*Cash*) is negatively related to default risk, indicating that the default risk increases when a firm's cash level is low (e.g., Brogaard et al., 2017). Meanwhile, the profitability (*ROE*) is negatively related whereas financial leverage (Leverage) is positively related to default risk, which is consistent with prior literature (e.g., Collin-Dufresne et al., 2001; Ericsson et al., 2009; Liu and Zhong, 2017; etc.). Also, we note that state ownership indicator (*SOE*) is positively related to the default risk of a firm. In terms of macroindicators, GDP growth rate (*GDP Growth*), return of the market index (*Index return*), and the risk-free rate (*Risk free*) harm firm's default risk, whereas the volatility of market index return (*Index vol*) positively affects default risk.

4.3. Impact of environmental performance on the term structure of default risk

We use the 1-year PD in our baseline results. Using Duan et al.'s (2012) approach has several advantages such as calculation of the forward PDs with different maturities and provision of consistent term structure for PDs. We extract the 1-month, 3-month, 6-month, 2-year, 3-year, and 5-year PD from CRI's database to proxy for the default risk with various maturities. The regression results in Table 4 reveal a consistently negative relation between environmental score and firm default risk across all the maturities. These findings

[15] According to Table 1, the standard deviation of *Environmental Score* is 0.370. The means of *DFR_1* is 0.276. According to Table 3, the coefficient of *Environmental Score* is about −0.0710. The magnitude of the impact of one standard deviation increase in *Environmental Score* on *DFR_1* is calculated as 0.370*(−0.0710)/0.276 = 9.5%.

provide further support for our baseline results.

Results shown in Table 4 show that the PDs across all maturities are significantly affected by environmental performance. In terms of magnitude, we observe that the coefficients vary across different maturities. To examine how environmental performance affects the term structure of default risk, we use the difference between 5-year and 1-year PD to measure the slope of term structure and conduct similar regression. We find that the slope of the term structure significantly decreases when the environmental score increases. It suggests that the improvement of environmental performance has a stronger impact on a firm's default risk in the short run than that in the long run, which flattens the term structure of the PD.

4.4. The components of environmental performance

The environmental scores in our dataset consist of three components: green income, bad news, and environmental punishment. To understand the impact of each component on default risk, we conducted multiple regressions using each component's measure to replace *Environmental score* in regression model (6). The results are reported in Table 5.

In Panel A of Table 5, we use the 1-year PD as the dependent variable. The coefficient of green income is negative and significant at the conventional level. Meanwhile, we find insignificant coefficients of bad news and environmental fine. Then, we use the 5-year PD to conduct similar regression and find consistent results, as shown in Panel B of Table 5. This evidence suggests that green income is a key factor in the environmental score that reduces a firm's default risk. Green income measures the impact of a firm's products (or outputs) on the environment. The higher percentage of green income is associated with a lower negative impact on the environment caused by firms' productivities. Our findings highlight the importance of incorporating green income into the evaluation system of environmental performance from the perspective of risk management.

4.5. Endogeneity

Previous sections demonstrate a significant statistical relation between a firm's environmental performance and default risk. In this section, we examine the robustness of our findings on the impact of environmental performance on default risk by addressing possible endogeneity concerns, such as reverse causality and simultaneity, by employing the instrumental variables approach and placebo tests.

First, default risk may have a potential reverse effect on environmental performance. For instance, firms with high default risk would have limited resources to invest in projects that reduce environmental damage and improve environmental performance. Such reverse causality could also lead to a negative relation between environmental performance and default risk. To mitigate this endogeneity concern, we adopt a two-stage instrumental variable regression approach. We choose instrumental variables that directly affect corporate environmental performance but not the firm's default risk. Specifically, we chose two instrumental variables: (a) the average environmental score of peer firms in the same industry except for the firm itself (henceforth, the *target firm*) and (b) the average of the environmental scores of peer firms in the same province exluding the target firm. The average environmental score of peer firms in the same industry excluding the target firm reflects the environmental performance of peer firms that are competing with the target firm. Cao et al. (2018) show that the implementation of CSR (*CSR*) proposals in a firm generates spillover effects on the likelihood of peer firms' adoption of similar CSR practices in the same industry. Similar evidence is presented by Liu and Wu (2016). Considering that the adoption of CSR is a strategic response to competitive threats, the target firm is most likely to follow its peers' actions to adjust their environmental performance. Therefore, we expect a positive relation between the average environmental score of peer firms and the target firm's environmental performance, satisfying the relevance criteria of IVs. Meanwhile, because the target firm is excluded from the average environmental score of peer firms, the default risk of a target firm is unlikely to be affected directly by the average environmental score of peer firms. Previous studies (Cao et al., 2018; Liu and Wu, 2016) show that the average environmental score of peer firms generates spillover effects on the environmental score of target firms, through which the IV affects the default risk of target firms. Thus, this IV satisfies the exclusion criteria of being an appropriate instrumental variable.[16] Further, we use the average environmental score of peer firms in the same province excluding the target firm as an alternative instrumental variable to check the robustness of the results. In China, the provincial government has the flexibility to enforce local policies within the guidelines issued by the central government. The autonomy of local governments has created a geographical heterogeneity in local environmental policies and regulations. The average environmental score of firms whose headquarters are in the same province reflects the stringency and effectiveness of local environmental regulations to a certain extent. Therefore, we expect a positive relation between the average environmental score of firms (excluding the target firm's score) in the same province and the environmental score of the target firm. The default risk of a firm (target firm) possibly affects its environment performance. The calculation of the average environmental score in a province (IV) excludes the target firm; therefore, the change in environmental score of the target firm caused by the change in default risk in the target firm does not affect our IV, which satisfies the exclusion condition.

[16] The default risk of the target firm might generate a spillover effect on the default risk of all peer firms in the same industry. The default risk of peer firms could affect their environmental performance and change the average environmental score of all peer firms. We admit that such a possibility exists, but the probability of its occurrence is extremely low. To generate a noticeable spillover effect on an industry-wide peer firm, the target firm itself must be large and the increase of default risk must be extremely high. Although the firms in our sample are those with large market capitalization and have the most liquid stocks, we did not observe extreme events that could generate noticeable spillover effects on the default risk of industry-wide peer firms during our sample period. Thus, it is unlikely that the default risk of the target firm would affect the average score of all peer firms.

Table 6
Endogeneity analysis: instrumental variable approach.

Dependent variables	Industry		Provincial	
	Average Environmental Score		Average Environmental Score	
	Environmental score	Default prob 1y	Environmental score	Default prob 1y
	1st stage	2nd stage	1st stage	2nd stage
Environmental Score		−0.1928**		−0.4067***
		(0.0932)		(0.0896)
Average environmental score	0.7578***		0.3120**	
	(0.0372)		(0.0655)	
Tangibility	0.1526	0.0915***	0.2496	0.1409***
	(0.1866)	(0.0062)	(0.2800)	(0.0127)
Cash	−0.1182**	−0.1216***	−0.0326	−0.1180***
	(0.0168)	(0.0129)	(0.0931)	(0.0019)
Log Assets	0.0109	−0.0326***	0.0099	−0.0303*
	(0.0041)	(0.0117)	(0.0132)	(0.0159)
ROE	−0.0010**	−0.0161***	−0.0012	−0.0165***
	(0.0002)	(0.0005)	(0.0011)	(0.0001)
EBITDA	0.1758	0.1831***	0.1682*	0.2239***
	(0.1107)	(0.0281)	(0.0524)	(0.0030)
Leverage	−0.0368	0.9302***	−0.0411	0.9248***
	(0.1248)	(0.0145)	(0.1989)	(0.0269)
SOE	−0.0485***	0.0222***	−0.0599***	0.0081
	(0.0032)	(0.0022)	(0.0046)	(0.0144)
GDP Growth	−0.0330	−0.2893***	−0.1074***	−0.3208***
	(0.0116)	(0.0403)	(0.0080)	(0.0157)
Index return	−0.0020***	−0.0110***	−0.0035***	−0.0120***
	(0.0001)	(0.0013)	(0.0000)	(0.0005)
Index vol	0.0265	0.2480***	0.0418	0.2554***
	(0.0357)	(0.0060)	(0.0669)	(0.0143)
Risk free	0.0029	−0.0269***	0.0176***	−0.0216***
	(0.0053)	(0.0007)	(0.0001)	(0.0037)
Constant	−0.1145	2.6176***	0.3884***	2.7750***
	(0.2136)	(0.5862)	(0.0103)	(0.4616)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
N	1482	1482	1482	1482
r2	0.2771	0.5196	0.1314	0.4294
Kleibergen-Paap rk	99.171***		10.698***	
Wald F statistic	(*p*-value = 0.0000)		(*p*-value = 0.0011)	

This table reports the multivariate panel regression results for the default probability of a firm 2012 to 2017 using various models. *Default prob 1y* and *Default prob 5y* denote the 1- and 5-year default probability of enterprises, respectively, according to Duan et al.'s (2012) model. We defined the instrument variable as the average environment performance of the industry (or of the province) excluding the firm itself, which is denoted by *Average environmental score*. The definitions of other variables are given in Appendix Table A1. The standard errors are robust and clustered at the industry level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

In the first stage, we examine the impact of the average environmental score of peer firms in the same industry and in the same province on the environmental score of the target firm. Results in Table 6, as expected, reveal significant and positive coefficients for the average environmental score of peer firms in the same industry and province. Also, our instrumental variables pass the weak instrument tests by rejecting the null hypotheses that the instruments are weak (Table 6). We use the predicted environmental score from the first stage to replace *Environmental score* in the second-stage regression and perform multivariate regression (6). We find significant and negative coefficients for the predicted environmental scores using both instrumental variables, as reported in the second and fourth columns.[17] These results provide strong support that better environmental performance significantly reduces the default risk of a firm.

Second, the negative relation between environmental performance and default risk may be driven by some unobserved factors that drive both variables simultaneously but in opposite directions. If such a conjecture were true, then the negative relation between environmental score and default risk presented in this study might be an illusion—the so-called *simultaneity concern*. We used a placebo test to address this concern by simulating "wrong" environmental scores. In each simulation, we adopt a resampling approach to randomly assign "wrong" environmental scores to each firm-year observation and perform the baseline regression using such "wrong" environmental scores. Then, we record the *t*-statistics value of the coefficients for the environmental score. If the negative relation between environmental score and default risk is driven by unobserved variables or a predetermined trend, a high likelihood of

[17] Table 6 reports the results of two-stage instrumental variable regression for 1-year probability of default. We also conduct similar regressions for 5-year PDs and found consistent results. This result is reported in the appendix, which is available upon request.

Table 7
Endogeneity analysis: placebo tests.

Panel A: Summary Statistics						
1000 Times	No. of Simulation	Mean	STD	25%	Median	75%
t-value1	1000	−0.106	1.049	−0.757	−0.101	0.559
t-value2	1000	1.188	0.514	0.844	1.185	1.521
|*t*-value1|	1000	0.818	0.664	0.309	0.648	1.183
|*t*-value2|	1000	1.192	0.504	0.844	1.185	1.521
5000 Times	No. of Simulation	Mean	STD	25%	Median	75%
t-value1	5000	−0.037	1.081	−0.752	−0.037	0.678
t-value2	5000	1.173	0.505	0.834	1.157	1.498
|*t*-value1|	5000	0.853	0.665	0.336	0.714	1.218
|*t*-value2|	5000	1.176	0.496	0.834	1.157	1.498
10,000 Times	No. of Simulation	Mean	STD	25%	Median	75%
t-value1	10,000	−0.015	1.090	−0.731	−0.016	0.705
t-value2	10,000	1.179	0.502	0.843	1.166	1.499
|*t*-value1|	10,000	0.859	0.671	0.338	0.718	1.231
|*t*-value2|	10,000	1.182	0.495	0.843	1.166	1.499
Panel B: Probability of lower than the critical value						
	1000 Times		5000 Times		10,000 Times	
	t-value1	*t*-value2	*t*-value1	*t*-value2	*t*-value1	*t*-value2
$P < 10\%$	0.099	0	0.0994	0	0.981	0.0001
$P < 5\%$	0.051	0	0.0502	0	0.0494	0
$P < 1\%$	0.010	0	0.0066	0	0.0077	0

This table presents the descriptive statistics of the placebo test. We use the simulated sampling approach to assign the "wrong" environmental score. In each simulation, we randomly assign the value of *Environmental Score* to an observation. Then, we perform regression model (6) using the "wrong" *Environmental Score* and retain the t-statistics value for the coefficient of *Environmental Score* in each regression. Specifically, we adopt two methods of random assignment in this exercise: (a) randomly assigning all the *Environmental Score* observations to a certain observation; and (b) separating the samples into two groups according to the level of *Environmental Score* and randomly assigning the *Environmental Score* value of the higher group to the observations of the lower group, and vice versa. We conduct 1000, 5000, and 10,000 simulations using each method. The *t*-statistics values using the methods (1) and (2) are denoted as *t-value1* and *t-value2*, respectively. In Panel A, we report descriptive statistics of *t-value1* and *t-value2*, and their corresponding absolute values, denoted by |*t-value1*| and |*t-value2*|. In Panel B, we calculate the percentage of significant *t-value1* and *t-value2* that are defined as smaller than 10%, 5%, and 1% critical values on the left tail. Those critical values are calculated using the model's degree of freedom of the basic mode in Regression 3 in Table 2.

obtaining negative and significant *t*-statistics when using "wrong" environmental scores is expected. However, if lower default risk is caused by a higher environmental score, the probability of observing negative and significant *t*-statistics should be low when the "wrong" environmental score is used. After repeating this simulation for 1000, 5000, and 10,000 times, we report the corresponding percentage of negative and significant *t*-statistics observations of the coefficients of an environmental score as *t-value1* in Table 7, at the 1%, 5%, and 10% significance levels, respectively. We find less than 1% probability of observing negative and significant *t*-statistics at a 1% significance level in all cases using "wrong" environmental scores. This alleviates the concern that unobserved variables drive our results. Further, we use an alternative resampling technique to check the robustness of the placebo tests. Particularly, we divide the whole sample into two groups—high score and low score—according to the median of environmental scores. In each simulation, firms belonging to the high-score group are assigned a "wrong" environmental score that is randomly picked from the low-score group and vice versa. Results in Panel B of Table 7 show consistent results that lend credence to the negative impact of corporate environmental performance on default risk.

5. Further analyses

In previous sections, we have presented profound evidence of a significant reduction in a firm's default risk caused by corporate environmental performance. In this section, we show further analyses on how cross-sectional heterogeneity of firms, such as firm characteristics, risk profile, business lines, affects the relation between corporate environmental performance and default risk. Particularly, we analyze the influence of the volatility of profitability, default risk, and industry effects.

5.1. Equity volatility

The structural models show asset volatility as a key determinant of a firm's default risk. Equity volatility directly affects a firm's default risk because the value of corporate equity is like the payoff of a call option written on a firm's unleveraged asset value (e.g., Campbell and Taksler, 2003). To gain further insight into the influence of equity volatility on the relation between environmental performance and default risk, we adopt three proxies for equity volatility: total volatility (*Vol*), systematic volatility (*Systematic Vol*), and idiosyncratic volatility (*Idiosyncratic Vol*). In particular, we compute the total volatility using the monthly excess return rate, $r_{i,\,t} - r_{f,\,t}$, in a year. Then, we use the capital asset pricing model given below to decompose total volatility into systematic volatility and idiosyncratic volatility.

Table 8
Cross-sectional analysis: equity volatility.

Panel A: 1-year Default Probability						
Dependent variables	Low Vol	High Vol	Low Systematic Vol	High Systematic Vol	Low Idiosyncratic Vol	High Idiosyncratic Vol
Environmental Score	−0.0664**	−0.0683*	−0.0159	−0.1337**	−0.0836*	−0.0635*
	(0.0294)	(0.0390)	(0.0254)	(0.0514)	(0.0416)	(0.0344)
Other Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
N	721	761	756	726	715	767
r2	0.5722	0.5857	0.5847	0.5609	0.5721	0.5917
Null Hypotheses: Environmental Score (1) = Environmental Score (2)						
Empirical *p*-value	0.4789		0.0009***		0.7066	
Panel B: 5-year Default Probability						
Dependent variables	Low Vol	High Vol	Low Systematic Vol	High Systematic Vol	Low Idiosyncratic Vol	High Idiosyncratic Vol
Environmental Score	−0.2572***	−0.1952*	−0.0969	−0.4127***	−0.2849***	−0.2175**
	(0.0853)	(0.1064)	(0.0827)	(0.1280)	(0.0931)	(0.0979)
Other Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
N	721	761	756	726	715	767
r2	0.6426	0.6466	0.6403	0.6269	0.6408	0.6530
Null Hypotheses: Environmental Score (1) = Environmental Score (2)						
Empirical *p*-value	0.6907		0.0052***		0.7020	

This table reports the multivariate panel regression results for 1-year probabilities of default (PDs) (*Default prob 1y*) and 5-year PDs (*Default prob 5y*) for the period 2012–2017. First, we calculate the volatility of the monthly stock return over the risk-free date in the recent year as the total return volatility of stock return. Then, we decompose the total volatility into two parts using the capital asset pricing model. The volatility of the fitted return premium is defined as the systematic return volatility, whereas the volatility of residuals is defined as the individual return volatility. Finally, we separate the full sample into two parts according to the total, systematic, and individual return volatilities. *Default prob 1y* and *Default prob 5y* are the 1-year and 5-year probabilities of default according to Duan et al.'s (2012) model. *Environmental Score* denotes the environmental score. The definitions of other variables are given in Appendix Table A1. We perform the difference test with the null hypotheses that the coefficients of *Environmental Score* in models (1,2) are the same. We use a bootstrapping procedure (Cleary, 1999) to calculate empirical *p*-value that estimates the likelihood of obtaining the null hypotheses. The standard errors are clustered at the industry level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

$$r_{i,t} - r_{f,t} = \alpha + \beta\left(r_{m,t} - r_{f,t}\right) + \varepsilon_{i,t} \tag{7}$$

where $r_{i,\,t}$ denotes stock i's return in month t and $r_{f,\,t}$ denotes the risk-free rate in month t. We use 3-month SHIBOR in China to proxy for the risk-free rate. $r_{m,\,t}$ denotes market return in month t. The Shanghai Composite Index was used as a proxy for market return. We run this regression for each firm-year and retain the model's predicted returns and residuals. The systematic and idiosyncratic risk are the standard deviations of the model predicted monthly returns and residuals, respectively.

We divide the full sample into subsamples according to the medians of equity volatilities and perform baseline regressions in each subsample. We report the coefficients for environmental scores in all subsamples in Table 8. Consistent with our baseline results, we find a significant and negative relation between corporate environmental responsibility and default risk for all subsamples except for the one with low systematic volatility. On comparing the coefficients for environmental performance in each pair of subsamples, we find a significant impact of systematic volatility on the relation between corporate environmental responsibility and default risk, whereas total volatility and idiosyncratic volatility have no significant impact. Particularly, the negative influence of environmental performance on default risk is stronger in firms with high systematic volatility. This result suggests systematic volatility as a potential channel through which improvements in environmental performance reduce the firm's default risk.

5.2. *The volatility of profitability*

Prior literature shows that profitable firms are less likely to default (e.g., Ericsson et al., 2009; Huang and Huang, 2012; Liu and Zhong, 2017). If the volatility of profitability is high, it should be associated with a high risk profile of a firm, such as volatile cash flow, lower asset value, and high financing costs, which results in an increased probability of bankruptcy. The volatility of profitability relies on revenue and costs of goods sales. Revenue could affect the volatility of profitability significantly because the cost of goods sales is relatively stable. The trend in China in recent years has been that if a firm's final products belong to the green catalog according to certain guidelines or classification, the production of such goods is expected to be less affected by regulations to protect the environment. Therefore, revenue with a high percentage of green income would be stable compared to the revenue with a low percentage of green income. Stabilizing the fluctuation of revenue could be a possible channel through which environmental performance affects a firm's default risk. If this conjecture is true, there would be a stronger negative impact of the firm's environmental score on its default risk measure.

To examine the validity of this conjecture, we use the volatility of the net profit margin of the previous 5 years to measure the

Table 9
Cross-sectional analysis: profitability volatility.

Panel A: 1-year Default Probability		
	Default prob 1y	*Default prob 1y*
	(1)	(2)
	Lower net profit margin volatility	Higher net profit margin volatility
Environmental Score	−0.0174	−0.0986***
	(0.0402)	(0.0344)
Other Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
N	732	750
r2	0.5659	0.5954
Null Hypotheses: Environmental Score (1) = Environmental Score (2)		
Empirical *p*-value: 0.0127**		
Panel B: 5-year Default Probability		
	Default prob 5y	Default prob 5y
	(1)	(2)
	Lower net profit margin volatility	Higher net profit margin volatility
Environmental Score	−0.0875	−0.3121***
	(0.1362)	(0.0962)
Other Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
N	732	750
r2	0.6281	0.6683
Null Hypotheses: Environmental Score (1) = Environmental Score (2)		
Empirical *p*-value: 0.0367**		

This table reports the multivariate panel regression results for 1-year probabilities of default (PDs) (*Default prob 1y*) and 5-year PDs (*Default prob 5y*) for the period 2012–2017. We use the net profit margin as a proxy for a firm's profitability. We calculated the volatility of profitability using the observations in the previous five years. We divide the whole sample into two subsamples according to the volatility of profitability and perform regression model (6). *Default prob 1y* and *Default prob 5y* are the 1-year and 5-year probability of default according to Duan et al.'s (2012) model. *Environmental Score* denotes environmental score. The definitions of other variables are given in Appendix Table A1. We perform the difference test with the null hypotheses that the coefficients of *Environmental Score* in models (1, 2) are the same. We use a bootstrapping procedure (Cleary, 1999) to calculate the empirical *p*-value that estimates the likelihood of obtaining the null hypotheses. The standard errors are clustered at the industry level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

volatility of profitability. We divide the whole sample into two subsamples according to the median of the volatility of profitability and perform the baseline results in each subsample. Table 9 reports the regression results. Using the 1-year PD as the dependent variable, we find a negative and significant coefficient of an environmental score in the subsample with the high volatility of net profit margin. By contrast, the one in the subsample with low volatility is not significant; this result is consistent with our conjecture. Based on Cleary's (1999) work, we use the bootstrapping resampling approach to test the statistical difference between the coefficients of the environmental score in subsamples. We find that the difference between the coefficients of the environmental score in the subsamples is statistically different from zero at a 5% significance level. This evidence strongly supports our conjecture that stabilizing the profit volatility of a firm can be a channel through which the improvement of environmental performance reduces a firm's default risk. Additionally, we use the 5-year PD as an alternative proxy for default risk to conduct similar exercises and record robust results.

5.3. Firm's probability of default

The structural model (e.g., Merton, 1974; Leland and Toft, 1996) likens corporate debt to writing a put option on a firm's unleveraged assets. The debt value is more sensitive to the fluctuation of asset value when a firm's asset value approaches the default boundary. The distance between current asset value and default boundary is defined as the *DTD*. Low *DTD* is associated with a high PD. In the previous section, we show the potential of good environmental performance to reduce default risk by stabilizing the volatility of profit. Presumably, profit volatility is positively related to asset volatility; hence, the negative impact of environmental performance on default risk should be more pronounced for firms with high default risk. Moreover, a firm's actions to improve environmental protection or produce green income build a good public image, which might help the firm accumulate social trust. Lins et al. (2017) show that high social trust alleviates the negative impact of extreme events on firm performance, such as financial crisis. In this vein, when a firm faces financial distress or high default risk, the impact of good environmental performance on mitigating default risk is expected to be enhanced, supporting H2.

We use a similar difference analysis between subsamples and examine the heterogeneity of the relation between environmental performance and default risk. We divide the whole sample into two subsamples according to the median of default risk and then conduct multivariate regression using each subsample. Table 10 shows a significantly stronger negative impact of the environmental

Table 10
Further analysis: default risk.

Panel A: 1-year Default Probability		
	Default prob 1y	Default prob 1y
	(1)	(2)
	Lower Default risk	Higher Default risk
Environmental Score	−0.0213***	−0.0841*
	(0.0052)	(0.0468)
Other Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
N	736	746
r2	0.6348	0.4715
Null Hypotheses: Environmental Score (1) = Environmental Score (2)		
Empirical *p*-value: 0.0433**		
Panel B: 5-year Default Probability		
	Default prob 5y	Default prob 5y
	(1)	(2)
	Lower Default risk	Higher Default risk
Environmental Score	−0.0797**	−0.2097
	(0.0286)	(0.1280)
Other Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
N	740	742
r2	0.6445	0.5098
Null Hypotheses: Environmental Score (1) = Environmental Score (2)		
Empirical *p*-value: 0.1461		

This table reports the multivariate panel regression results for 1-year probabilities of default (PDs) (*Default prob 1y*) and 5-year PDs (*Default prob 5y*) for the period 2012–2017. We divide the whole sample into two subsamples according to the *Default prob 1y* and *Default prob 5y* and perform regressions model (6). *Default prob 1y* and *Default prob 5y* are the 1-year and 5-year PDs according to the model of Duan et al. (2012). *Environmental Score* denotes environmental score. The definitions of other variables are given in Appendix Table A1. We perform the difference test with the null hypotheses that the coefficients of *Environmental Score* in models (1, 2) are the same. We use a bootstrapping procedure (Cleary, 1999) to calculate empirical *p*-value that estimates the likelihood of obtaining the null hypotheses. The standard errors are clustered at the industry level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

score on 1-year default risk for firms with high default risk (vs. low default risk), which is consistent with our conjecture. For the 5-year PD, although we observe a larger magnitude for the negative impact of environmental performance on default risk for firms with high default risk, the coefficients of environmental performance scores between high- and low-default risk subsamples are not statistically different from zero at the conventional level.

5.4. Pollution and overcapacity

The nature of the business line is a determinant of environmental performance. For instance, dairy products, beverages, and retail stores have a relatively smaller negative impact on the environment in contrast to high-pollution industries, such as mining, chemicals, and steelworks. In China, the government identifies industries with high pollution, high energy consumption, and excess productivity and classifies them as "two-high-and-one-overcapacity" (*THOO*) industries. According to the descriptive statistics in Table 1, the firms in *THOO* industries are associated with low environmental scores and high default risk. The National Development and Reform Commission, People's Bank of China, and other related authorities issued a series of strict regulations to restrict productivity and financial capacity to force them to transit to a business model with low pollution and less environmental damage, especially in the immediate past decade. Thus, we expect a much stronger impact of the environmental score on default risk for the firms in the *THOO* industries.

To examine the heterogeneity of the impact of environmental performance on default risk, we perform multivariate regression in the *THOO* and *N-THOO* industries; the results are reported in Table 11. As expected, there is a statistically significant stronger impact of the environmental score on a firm's default risk. This evidence suggests that the marginal contribution of improving environmental performance on mitigating default risk is greater for firms with high pollution and high energy consumption, thus providing strong support for H3.

5.5. Firms' ownership

In China, SOEs are undeniably crucial to the economy. First, SOEs account for about one-third of the total listed companies and two-

Table 11
Further analysis: pollution and overcapacity.

Panel A: 1-year Default Probability		
	Default prob 1y	Default prob 1y
	(1)	(2)
	N-THOO Industries	THOO industries
Environmental Score	−0.0474**	−0.1348*
	(0.0223)	(0.0637)
Other Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
N	1166	316
r2	0.5670	0.6395
Null Hypotheses: Environmental Score (1) = Environmental Score (2)		
Empirical *p*-value: 0.0273**		
Panel B: 5-year Default Probability		
	Default prob 5y	Default prob 5y
	(1)	(2)
	N-THOO Industries	THOO industries
Environmental Score	−0.2002**	−0.4608*
	(0.0846)	(0.2110)
Other Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
N	1166	316
r2	0.6319	0.6928
Null Hypotheses: Environmental Score (1) = Environmental Score (2)		
Empirical *p*-value: 0.0445**		

This table reports the multivariate panel regression results for 1-year probabilities of default (PDs) (*Default prob 1y*) and 5-year PDs (*Default prob 5y*) for the period 2012–2017. We divide the whole sample into two subsamples according to the industry classification and perform regression model (6). The two-high-and-one-excess industry is denoted by *THOO* industries, whereas the rest of the industries are denoted by *N-THOO* industries. *Default prob 1y* and *Default prob 5y* are the 1-year and 5-year probability of default according to Duan et al.'s (2012) model. *Environmental Score* denotes environmental score. The definitions of other variables are given in Appendix Table A1. We perform the difference test with the null hypotheses that the coefficients of *Environmental Score* in models (1, 2) are the same. We use a bootstrapping procedure (Cleary, 1999) to calculate empirical *p*-value that estimates the likelihood of obtaining the null hypotheses. The standard errors are clustered at the industry level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

thirds of stock market capitalization. Second, SOEs differ significantly from non-SOEs in corporate governance (Jiang and Kim, 2020) and “social goals” (Hsu et al., 2020). Third, with “deep pockets,” the government tends to support the firms they own in challenging times (Ding et al., 2020). Last but not least, the credit of SOEs is usually backed by the government. Thus, we expect a much stronger impact of the environmental score on default risk for non-SOEs.

Here, we continue to analyze the heterogeneity of the impact of environmental performance between SOEs and non-SOEs. Table 12 reports the regression results. The coefficient of an environmental score in non-SOEs is negative and significant while that in SOEs is not significant, which is consistent with our conjecture. However, the difference in the coefficients of environmental performance scores between SOEs and non-SOEs is not statistically different from zero at the conventional level.

6. Conclusion

This study investigates the influence of corporate environmental responsibility on the default risk of a firm in the context of Chinese listed firms experiencing a transition toward a green economy. We use a novel dataset for corporate environmental performance, which provides enriched information about the corporate environmental performance and allowed us to examine the impact of environmental performance from a new perspective. We adopt a comprehensive approach developed by Duan et al. (2012) that combines reduced-form and structural models to calculate the PD. It provides a clean and relatively objective measure of default risk in contrast to credit ratings and cost of debts.

We find profound evidence of the association between good environmental performance and low default risk. This negative relation is robust based on various regression models. We used instrumental variable regressions and placebo tests to control for possible endogeneity concerns and demonstrate the negative influence of corporate environmental performance on a firm's default risk. Further, we conduct cross-sectional analysis and find that environmental performance's negative impact on default risk is more pronounced for firms with greater systematic risk, high volatility of profit, high default risk, severe pollution, and high energy consumption. These results are consistent with volatility and environmental regulation uncertainty channels.

Table 12
Further analysis: state ownership.

Panel A: 1-year Default Probability		
	Default prob 1y	Default prob 1y
	(1)	(2)
	Non-SOE	SOE
Environmental Score	−0.0558**	−0.0821
	(0.0224)	(0.0508)
Other Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
N	579	903
r2	0.6623	0.5666
Null Hypotheses: Environmental Score (1) = Environmental Score (2)		
Empirical *p*-value: 0.2473		
Panel B: 5-year Default Probability		
	Default prob 5y	Default prob 5y
	(1)	(2)
	Non-SOE	SOE
Environmental Score	−0.2192***	−0.2392
	(0.0753)	(0.1448)
Other Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
N	579	903
r2	0.7076	0.6389
Null Hypotheses: Environmental Score (1) = Environmental Score (2)		
Empirical *p*-value: 0.4415		

This table reports the multivariate panel regression results for 1-year probabilities of default (PDs) (*Default prob 1y*) and 5-year PDs (*Default prob 5y*) for the period 2012–2017. We divide the whole sample into two subsamples according to the ownership classification (SOE and Non-SOE) and perform regression model (6). *Default prob 1y* and *Default prob 5y* are the 1-year and 5-year PDs according to Duan et al. (2012). *Environmental Score* denotes environmental score. The definitions of other variables are given in Appendix Table A1. We perform the difference test with the null hypotheses that the coefficients of *Environmental Score* in models (1, 2) are the same. We use a bootstrapping procedure (Cleary, 1999) to calculate empirical *p*-value that estimates the likelihood of obtaining the null hypotheses. The standard errors are clustered at the industry level and reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

The study's findings elucidate the role of environmental responsibility in firms' default risk profiles. The study provides empirical support for practitioners, such as institutional investors, rating agencies, and risk managers, to incorporate environmental factors into their decisions for investments and risk management rationally. Moreover, our findings deepen the understanding of the externality of environmental responsibility and present immediate implications for policymakers to promote sustainable development.

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Appendix A. Appendix

Table A1
Variable definitions

Dependent variables	
Default prob 1y (%)	One-year default probability of a firm according to Duan et al.'s (2012) model. Higher default probability indicates a higher default risk. These data are extracted from extracted from the database provided by the Credit Risk Initiative (CRI) at the National University of Singapore.

(*continued on next page*)

Table A1 (*continued*)

Dependent variables	
Default prob 5y (%)	The five-year default probability of a firm according to Duan et al.'s (2012) model. Higher default probability indicates a higher default risk. These data are extracted from extracted from the database provided by the Credit Risk Initiative (CRI) at the National University of Singapore.
Independent variables	
Environmental Score	The environmental performance score of enterprises. The higher the score, the better the environmental performance of enterprises. This score is made up of three parts: *Green income*, *Bad news* and *Fine*.
Green income	The score is calculated according to the ratio of green income to total income. The higher the score is, the higher the proportion of green income in corporate income.
Bad news	The score is calculated according to the bad news of environmental protection of enterprises. The higher the score, the more bad news enterprises have.
Fine	The score is calculated according to the environmental penalties imposed on enterprises. The higher the score, the more serious the environmental penalties for enterprises.
Control Variables	
Tangibility	The ratio of tangible assets to total assets. The tangible assets include property, plant and equipment. These data are extracted from WIND database.
Cash	The ratio of cash and cash equivalents to total assets. These data are extracted from WIND database.
Log Assets	The logarithm of total assets. These data are extracted from WIND database.
ROE	The ratio of net income to total equity. These data are extracted from WIND database.
EBITDA	The ratio of the earnings before interest, tax, depreciation and amortization (EBITDA) to total sales. These data are extracted from WIND database.
Leverage	The ratio of total debt to total assets. These data are extracted from WIND database.
SOE	A dummy variable for state ownership. This variable equals 1 for state-owned enterprises, and 0 otherwise.
GDP growth(%)	GDP growth rate, which equals the percentage change of GDP per year.
Index return(%)	The annualized return of HS300 index.
Index vol(%)	The volatility of the weekly return of HS300 index.
Risk free(%)	The risk-free rate. We use the 3-month SHIBOR rate to proxy for the risk-free rate.

Table A2
Correlation matrix

	Default prob 1y	Default prob 5y	Environmental Score	Tangibility	Cash	Log assets	ROE	EBITDA	Leverage	SOE
Default prob 1y	1									
Default prob 5y	0.9683***	1								
Environmental Score	−0.0857***	−0.0661***	1							
Tangibility	0.0403	0.0445*	0.0165	1						
Cash	−0.3310***	−0.3302***	0.0074	0.0681***	1					
Log assets	0.2972***	0.3928***	0.0609***	0.1012***	−0.2524***	1				
ROE	−0.3913***	−0.3741***	0.0219	0.0498**	0.2496***	−0.0678***	1			
EBITDA	−0.1543***	−0.2111***	0.1262***	−0.0247	0.0311	−0.0451*	0.3525***	1		
Leverage	0.5917***	0.6671***	−0.0107	0.1031***	−0.3514***	0.6058***	−0.1866***	−0.2773***	1	
SOE	0.1501***	0.1516***	−0.1014***	0.0760***	−0.0711***	0.2893***	−0.2139***	0.0021	0.1353***	1

This table is the correlation matrix of main variables in the paper. The detailed definitions of the variables are shown in Appendix Table A1. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pacfin.2021.101596.

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