Green Bond Issuance by Firms, External Monitoring, and Probability of Default: An Empirical Research Based on Green Policies

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Green Bond Issuance by Firms, External Monitoring, and Probability of Default: An Empirical Research Based on Green Policies*

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Abstract

Utilizing a staggered Difference-in-Differences (DID) approach, we investigate the impact of green bond issuance on the probability of default among Chinese firms from 2016 to 2022. We find that issuing a green bond significantly reduces the firm's default probability, highlighting the joint advantage of financial stability and environmental sustainability. The effect is particularly strong for firms that lack strong external monitoring by financial analysts and media, for high-polluting firms, and for firms facing a high level of competition. Our results also suggest that the transmission from green bond issuance to improved financial resiliency works both through alleviating financial constraints and through increasing stock liquidity.

JEL classifications: G14, G32, G33
Keywords: green bond issuance, default probability, analyst and media coverage, financial constraints, stock liquidity

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1 Introduction

The importance of environmental factors has been recognized by the business community, policymakers, and the general public (Brooks & Schopohl, 2020; Flammer, 2021; Krueger et al., 2020). Consequently, corporations are increasingly incentivized to issue so-called green bonds to finance environmental projects, such as renewable energy initiatives, energy efficiency improvements, waste reduction, and pollution control. By issuing such green bonds, companies can not only secure the necessary capital for eco-friendly projects but also enhance their reputation as environmentally responsible entities (Sangiorgi & Schopohl, 2023). This, in turn, can attract a broader base of environmentally conscious investors and customers, fostering long-term financial and environmental benefits.[1]

Given this intricate relation between financial and environmental incentives facing firms and their investors, it is sometimes difficult to isolate the causal impact of green bond issuance on the financial resilience of the firms that issue them. In this paper, we take on this problem by relying on the specific institutional framework that recently emerged in China. Unlike in other countries, the issuance of green bonds by Chinese firms is significantly influenced by the official green policies (L. Lin & Hong, 2022; S. Liu et al., 2022). These policies are arguably exogenous from the point of view of individual firms and can therefore serve as a basis for a quasi-natural experiment exploited in this paper.

We employ a staggered Difference-in-Differences (DID) approach to examine the effect of green bond issuance on the probability of default among Chinese firms over the period from 2016 to 2022. By focusing on this timeframe, we capture the initial impact of the Chinese government's

[1] See also Bhutta et al. (2022), Z. Cheng & Wu (2024), Gianfrate & Peri (2019), or T. Wang et al. (2022).

"Guidelines on the Issuance of Green Bonds" issued at the end of 2015, as well as subsequent green policies aimed at encouraging corporate green financing. As discussed in more detail in the next section, Chinese companies issuing green bonds must follow these policies as well as comply with stringent disclosure requirements.

The staggered DID setting allows us to accommodate variations in the timing of green bond issuance across different firms, thereby allowing for a more precise estimation of the treatment effects. We can therefore better account for unobserved heterogeneity and potential confounding factors that could bias the results, providing a clearer understanding of how issuing green bonds influences firms' financial health and stability over time.

Our framework allows us both to identify the overall impact of green bond issuance on firms' default probability and to examine potential transmission channels driving this headline result.[2] First, we show that green bond issuance decreases the probability of default. By issuing green bonds, the probability of default for firms decreases by 0.19 percentage points. This finding suggests that the benefits of green bond issuance extend beyond environmental impact, providing a dual advantage of financial health and sustainability. Second, we identify two transmission channels that drive our main result. The green bonds seem to lower the firms' default probability both by reducing the financial constraints they are facing and by increasing their stock liquidity.

While green bonds generally help to lower their default risk, this benefit is less pronounced for firms under intense external scrutiny. In particular, the positive effect of green bond issuance on reducing the probability of default is diminished when firms are closely followed by analysts and receive extensive media coverage. At the same time, we show that the reduction in default

[2] Appendix I reports the research framework of this paper.

probability due to green bond issuance is particularly pronounced among high-polluting firms and firms operating in highly competitive industries.

Our paper is related to four distinct strands of literature. First, the paper strives to better understand both the impact of green finance on firms' financial stability and the potential transmission channels driving this relationship. Previous studies on green finance have mostly focused on the cost advantages of green bond financing (Gianfrate & Peri, 2019; Tang & Zhang, 2020; T. Wang et al., 2022) and the green premium in developed countries (Caramichael & Rapp, 2024; MacAskill et al., 2021; Nanayakkara & Colombage, 2019). We focus on the impact of green bonds on default probability in China, which is one of the two largest markets for green bonds in the world. Moreover, the unique institutional and policy framework in China allows us to use an identification strategy based on the implementation of top-down governmental policies that are exogenous from the point of view of firms issuing green bonds.

Second, our paper contributes to the corporate governance literature by examining the role of analyst and media coverage as external monitors in the context of green finance. Green bond issuance often serves not only as a financing tool but also as a signal of either environmental responsibility (Dutordoir et al., 2024; Flammer, 2021) or greenwashing tactic (Shi et al., 2023; Tuhkanen & Vulturius, 2022; Xu et al., 2022). By analyzing the effects of external monitoring through analyst and media coverage, our paper contributes to the discussion on the "greenwashing controversy" within the context of green finance. In particular, our results suggest that i) firms lacking sufficient analysts and media coverage can disproportionately benefit from the additional signal provided by green bond issuance, and ii) high levels of external scrutiny can help to alleviate the risk of greenwashing.

Third, we contribute to the existing research on the factors influencing the probability of corporate defaults. We know that sound financial conditions reduce default likelihood, with higher solvency (Molina, 2005), operating capacity (Altman, 1968), and profitability (Campbell & Dietrich, 1983) being associated with lower default probabilities. Additionally, robust corporate governance structures mitigate default risk, evidenced by more dispersed ownership structures (Zeitun & Gang Tian, 2007) and higher institutional shareholding (Chiang et al., 2015). Firms' behavioral decisions, such as fulfilling social responsibilities, establishing social networks (W. Sun & Cui, 2014), investing in R&D, and allocating financial assets (Hsu et al., 2015), also impact default probability. However, there is a certain gap in the literature regarding the influence of firms' green policies on their default probability.

Fourth, our findings offer important guidance for corporate management on green financing strategies. Firms lacking sufficient levels of analyst and media coverage, firms involved in high-polluting activities, and firms facing intense competitive pressures in their respective industries would benefit from issuing green bonds. On the other hand, firms already exposed to high levels of analyst and media scrutiny should be aware of potential risks when relying on green bonds without the corresponding environmental efforts (greenwashing).

The rest of the paper is structured as follows. Section 2 outlines the institutional background in China that motivates our identification strategy. Section 3 develops our hypotheses in the context of existing literature. Section 4 introduces our research design and data. The empirical results are presented in Section 5, and we offer our conclusions in Section 6.

2 Institutional background

The longstanding development model of Chinese firms, characterized by high consumption and pollution, has arguably contributed to extreme weather and environmental degradation, severely hindering sustainable economic growth (T. Li et al., 2016; Y. Sun et al., 2021). Balancing economic development with environmental protection has therefore become crucial for both the Chinese government and enterprises, with green bonds playing a vital role in facilitating the green transformation of the economy (Z. Cheng & Wu, 2024).

The green bond market in China is to a significant extent shaped by official governmental policies and regulations whose timing and stringency are exogenous from the point of view of individual firms. At the end of 2015, the People's Bank of China (PBOC, the Chinese central bank) and China's National Development and Reform Commission (NDRC) issued guidelines for issuing green bonds. These guidelines specified that green bonds could be used for projects such as energy-saving and emission-reduction technological transformation, green urbanization, and other green and low-carbon development initiatives. This includes support for energy-saving technology transformation and 12 other major projects. Various government agencies as well as Shanghai and Shenzen stock exchanges have consequently published additional guidelines managing the green bond market (see Appendix II for more detail).

Following the guidelines of PBOC and NDRC, Chinese companies started to issue green bonds in 2016. There is thus a clear policy intervention establishing a green bond market for Chinese companies that can be used as a basis for a staggered DID approach introduced in Subsection 4.1. Besides the existence of a unique institutional framework allowing for a cleaner causal analysis, the top-down approach to green bond issuance in China has two other implications relevant to our empirical analysis.

First, the issuers of green bonds can often gain easier access to preferential policies such as discounts and subsidies (S. Liu et al., 2022). For instance, the General Office of the State Council issued a circular in 2021, advocating for financial reform and innovation in regions like Beijing, Shanghai, Jiangsu, Zhejiang, and Shandong. This included supporting qualified enterprises to issue innovative financial products, such as green corporate credit bonds. Such preferential government measures further reduce financing costs for firms issuing green bonds, thus reinforcing the original financing effect of selling corporate bonds to investors.

Second, the official guidelines and policies often link green bond issuance with mandatory and comprehensive information disclosure. For instance, in 2022, the Shanghai Stock Exchange (SSE) enhanced regulations on green bonds through the "Notice on Doing a Good Job in Disclosing Information on Green Corporate Bonds in 2022." This notice requires issuers with environmental information disclosure obligations to publish annual environmental information on the Institute's website and to provide temporary disclosures if material environmental matters affect their solvency. The mandatory disclosure of additional internal information can arguably help in alleviating information asymmetries between the issuers of green bonds and their investors. Such reductions in firm-investor information asymmetries usually lead to better financing terms for firms with positive ramifications for their financial resilience.

Besides these institutional characteristics, there are also reasons of practical relevance for exploring the impact of green bond issuance on default probability in the specific context of Chinese firms. Firstly, China is one of the largest markets in the world for issuing green bonds. According to the Climate Bonds Initiative and CCDC Research (2022), by the end of 2021, China's cumulative green bond issuance was $199.2 billion (approximately RMB 1.3 trillion), ranking second globally behind the United States.[3] China also initiates most of the world's green bonds, accounting for more than one-third of global issuance. According to the Wind database, 626 green bonds were issued in 2021, totaling RMB 602.5 billion (approximately $93.4 billion). Secondly, defaults in China's bond market have recently become increasingly common. In 2022, the total default amount reached RMB 290.221 billion (approximately $43.124 billion), a year-on-year increase of 3.19% (Cai, 2022). The bond rollover scale also surged by 134.42% year-on-year, reaching a record high.

3 Literature review and hypotheses development

3.1 The impact of firms' green bond issuance on their default probability

One way to understand the relationship between green bond issuance and corporate default probability is to examine their connection through the lenses of the signaling theory (Spence, 1973). By issuing green bonds, enterprises secure funding for environmentally friendly projects, reflecting the enterprises' commitment to social responsibility. A firm's green behavior thus sends positive signals to investors, enhancing its reputation. A strong green reputation as one aspect of corporate social responsibility can then boost the firms' competitiveness, attract investor favor and ultimately help companies to secure additional funding at lower costs, thus lowering their default probability (see also Do, 2022).

Moreover, the issuers of green bonds in our sample are required to disclose additional information as mandated by Chinese green bond policies discussed in the previous section, leading to reduced information asymmetry compared to firms that do not issue green bonds. This

[3] Link: https://www.climatebonds.net/files/reports/cbi_china_sotm_2021_0.pdf.

transparency enables investors to gain a more thorough understanding of the company's operations, lowering the perceived risk and the corresponding risk premium, thereby facilitating bond transactions and easing financial constraints. The increased disclosure of information can also mitigate the risk of opportunistic behavior by managers, further strengthening the financial resilience of the firms issuing green bonds.

Finally, compared to other financing instruments, the financing costs of firms issuing green bonds are lower, which makes it more likely to reduce corporate default probability. Compared to indirect financing methods like bank loans, green bonds, as direct financing instruments, eliminate the need for financial institutions as intermediaries, offer lower financing costs, and can be held over the long term. Although corporate issuance of green bonds can potentially result in green premiums (defined as a lower yield for green bonds compared to conventional bonds) (Kapraun & Scheins, 2019; MacAskill et al., 2021; Partridge & Medda, 2020; Zerbib, 2019), the low financing costs of issuing green bonds can be considered the main driver for corporate issuance of green bonds. In our context, 77% of green bonds in China's primary market had lower issuance costs in 2021 compared to similar ordinary bonds (issued by the same issuer in the same quarter, excluding the maturity premium factor), according to China Central Depository & Clearing Co., Ltd. (CCDC). The green bonds have enjoyed increased trading activity and price advantages also in the secondary market. Since September 2021, market participants have demonstrated a growing preference for green bonds, as evidenced by their higher trading prices compared to ordinary bonds. This increased demand allows enterprises to lower their financing costs by issuing green bonds at more favorable rates. Reduced financing costs mean that firms have more cash to invest in their ongoing operations and repay debt. This helps to improve a firm's liquidity position and makes it easier to fulfill short-term debt obligations, thereby reducing their probability of default.

Based on all the factors discussed above, we propose the following main hypothesis of our study:

> ***Hypothesis 1****: Enterprises issuing green bonds have a lower probability of default compared to those that do not issue green bonds.*

3.2 Transmission mechanisms: Financial constraints and Stock liquidity

Financial constraints significantly impact firms' ability to invest, expand, or undertake other value-enhancing activities (Almeida & Campello, 2007; D. Li, 2011). These constraints can stem from several sources, including instability in financial markets, a decline in credit ratings, or lending difficulties due to the limited availability of funds (Campello et al., 2010). Financial instability can disrupt access to capital, while lower credit ratings increase borrowing costs and limit funding options (Haubrich, 2020). Additionally, insufficient fund supply from financial institutions can restrict firms' growth opportunities, hampering their overall economic performance (Behr et al., 2013).

The issuance of green bonds can alleviate financial constraints, ultimately leading to a decreased probability of corporate default. Companies following green policies often enjoy a good social image, strong market reputation, high credit ratings, and easier access to capital (Flammer, 2013). Furthermore, Caggese and Cuñat (2013) found that financial constraints are negatively correlated with the total factor productivity of enterprises; reducing these constraints thus increases enterprise productivity, which in turn boosts profits and further reduces the likelihood of corporate default in a virtuous cycle.

The transmission mechanism operating via green bonds reducing financial constraints could be particularly strong in China, especially when compared with more developed economies. The financial landscape in China is still characterized by the predominant reliance on bank credit as the primary source of financing, coupled with the slower development of the bond market (Fan et al., 2015; Firth et al., 2009). Financial constraints thus arguably exert a heightened influence on the probability of default among Chinese firms, contrasting with the dynamics observed in other nations where financing options are more diversified and robust.

At the same time, green bond issuers in China benefit from more favorable government policies compared to ordinary bond issuers. This enhances issuance efficiency (Saravade et al., 2023), allowing companies to expedite the bond issuance process and thereby ease financial constraints. Green bonds, as a form of direct financing, have also lower financing costs than indirect methods such as bank loans (B. Lin & Su, 2022). With increasing support for green financial policies, the cost advantage of green bonds is expected to grow. For instance, the "16 Fresh Green Bond" issued by A-share listed company Beijing Fresh Environmental Technology Co., Ltd. has a coupon rate of 3.70%, nearly 70% lower than that of ordinary corporate bonds issued during the same period. Furthermore, market investors hold positive expectations for companies issuing green bonds (Tang & Zhang, 2020).

Considering the above arguments, we formulate our second hypothesis as follows:

> ***Hypothesis 2****: The alleviation of financial constraints serves as a transmission mechanism linking green bonds to default probability. Issuing green bonds reduces these constraints, which subsequently lowers the probability of default.*

Stock liquidity can serve as another transmission channel connecting green bond issuance to the reduced default probability. If a listed company has high stock liquidity, it indicates that its stock is actively traded (Fang et al., 2009). Active stock trading enhances the company's visibility in the capital market, attracting additional capital (Bushee & Miller, 2012), which can lower the probability of corporate debt defaults through improved capital market financing.

As for the link connecting green bond issuance with stock liquidity, Tang and Zhang (2020) find that companies issuing green bonds can improve their stock liquidity. According to signaling theory, the successful issuance of green bonds represents a positive signal, prompting favorable feedback from the capital market (Flammer, 2013). For instance, the stock market may adjust its expectations for the company's potential, leading to higher trading volumes and improved stock liquidity. This "reputation spillover" effect from issuing green bonds can boost stock liquidity and investment efficiency, thereby increasing total factor productivity.

The above arguments lead to our third hypothesis:

> ***Hypothesis 3****: Stock liquidity serves as a transmission mechanism from green bonds to default probability. Companies issuing green bonds enhance their stock liquidity, which in turn reduces their default probability.*

3.3 Impact of the green bonds under external scrutiny

The impact of green bonds on reducing default risk can be affected by the level of external scrutiny due to the nuanced interplay between green financing, corporate transparency, and market perceptions. Both financial analysts and media coverage tend to highlight the strengths and weaknesses of a company's operations, governance, and financial health. They can therefore influence investors' perceptions and consequently alter the ultimate impact of green bond issuance on a firm's default probability. A heightened visibility also pressures firms to meet more rigorous standards and continually justify their green financing strategies to a potentially skeptical audience, introducing additional challenges in managing public perceptions and maintaining a favorable market position.

Financial analysts are crucial observers and evaluators of companies in the capital market. Acting as an information intermediary between investors and companies, analysts gather data from both internal and external sources to provide earnings forecasts and other valuable information to the market (J. Sun, 2009; To et al., 2018). Higher analyst coverage thus strengthens the external monitoring of the company (Irani & Oesch, 2013; Lang et al., 2004; Yu, 2008).

In China, companies seeking to issue green bonds must disclose additional internal information to comply with policy requirements, resulting in heightened scrutiny from capital market investors (Tang & Zhang, 2020). This increased scrutiny attracts the attention of analysts with specialized backgrounds. Consequently, the requirement for firms to disclose more operational information is a double-edged sword; while it helps reduce information asymmetry between firms and external investors (Armstrong et al., 2011; Roulstone, 2003; Zhang et al., 2021), it also provides analysts with greater opportunities to interpret the internal information of firms (Kelly & Ljungqvist, 2012). This can negatively impact firms with "adverse incentives" for issuing green bonds (Wei, 2023).

According to a study by Shi et al. (2023) on China's green bond market, firms, especially high-polluting ones, often use green bond issuance for "greenwashing" due to the high costs of innovation and regulatory pressures from the government. These firms misrepresent their investments in green activities using funds raised from green bonds. Tuhkanen & Vulturius (2022) find that there is often a disconnect between issuers' climate goals and their green bond frameworks, with deficiencies in companies' post-issuance green bond reporting. Xu et al. (2022) also highlight the risk of "greenwashing" in China's green bond market, leading to high credit spreads.

When analysts identify such greenwashing behavior and convey these concerns to market investors, it can cause investors to doubt the companies' financing motives and their commitment to social responsibility. Ghitti et al. (2023) explore the importance of these issues in the related context of formal certification via so-called Second Party Opinions. Consequently, an increased analyst coverage in China's green bond market can weaken the positive signals emanating from green bond issuance and thus weaken the link between green bonds and the financial resilience of the issuing firms.

Considering the above points, we establish our fourth hypothesis:

> ***Hypothesis 4***: *The capacity of green bond issuance to decrease the default probability of the issuing firms is stronger [weaker] for firms with low [high] levels of analysts' coverage.*

With the advancement of new media technology in recent years, media coverage has become another crucial tool for stakeholders to understand and monitor the operating conditions of enterprises. Dyck et al. (2010) argue that the media can influence and regulate the behavior of business operators through information exposure and other means, ultimately impacting business operational efficiency.

While issuing green bonds can effectively signal a company's commitment to green transformation and high-quality development, increased media coverage can dilute this positive effect, particularly in China's financial market. Since Chinese companies began issuing green bonds in 2016 under new green policies, the market is still emerging, and the legal framework remains incomplete. This lack of familiarity can lead to illegal or unethical behaviors, such as greenwashing (Shi et al., 2023; Tuhkanen & Vulturius, 2022; Xu et al., 2022). Media exposure of these actions brings controversy and public scrutiny, damaging the companies' green reputation and reducing their chances of securing investor funds, thereby weakening the beneficial impact of green bond issuance on lowering default probability.

Moreover, media reports on corporate green bond issuance, particularly from state-owned media organizations might evoke negative perceptions. In China, the public tends to view official media coverage of government-guided corporate behavior as biased and serving governmental propaganda purposes (e.g., green propaganda), often dismissing it as "Political Propaganda Articles" (C. Y. Wang, 2024). Consequently, increased media coverage could undermine the positive signals sent by companies issuing green bonds, thereby weakening the impact of green bond issuance on reducing corporate default probability.

With the above arguments in mind, we set our fifth hypothesis:

> ***Hypothesis 5****: The capacity of green bond issuance to decrease the default probability of the issuing firms is stronger [weaker] for firms with low [high] levels of media coverage.*

3.4 Heterogeneous firms: The role of pollution and competition

Finally, firm heterogeneity might play an important role in understanding the relationship between green finance and the financial resilience of the firms. In particular, the transmission process from the green bond issuance to a lower default probability might operate differently for high-polluting firms as well as for firms facing intense competition.

The unchecked growth of high-polluting companies is considered a major challenge to China's environmental controls (Zhu et al., 2015). The government therefore imposes strict financial regulations and resource allocation policies to limit the financing of these companies, encouraging them to undergo green transformation (Dong et al., 2021; Shi et al., 2023; Xiao & Wang, 2020). Consequently, high-polluting companies face significant constraints in traditional financing channels such as bank loans and commercial credit (Xiao & Wang, 2020). High-polluting firms might thus disproportionately benefit from issuing green bonds, as they improve their reputation and reduce perceived risk, ultimately securing more favorable financing terms.

Based on these arguments, we develop our sixth hypothesis:

> ***Hypothesis 6****: High-polluting [low-polluting] firms experience a stronger [weaker] decrease in default probability when they issue green bonds.*

Firms facing more intense competition might also disproportionately benefit from green bond issuance. In highly competitive industries, green bond issuance can serve as a strategic tool for differentiation, attracting environmentally conscious investors and customers, thereby improving the financial position of the issuing firms. For instance, Kemper et al. (2013) find that strong social responsibility performance helps firms stand out, gain a competitive edge, and improve financial performance. As a relatively new financing tool, green bonds can be especially helpful for firms that need to differentiate themselves from their competitors.

Intense competition also compels corporate management to strengthen internal controls and address stakeholders' needs to reduce information asymmetry (Cui et al., 2018). Firms facing intense competition should therefore particularly benefit from the strict disclosure requirements imposed by the official government policies on firms issuing green bonds in China. This additional disclosure can further strengthen the role of green bonds as a tool for differentiation from the firm's competitors.

We thus state our last hypothesis as follows:

> ***Hypothesis*** *7: Firms facing a high [low] level of competition experience a stronger [weaker] decrease in default probability when they issue green bonds.*

4 Research design and data

4.1 Econometric model

We employ a standard staggered difference-in-differences specification to analyze the impact of green bond issuance on the probability of default. This model is particularly suitable for our study because Chinese companies began issuing green bonds in 2016 following the introduction of new state policies.

Our model takes the following form:

$$EDP_{i,t} = \alpha + \beta Green_i \cdot Post_{i,t} + \gamma Control_{i,t} + Firm_i + Time_t + \varepsilon_{i,t} \quad (1)$$

In the above specification, *EDP* represents the corporate default probability, with higher values indicating a greater likelihood of default. The main explanatory variable is the interaction term *Green*Post*. *Green* is a binary indicator that equals one if a firm has publicly issued green bonds (at any time during our sample period). Such firms are categorized into the treated group. Firms that have not issued any green bonds fall into the control group. *Post* is a binary indicator that equals one from the year a firm issues a green bond onwards and zero if a firm has not yet issued a green bond at time *t*. *Control* represents firm-level characteristics used in the regression, while *Firm* and *Time* indicate firm- and year-fixed effects. Finally, ε denotes the error term. In all regressions, we cluster at the firm level to account for within-firm correlation and ensure robust standard errors. This approach is necessary because some firms may issue green bonds multiple times, introducing potential correlations.

As in Beck et al. (2010), the model uses only the interaction term *Green*Post* to avoid the issue of multicollinearity. If our hypothesis is correct, then the coefficient of the interaction term should be negative and statistically significant.

4.2 Sample selection and variable construction

Chinese firms began issuing green bonds in 2016, following the publication of the official governmental guidelines in late 2015. In this study, we analyze Chinese A-share listed companies from 2016 to 2022, applying several selection criteria to refine our sample. We exclude banks, insurance companies, and other financial institutions. Since non-financial enterprises issuing green bonds are primarily concentrated in five industries — 'manufacturing', 'electric power, heat, gas and water production and supply', 'water conservancy, environment and public facilities management', 'construction', and 'mining' — we focus on listed companies within these sectors to ensure accurate matching between the treatment and control groups. Additionally, we exclude firms that have been listed for less than three years, ST or ST* companies,[4] and firms that issued green bonds for the first time after 2022.

All data for the variables in this study are sourced from the CSMAR database, except for media coverage data, which is obtained from the CNRDS database. The study includes data from 2,696 A-share listed companies from 2016 to 2022, totaling 13,103 observations. Among these, 74 companies issued green bonds, accounting for 204 observations (used as the treatment group), while 2,622 companies did not issue green bonds, comprising 12,899 observations (used as the control group). We winsorize all continuous variables at the 1st and 99th percentile to mitigate the impact of outliers. We present more details regarding our variables in Table 1.

[Insert Table 1 about here]

[4] The reason for excluding ST (special treatment) and ST* samples is that such companies have abnormal financial conditions and including them could affect the accuracy of the results. ST* indicates that the company is at risk of delisting.

4.2.1 Dependent variable: corporate default probability

Our primary dependent variable is the corporate default probability. To construct this variable, we use the methodology outlined by Bharath and Shumway (2008) to create a simplified expected default probability (*EDP*). Their analysis is based on option pricing theory, which posits that a firm's equity can be viewed as a call option on the firm's potential value, while the book value of the firm's debt acts as the strike price of the option. When the strike price exceeds the asset value, the debt is forfeited, indicating a default. Following the procedure outlined below, we obtain EDP values that closely match those reported by other scholars using Chinese data (T. Liu et al., 2023; Nie et al., 2023; Zhitao & Xiang, 2023).

To provide clarity, we briefly outline the method used by Bharath and Shumway (2008) to construct the EDP measure.

First, suppose that the market value of a firm's debt (V_D) is equal to its book value (*D*):

$$V_D = D. \tag{2}$$

The point of default is the point at which short-term debt (*SD*) plus one-half of long-term debt (*LD*), i.e., the book value of the debt, is equal to the sum of all of a firm's short-term debt and times 0.5 times its long-term debt:

$$D = SD + 0.5 \times LD. \tag{3}$$

Since a firm's debt risk is highly correlated with its equity risk, the firm's debt volatility (σ_D) can be approximated by the firm's equity volatility (σ_E), where 5 % is the structural volatility of the firm's debt and 25 % is the volatility associated with default probability:

$$\sigma_D = 0.05 + 0.25 \times \sigma_E. \tag{4}$$

Combining equations (2) and (4) gives and approximate estimate of total firm value volatility (σ_V):

$$\sigma_V = \frac{\sigma_E \times V_E}{V_E + V_D} + \frac{\sigma_D \times V_D}{V_E + V_D} = \frac{\sigma_E \times V_E}{V_E + D} + \frac{(0.05 + 0.25 \times \sigma_E) \times D}{V_E + D}. \tag{5}$$

Now, assume that the expected rate of return on the firm's assets (μ) is equal to the firm's stock return for the previous year ($Return_{i,t-1}$):

$$\mu = Return_{i,t-1}. \tag{6}$$

Further, based on the formula for the default distance in Merton's (1974) DD model, a simplified default distance (*naïveDD*) can be obtained as follows:

$$naïveDD = \frac{[ln(V_E+D)-ln(D)]+\left(Return_{i,t-i}-0.5\times\sigma_V^2\right)\times T}{\sigma_V\times\sqrt{T}}. \tag{7}$$

In the above calculation, following standard practice, the expiry time T of the option is set to 1 year, i.e., $T=1$.

Finally, a cumulative standard normal distribution is applied to the results of the calculation of the default distance (Eq. 7) to obtain the EDP:

$$EDP = \pi_{naïve} = N(-naïveDD). \tag{8}$$

The value of EDP is in the range of [0, 1] and follows a normal distribution. The larger its value, the higher the default probability.

4.2.2 Main explanatory variable: green bond issuance by firms

Since the duration of enterprises affected by bond issuance behavior is usually maintained from the bond issuance date to the bond maturity date, the setting of explanatory variables in this study is based on the approach of Flammer (2021), which constructs a multi-temporal dummy variable for firms' issuance of green bonds as the core explanatory variable, i.e., '$Green_i \cdot Post_{it}$', where '$Green_i$' is the dummy variable for whether firms issue green bonds, '$Post_{it}$' is the time dummy variable ; the method of assigning values is strictly by the staggered DID model's approach to the setting of the core explanatory variable; a detailed explanation is provided in 4.1.

4.2.3 Mediating variables: financial constraints and stock liquidity

Our Hypothesis 2 and Hypothesis 3 explore the potential transmission mechanisms behind our main result. To test these hypotheses, we rely on two variables that could mediate the transmission from the original issuance of green bonds to the ultimate decrease in the corporate default probability.

The first variable we incorporate into our mediation models is financial constraints. There is no universally accepted standard for measuring financial constraints, but a commonly used approach involves constructing a financial constraint index based on multiple indicators. This entails selecting various financial indicators of enterprises and creating an index using methods such as multivariate discriminant analysis, ordered logistic model construction, and Fisher's discriminant function. Examples of such indices include the KZ index (Kaplan & Zingales, 1997), the WW index (Whited & Wu, 2006), and the SA index (Hadlock & Pierce, 2010). The SA index's applicability is limited because companies issuing green bonds cannot directly influence their size and age. This study therefore utilizes the KZ index to measure financial constraints. The KZ index used in this study is primarily sourced from the CSMAR database, specifically focusing on the business distress of listed companies in China.

To calculate the KZ index, we require the following accounting variables: the net cash flow from operations divided by total assets at the beginning of the year $\left(\frac{Cf_{it}}{Asset_{i,t-1}}\right)$, cash dividends divided by total assets at the beginning of the year $\left(\frac{Div_{it}}{Asset_{i,t-1}}\right)$, cash holdings divided by total assets at the beginning of the year, $\left(\frac{Cash_{i,t}}{Asset_{i,t-1}}\right)$, gearing (Lev_{it}), and Tobin's Q $\left(Q_{i,t}\right)$. KZ_1 takes value one if the value of $\left(\frac{Cf_{it}}{Asset_{i,t-1}}\right)$ is below the media (zero otherwise); KZ_2 takes value one if $\frac{Div_{it}}{Asset_{i,t-1}}$ is below median (zero otherwise); KZ_3 takes value one if $\frac{Cash_{i,t}}{Asset_{i,t-1}}$ is below median (zero otherwise); KZ_4 takes value one if Lev_{it} is above median (zero otherwise); KZ_5 takes value one if $Q_{i,t}$ is above the median (zero otherwise). Then, the final KZ index equals the sum of the aforesaid five components. The next step that follows is to estimate the regression coefficients of the above five components. We estimate those using an Ordered Logistic Regression (OLR) for the following model: $KZ_{i,t} = \alpha_1 \frac{Cf_{i,t}}{Asset_{i,t-1}} + \alpha_2 \frac{Div_{i,t}}{Asset_{i,t-1}} + \alpha_3 \frac{Cash_{i,t}}{Asset_{i,t-1}} + \alpha_4 Lev_{i,t} + \alpha_5 Q_{i,t}$. Using the estimation results from the aforementioned regression model, the KZ index for each listed company is calculated annually to assess the extent of financial constraints. A higher KZ index indicates greater financial constraints faced by the company.

The second mediating variable is stock liquidity, which represents the ability of an asset to be quickly bought or sold in the market at a price reflecting its intrinsic value. This liquidity significantly influences the share price and investors' perception of a firm's value, which in turn affects the firm's access to investment capital and its probability of default. In this study, we use the approach developed by Pastor and Stambaugh (2003) to measure stock liquidity through the PS indicator, with data for this indicator obtained directly from the CSMAR database.[5]

4.2.4 Moderating variables: analysts and media coverage

Our Hypothesis 4 and Hypothesis 5 argue that the effect of green bond issuance on the corporate default probability can be weakened in the presence of intense external scrutiny. To test these hypotheses, we rely on two variables capturing such moderating effect.

[5] Other common metrics for quantifying stock liquidity include the turnover ratio, Amihud indicator, Roll indicator, and Zeros indicator.

The first moderating variable that we use is analyst coverage. When a team of analysts issues a profit forecast or other judgment on a company, it signifies that the company is under the team's scrutiny. There are two main types of research in the field of analysts' forecasts. The first type focuses on the standard deviation of analysts' expectations, where the variance indicates the level of uncertainty in analysts' predictions for the firm. The second type involves the number of analysts' attention, commonly used to quantify analyst coverage. The degree of analyst attention to a company helps determine how effectively the company is signaling to the market and how well investors understand the company's situation. In this study, we adopt the method of Hilary & Hsu (2013) to measure analyst coverage by the number of analysts monitoring a firm. Specifically, the variable is quantified by adding one to the number of analysts (or analyst teams) and then taking the logarithm. If a team of analysts follows the firm, it is recorded as 1, regardless of the number of team members.

The second moderating variable is media coverage. We consider this variable based on the premise that greater internal information disclosure by a firm increases the likelihood of receiving media attention (Aman & Moriyasu, 2022; Zyglidopoulos et al., 2012). Media coverage intensity is measured by the annual number of newspaper articles mentioning the firm's name, stock name, ticker symbol, or name abbreviation (Zyglidopoulos et al., 2012). A higher number of news stories indicates more media attention. Following He et al. (2024) and Ren et al. (2023), this study uses the total number of news stories featuring the companies in the headlines of financial news as a quantitative indicator and adds one to this total before taking the logarithm in the empirical process.

Finally, we utilize standard control variables that prior research has shown to be associated with the probability of default.

4.2.5 Descriptive statistics for variables

Detailed descriptive statistics for these variables can be found in Table 2. According to the statistical results, there are 13,103 observations in the total sample; among them, there are 204 observations in the treatment group (issuing green bonds) and 12,899 observations in the control group (not issuing green bonds), which is an imbalance between the two groups (the ratio between the two groups is 1.58%). We utilize propensity score matching to effectively mitigate the imbalance between the treatment and control group samples.

[Insert Table 2 about here]

Further, table 3 exhibits the results of the Pearson correlation test for each variable. The results of the correlation coefficient matrix indicate that there is no serious correlation problem with the variables in this study. Besides, without controlling for other factors, green bond issuance is negatively correlated with the probability of default, as expected.

[Insert Table 3 about here]

4.3 PSM method

Green bond issuance is essentially a non-randomized experiment; therefore, the DID method used for policy effects estimation inevitably suffers from self-selection bias. The Propensity Score Matching (PSM) method can match each treatment group sample to a specific control group sample, making the quasi-natural experiment approximately randomized. Due to the complexity of the data dimensions of the staggered DID model we used, which considers green bond issuance and non-issuance in different time dimensions, we adopt a kernel matching approach to match propensity scores for the samples in this study's treatment and control groups. Specifically, we select control variables as matching variables for matching. We use a logit approach to estimate propensity scores, matching the treatment group to the control group for propensity scores using a bandwidth of 0.06 for kernel matching.

Figure 1 shows the results of the PSM using kernel matching. Compared to before matching, the differences in the covariates are significantly decreased, and there is no significant difference in the mean values of the matched variables between the treatment and control groups after matching. The absolute values of the standard deviations of the matched variables are less than 10%. The data characteristics converge and satisfy the comparability requirement. The matched data are used for the PSM-DID analysis in this study, using 9,538 observations after matching.

[Insert Figure 1 about here]

5 Empirical results and analysis

5.1 Results of the main effect

We present the main results of this study in Table 4, where columns (1) and (2) show the results before propensity score matching, without and with the inclusion of control variables, respectively, and column (3) shows the results after PSM. The regression results before and after PSM exhibit similar coefficient directions and significance. The interaction term *Green*Post* has a negative and statistically significant coefficient at the 5% level. This suggests that after issuing green bonds, a firm's probability of default decreases by 0.19 percentage points (after PSM), indicating that the issuance of green bonds by Chinese-listed firms significantly reduces the corporate default probability. Hypothesis 1 is verified.

Among the control variables, the coefficients for size, age, and Tobin's Q are positive and statistically significant. This indicates that larger and older firms, as well as firms with higher value, are associated with an increased probability of default.

The results we obtain might seem counterintuitive at first sight. Larger and older firms are generally less likely to default due to several key factors (Frank & Goyal, 2008). These firms often possess greater financial stability through diversified revenue streams, substantial cash reserves, and better access to capital markets. Their established market presence, longstanding customer and supplier relationships, and experienced management teams provide resilience against economic fluctuations. Additionally, their reputation and creditworthiness enable more favorable financing terms. Economies of scale also afford cost efficiencies, enhancing profitability and buffering against financial distress.

However, the above is not the only mechanism that can explain the relationship between size and the probability of default. Alfaro et al. (2019) find that firms in emerging economies tend to be more financially vulnerable. In addition, our results align with the findings of Meng et al. (2023) and Zhitao and Xiang (2023), who also study the determinants of default probability. Our sample comprises Chinese firms from selected industries, many of which are large state-owned enterprises (SOEs) with significant levels of debt. This may explain our results, as SOEs often suffer from inefficiencies and mismanagement, leading to poor financial performance and higher default risk. Additionally, these firms face regulatory challenges and may engage in riskier behavior due to expected government bailouts, leading to moral hazard.

Regarding the result we find for Tobin's Q, one reason why firms with higher Tobin's Q have a higher probability of default is their tendency to engage in risky projects or aggressive growth strategies, often financed by substantial debt. Additionally, these firms face significant pressure to meet or exceed market expectations. If they fail to do so, it can result in a loss of investor confidence, a decline in stock price, and difficulties in refinancing their debt. Conversely, the coefficient for *Lncash* is significantly negative at the 10% level, suggesting that a higher amount of cash held by the firm reduces the probability of default.

Additionally, in the corporate governance dimension, the coefficient for *Bordsize* is significantly positive at the 5% level, indicating that a larger board of directors correlates with a higher probability of default. This could be because larger boards may introduce inefficiencies, communication barriers, and potential conflicts, all of which could increase the probability of default (S. Cheng, 2008; Jensen, 1986; Yermack, 1996). However, the coefficient for the proportion of shares held by the largest shareholder is insignificant, suggesting that equity concentration does not have a significant correlation with default probability.

[Insert Table 4 about here]

5.2 Robustness tests

5.2.1 Parallel trends test

The staggered DID model requires the parallel trends assumption to be met, meaning that the treatment and control groups must exhibit parallel trends prior to the implementation of the policy. This study follows the methodologies of Beck et al. (2010), Ren et al. (2024), and Zhang et al. (2024) to test for parallel trends within the sample. The model constructed for this purpose is as follows.

$$EDP_{i,t} = \alpha + \beta_t \sum_{k=x,k\neq x}^{x} \theta_k \cdot Green_i \cdot Post_{i,t} + \gamma Control_{i,t} + Firm_i + Time_t + \varepsilon_{it} \tag{9}$$

Where θ_k denotes a time indicator variable, the subscript k denotes the number of periods relative to the base period. The equation focuses on β_t, which represents the difference between the control and treatment groups before and after the issuance of green bonds. In this study, the year in which the company first issued green bonds is taken as the base year, and "*pre k*" is set as an indicator variable for the k years before companies first issued green bonds, "*current*" (base period) is the year in which companies first issued green bonds, and "*post k*" is an indicator variable for the k years after companies first issued green bonds.

We show the results of the parallel trends assumption in Figure 2. Prior to the issuance of green bonds, there is no significant difference in corporate default probability among firms. However, once firms are subject to green policies and begin issuing green bonds, the impact of the issuance gradually becomes evident. From the year of green bond issuance onward, the probability of corporate default is significantly reduced. These results indicate that, before issuance, the treatment and control groups meet the pre-treatment trend test requirements, confirming that the parallel trend assumption holds. Therefore, the staggered DID approach is appropriate for this study.

[Insert Figure 2 about here]

5.2.2 Placebo test

To mitigate potential bias in the study results caused by unobservable factors, a placebo test is conducted to further validate the effect of green bond issuance. Specifically, the study performs non-repetitive random sampling of all individuals, randomly designating some as the virtual treatment group and the rest as the virtual control group for each sample. The baseline regression model is then applied, and this process is repeated 500 times to create 500 virtual treatment groups.

The estimated coefficients of the dummy variable *Green*Post*, representing the virtual policy, are obtained and plotted to show the kernel density distribution of these estimated coefficients.

As shown in Figure 3, the estimated coefficients of the core explanatory variables *Green*Post* all obey normal distribution with mean zero. The placebo results verify from the counterfactual perspective that green bond issuance does decrease corporate default probability to some extent and is less affected by potentially unobservable factors.

[Insert Figure 3 about here]

5.2.3 Excluding the sample of firms that do not issue bonds

The underlying reason companies choose to issue new bonds, not necessarily green bonds, may be that corporate managers believe such behavior helps reduce their probability of default. Therefore, to further verify that firms issuing green bonds and traditional bonds may have different impacts on firms, we exclude firms in the sample that do not issue bonds. Then, we take the samples of firms that only issue traditional bonds as the control group and the samples of firms with green bond issuance as the treatment group. We observe that there are a total of 231 firms that issue bonds in our sample, of which 74 issue green bonds, compared to 157 firms that issue only traditional bonds. We apply the staggered DID method, consistent with the main regression model, to regress and analyze the data.

Table 5 exhibits the regression results after excluding the sample of firms that do not issue bonds. The coefficient on the core explanatory variable Green*Post is negative and statistically significant at the 5% level, both before and after PSM; this suggests that in contrast to issuing regular bonds, green bond issuance has a significant effect on firms in reducing their probability of default, and our finding is robust.

[Insert Table 5 about here]

5.2.4 The impact of corporate green bond size on default probability

In this study, we focus on whether a company issues green bonds; the issuance of green bonds by a company is a behavior that can send a green signal to the market and thus bring more funding to the company. Someone may wonder whether the size of green bond issuance also has an impact on the default probability of firms; we thus set up an OLS model as follows, which is different from the main effects regression model to analyze whether the size of firms' green bond issuance has an impact on their default probability.

$$EDP_{i,t} = \alpha + \beta G\_Scale_{i,t} + \gamma Control_{i,t} + Firm_i + Time_t + \varepsilon_{i,t} \quad (10)$$

Where G_Scale is a continuous variable indicating the size of green bonds of companies that have issued green bonds; measured by the total amount of money raised by the bond issuer at the time of issuance, and the data is obtained from the CSMAR database. The regression results are shown in Table 6. The coefficient of the core explanatory variable G_Scale is significantly negative at the 5 % level, which proves that the larger the issuance scale of corporate green bonds is, the more it reduces the default probability of firms.

[Insert Table 6 about here]

5.2.5 Tests of alternative dependent variables

In this study, firms' default probability can be considered as a kind of corporate risk arising from firms' over-indebtedness. Therefore, we use the corporate risk coefficient (*RCoefficient*) calculated by combining the O-Score, the Z-Score (*Z*) which measures the financial warning of firms, and the RER model which measures the downside risk of firms as alternative indicators of the dependent variable, default probability (EDP), to test whether our main conclusions still hold.

To calculate our first alternative indicator, the corporate risk coefficient (*RC*), we first need to calculate the OScore; we refer to (Ohlson, 1980) and use the following formula: *OScore = -1.32 - 0.407 × Size + 6.03 × Total liabilities/Total assets + 1.43 × Working capital/Total assets + 0.077 × Current liabilities/ Current assets - 2.37 × Net profit/Total assets - 1.83 × Net operating cash flow/Total liabilities + 0.285 × INTWO - 1.72 × OENEG - 0.521 × CHIN*. Where, regarding *INTWO*, if a company's net profit of the last two years is both negative it is given a value of 1, otherwise it is 0. Concerning *OENEG*, if a firm's total liabilities are greater than its total assets it is assigned a value of 1, otherwise it is 0. Further, the formula for the *CHIN* is $CHIN = (NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$, where *NI* denotes a firm's net income. After calculating the O-Score, we further combine the natural constants to calculate the corporate risk coefficient (*RC*), which is given by the formula: $RC = e^{OScore}/(1 + e^{OScore})$. The greater the *RC*, the greater the risk the company faces, including a high probability of corporate default.

The second alternative indicator on the probability of firm default, Z-Score (*Z*), originates from the early warning model of financial distress constructed by Altman (1968) using multivariate analysis and has been used in some literature to measure firms' default risk (Favara et al., 2017). The specific calculation process of Z score is *Z = 0.012 × Working capital / Total assets + 0.014 × Retained earnings / Total assets + 0.033 × Earnings before interest and tax / Total assets + 0.006 × Total market value / Book value of liabilities + 0.999 × Sales revenue / Total assets.* A larger Z-Score means the company is less likely to default.

The third alternative indicator of the default probability is the firm's downside risk as measured by the RLPM model (Miller & Leiblein, 1996). The formula for calculating a firm's downside risk is as follows: $RLPM_{i,t} = \sqrt{\frac{1}{5}\sum_{t=1}^{5}(ROA_{i,t-1} - iROA_{i,t-1})^2}$, where $iROA_{i,t-1}$ represents the average performance (measured by ROA) of all firms in the industry to which firm i belongs in year t-1, which can be considered as the target performance. Additionally, $ROA_{i,t-1}$ represents the actual performance of firm i in year t-1. The RER model is applied under the condition that the company's target level of performance is greater than the actual annual net profit margin on total assets; if the target value is less than the actual annual return on assets, it is given a value of zero. Larger RLPM values mean that firms face greater downside risk, implying a greater likelihood of default. We adopt a regression model consistent with the main effects to test the impact of firms issuing green bonds on the three alternative dependent variables.

$$RC_{i,t};\ \mathrm{Z}_{i,t};\ RLPM_{i,t} = \alpha + \beta G\_Scale_{i,t} + \gamma Control_{i,t} + Firm_i + Time_t + \varepsilon_{i,t} \quad (11)$$

where *RC*, *Z* and *RLPM* are three alternative dependent variable indicators representing firm risk coefficients, Z-scores and downside risk, respectively.

The regression results are shown in Table 7. Columns (1) and (2) report the regression results of firms' issuance of green bonds on their risk coefficients; the coefficients of RC are significantly negative both before and after PSM, which suggests that firms' issuance of green bonds reduces their default risk. Columns (3) and (4) report regression results on Z-Score, where the core variable *Z* is significantly positively related to *Grenn*Post* both before and after PSM, suggesting that firms' issuance of green bonds reduces their likelihood of default. Columns (5) and (6) report regression results regarding firms' downside risk, where the core variable RLPM is significantly positively correlated with Grenn*Post both before and after PSM, which suggests that firms' issuance of green bonds reduces their downside likelihood.

Therefore, our findings are robust to the fact that a firm's issuance of green bonds can significantly affect the three proxies associated with a firm's probability of default and get similar results to the main effects.

[Insert Table 7 about here]

5.3 Tests for transmission mechanisms, moderating effects, and heterogeneity

5.3.1 Results of transmission mechanisms

We start this section with the analysis of transmission mechanisms. We use financial constraints (*KZ*) and stock liquidity (*PS*) as mediating variables to explore the transmission mechanism of corporate green bond issuance of firm default probability. We follow the three-step test proposed by Baron and Kenny (1986) to investigate whether financial constraints and stock liquidity play a mediating, with the following test steps.

$$EDP_{it} = \alpha_0 + \alpha_1 Green_i \cdot Post_{it} + \alpha_2 Control_{it} + Firm_i + Time_t + \varepsilon_{it}, \tag{12}$$

$$Med_{it} = \beta_o + \beta_1 Green_i \cdot Post_{it} + \beta_2 Control_{it} + Firm_i + Time_t + \varpi_{it}, \tag{13}$$

$$EDP_{it} = \gamma_0 + \gamma_1 Green_i \cdot Post_{it} + \gamma_2 Med_{it} + \gamma_3 Control_{it} + Firm_i + Time_t + u_{it}. \tag{14}$$

In the above specification, Med_{it} stands for the mediating variable, including financial constraints and stock liquidity.

We begin with the results for the first mediating variable, financial constraints, as shown in Table 8. This table presents results for both the entire sample and a sample that has been adjusted using propensity score matching. Notably, firms that have issued green bonds exhibit lower financial constraints, with the coefficients in columns 2 (before PSM) and 5 (the PSM-DID sample) being negative and statistically significant at the 1% level. When the financial constraint variable is included as a control alongside *Green*Post* in column 6 (the PSM-DID sample), the interaction term loses its statistical significance while the mediator is statistically significant at the 10% level, indicating a full mediation effect. Considering that in the before PSM sample, the coefficient of KZ on EDP (column 3) is insignificant in the third step of testing the effect of financial constraints on the probability of default, which is slightly inconsistent with the PSM-DID results, we further perform the Sobel test and Bootstrap test,[6] and the test results further support the effectiveness of reducing the financial constraints as a transmission mechanism. This is in accordance with our Hypothesis 2.

[Insert Table 8 about here]

Table 9 demonstrates the mediation effect of stock liquidity. For the PSM-DID sample, shown in columns (4) to (6), we observe a full mediation effect. Specifically, column (5) indicates that green bond issuance increases stock liquidity (see also Tang & Zhang, 2020). Crucially, when stock liquidity is included as a control variable, the *Green*Post* interaction loses its statistical significance, signifying a full mediation effect. Further, in the sample before PSM (columns 1-3), the coefficient of PS on EDP (column 3) is insignificant in the third step of testing the effect of stock liquidity on the probability of default, which is slightly inconsistent with the PSM-DID results. Therefore, we further perform the Sobel test and Bootstrap test, and the test results further support the effectiveness of decreasing stock liqudity as a transmission mechanism, supporting our Hypothesis 3.

[6] In the three-step test of mediating effects, the coefficient of α_1 in model (10) is significant. Under this condition, if only one of the estimated coefficients of β_1 in model (11) and γ_2 in mode (12) is significant, the Sobel and Bootstrap tests is needed to determine whether the mediating variable plays a role. In the bootstrap test, we perform 1,000 times sampling from the original data with put-back to create a number of bootstrap samples to estimate confidence intervals for the mediating effect.

[Insert Table 9 about here]

5.3.2 Results of moderating effects

We now transition to analyzing the moderating effects. Our focus shifts to the impact of analyst and media coverage on firms' issuance of green bonds and their subsequent probability of default. Specifically, we investigate how two forms of external monitoring—analyst coverage and media coverage—moderate this relationship. The model employed for this analysis is as follows.

$$EDP_{it} = \alpha + \beta Green_i \cdot After_{it} + \theta Mod_{it} + \eta Green_i \cdot After_{it} * Mod_{it} + \gamma Control_{it} + Firm_i + Time_t + \varepsilon_{it}. \quad (15)$$

In the above specification, Mod_{it} denotes the moderating variables—analyst and media coverage.

We show the results for analysts and media coverage in Table 10. After including analyst coverage as a moderating variable, the coefficient for the core explanatory variable *Green*Post* is negative and significant at the 1% level, while the coefficient for "Analyst" is negative and significant at the 5% level. This indicates that the issuance of green bonds and increased analyst coverage effectively reduces corporate default probability. The coefficient for the interaction term *Green*Post*Analyst* is positive and significant at the 5% level, suggesting that increased analyst coverage weakens the effect of green bond issuance in reducing default probability, thereby supporting Hypothesis 4. Additionally, the regression results are consistent both before and after applying propensity score matching (PSM).

In the same table we present the regression results for the moderating effect of media coverage on the relationship between green bond issuance and default probability. When media coverage is included as a moderating variable, the coefficient for the core explanatory variable *Green*Post* is negative and significant at the 5% level. The coefficient for the interaction term *Green*Post*Media* is positive and significant at the 5% level, indicating that increased media coverage weakens the effect of green bond issuance on reducing default probability, supporting Hypothesis 5. The regression results are consistent both before and after applying propensity score matching (PSM).

[Insert Table 10 about here]

5.3.3 Results of heterogeneity test

Next, we test the heterogeneity of the impact of green bond issuance on corporate default probability between high-polluting and low-polluting firms, and between firms facing high level versus low level of competition. We use group regression to analyze heterogeneity and, on this basis, test for differences in coefficients between groups to indicate the presence of heterogeneity. The model used for grouped regression testing is as follows.

$$EDP_{it} = \alpha_a + \beta_a Green_i \cdot After_{it} + \gamma_a Control_{it} + Corporate_i + Time_t + \varepsilon_{it}, \ \text{Heterogeneous variable} = 1 \quad (16)$$

$$EDP_{it} = \alpha_b + \beta_b Green_i \cdot After_{it} + \gamma_b Control_{it} + Corporate_i + Time_t + \varepsilon_{it}, \ \text{Heterogeneous variable} = 0 \quad (17)$$

Based on the above model, the samples are grouped according to the heterogeneity variable; high-polluting firms are recorded as 1 and low-polluting firms as 0.aFirms facing a high level of competition are recorded as 1, and firms facing low competition as 0. We compare the difference in significance and direction of β_a and β_b to explain that the issuance of green bonds by different firms has different impacts on their default probability.

Firstly, we focus our analysis on two groups of firms: high-polluting and low-polluting. We classify the sample firms into high-polluting and low-polluting categories based on the CSMAR database records, which identify firms as key pollution source monitoring units. This classification allows us to examine the heterogeneity in the effect of green bond issuance across different types of firms. After categorization, the sample consists of 1,000 high-polluting firms and 1,696 low-polluting firms.

We show the results of this analysis in Table 11. In column (1), the coefficient of the core explanatory variable *Green*Post* for the group of high-polluting firms is negative and significant at the 5% confidence level. Conversely, in column (2), the coefficient of *Green*Post* for low-polluting firms is negative but not significant, with the absolute value of the coefficient being larger for high-polluting firms than for low-polluting firms. This indicates that the issuance of green bonds by high-polluting firms significantly reduces their default probability compared to low-polluting firms, supporting hypothesis 6. Columns (3) and (4) of Table 11 present the results of the heterogeneity test after propensity score matching, which are consistent with the regression results in columns (1) and (2). We further conduct Fisher's permutation test to examine the difference in coefficients between the groups based on the regression results. As shown in the last row of Table 11, the p-value for the coefficient difference of the core variable *Green*Post* is 0.002. This indicates that the difference in coefficients between high-polluting firms and low-polluting firms is significant at the 1% level, confirming a significant difference between the groups and demonstrating the high stability of the heterogeneity analysis results.

[Insert Table 11 about here]

Our second heterogeneity test uses the Herfindahl-Hirschman Index (HHI) to measure the level of competition within an industry. We then divide the sample into two groups: firms facing a high level of competition and firms facing low competition, based on the median HHI in the sample. After categorization, there are 1,296 firms in highly competitive industries and 1,400 firms in less competitive industries. As shown in Table 12, the coefficient of *Green*Post* for firms facing a high level of competition in column (1) is negative and significant at the 5% confidence level. Conversely, the coefficient for firms facing a low level of competition in column (2) is negative but not significant, with the absolute value of the coefficient being larger for firms with high industry competitiveness. This suggests that the issuance of green bonds by firms facing a high level of competition significantly reduces their default probability compared to firms facing a low level of competition, supporting Hypothesis 7. Columns (3) and (4) of Table 12 present the results of the heterogeneity test after propensity score matching, confirming the stability of these findings.

We further conducted Fisher's permutation test. As shown in the last row of Table 12, the p-value for the coefficient difference of the core variable *Green*Post* is 0.045. This indicates that the difference in coefficients between firms with high industry competitiveness and those with low industry competitiveness is significant at the 5% level. The results demonstrate a significant difference between the groups, confirming the high stability of the heterogeneity analysis.

[Insert Table 12 about here]

6 Conclusion

This paper quantifies the overall impact of green bond issuance on firms' default probability and investigates the transmission process behind this effect. We examine these issues in the context of China where the issuance of green bonds is to a large extent shaped by official governmental policies and guidelines. These policies are exogenous from the point of view of individual firms and can therefore serve as a basis for our staggered Difference-in-Differences (DID) empirical approach. Moreover, the broader context of these policies can further strengthen the impact of green bond issuance on the probability of default among Chinese firms. On one hand, the official guidelines link green bond issuance with strict information disclosure, leading to reduced information asymmetry between firms and their investors compared to firms that do not issue green bonds. On the other hand, issuers of green bonds can gain easier access to preferential government policies such as discounts and subsidies that are not available to other firms.

We find that green bond issuance indeed reduces the default probability of the issuing firms. We provide evidence that this effect is transmitted both by reducing the financial constraints the issuing firms are facing and by increasing their stock liquidity. A further analysis of the transmission process from green bonds issuance to a reduced default probability reveals that the effect is particularly strong for firms that lack strong external scrutiny by financial analysts or media, for high-polluting firms, and firms that face intense competition in their respective industries. Such firms would therefore particularly benefit from deeper involvement of green finance in their financing choices. For instance, high-polluting firms could leverage green financing to facilitate their green transformation while firms in highly competitive industries could use green bond issuance as a tool for enhancing their differentiation and CSR performance.

Building upon these results, we see two main areas for future research. On the micro level, the role of external monitoring in the context of green finance looks like a promising avenue for further examination. We found that the positive effect of green bond issuance on reducing the probability of default is diminished when firms are closely followed by analysts and receive extensive media coverage. There are two mutually non-exclusive interpretations of this result that deserve further scrutiny. First, external monitors seem to be efficient at identifying potential greenwashing and raising investor awareness of firms with opportunistic motives to issue green bonds. Second, the increased public scrutiny associated with green bond issuance can replace the more traditional external monitors in alleviating information asymmetries, thus disproportionately helping firms that lack sufficient analyst and media coverage.

On the macro level, the results from the highly regulated Chinese market for green bonds might offer some insights into the potential role of additional public support and strict disclosure requirements on the relationship between green finance and firms' financial resilience. Moreover, the significant disparity between our sample sizes of the treatment and control groups indicates that the large majority of Chinese firms still rely on traditional financing, leaving significant scope for future expansion of green financing. As the size of the green bond market in China increases and we gain additional treatment years for policies adopted from late 2015 onwards, future research can hopefully gain further policy lessons from the unique institutional framework that we utilize in this paper.

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FIGURES

Figure 1 Results for propensity score matching

This figure presents the bias across covariates of the control variables before and after propensity score matching using kernel matching. A complete description of variables along with their sources is in Table 1.

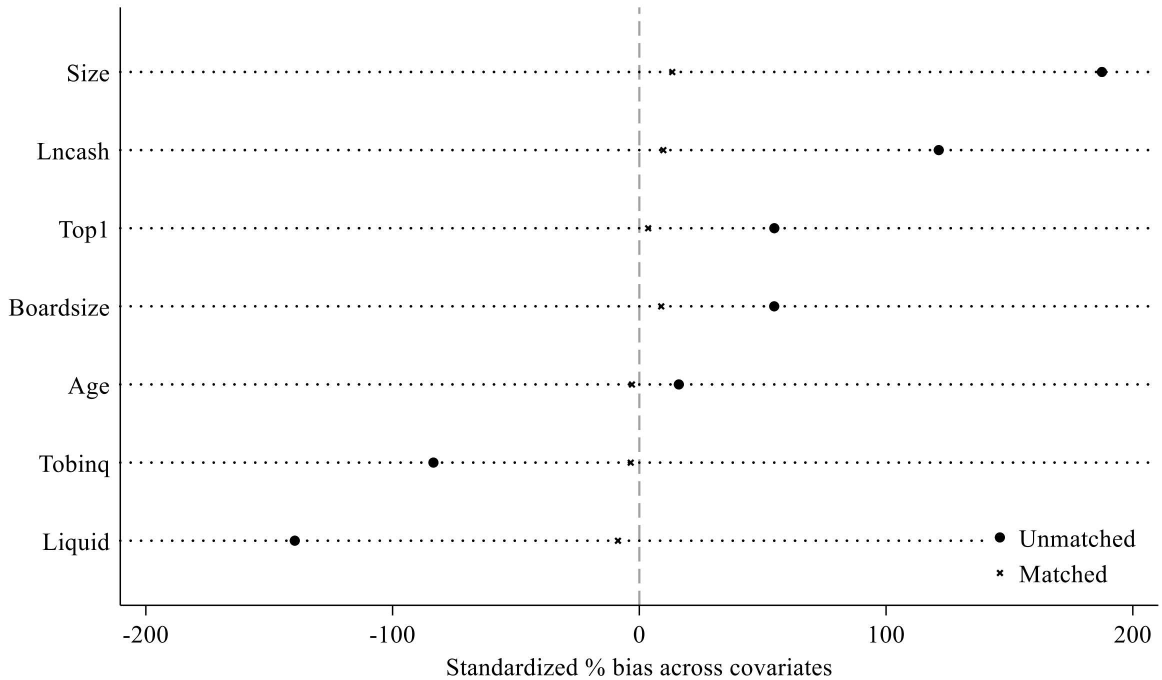


Figure 2 Results of Parallel trend test

This figure presents the results of the parallel trend test. The horizontal axis represents the years relative to the firm's first green bond issuance, while the vertical axis shows the regression coefficients for corporate default probability. The hollow dots denote the magnitude of the difference between the estimated coefficients for the treated and control groups for the explanatory variable *Green*Post* for each respective period.

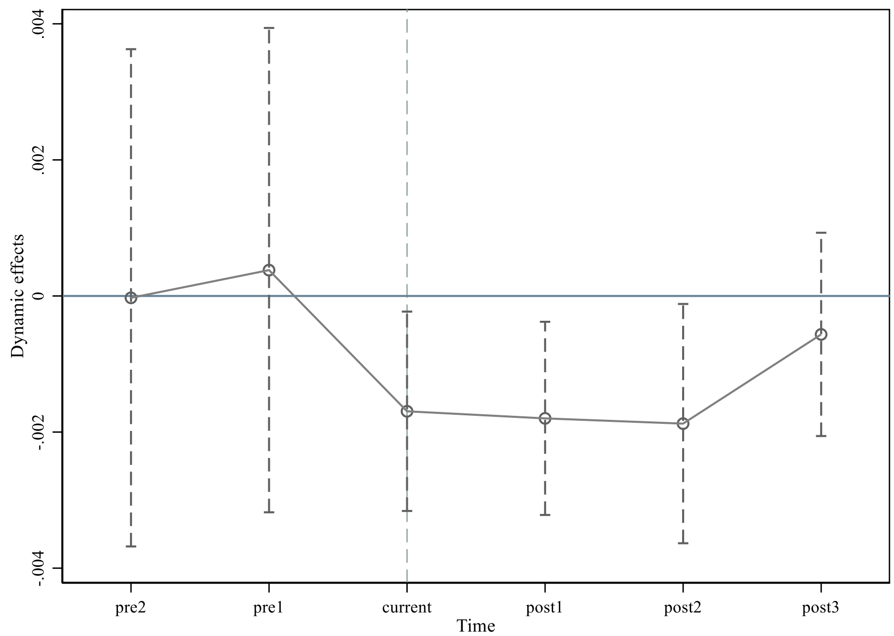
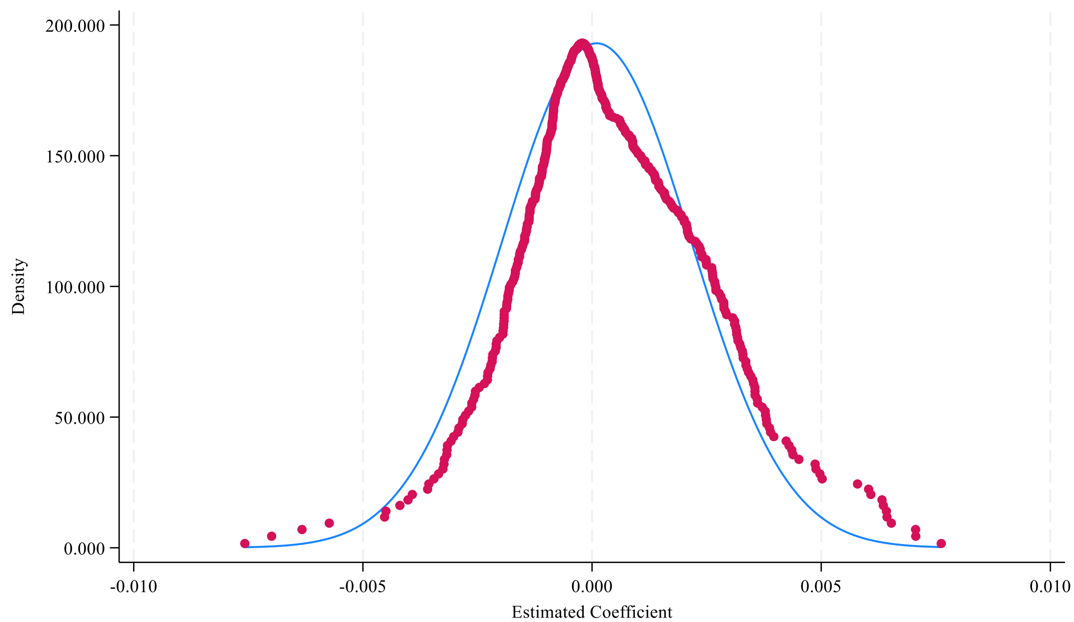


Figure 3 Placebo test results

This figure presents the results of the placebo test. The horizontal axis displays the estimated coefficients of the core explanatory variable *Green*Post*, while the vertical axis shows the density. This is used to assess whether the estimated coefficients of *Green*Post* follow a normal distribution.



TABLES

Table 1 Variables definition

The table reports the definitions and measurements of the variables used in the analysis.

Variable	Description	Source
EDP	This variable denotes corporate default probability; it is calculated using the method of Bharath and Shumway (2008).	CSMAR (China Stock Market & Accounting Research Database)
Green	This is an indicator variable taking value one if a firm has issued a green bond and zero otherwise.	CSMAR
Post	This is an indicator variable taking value one from the year a firm has issued its first green bond and zero in the year in which a firm has not yet issued a green bond.	CSMAR
Size	= log (total assets)	CSMAR
TobinQ	= (stock market value + net debt)/current value of tangible assets	CSMAR
Lncash	= log (money funds by the end of the year)	CSMAR
Liquid	= current assets/total assets	CSMAR
Age	= log (sample year - establishment year + 1)	CSMAR
Boardsize	= log (the number of board members)	CSMAR
Top1	= shareholding ratio or ownership percentage of the largest shareholder	CSMAR
G_Scale	Total amount of money raised by a firm in issuing green bonds	CSMAR
RC	This variable denotes corporate risk coefficient; it is calculated with reference to Ohlson (1980).	CSMAR
Z	This variable denotes financial early warning index; it is calculated using the method of Altman (1968).	CSMAR
RLPM	This variable denotes corporate downside risk; it is calculated using the method of Miller and Leiblein (1996).	CSMAR
KZ	This is a proxy for financial constraints; own calculations based on the insights of Kaplan and Zingales (1997).	CSMAR
PS	This is a proxy for stock liquidity; own calculations based on the insights of Pastor and Stambaugh (2003).	CSMAR
Analyst	= log(1+number of analysts following a firm)	CSMAR
Media	= log(1+total number of financial news articles)	CNRDS (Chinese Research Data Services Platform)
KZ	This is a proxy for financial constraints; own calculations based on the insights of Kaplan and Zingales (1997).	CSMAR
Heterogeneity 1	This variable takes the value one if it is a high-polluting company and zero if it is a low-polluting company; it is judged according to whether the firm is a key pollution source monitoring unit.	CSMAR
Heterogeneity 2	This variable takes value one if a firm is in a highly competitive industry and zero otherwise. The intensity of the competition within the industry is judged based on Herfindahl-Hirschman Index.	CSMAR

Table 2 Summary statistics

The table reports the statistics of the main research variables in this study, where *Panel A* reports the statistics of the variables in the full sample, and *Panel B* reports the statistics of the subgroups in the treatment group (issuing green bonds) and the control group (not issuing green bonds). A complete description of variables along with their sources is in Table 1.

Panel A: Total sample

Variable	Obs.	Mean	SD	Min	Max
EDP	13,103	0.0013	0.0286	0.0000	0.9793
Green*Post	13,103	0.0156	0.1238	0.0000	1.0000
Size	13,103	22.5748	1.2495	20.2340	26.4438
Age	13,103	3.0405	0.2548	2.3026	3.5553
TobinQ	13,103	1.9577	1.2135	0.8281	7.9006
Lncash	13,103	20.6041	1.3954	17.3657	24.6759
Liquid	13,103	0.5376	0.1796	0.1050	0.8886
Boardsize	13,103	2.1134	0.1949	1.6094	2.6391
Top1	13,103	0.3222	0.1403	0.0854	0.7004
KZ	13,014	1.2729	2.1893	-10.5007	11.1975
PS	13,008	0.5038	0.0055	0.4650	1.0000
Analyst	13,102	1.3265	1.2260	0.0000	4.3307
Media	12,855	3.0403	1.3513	0.6931	9.2869

Panel B: Summary statistics by group

	Treatment group					Control group				
Variable	Obs.	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max
EDP	204	0.00002	0.0002	0.0000	0.0016	12,899	0.0013	0.0288	0.0000	0.9793
Green*Post	204	1.0000	0.0000	1.0000	1.0000	12,899	0.0000	0.0000	0.0000	0.0000
Size	204	24.6593	1.0771	22.2289	26.4438	12,899	22.5419	1.2239	20.2340	26.4438
Age	204	3.1166	0.2449	2.3026	3.5553	12,899	3.0393	0.2547	2.3026	3.5553
Tobinq	204	1.2125	0.4258	0.8281	3.8100	12,899	1.9694	1.2182	0.8281	7.9006
Lncash	204	22.0984	1.2598	18.9768	24.6759	12,899	20.5804	1.3846	17.3657	24.6759
Liquid	204	0.3112	0.1406	0.1050	0.7629	12,899	0.5412	0.1778	0.1050	0.8886
Boardsize	204	2.1929	0.2065	1.6094	2.6391	12,899	2.1122	0.1944	1.6094	2.6391
Top1	204	0.3813	0.1552	0.0854	0.7004	12,899	0.3212	0.1398	0.0854	0.7004
KZ	201	1.4756	1.8222	-6.7443	5.43525	12,813	1.2713	2.19197	-10.501	11.1975
PS	200	0.5041	0.0002	0.50355	0.5051	12,808	0.50378	0.00549	0.4650	1.0000
Analyst	204	2.008	1.18598	0.00000	4.04305	12,898	1.31685	1.22383	0.0000	4.33073
Media	193	4.0197	1.38777	0.69315	8.76374	12,662	3.03096	1.34757	0.6932	9.28693

Table 3 Correlation matrix

The table reports the results of the Pearson correlation analysis of the explanatory, explained and control variables of this study. A complete description of variables along with their sources is in Table 1. ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively.

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
EDP	[1]	1								
Green*Post	[2]	-0.005	1							
Size	[3]	0.055***	0.210***	1						
Age	[4]	0.019**	0.038***	0.076***	1					
TobinQ	[5]	-0.032***	-0.077***	-0.365***	-0.052***	1				
Lncash	[6]	0.034***	0.135***	0.863***	0.071***	-0.251***	1			
Liquid	[7]	-0.034***	-0.159***	-0.171***	-0.061***	0.150***	0.082***	1		
Boardsize	[8]	0.050***	0.051***	0.261***	0.104***	-0.117***	0.216***	-0.097***	1	
Top1	[9]	0.018**	0.053***	0.238***	-0.021**	-0.063***	0.233***	-0.031***	0.028***	1

Table 4 Baseline regression results

The table reports the effect of firms' green bond issuance on their probability of default. The dependent variable is the probability of default (EDP). Robust standard errors, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively. A complete description of variables along with their sources is in Table 1.

	DID	DID	PSM-DID
	(1)	(2)	(3)
Variables	EDP	EDP	EDP
Green*Post	-0.0014**	-0.0017**	-0.0019**
	(0.0007)	(0.0007)	(0.0009)
Size		0.0029**	0.0042**
		(0.0012)	(0.0017)
Age		0.0050*	0.0074*
		(0.0029)	(0.0042)
TobinQ		0.0003*	0.0005
		(0.0002)	(0.0004)
Lncash		-0.0023*	-0.0033*
		(0.0013)	(0.0019)
Liquid		0.0068	0.0108
		(0.0064)	(0.0107)
Boardsize		0.0060**	0.0079**
		(0.0026)	(0.0035)
Top1		0.0054	0.0080
		(0.0051)	(0.0070)
Constant	0.0013***	-0.0508***	-0.0739***
	(0.0000)	(0.0178)	(0.0249)
Observations	13,103	13,103	9,538
R-squared	0.344	0.346	0.347
Adj.R-squared	0.174	0.175	0.167
Cluster	Firm	Firm	Firm
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 5 Robustness test: excluding the sample of non-issuing bonds

The table reports regression results after excluding the non-issuing sample, with firms with green bond issuance as the treatment group and firms that only issue traditional bonds as the control group. The dependent variable is the probability of default (EDP). Robust standard errors, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively. A complete description of variables along with their sources is in Table 1.

	DID	DID	PSM-DID
	(1)	(2)	(3)
Variables	EDP	EDP	EDP
Green*Post	-0.0211***	-0.0435**	-0.0478**
	(0.0069)	(0.0101)	(0.0228)
Size		0.0044**	-0.0082
		(0.0018)	(0.0276)
Age		0.0058	-0.1555
		(0.0041)	(0.1778)
TobinQ		0.0005	0.0058
		(0.0003)	(0.0043)
Lncash		-0.0036*	-0.0069
		(0.0021)	(0.0140)
Liquid		0.0114	-0.1023
		(0.0100)	(0.0997)
Boardsize		0.0074*	0.0286
		(0.0039)	(0.0243)
Top1		0.0082	-0.0121
		(0.0072)	(0.2234)
Constant	0.0160***	0.4185	0.8330
	(0.0011)	(0.0253)	(0.9248)
Observations	1,413	1,413	659
R-squared	0.7286	0.7556	0.7157
Adj.R-squared	0.4690	0.4845	0.4940
Cluster	Firm	Firm	Firm
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 6 The impact of firms' green bond issuance scale on default probability

The table reports results on the effect of green bond issuance scale on the default probability for firms that have issued green bonds. The dependent variable is the probability of default (EDP). Robust standard errors, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively. A complete description of variables along with their sources is in Table 1.

Variables	(1) EDP	(2) EDP
Green_Scale	-0.0004**	-0.0003**
	(0.0001)	(0.0001)
Size		0.0010***
		(0.0004)
Age		0.0055
		(0.0027)
TobinQ		0.0001
		(0.0005)
Lncash		-0.0006**
		(0.0003)
Liquid		-0.0023
		(0.0020)
Boardsize		-0.0018*
		(0.0008)
Top1		-0.0021
		(0.0009)
Constant		-0.0201*
		(0.0093)
Observations	202	202
R-squared	0.6543	0.7841
Adj.R-squared	0.1018	0.1283
Cluster	Firm	Firm
Firm FE	Yes	Yes
Year FE	Yes	Yes

Table 7 Robustness test with alternative dependent variable

The table reports the regression results of firms issuing green bonds on three alternative dependent variables: firm risk coefficient (*RC*), Z-scores (*Z*) and downside risk (*RLPM*). The dependent variable is the probability of default (EDP). Robust standard errors, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively. A complete description of variables along with their sources is in Table 1.

	DID	PSM-DID	DID	PSM-DID	DID	PSM-DID
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	RC	RC	Z	Z	RLPM	RLPM
Green*Post	-0.0014*	-0.0022***	0.4360***	0.2367***	-0.0173**	-0.0103**
	(0.0007)	(0.0004)	(0.1147)	(0.0913)	(0.0075)	(0.0052)
Size	-0.0068**	-0.0014	-0.3180	-0.4780***	-0.0545***	-0.0310***
	(0.0033)	(0.0012)	(0.2242)	(0.1520)	(0.0211)	(0.0051)
Age	-0.0029	0.0047	-4.9983***	-0.4370	-0.0478	0.0334
	(0.0137)	(0.0039)	(1.1975)	(0.8526)	(0.1254)	(0.0318)
TobinQ	0.0020***	0.0009	2.3890***	1.8984***	0.0023*	0.0002
	(0.0007)	(0.0007)	(0.1143)	(0.1365)	(0.0013)	(0.0014)
Lncash	-0.0006	-0.0017***	0.4880***	0.2930***	0.0005	-0.0007
	(0.0018)	(0.0006)	(0.0973)	(0.0983)	(0.0017)	(0.0016)
Liquid	-0.0075	0.0022	1.7610**	1.4065**	-0.0874	-0.0030
	(0.0113)	(0.0060)	(0.8261)	(0.5746)	(0.0927)	(0.0141)
Boardsize	0.0075*	0.0005	-0.0356	-0.0074	0.0082	0.0070
	(0.0042)	(0.0014)	(0.3397)	(0.1963)	(0.0057)	(0.0054)
Top1	0.0031	0.0011	0.1637	-0.2385	-0.1269	-0.0162
	(0.0039)	(0.0028)	(0.6024)	(0.4947)	(0.1089)	(0.0203)
Constant	0.1614**	0.0535*	10.9255**	5.5270	1.4728	0.6579***
	(0.0699)	(0.0284)	(4.5981)	(3.7136)	(0.9097)	(0.1283)
Observations	13,103	6,651	13,103	6,651	11,588	6,316
R-squared	0.3908	0.7269	0.8478	0.8646	0.3601	0.5912
Adj.R-squared	0.2320	0.6437	0.8082	0.8234	0.1847	0.4657
Cluster	Firm	Firm	Firm	Firm	Firm	Firm
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8 Results of the mediation effect: financial constraints

The table reports the mediation effect of financial constraints in the relationship between green bond issuance by firms and their probability of default. The dependent variables are shown in each column. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively. A complete description of variables along with their sources is in Table 1. The table also reports the results Sobel and Bootstrap tests for financial constraints as a mediating variable of firms issuing green bonds affecting their default probability.

	DID			PSM-DID		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	EDP	KZ	EDP	EDP	KZ	EDP
Green*Post	-0.0017**	-0.5567***	-0.0016*	-0.0019**	-0.5817***	-0.0017
	(0.0007)	(0.1783)	(0.0010)	(0.0009)	(0.1786)	(0.0011)
KZ			0.0004			0.0007*
			(0.0003)			(0.0004)
Size	0.0029**	1.4501***	0.0024*	0.0042**	1.5024***	0.0033*
	(0.0012)	(0.0880)	(0.0013)	(0.0017)	(0.0963)	(0.0019)
Age	0.0050*	2.4657***	0.0034	0.0074*	1.7054***	0.0057
	(0.0029)	(0.5710)	(0.0027)	(0.0042)	(0.5991)	(0.0040)
TobinQ	0.0003*	0.3838***	0.0002	0.0005	0.2552***	0.0003
	(0.0002)	(0.0262)	(0.0002)	(0.0004)	(0.0367)	(0.0004)
Lncash	-0.0023*	-1.5880***	-0.0017	-0.0033*	-1.4485***	-0.0025
	(0.0013)	(0.0451)	(0.0015)	(0.0019)	(0.0512)	(0.0021)
Liquid	0.0068	-0.8723***	0.0075	0.0108	-1.0282***	0.0122
	(0.0064)	(0.2887)	(0.0065)	(0.0107)	(0.3536)	(0.0109)
Boardsize	0.0060**	-0.2744*	0.0063**	0.0079**	-0.1479	0.0084**
	(0.0026)	(0.1478)	(0.0027)	(0.0035)	(0.1597)	(0.0037)
Top1	0.0054	-0.3914	0.0060	0.0080	-0.3663	0.0089
	(0.0051)	(0.3480)	(0.0055)	(0.0070)	(0.3779)	(0.0076)
Constant	-0.0508***	-5.7964**	-0.0471***	-0.0739***	-7.5157***	-0.0673***
	(0.0178)	(2.3434)	(0.0173)	(0.0249)	(2.5673)	(0.0240)
Observations	13,103	13,014	13,014	9,538	9,342	9,342
R-squared	0.346	0.808	0.347	0.347	0.792	0.348
Adj.R-squared	0.175	0.757	0.174	0.167	0.734	0.165
Cluster	Firm	Firm	Firm	Firm	Firm	Firm
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sobel (Z)		-3.405				
Sobel(p-value)		0.001				
Bootstrap test [95% conf. interval]		(-0.0011, -0.0002)				

Table 9 Results of the mediation effect: stock liquidity

The table reports the mediation effect of stock liquidity in the relationship between green bond issuance by firms and their probability of default. The dependent variables are shown in each column. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively. A complete description of variables along with their sources is in Table 1. The table also reports the results of Sobel and Bootstrap tests for stock liquidity as a mediating variable of firms issuing green bonds affecting their default probability.

	DID			PSM-DID		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	EDP	PS	EDP	EDP	PS	EDP
Green*Post	-0.0017**	0.0003**	-0.0004	-0.0019**	0.0004***	0.0006
	(0.0007)	(0.0001)	(0.0003)	(0.0009)	(0.0001)	(0.0008)
PS			-0.0567			-3.1170*
			(0.0769)			(1.8897)
Size	0.0029**	-0.0002*	0.0024*	0.0042**	0.0000	0.0034*
	(0.0012)	(0.0001)	(0.0013)	(0.0017)	(0.0000)	(0.0018)
Age	0.0050*	-0.0021	0.0023	0.0074*	-0.0004	0.0006
	(0.0029)	(0.0017)	(0.0031)	(0.0042)	(0.0003)	(0.0043)
TobinQ	0.0003*	-0.0000	0.0002	0.0005	0.0001***	0.0005
	(0.0002)	(0.0001)	(0.0002)	(0.0004)	(0.0000)	(0.0004)
Lncash	-0.0023*	-0.0001	-0.0017	-0.0033*	0.0001***	-0.0022
	(0.0013)	(0.0002)	(0.0013)	(0.0019)	(0.0000)	(0.0020)
Liquid	0.0068	0.0013**	0.0074	0.0108	0.0004***	0.0132
	(0.0064)	(0.0006)	(0.0067)	(0.0107)	(0.0002)	(0.0106)
Boardsize	0.0060**	-0.0002	0.0039**	0.0079**	0.0001	0.0039**
	(0.0026)	(0.0004)	(0.0015)	(0.0035)	(0.0001)	(0.0018)
Top1	0.0054	0.0004	0.0026	0.0080	-0.0004*	0.0005
	(0.0051)	(0.0006)	(0.0034)	(0.0070)	(0.0002)	(0.0042)
Constant	-0.0508***	0.5162***	-0.0107	-0.0739***	0.5019***	1.5216
	(0.0178)	(0.0121)	(0.0435)	(0.0249)	(0.0011)	(0.9501)
	-0.0017**	0.0003**	-0.0004	-0.0019**	0.0004***	0.0006
Observations	13,103	13,008	13,008	9,538	9,134	9,134
R-squared	0.346	0.478	0.351	0.347	0.458	0.355
Adj.R-squared	0.175	0.325	0.157	0.167	0.289	0.153
Cluster	Firm	Firm	Firm	Firm	Firm	Firm
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sobel (Z)		-5.079				
Sobel(p-value)		0.000				
Bootstrap test [95% conf. interval]		(-0.00269, -0.00003)				

Table 10 Moderating effects of analysts' coverage and media coverage

This table illustrates the impact of green bond issuance on the probability of default. Additionally, it demonstrates how this effect varies with the number of analysts following the firm and the extent of media coverage. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively. A complete description of variables along with their sources is in Table 1.

	DID	PSM-DID	DID	PSM-DID
	(1)	(2)	(3)	(4)
Variables	EDP	EDP	EDP	EDP
Green*Post	-0.0028***	-0.0029**	-0.0052**	-0.0055**
	(0.0010)	(0.0012)	(0.0023)	(0.0027)
Analyst	-0.0010**	-0.0015**		
	(0.0005)	(0.0007)		
Green*Post*Analyst	0.0007**	0.0007*		
	(0.0003)	(0.0004)		
Media			-0.0004	-0.0005
			(0.0002)	(0.0003)
Green*Post*Media			0.0008**	0.0009*
			(0.0004)	(0.0005)
Size	0.0032**	0.0047**	0.0023*	0.0034*
	(0.0013)	(0.0019)	(0.0013)	(0.0019)
Age	0.0043*	0.0070*	0.0003	0.0006
	(0.0024)	(0.0036)	(0.0017)	(0.0024)
TobinQ	0.0006**	0.0011**	0.0003**	0.0005*
	(0.0003)	(0.0005)	(0.0001)	(0.0003)
Lncash	-0.0021	-0.0030	-0.0021	-0.0031
	(0.0013)	(0.0019)	(0.0015)	(0.0022)
Liquid	0.0059	0.0094	0.0094	0.0153
	(0.0064)	(0.0106)	(0.0066)	(0.0108)
Boardsize	0.0059**	0.0079**	0.0016*	0.0020*
	(0.0026)	(0.0036)	(0.0009)	(0.0012)
Top1	0.0050	0.0075	-0.0012	-0.0011
	(0.0051)	(0.0070)	(0.0016)	(0.0022)
Constant	-0.0592***	-0.0887***	-0.0167	-0.0235
	(0.0211)	(0.0304)	(0.0117)	(0.0168)
Observations	13,102	9,517	12,855	8,808
R-squared	0.347	0.348	0.383	0.384
Adj. R-squared	0.176	0.168	0.207	0.200
Cluster	Firm	Firm	Firm	Firm
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 11 Heterogeneity analysis: high- vs. low-polluting firms

This table illustrates the impact of green bond issuance on the probability of default for high- vs. low-polluting firms. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively. A complete description of variables along with their sources is in Table 1. Further, the P-value for the test of difference in coefficients between groups for the heterogeneity analysis is calculated using Fisher's permutation test (sampling 1,000 times) and the table reports the test result for the core explanatory variable Green*Post.

	DID		PSM-DID	
	High-polluting	Low-polluting	High-polluting	Low-polluting
	(1)	(2)	(3)	(4)
Variables	EDP	EDP	EDP	EDP
Green*Post	-0.0076**	-0.0002	-0.0073*	-0.0004
	(0.0039)	(0.0003)	(0.0040)	(0.0005)
Size	0.0032	0.0033*	0.0037	0.0054*
	(0.0021)	(0.0020)	(0.0026)	(0.0033)
Age	0.0229**	0.0010	0.0284**	0.0016
	(0.0092)	(0.0032)	(0.0116)	(0.0051)
TobinQ	0.0004	0.0003*	0.0006	0.0007
	(0.0005)	(0.0001)	(0.0007)	(0.0005)
Lncash	-0.0009	-0.0026	-0.0011	-0.0042
	(0.0014)	(0.0020)	(0.0016)	(0.0032)
Liquid	-0.0016	0.0091	-0.0033	0.0174
	(0.0085)	(0.0092)	(0.0117)	(0.0180)
Boardsize	0.0184**	0.0012	0.0216**	0.0007
	(0.0089)	(0.0009)	(0.0106)	(0.0013)
Top1	0.0253	-0.0033	0.0294	-0.0033
	(0.0170)	(0.0046)	(0.0197)	(0.0073)
Constant	-0.1707**	-0.0302	-0.2041**	-0.0491
	(0.0719)	(0.0198)	(0.0863)	(0.0334)
Observations	5,338	7,765	4,509	5,029
R-squared	0.374	0.529	0.374	0.531
Adj. R-squared	0.129	0.327	0.122	0.297
Cluster	Firm	Firm	Firm	Firm
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
p-value of Fisher test for Green*Post	0.002			

Table 12 Heterogeneity analysis: high- vs. low-competing firms

This table illustrates the impact of green bond issuance on the probability of default for firms with high industry competitiveness vs. those with low industry competitiveness. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, ** and * indicate significance levels at the 1%, 5%, and 10%, respectively. A complete description of variables along with their sources is in Table 1. Further, the P-value for the test of difference in coefficients between groups for the heterogeneity analysis is calculated using Fisher's permutation test (sampling 1,000 times) and the table reports the test result for the core explanatory variable Green*Post.

	DID		PSM-DID	
	High competitiveness	Low competitiveness	High competitiveness	Low competitiveness
	(1)	(2)	(3)	(4)
Variables	EDP	EDP	EDP	EDP
Green*Post	-0.0031**	0.0004	-0.0034**	0.0006
	(0.0013)	(0.0004)	(0.0015)	(0.0006)
Size	0.0048**	0.0011	0.0066**	0.0018
	(0.0023)	(0.0007)	(0.0032)	(0.0012)
Age	0.0016	0.0019	0.0033	0.0019
	(0.0064)	(0.0032)	(0.0086)	(0.0048)
TobinQ	0.0006	0.0001	0.0012	0.0001
	(0.0004)	(0.0001)	(0.0009)	(0.0002)
Lncash	-0.0053*	0.0000	-0.0072*	-0.0001
	(0.0028)	(0.0003)	(0.0038)	(0.0004)
Liquid	0.0087	0.0050	0.0123	0.0087
	(0.0125)	(0.0046)	(0.0193)	(0.0080)
Boardsize	0.0112**	0.0021	0.0136**	0.0031
	(0.0056)	(0.0018)	(0.0069)	(0.0026)
Top1	0.0094	0.0022	0.0139	0.0030
	(0.0106)	(0.0031)	(0.0138)	(0.0043)
Constant	-0.0347	-0.0385	-0.0498	-0.0541
	(0.0311)	(0.0251)	(0.0425)	(0.0352)
Observations	6,417	6,686	4,927	4,611
R-squared	0.392	0.345	0.394	0.346
Adj. R-squared	0.203	0.133	0.201	0.114
Cluster	Firm	Firm	Firm	Firm
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
p-value of Fisher test for Green*Post	0.045			

Appendix

To accompany the paper:

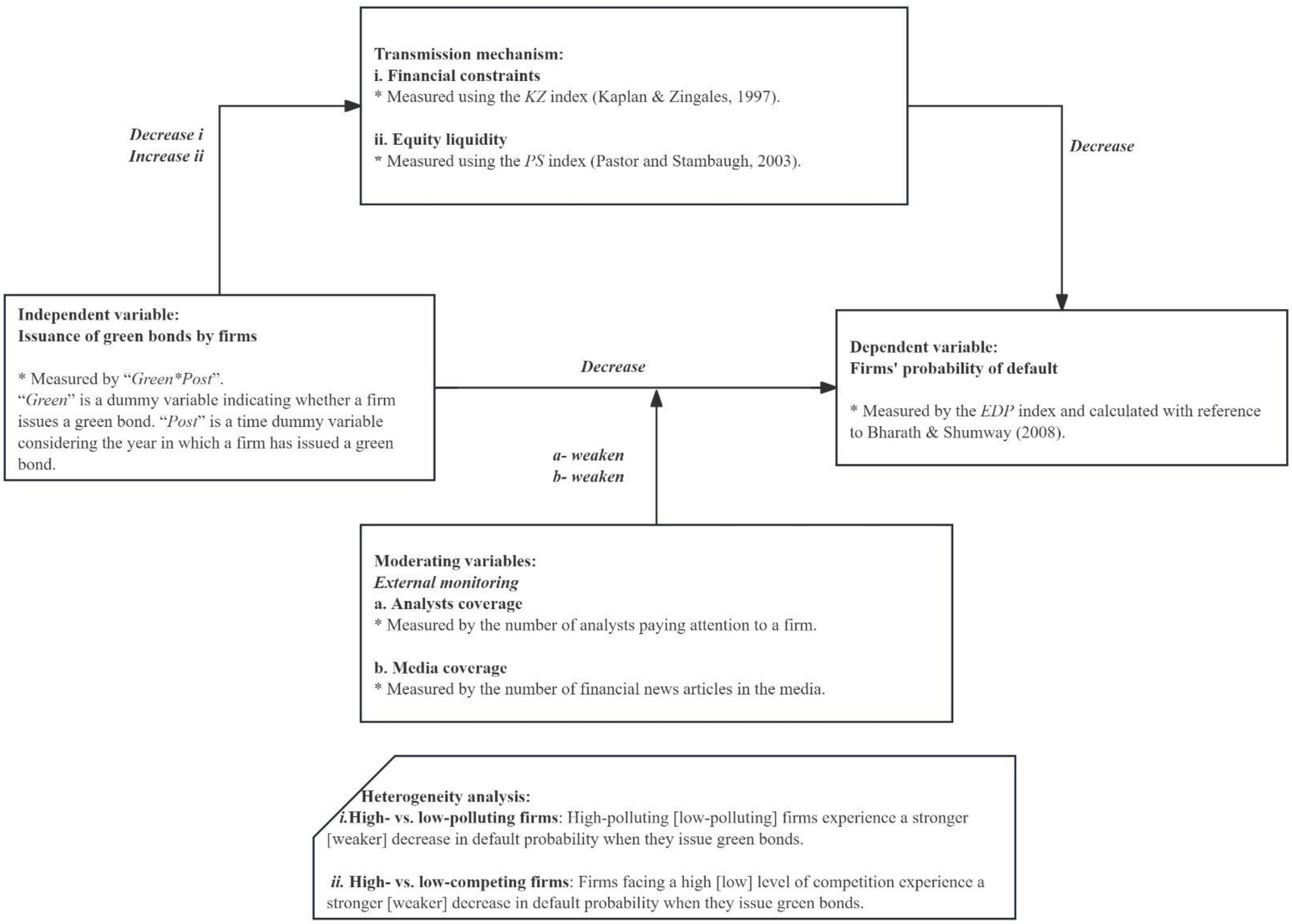
Green Bond Issuance by Firms, External Monitoring, and Probability of Default: Empirical Research Based on Green Policies

Appendix I – Figure: This figure shows the research framework of this study.

Appendix II - Table: This table shows the different government policies by year.

Appendix I - Figure. Research framework

This figure shows the research framework of this study, which explains how this study constructs the relationship between green bond issuance by firms and corporate default probability, as well as the construction of moderating effects, mediating effects, and heterogeneity.



Appendix II - Table. Government policies by year

The table reports on relevant green bond policies issued by Chinese government departments; of these departments, PBOC is the People's Bank of China, NDRC is the National Development and Reform Commission of China, SSE is the Shanghai Stock Exchange, SZSE is the Shenzhen Stock Exchange, CSRC is the China Securities Regulatory Commission, and IMDA is the Interbank Market Dealers' association.

Date	Agency	Policy title	Thrust
2015-12-15	PBOC	'Announcement Regarding the Issuance of Green Financial Bonds in the Interbank Bond Market'; 'Green Bond Support Project Catalog (2015)'	Provide guidance on the issuance of green financial bonds. Provides for six broad categories of green bond support areas.
2015-12-31	NDRC	'Guidelines on the Issuance of Green Bonds'	Clarify the scope of application, support priorities and vetting requirements for companies issuing green bonds.
2016-03-16 2016-04-22	SSE SZSE	'Notice on Launching Pilot Programs for Green Corporate Bonds'	Provide guidance on the issuance of green corporate bonds.
2017-03-02	CSRC	'Guidance on Supporting the Development of Green Bonds'	Provide guidance on the disclosure of information and use of funds for green bonds on the stock exchange.
2017-03-22	IMDA	'Business Guidelines on Green Debt Financing Tools for Non-Financial Enterprises'	Provides guidance on the issuance of green bonds and self-management by non-financial firms.
2017-10-26	CSRC, PBOC	'Guidelines on Green Bond Assessment and Certification Practices (Interim)'	Regulate the qualification, business implementation, report output, etc. of green bond issuers.
2018-02-05	PBOC	'Notice on Strengthening Supervision and Management of the Tenure of Green Financial Bonds'	Provide guidance on managing the duration of green financial bonds and enhancing the transparency of information disclosure.
2019-03	NDRC	'Green Industries Guidance Catalogue (2019 Edition)'	Identify six major green industries, e.g., energy conservation, environmental protection, clean production, and clean energy.
2021-03-18	IMDA	'Notification on clarification of mechanisms related to carbon neutral bonds'	Define carbon-neutral bonds and clarify the rules for dealers' carbon-neutral bond business.
2021-04-21	CSRC, PBOC, NDRC	'Green Bond Support Project Catalog (2021 Edition)'	Update to the catalogue of projects to support the issuance of green bonds
2021-07-13	SSE	'Guidelines for the Application of the SSE Corporate Bond Issuance and Listing Review Rules No. 2 - Specific Types of Corporate Bonds'	New requirements for the issuance and review of new types of green bonds, such as carbon-neutral green bonds, have been added.
2022-07-29	CSRC, PBOC	'Principles for Green Bonds in China'	Unify domestic green bond standards and establish formal green bond standards in line with international standards.