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The Impact of Climate Change Transition Innovations on the Default Risk Evidence from Low-Carbon Patents in China

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Abstract: In the process of climate change mitigation and adaptation, the focus on climate risks driven by transition innovations has received widespread attention from governments, regulators and investors. Based on the identification of low-carbon patents through the Green and Low-carbon Technology Inventory in China, we construct low-carbon innovation measurements of listed firms in China from 2015 to 2021 then an empirical model is used to investigate the impact and mechanism of climate transition innovations on the default risk. The baseline regression model shows that low-carbon innovations can mitigate the default risk of listed firms. Moreover, our findings are supported by instrumental variable regressions that use time costs of innovation. In addition, the mediation effect demonstrates that investor attention, total factor productivity, and technology spillovers are paths for transition innovations to affect the default risk. This study reveals that low-carbon technological advances have a positive effect on climate transition risks. Further, it provides empirical evidence for listed companies to develop low-carbon innovations.

Keywords: climate change transition; low-carbon innovations; default risk; distance-to-default; mediation effect; investor attention; technological spillovers

1. Introduction

After the Paris Agreement was signed to limit global temperature increase, climate change is increasingly becoming a social issue of high concern. However, at the UNFCCC COP28 meeting in Dubai in 2023, it was shown that the climate change adaptation progress is too slow across all areas of climate action. In the sixth IPCC report, insufficient financing and lack of incentives for finance are considered as a barrier to climate mitigation and adaptation with high confidence. For example, average annual investment requirements for 2020 to 2030 in scenarios that limit temperature increasing up to 2°C or 1.5°C are three to six greater than current levels across all sectors and regions with medium confidence. Indeed, an adequate decarbonization of production and consumption activities requires substantial financial support and involvement but there is not enough confidence and motivation. As a result, there is an urgent need to research on the impact on economics and the financial market from climate change transition and adaption before deep financial involvement.

The climate risk from climate change is classified as climate physical risks and climate transition risks. Climate change transition risks refer to economic impact arising from the change of valuation of carbon-intensive and low-carbon assets induced by climate transition action, including drivers like technological advances. Focusing on the technological driver to climate transition risks, which cover a range of effects on firms' operation and transition to a low-carbon economy, enterprises play a key role in making low-carbon innovations for climate change transition. Green innovations and patent information are often taken as indicators for climate related transition. To distinguish a patent of low-carbon innovation from other patents, the IPC code is identified referred to the IPC Green Inventory, which was developed by the World Intellectual Property Office (WIPO) with reference to the United Nations Framework Convention on Climate Change [1]. To make low-carbon innovation

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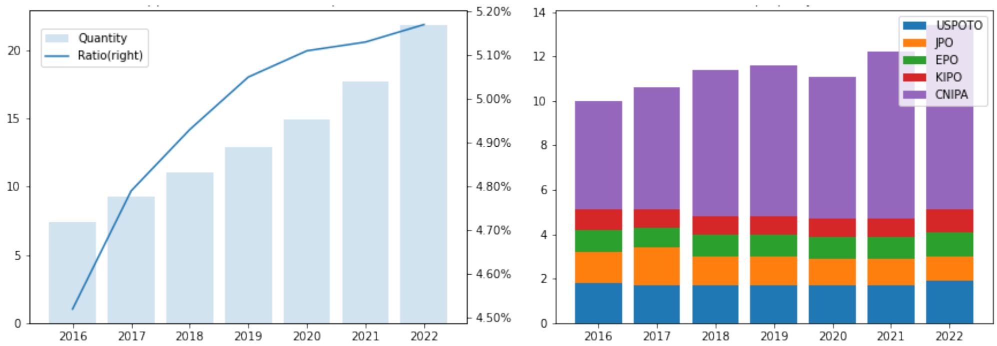
identification more relevant and accurate in the transition to a green development mode which promote carbon dioxide peaking and carbon neutrality, Chinese National Intellectual Property Administration (CNIPA) has proposed the Green and Low-carbon Technology Inventory. The new inventory highlights the carbon-reducing capacity of technologies. Further, it focuses on relevant technology that achieve the carbon-reduction, zero-carbon, or carbon-negative effect mainly through clean utilization of conventional energy, energy saving and efficiency enhancement, utilization of new energy, greenhouse gas capture, utilization and storage. With the help of low-carbon inventory, it is able to exclude pollution reduction technology and get pertinent low-carbon innovation measurements. From 2016 to 2022, the quantity and proportion of low-carbon patent display an increasing trend in figure 1, which confirm the transition to a low-carbon economy. Compared with other intellectual property administrations in Figure 1, the low-carbon patent application in CNIPA has the largest share and the trend is on the rise.



(**a**) (**b**)

Figure 1. (**a**): the quantity and ratio of applications for low-carbon patents in China with an increasing trend. (**b**): displays the distribution and trend of applications for low-carbon patents in global. Notes: USPTO, JPO, EPO, KIPO and CNIPA represent patent offices of United States, Japan, Europe, Korea and China.

With the innovation transition to a low-carbon economy, there is a possible channel to firms' credit risks. First of all, stringent climate and environmental regulation on the performance of business will devaluate carbon-intensive firms [2]. This channel can be explained under the framework of institutional and stakeholder theories, presenting that stakeholders consider an active strategy and incentive to mitigate carbon risk and revalue carbon-intensive assets [3,4]. Beyond the regulation and policy shocks on the climate transition risk, technological advances and changing consumer preferences could also damage high-carbon activities and favor low-carbon firms. Based on the production theory, the productivity presents a positive role in corporate default risk in the framework of climate change transition risk [5]. Other theoretical models suggest that technological progress have an overall positive effect, by presenting that the positive effect on the climate beta of uncertainty about exogenous, emissions-neutral technological progress overwhelms the negative effect on the uncertainty about the carbon-climate-response [6,7]. Empirical research also supports that the technological innovation on climate change transition leads to a good enterprise performance [8,9]. Through stranded assets and innovation, firms advance to low-carbon production has a positive effect on the default risk [10,11].

As the low-carbon innovations develop steadily, the main purpose of this paper is to analyze the influence from transition of low-carbon innovations on the firm credit and default risk, which is a realization of the climate transition risks. Therefore, we firstly label low-carbon patent of Chinese listed firms and construct three low-carbon innovation measurements [12] through the new inventory proposed by CNIPA. Then we investigate the direct effect of low-carbon technological innovations on default risks. Analyzing the straightforward relationship, we find that low-carbon innovations positively affects a firm's distance-to-default, which is the indicator of default risks, consistent with previous results of low-carbon transition and traditional innovations [11–13]. Taking alternative default risk measurements, normalization methods, heterogeneous analysis and instrumental variables, the straightforward effects are tested with robustness and endogeneity issues. By the means of several proxies for stakeholder attention, productivity and technology spillovers, we find that climate change transition innovations affect the credit risk through the mechanism of stakeholder theory and production theory, consistent with previous researches [5,10]. Indeed, the positive relationship between low-carbon innovations and distance-to-default suggests that the positive effect of transition to the carbon-neutral economy overwhelm the negative effect of costs and stakeholder theory is the main channel. Firms should take effort in transition innovations, showing their adaptation to the new economic development mode, which will enhance stakeholder confidence and reduce the likelihood of default.

This study contributes to the literature in several ways. First of all, our study extends the novel stream of research on the relationship between green and low-carbon innovations and corporate performance by verifying whether low-carbon innovations positively or negatively influence the measurement of default risk. Additionally, we enrich the research on climate change transition risks from technological advances by empirically tested the relationship between innovations and default risks. Secondly, we focus on the low-carbon technology advances by using a new patent inventory compared with IPC Green Inventory of WIPO. This label of low-carbon innovations can measure the technological driver of climate change risk accurately and we construct three low-carbon innovation measurements to make robust and comprehensive evaluation of innovation effects on default risks. Last, our results demonstrate possible mechanisms from theory like stakeholder attention. To our knowledge, this is the first study to analyze low-carbon innovations mediation channel of technological spillovers by using patent similarity to measure low-carbon technology spillovers.

The remainder of the paper is presented as follows. The second section summarizes the related literature and proposes the hypotheses. Section 3 details the data and research method and the fourth section present the empirical results. The last section is the conclusions.

2. Literature Review and Hypothesis Development

There is already a large body of research on the effect of innovation and firm performance with a long history. After a long period of research, a consensus has emerged on the positive effects of corporate innovation on business performance [14,15]. Innovations include products, processes, marketing and organization. Focused on the technological innovations, the effect has heterogeneous results. For example, Wang [16] finds out that radical innovation are positively related to firm performance in SMEs, but the incremental innovation strategies have a negative impact on firm performance. Xu et al. [17] conclude that a direct positive effect of innovation inputs on ROA is significant, and technological innovations can be the mediation of different types of capital. Based on studies of firm performance, the firm risk is a natural focus for research on the effects of innovation. Most research find that innovations, such as patent and R&D, can decrease the firm risk in terms of bond default and stock price [12,18,19].

With the basis of innovation and firm performance, when we turn to climate change transition field, green or climate change innovations have plenty of findings [20]. One insight is that the low-carbon technology can decrease cost with deployment [21] but the other side is that the low-carbon innovations seek investment difficultly because of long development and high costs [22]. However, with the support of government policy, many countries have made achievements of research and innovation for climate change transition, such as renewable energy policies across the Europe suggested by Zhou et al. [23] and the policy drivers behind the development of photovoltaics and wind power in the European Union [24]. In China, Zhu et al. [1] find that emission trading scheme increase low-carbon innovations by 5-10% without crowding other technology. For the effectiveness, Acemoglu et al. [25] suggest that climate friendly innovations can move away from reliance on carbon-intensive industries and Davis et al. [26] propose that transition to new infrastructure using fossil fuels is necessary for mitigation in the future. But in short-term and empirical study, climate-change technology do not always decrease the level of carbon dioxide, especially in the medium and low income countries [27]. At least we can conclude that the research in climate change innovations

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is growing with the effect of climate change, but the effectiveness is ambiguous right now. It is time to focus on the effect of climate change transition on individual firms.

Before analysis the risk of firms, the effects of climate change innovation on firm performance remain controversial. Early to 2014, organizational innovations can promote business performance through eco-process and eco-product innovation by Cheng et al. [28]. As for positive effects, Liao [29] presents a theoretical model and tests the promotion effect from environmental innovation on a firm's financial performance, through different types of culture. Huang and Li [30] test the positive effect from green product innovation and green process innovation on environmental and organizational performance of information and communication technology industry. Rezende et al. [31] prove a lagged positive relationship between green innovation intensity and financial performance, yet no significant effects in the immediate year. Li et al. [8] focus on the low-carbon innovation in manufacturing companies. They present that carbon reduction innovation can significantly and positively affect firm performance, with the mechanism of green competence and firm size.

In the other side, studies resulted in negative effects are relatively less than the positive effect. From a broad perspective, the negative effect associates with general innovations. The negative effect stems from complexity and risk during innovation [32], investment crowding-out [33,34] and disruptive product innovation [35]. Javier and Natalia [36] observe that green innovative firms do not show improved financial performance compared to non-green innovative firms. However, the positive effect exists when focusing on green innovative firms. Other studies tend to an ambiguous result. Aastvedt et al. [37] investigate a non-linear effect on financial performance of oil and gas companies. The effect transforms from positive to negative in different areas and different levels of innovation.

Based on the empirical result from effect on firm performance, company risks are also impacted, although the research is much less. Positive effect originates from many aspects. As a result, Gutiérrez-López et al. [11] investigate empirically that firms take efforts in the low-carbon production operate more safely, with moderating effect of stranded assets and innovation. A related analysis is presented by Bannier et al. [9]. They reveal that the higher corporate social responsibility, the lower default risk for U.S. and European firms. Another positive relation is presented by Safiullah et al. [10], with the hypothesis explanation of pro-environmental orientation and information asymmetry.

Hypothesis 1a: Low-carbon innovation is positively associated with firm default risks.

An important source of potential risks from climate adaption is getting rid of stranded assets. Since low-carbon transition requires a significant decline in fossil fuel usage, so-called fossil shock can generate risks in all production activities, which is highlighted by Cahen-Fourot et al. [38]. The potential damages of stranded assets are also presented in environmental-related risk factors [39] and early obsolescence [40]. Chevallier et al. [41] prove that If firms operate with substantial stranded assets, they become vulnerable to the financial risks of default based on the simulation from a stochastic model. In summary, the uncertain low-carbon innovation can make stranded assets lose value but not providing competence from new technology.

Hypothesis 1b: Low-carbon innovation is negatively associated with firm default risks.

With the existence of innovation effects on the default risks, the effect can be explained by instrumental stakeholder theory and information asymmetry. As firms take effort on the green innovations, stakeholders tend to pay attention to other firms because of the disclosure effect of innovations. Significant relations between investor attention and green innovations are supported by He et al. [42] and Gao et al. [43]. Liu et al. [44] also prove that firm green performance can affect stock price with the mediation of investor attention. Specifically, firms with high pollution receive more attention on trading days, translating into stock prices. Deng et al. [38] present that investor attention can affect energy-intensive enterprises negatively with spillovers, and sometimes environmental events are significantly related with individual attention. Another research conducted by Hao and Xiong [46] also confirm the positive effect from investor attention to the firms' risk in China, through the Baidu search index. From the evidence before, we assume that investor attention should be a channel between low-carbon innovation and firm default risks, similarly with that in the pollution performance [44].

Hypothesis 2: Investor attention is a mediation actor between low-carbon innovations and the default risk.

The positive effect of corporate low-carbon innovations on firm performance and default risk is abundant based on comprehensive literature review [15] and representative research [8,11,12]. Investors consider a firm competitive with owning more and higher-quality patent. As for low-carbon innovations, the transitions to low-carbon production also imply relatively high productivity and enterprise competitiveness, since low-carbon innovations often occur in the well-performed firms as an adaption for climate change. There are numerous empirical studies that reveal positive correlation between climate change transition and total factor productivity, including transition policy [47] and innovations [48,49]. Better competitiveness indicates better firm performance and lower risks [50]. The theoretical mechanism is indirectly proved by the climate change risk theory model [5], Battison et al. present a systemic theory for climate change default risk, in which the default probability is negatively related with firms total factor productivity.

Hypothesis 3: Total factor productivity is a mediation actor between low-carbon innovations and the default risk.

Research and innovation spillovers can affect the performance and risks of firms. As literature before presented, innovations take effects on the performance and risks of firms. Furthermore, the existence and effects of technological spillovers from innovation is widely recognized by de Faria and Lima [51], who argue that there is a positive spillover of innovation on firm values in different innovation types. Another empirical evidence is presented by Aiello and Cardamone [52], they find a positive effect from R&D spillovers on firms production. Yao et al. [53] reveal that the type of firm dual network structure has positive influence on firm performance, on the basis of social network theory. With the development of natural language processing, we can measure patent similarity, knowledge linkage and technology spillovers by text analysis [54,55]. Thus, as we prove the effects from low-carbon innovations on firm risks, we assume innovation spillovers measured by centrality in network is a mediation actor.

Hypotheses 4: Technology spillover is a mediation actor between low-carbon innovations and the default risk.

3. Data and Method

3.1. Sample Selection and Data Source

Chinese A-share listed firms, excluded financial firms and ST, from 2015 to 2021 are selected as the sample in this article. The time of data is after the carbon emissions trading market pilot, which is the most important policy for reducing carbon directly. Data used in this study can be divided into three parts. First of all, the patent data comes from CCER[1]. This dataset collects daily patent application details for listed firms in China from 1990 to 2022, which consists of applicant, application date, application number, patent classification, patent name and patent abstract. In addition to the patent data, we collect patent citation data for patent importance measurement from CNRDS[2].

[1] CCER is a database of economics and finance, which is built by Sinofin and China Centre for Economic Research, Peking University.

[2] CNRDS is Chinese Research Data Services Platform, which provides high-quality and open data for Chinese economic researches.

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Secondly, the risk variables and covariates of Chinese listed firms are collected from CSMAR[3], including financial variables, such as distance-to-default, z-score, net ROA, ROE and so on. Last, we select Baidu search index with the stock code of listed firms to represent investor attention, which is provided by CNRDS. In summary, we transform daily data into yearly data, and merge three parts of data based on the stock code of each dataset. Then we fill the missing value of patent and investor attention as zero. Finally, we get 4474 firms panel data from 2015 to 2021.

3.2. Dependent Variables

In this study, we need to measure firm default risks with the dependent variable. According to the research from Bannier et al. [9], Gutierrez-Lopez et al. [11] and Meles et al. [13], we use distance-to-default(DD) as main dependent variables. The distance-to-default measures credit default risks, meaning that firms with higher DD have lower default risks. We use three types of DD [56,57] from CSMAR. The Merton DD from Bharath and Shumway [57] is our main dependent variable and other two dependent variables are used for robustness test. The DD from Bharath and Shumway can be calculated as follows:

$$DD_{i,t} = \frac{\log\left(\frac{E+D}{D}\right) + \left(r_f - \frac{\sigma_V^2}{2}\right) \times T}{\sigma_V \times \sqrt{T}} \tag{1}$$

$$\sigma_V = \frac{E}{E+D}\sigma_E + \frac{E}{E+D}\sigma_D \tag{2}$$

$$\sigma_E = \sqrt{\frac{1}{n-1} \times \Sigma_{i=1}^{n}(r_i - \bar{r})^2} \tag{3}$$

where E means the market value of firm equity and D means overall value of firm liquid liability and illiquid liability. Other notations are that risk-free interest rate r_f and prediction range T. $\sigma_V, \sigma_E, \sigma_D$ mean the volatility about firm asset value, equity and debt respectively, and we take an approximation as $\sigma_D = 0.05 + 0.25\sigma_E$. And σ_E is calculated based on the variance of the logarithmic stock return.

3.3. Independent Variables

Independent variables include low-carbon patent measurement, financial covariates, investor attention measurement and patent network measurement, in which low-carbon patent classification and measurement is the core variable of this study. The low-carbon patent classification refers to the Patent Classification System for Green and Low Carbon Technologies. In this system, classification standard bases on the International Patent Classification (IPC) and keyword search. In the IPC classification part, the system takes IPC 2022 as reference base to identify a patent as low-carbon technologies in 142 technological branches. In some branches the IPC covers too much patent not related with carbon emission reduction, therefore the system provides keywords for these branches. For example, in the branch of carbon capture, “carbon dioxide” and “carbon monoxide” should be added to our search statements other than IPC classification. In summary, we classify all patents of Chinese listed firms into low-carbon patent or non-low-carbon patent in order to mark these patents. Then we calculate green patent quantity, generality and importance as the measurement for climate change transition. Low-carbon patent measurements are yearly for each listed firm, which are summarized from daily patent classification. Low-carbon quantity is the number of low-carbon patents in a year. Low-carbon generality is the number of low-carbon classification which the patent is classified into in a year. Low-carbon importance is the green quantity weighted by the citation of each low-carbon patents. The quantity, generality and importance measurements partly refer to the

[3] CSMAR is China Stock Market and Accounting Research Database, which provides various datasets for Chinese stock market.

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research of Hsu et al. [12]. Another low-carbon patent measurement is the low-carbon time cost, which is calculated by the industry average duration from application to approval. Low-carbon time cost is taken as the instrumental variable, reflecting time costs of firms' low-carbon patenting activities [12].

Financial covariates are selected to control other financial measurements which would influence the default risk of listed firms. We use the annual financial statements and financial indicators, describing solvency, operation, profitability and growth. These characters are main elements deciding the default risk [10,11]. Investor attention is measured by daily Baidu search index. In order to prove our hypothesis from annual panel data, we group the search index by each listed firms and use average and median index to describe the annual investor attention.

To measure technology spillovers, we need to build patent network from their association. Patent network is built from patent similarity from their claimant and abstract, which is better than traditional citation relation for representing technology spillovers [54,55,58]. To build patent similarity, the Doc2vec model is used for this study. Each patent is transformed into vector and we calculate cosine similarity. On purpose of describing firms' technology spillovers, we merge patent similarity into firm-level similarity and build patent spillovers network. Finally, we calculate degree centrality for testing potential mechanisms. In the end, the descriptions of our dependent variables and independent variables are shown in the Table 1.

Table 1. Variable definitions.

Variables	Definition
Distance-to-default (DD)	The measurement of default risks developed by Merton model [57], the more is DD, the less is default risk
Current ratio	Current ratio is the ratio of current assets and current liabilities, which measures the ability to pay short-term obligations within one year.
Interest coverage	Interest coverage is EBIT divided by the interest expense of the firm. Higher interest coverage means
Debt-to-asset ratio	Debt-to-asset ratio is total liabilities divided by total assets, which measures the level of debt.
Total asset turnover	Total asset turnover ratio is the ratio that net sales divided by the average total assets, which measures the efficiency of generating revenue and sales.
Net ROA	The return on net assets is the ratio that net income divided by average net assets, which measures the profitability of the business.
ROE	The return on equity is the ratio that net income divided by average shareholders' equity, which measures the profitability and efficiency of generating profits.
Total asset change	Total asset change is the percentage of total asset change, which measures the growth of assets.
ROA change	ROA change is the percentage of ROA change, which measures the growth of profitability.
Low-carbon patent quantity	The quantity measurement of low-carbon patent, denoting the number of climate change transition innovations
Low-carbon patent generality	The generality measurement of low-carbon patent, denoting the intensity of broad usage of climate transition
Low-carbon patent importance	The importance measurement of low-carbon patent citations, denoting the quality and importance for climate change transition innovations
Low-carbon patent time costs	The difference between the application date and the approval date of the low-carbon patent in the industry level, indicating time costs of innovations.
Investor attention score	The annual median of daily Baidu search index for listed firms
Total factor productivity	Total factor productivity (TFP) is the efficiency of productive activities over time, a productivity indicator that measures total output per unit of total inputs and is calculated by generalized method of moments

Patent centrality	The centrality degree of patent similarity network to describe the technology spillovers

3.4. Empirical Method

To investigate the relationship between low-carbon innovations and default risks and prove the theoretical hypothesis, this paper mainly builds panel fixed effect empirical model. To test hypothesis H1a and H1b, regression models are constructed as the benchmark model.

$$DD_{it} = \beta_0 + \beta_1 LCI_{it} + \beta_n Controls_{it} + \lambda_i + \theta_t + \epsilon_{it} \tag{4}$$

In Equation (4), DD represents the distance-to-default, which is the measurement of firm default risks, the LCI indicates the low-carbon innovation measurements referred to previous studies [12], and controls are the control variables listed in Table 1. i is the firm and t is the time. λ_i is the individual fixed effect and θ_t is the time fixed effect. β_1 is the coefficient of the effect of low-carbon innovations on firm default risks. If $\beta_1 < 0$, we can test the hypothesis H1a and opposite result can prove hypothesis H1b. As for robustness test, we take different distance-to-default measurements and standardization methods to test.

To inspect the heterogeneous effect of climate change transition innovations on default risks, we build a regression model with the introduction of intersection terms as Equation (5).

$$DD_{it} = \beta_0 + \beta_1 LCI_{it} + \beta_2 H_{it} + \beta_3 LCI_{it} * H_{it} + \beta_n Controls_{it} + \lambda_i + \theta_t + \epsilon_{it} \tag{5}$$

In Equation (5), H_{it} denotes the group identification. If the firm is in the group, such as policy treatment, $H_{it} = 1$. Otherwise, $H_{it} = 0$. If $H_{it} = 0$, the Equation (5) is the same as Equation (4). If β_3 is significantly not equal to zero, there is significant innovation effect difference between groups. The heterogeneous effect also indicates an exogenous shock because the group assignments are independent of the innovation measurements [12].

The regression model often involves endogenous issues as previous studies presented. We take accurate low-carbon patent classification to solve measurement error and use control variables and individual fixed effect to mitigate the problem of missing variables. However, simultaneity occurs if firms with lower risk have conditions for more low-carbon innovations. Therefore, we construct the IV-2SLS model for the endogeneity issue. Equation (6) is the first stage of IV-2SLS model and Equation (7) is the second stage, which uses the estimated low-carbon innovations in the regression model.

$$LCI_{it} = \alpha_0 + \alpha_1 IV_{it} + \alpha_n Controls_{it} + \lambda_i + \theta_t + \epsilon_{it} \tag{6}$$

$$DD_{it} = \beta_0 + \beta_1 \widehat{LCI_{it}} + \beta_n Controls_{it} + \lambda_i + \theta_t + \epsilon_{it} \tag{7}$$

In Equation (6), IV_{it} denotes the instrumental variable, which is the time costs of low-carbon patent as demonstrated in Table 1. We implement the F-test, under-identification test, and the weak instrument test for Equation (6). In Equation (7), $\widehat{LCI_{it}}$ denotes the estimated low-carbon innovations based on the Equation (6). The β_1 is the effect of transition innovations on default risks and it is compared with the baseline model in Equation (4) to test the endogeneity issue. If the effect of Equationa (4) and (7) is the same direction, the endogeneity will not have significant influence on the effect.

To verify the mechanisms of innovation impact on default risks, we construct a mediation effect model. Equation (8) shows the relationship between low-carbon innovations and intermediary variables and Equation (9) reveals the effects of low-carbon innovations and intermediary variables on the default risks.

$$M_{it} = \alpha_0 + \alpha_1 LCI_{it} + \alpha_n Controls_{it} + \lambda_i + \theta_t + \epsilon_{it} \tag{8}$$

$$DD_{it} = \beta_0 + \beta_1 LCI_{it} + \beta_2 M_{it} + \beta_n Controls_{it} + \lambda_i + \theta_t + \epsilon_{it} \tag{9}$$

In the Equations (8) and (9), M_{it} denotes the intermediary variable, which is the investor attention, total factor productivity and patent centrality measurement. If α_1 and β_2 are significantly different from zero, the mechanism of H2, H3 and H4 is verified.

4. Empirical Result

4.1. Summary Statistics

Table 2 shows the descriptive statistics of the variables used in the empirical model. In Table 2, the panel data has 23580 observations and 4474 firms from 2015 to 2021. Firstly, the means of the main dependent variable, distance-to-default, is 10.10, with minimum and maximum values of 0.824 and 3306, respectively. It is suggested that the default risk of is diversified and thick-tailed among listed firms. As for independent variables, we build low-carbon innovation measurements, including quantity, generality and importance. The means of quantity, generality and importance is 0.556, 0.603 and 0.864, respectively, with standard deviation of 6.937, 7.465 and 11.87. The measurements of low-carbon innovations are similar in sample distribution. Other control variables are selected and calculated from the financial statements of sample listed firms. Most of them are similar within the same group of financial indicators. For example, current ratio and asset loan rate, which measure the solvency capability of firms, have similar average values, standard deviation, minimum values and maximum values.

Table 2. Descriptive statistics of main variables.

Variables	Signal	Observations	Mean	SD	Min	Max
Distance-to- default	DD	23,580	10.10	17.19	0.824	3,306
Current ratio	CR	23,580	2.726	3.958	-5.132	190.9
Interest cover	IC	23,580	35.88	1,037	-19,622	125,199
Asset loan rate	AL	23,580	0.448	1.347	-0.195	178.3
Total asset turnover	TAT	23,580	0.670	0.556	-0.0479	12.37
Net ROA	ROA	23,580	0.0412	0.192	-16.11	20.79
ROE	ROE	23,580	0.0520	0.941	-174.9	21.90
Total asset change	TAG	23,580	0.222	0.686	-1.000	41.46
ROA change	ROAG	23,580	-8.804	886.7	-171,184	22,677
Low-carbon patent quantity	LCQ	23,580	0.556	6.937	0	417
Low-carbon patent generality	LCG	23,580	0.603	7.465	0	450
Low-carbon patent importance	LCI	23,580	0.864	11.87	0	750
Low-carbon patent time costs	LCT	23,580	19.11	67.48	0	1,250
Total factor productivity	TFP	23,580	3.095	1.375	-0.527	9.437
Investor attention score	IA	23,580	750.3	1,348	0	49,556
Patent centrality	PC	23,580	0.0182	0.0550	0	0.888

4.2. The Effect of Low-Carbon Innovations on Default Risks

To test the Hypothesis 1, Table 3 presents the baseline empirical result of innovation effects on the default risk based on the Equation (4). As shown in Table 3, Columns (1) and (2) report the results of model (4), with the low-carbon patent quantity as the climate change transition measurement. They omit and control the province fixed effect and industry fixed effect respectively. Columns (3) and (4) present the results of innovation effect, with the low-carbon patent generality as the climate change transition measurement. Columns (5) and (6) show the low-carbon innovation effects on default risks, by using low-carbon patent importance as the innovation measurement. First of all, the results are robust and similar with and without the controlling of province fixed effect and industry fixed effect, especially the difference concentrates on the constant terms. Secondly, three low-carbon innovation

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measurements all show positive and significant effects on the default risk, and the effect of low-carbon importance is relatively smaller than other two measurements. The effect of low-carbon patent quantity and generality is significantly positive and at 5% level, and the coefficients of the low-carbon patent importance is significantly positive and at 10% level.

The results of baseline model support the hypothesis H1b, that low-carbon innovations have negative impacts on the default risk. Although this finding is similar with the innovation effect on default risks [12,15], it is a new result for climate change transition innovations. The baseline result suggests that low-carbon transitions can have a new positive impact on the firm situation. However, the empirical result could be influenced by the default risk indicator and data scale, the robustness check needs to be done for the hypothesis verification.

Table 3. Default risks and Low-carbon innovations.

	(1)	(2)	(3)	(4)	(5)	(6)
LCQ	0.007**	0.007**				
	(0.003)	(0.003)				
LCG			0.007**	0.007**		
			(0.003)	(0.003)		
LCI					0.004*	0.004*
					(0.002)	(0.002)
CR	0.273***	0.271***	0.273***	0.271***	0.273***	0.271***
	(0.048)	(0.049)	(0.048)	(0.049)	(0.048)	(0.049)
IC	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AL	-0.029*	-0.021	-0.029*	-0.021	-0.029*	-0.021
	(0.016)	(0.022)	(0.016)	(0.022)	(0.016)	(0.022)
TAT	0.356**	0.352*	0.356**	0.351*	0.358**	0.353*
	(0.177)	(0.180)	(0.177)	(0.180)	(0.177)	(0.180)
ROA	-0.478***	-0.494***	-0.478***	-0.494***	-0.476**	-0.492***
	(0.185)	(0.187)	(0.185)	(0.187)	(0.185)	(0.187)
ROE	-0.009	-0.010	-0.009	-0.010	-0.009	-0.010
	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.009)
TAG	0.316***	0.339***	0.316***	0.339***	0.316***	0.339***
	(0.081)	(0.091)	(0.081)	(0.091)	(0.081)	(0.091)
ROAG	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cons	5.954***	10.234***	5.954***	10.234***	5.956***	10.235***
	(0.166)	(1.348)	(0.166)	(1.348)	(0.166)	(1.348)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Prov FE	NO	YES	NO	YES	NO	YES
Ind FE	NO	YES	NO	YES	NO	YES
Obs	23,580	23,580	23,580	23,580	23,580	23,580
R^2	0.050	0.053	0.050	0.053	0.050	0.053

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively, and the values in parentheses are robust standard errors of clustering in the firm–year dimension.

As shown in Table 4, columns (1), (2) and (3) show the robustness check by standardization of z-score, which transform the low-carbon innovation indicator by $s = (x_i - \mu(x_i))/\sigma_x$. s is numeric data after normalization, and μ, σ denote the group mean and standard deviation respectively. Columns (4), (5) and (6) present the robustness check by min-max normalization, which normalize the low-carbon innovation indicators by $s = (x_i - \min(x_i))/(max(\mathrm{x_i}) - \min(x_i))$. After normalization, we can compare effects on the default risk from different innovation measurements

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[59]. All effects remain significantly positive as the baseline model. Further, the magnitude of low-carbon innovation effect is almost the same between three measurements, with difference in the standard deviation of estimation, indicating the robustness and comparability between different low-carbon innovation measurements.

Table 4. Robustness test for normalization.

	(1)	(2)	(3)	(4)	(5)	(6)
	z-score normalization			Min-max normalization		
LCQ	0.005***			3.042***		
	(0.002)			(1.187)		
LCG		0.005**			3.056**	
		(0.002)			(1.251)	
LCI			0.005*			3.228*
			(0.002)			(1.801)
CR	0.016***	0.016***	0.016***	0.000***	0.000***	0.000***
	(0.003)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)
IC	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AL	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
TAT	0.020*	0.020*	0.021*	0.000*	0.000*	0.000*
	(0.010)	(0.010)	(0.011)	(0.000)	(0.000)	(0.000)
ROA	-0.029***	-0.029***	-0.029***	-0.000***	-0.000***	-0.000***
	(0.011)	(0.011)	(0.011)	(0.000)	(0.000)	(0.000)
ROE	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TAG	0.020***	0.020***	0.020***	0.000***	0.000***	0.000***
	(0.005)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)
ROAG	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cons	0.008	0.008	0.008	0.003***	0.003***	0.003***
	(0.078)	(0.078)	(0.078)	(0.000)	(0.000)	(0.000)
Obs	23,580	23,580	23,580	23,580	23,580	23,580
R^2	0.053	0.053	0.053	0.053	0.053	0.053

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively, and the values in parentheses are robust standard errors of clustering in the firm–year dimension.

In Table 5, columns (1), (2) and (3) display the robustness check by changing distance-to-default from method of Bharath and Shumway [57] to Merton [56], and columns (4), (5) and (6) display the robustness check by calculating distance-to-default according to the Kealhofer Merton Vasicek (KMV) model. All the low-carbon innovation effects show significantly positive for three measurements at 1% level. The difference is the standard deviation of estimation for the low-carbon importance measurement. The hypothesis is verified by different default risk measurements and the positive effect of low-carbon innovation shows robustness.

Table 5. Robustness test for different default risk indicators.

	(1)	(2)	(3)	(4)	(5)	(6)
	Merton	**Merton**	**Merton**	**KMV**	**KMV**	**KMV**
LCQ	0.009***			0.003***		
	(0.003)			(0.001)		
LCG		0.009***			0.003***	
		(0.003)			(0.001)	

LCI			0.006***			0.004***
			(0.002)			(0.001)
CR	0.325***	0.325***	0.325***	0.068***	0.068***	0.068***
	(0.055)	(0.055)	(0.055)	(0.014)	(0.014)	(0.013)
IC	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AL	-0.023	-0.023	-0.023	-0.048***	-0.048***	-0.048***
	(0.028)	(0.028)	(0.028)	(0.018)	(0.019)	(0.018)
TAT	0.498**	0.498**	0.500**	0.173	0.173	0.174
	(0.199)	(0.199)	(0.199)	(0.120)	(0.120)	(0.120)
ROA	0.079	0.079	0.081	0.412***	0.412***	0.413***
	(0.253)	(0.253)	(0.253)	(0.155)	(0.155)	(0.155)
ROE	-0.013**	-0.013**	-0.013**	0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.012)	(0.012)	(0.012)
TAG	0.259***	0.259***	0.259***	0.009	0.009	0.008
	(0.086)	(0.086)	(0.086)	(0.022)	(0.022)	(0.022)
ROAG	0.000**	0.000**	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cons	11.399***	11.399***	11.400***	2.987**	2.987**	2.988**
	(1.457)	(1.457)	(1.458)	(1.384)	(1.384)	(1.386)
Obs	23,580	23,580	23,580	23,580	23,580	23,580
R^2	0.036	0.036	0.035	0.076	0.076	0.076

Note: **, *** denote significance at the 5% and 1% levels, respectively, and the values in parentheses are robust standard errors of clustering in the firm–year dimension.

4.3. Heterogeneity Effects

After verifying the hypothesis 1, the climate change transition effect on the default risk could be heterogeneous among different groups. In the first heterogenous analysis, the low-carbon city pilot policy (LCCP), which has become one of the most significant development initiatives, is introduced as a treatment assignment to explore the intergroup difference of innovation effects. We use the first and the second batches of LCCP projects by consulting governmental documents in 2010 and 2012 [60,61]. In the Table 6, columns (1), (2) and (3) demonstrate the heterogeneous effects for three low-carbon innovation measurements respectively, especially the coefficient of LCCP×Innovation. The low-carbon innovation effect is significantly –0.018 and -0.016 for quantity and generality measurements at 10% level, but it is significantly 0.006 for the innovation importance measurement at 5% level. There is different heterogeneous effect for different measurements. As for firms in low-carbon city pilot, the significantly positive innovation effect on default risks is less than other firms for average low-carbon patent quantity and the innovation effect on default risks is more than other firms for average low-carbon patent citation. It is suggested that high-quality low-carbon innovation does have more effects on alleviating default risks under low-carbon regulations.

Table 6. Heterogeneous analysis from low-carbon city pilot.

	(1)	**(2)**	**(3)**
Innovation=	Quantity	Generality	Importance
LCCP×Innovation	-0.018*	-0.016*	0.006**
	(0.010)	(0.010)	(0.003)
LCCP	0.166	0.166	0.158
	(0.559)	(0.559)	(0.558)
Innovation	0.024**	0.022**	0.000
	(0.010)	(0.009)	(0.001)
CR	0.273***	0.273***	0.273***
	(0.048)	(0.048)	(0.048)

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IC	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
AL	-0.029*	-0.029*	-0.029*
	(0.016)	(0.016)	(0.016)
TAT	0.355**	0.355**	0.356**
	(0.177)	(0.177)	(0.177)
ROA	-0.479***	-0.479***	-0.476***
	(0.185)	(0.185)	(0.185)
ROE	-0.009	-0.009	-0.009
	(0.007)	(0.007)	(0.007)
TAG	0.316***	0.316***	0.316***
	(0.081)	(0.081)	(0.081)
ROAG	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)
Cons	5.858***	5.858***	5.866***
	(0.349)	(0.349)	(0.349)
Obs	23,580	23,580	23,580
R^2	0.050	0.050	0.050

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively, and the values in parentheses are robust standard errors of clustering in the firm–year dimension.

Another heterogeneous effect comes from the green credit policy shock in 2012, which may affect the effect on default risk of firms [62]. We select heavily polluting industries including the textile industry, paper industry, petrochemical industry, metallic manufacturing and non-metallic manufacturing industry as the group treated by green credit policy [63]. Based on the columns (1), (2) and (3) in Table 7, firms in green credit policy have significantly -0.062, -0.052 and -0.049 less low-carbon innovations effect compared with other firms without supporting by green credit. It could be explained that green credit policy reduces firm performance in these polluting industries [62], thus the improvement from low-carbon innovation to default risk could be weakened. Furthermore, the heterogeneous effects are similar in number and sign among three low-carbon innovation measurements.

Table 7. Heterogeneous analysis from green credit policy shocks.

	(1)	**(2)**	**(3)**
Innovation=	Quantity	Generality	Importance
Policy×Innovation	-0.062***	-0.052***	-0.049*
	(0.020)	(0.018)	(0.029)
Policy	1.309**	1.309**	1.376**
	(0.618)	(0.619)	(0.610)
Innovation	0.007**	0.006**	0.003
	(0.003)	(0.003)	(0.002)
CR	0.145***	0.145***	0.146***
	(0.018)	(0.018)	(0.018)
IC	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
AL	-0.030	-0.030	-0.030
	(0.027)	(0.027)	(0.027)
TAT	-0.262**	-0.262**	-0.262**
	(0.125)	(0.125)	(0.125)
ROA	-0.243	-0.244	-0.241
	(0.158)	(0.158)	(0.158)
ROE	-0.008	-0.008	-0.007

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	(0.006)	(0.006)	(0.006)
TAG	-0.050	-0.050	-0.050
	(0.035)	(0.035)	(0.035)
ROAG	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Cons	7.636***	7.636***	7.634***
	(0.604)	(0.604)	(0.603)
Obs	23,580	23,580	23,580
R^2	0.272	0.272	0.271

Note: **, *** denote significance at the 5% and 1% levels, respectively, and the values in parentheses are robust standard errors of clustering in the firm–year dimension.

4.4. Endogeneity Issues

The endogeneity issue is introduced in the Section 3.4 before, so we construct the IV-2SLS model to test the simultaneity issue. We choose the low-carbon time cost as instrumental variable for three low-carbon innovation measurements in the model as shown in Table 1. This instrumental variable is time costs of firms' patenting activities and should influence low-carbon innovation incentives to innovate to a great extent. On the other hand, it is exclusive by being uncorrelated with the dependent variable, that is distance-to-default, because the firm's relative patenting performance in industry level has no effect on dependent variables. In addition to these conceptual arguments, we also conduct relevant statistical tests, including F-test, under-identification and weak identification test, to empirically justify the validity of the instrumental variable in Table 8.

In Table 8, columns (1) and (2) demonstrate the effect of low-carbon innovation quantity in two stages. Columns (3) and (4) present innovation effects of low-carbon generality and columns (5) and (6) present innovation effects of low-carbon importance. For all innovation measurements, there are significantly overall positive effects on default risks, indicating the validity of our verification for hypothesis 1. In the columns (1), (2), (3) and (4), the coefficient estimates of the instrument variable is significantly positive at the 5% level. In the columns (5) and (6), estimates for low-carbon importance are significantly negative at the 10% and 5% level, respectively. As for statistic tests, the first-stage F-statistics for excluded instrument are 5.06, 5.12 and 6.17, which are significant at 5% level. Furthermore, the Kleibergen-Paap rk LM statistics are significant at 5% level for under-identification and the Cragg-Donal Wald F-statistics for weak identification are 201.65, 201.79 and 113.31, which all exceed the critical value of 16.38 at the 10% weak instrument bias level according to the Stock-Yogo weak instrument threshold.

Table 8. Endogeneity issues in 2SLS without endogeneity.

	Quantity		**Generality**		**Importance**	
	1st-stage	**2nd-stage**	**1st-stage**	**2nd-stage**	**1st-stage**	**2nd-stage**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
LCT	0.047**		0.052**		-0.058**	
	(0.021)		(0.023)		(0.023)	
Innovations		0.187**		0.174**		-0.156*
		(0.097)		(0.090)		(0.081)
Obs	23,059	23,059	23,059	23,059	23,059	23,059
R^2	0.021	0.021	0.021	0.021	0.126	0.126
Controls	YES	YES	YES	YES	YES	YES
Instrument Validity Tests for IV regression						
(i) F-test for excluded						

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instrument in first stage			
Sanderson-Windmeijer F-test	5.06**	5.12**	6.17**
(ii)Under-identification test			
Kleibergen-Paap LM statistic	4.891**	4.941**	6.04**
(iii)Weak identification test			
Cragg-Donald Wald F statistic	201.65	201.79	113.31
Stock-Yogo weak ID test			
10% max IV size	16.38	16.38	16.38
15% max IV size	8.96	8.96	8.96
20% max IV size	6.66	6.66	6.66
25% max IV size	5.53	5.53	5.53

Note: *, ** denote significance at the 10% and 5% levels, respectively, and the values in parentheses are robust standard errors of clustering in the firm–year dimension.

4.5. Mechanism of Low-Carbon Innovation Effects

To test the Hypothesis 2 and Hypothesis 3, we construct three mediation models based on 2-step regression. As for Hypothesis 2 based on instrumental stakeholder theory and information asymmetry, we take investor attention of listed firms as the mediation variable as shown in Table 1. In Table 9, columns (1), (3) and (5) display the first stage result from mediator to independent variables and columns (2), (4) and (6) show the second stage regression including independent variables and mediation variables. In columns (1) and (2), the coefficients are -6.275 and -0.001 significantly at the 1% level which shows incomplete mediation. In columns (3) and (4), the estimates are significant -5.840 and insignificant 0.006, and significant -5.397 and insignificant 0.000 in columns (5) and (6). The investor focus is complete mediation for low-carbon patent generality and importance. Overall, for three low-carbon innovation indicators, there is a significant path from low-carbon innovation to alleviate default risks through decreasing the investor focus.

Table 9. Mediator effects from investor attentions.

	(1) investor attention	(2) DD	(3) investor attention	(4) DD	(5) investor attention	(6) DD
IA		-0.001***		-0.001***		-0.001***
		(0.000)		(0.000)		(0.000)
LCQ	-6.275***	0.007*				
	(1.598)	(0.004)				
LCG			-5.840***	0.006		
			(1.531)	(0.004)		
LCI					-5.397***	0.000
					(1.643)	(0.002)
CR	-9.765***	0.141***	-9.767***	0.141***	-12.818***	0.262***
	(3.299)	(0.018)	(3.299)	(0.018)	(2.909)	(0.048)
IC	0.008	-0.000	0.008	-0.000	0.006	0.000
	(0.008)	(0.000)	(0.008)	(0.000)	(0.007)	(0.000)
AL	9.565	-0.030	9.569	-0.030	6.476	-0.017
	(5.955)	(0.026)	(5.956)	(0.026)	(5.004)	(0.020)

TAT	65.143**	-0.232*	65.171**	-0.232*	43.898*	0.385**
	(28.621)	(0.122)	(28.625)	(0.122)	(26.622)	(0.180)
ROA	83.995*	-0.226	84.059*	-0.226	60.848*	-0.447**
	(43.369)	(0.147)	(43.378)	(0.147)	(36.741)	(0.184)
ROE	1.341	-0.007	1.340	-0.007	2.582**	-0.008
	(0.945)	(0.006)	(0.946)	(0.006)	(1.079)	(0.009)
TAG	-15.286*	-0.057*	-15.298*	-0.057*	-19.690***	0.324***
	(7.960)	(0.034)	(7.961)	(0.034)	(7.097)	(0.088)
ROAG	-0.010***	0.000***	-0.010***	0.000***	-0.010***	0.000**
	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)
Cons	2,354.184***	8.646***	2,354.560***	8.646***	2,192.537***	11.850***
	(185.072)	(0.612)	(185.111)	(0.612)	(170.333)	(1.446)
Obs	23,580	23,580	23,580	23,580	23,580	23,580
R^2	0.215	0.286	0.215	0.286	0.199	0.063

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively, and the values in parentheses are robust standard errors of clustering in the firm–year dimension.

To verify the hypothesis 3, we calculate total factor productivity (TFP) by the general moment model [64]. With the TFP as the mediator, we try to argue that low-carbon innovations can improve the risk profile through overall production performance. In Table 10, columns (1), (3) and (5) show the first stage result of three low-carbon innovation measurements on TFP. Columns (2), (4) and (6) display the second stage result including mediators and independent variables. As shown in columns (1), (2), (3) and (4), these mediation effects are significantly positive for low-carbon quantity and generality measurements. However, the mechanism is not significant for the low-carbon innovation importance based on columns (5) and (6). In conclusion, the TFP acts as a suppression mediator in the low-carbon innovation effects on default risks and the hypothesis 3 is partly tested.

Table 10. Mediator effects from production efficiency.

	(1) TFP	(2) DD	(3) TFP	(4) DD	(5) TFP	(6) DD
TFP		0.227***		0.227***		0.973***
		(0.053)		(0.053)		(0.119)
LCQ	0.001*	0.010**				
	(0.001)	(0.004)				
LCG			0.001*	0.008**		
			(0.000)	(0.004)		
LCI					-0.001	0.004
					(0.000)	(0.003)
CR	0.005	0.147***	0.005	0.147***	-0.069***	0.204***
	(0.004)	(0.018)	(0.004)	(0.018)	(0.009)	(0.042)
IC	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AL	0.000	-0.034	0.000	-0.034	0.004	-0.018
	(0.010)	(0.026)	(0.010)	(0.026)	(0.007)	(0.019)
TAT	0.843***	-0.069	0.843***	-0.069	0.475***	0.816***
	(0.071)	(0.128)	(0.071)	(0.128)	(0.050)	(0.221)
ROA	0.294**	-0.196	0.294**	-0.196	0.427***	-0.077
	(0.130)	(0.136)	(0.130)	(0.136)	(0.103)	(0.162)
ROE	-0.007*	-0.009	-0.007*	-0.009	-0.009**	-0.019***
	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)
TAG	-0.021*	-0.056	-0.021*	-0.056	-0.217***	0.127**
	(0.012)	(0.035)	(0.012)	(0.035)	(0.048)	(0.065)

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ROAG	0.000	0.000***	0.000	0.000***	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cons	0.702**	7.779***	0.702**	7.777***	-0.068	10.169***
	(0.293)	(0.564)	(0.293)	(0.565)	(0.279)	(1.325)
Obs	23,580	23,580	23,580	23,580	23,580	23,580
R^2	0.260	0.272	0.260	0.272	0.178	0.078

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively, and the values in parentheses are robust standard errors of clustering in the firm–year dimension.

As for verifying the Hypothesis 4, we try to test the mediation effect through the technology spillovers. It is demonstrated in Table 11 that columns (1), (3) and (5) show the first-stage mediation result and columns (2), (4) and (6) show the second-stage mediation regression. In columns (1) and (2), the two-step mediation effects are 0.003 and 2.488 at 1% and 10% level respectively. In columns (3) and (4), the mediation effects are 0.003 and 2.500 significantly at 1% and 10% level, and columns (5) and (6) show significant mediation effects as 0.001 and 2.435 at 1% and 5% level. We can test the Hypothesis 4 with these complete mediation effects for all low-carbon innovation measurements. Low-carbon technology similarity network centrality act as the influence power in the field of low-carbon technology. This finding provides evidence that firms' low-carbon innovations can alleviate default risks through their low-carbon technology spillovers.

Table 11. Mediator effects from technology spillovers.

	(1) spillovers	(2) DD	(3) spillovers	(4) DD	(5) spillovers	(6) DD
PC		2.488*		2.500*		2.435**
		(1.332)		(1.344)		(1.126)
LCQ	0.003***	-0.000				
	(0.001)	(0.004)				
LCG			0.003***	-0.000		
			(0.001)	(0.004)		
LCI					0.001***	0.004
					(0.000)	(0.003)
CR	-0.000	0.272***	-0.000	0.272***	-0.000	0.272***
	(0.000)	(0.049)	(0.000)	(0.049)	(0.000)	(0.049)
IC	0.000**	-0.000	0.000**	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AL	0.000*	-0.022	0.000*	-0.022	0.000*	-0.022
	(0.000)	(0.022)	(0.000)	(0.022)	(0.000)	(0.022)
TAT	0.001*	0.348*	0.001*	0.348*	0.000	0.349*
	(0.001)	(0.180)	(0.001)	(0.180)	(0.001)	(0.180)
ROA	0.004*	-0.503***	0.004*	-0.503***	0.005**	-0.503***
	(0.002)	(0.187)	(0.002)	(0.187)	(0.002)	(0.187)
ROE	0.000	-0.010	0.000	-0.010	0.000	-0.010
	(0.000)	(0.009)	(0.000)	(0.009)	(0.000)	(0.009)
TAG	0.000	0.339***	0.000	0.339***	0.000	0.338***
	(0.000)	(0.091)	(0.000)	(0.091)	(0.000)	(0.091)
ROAG	-0.000	0.000***	-0.000	0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cons	0.016***	10.193***	0.016***	10.193***	-0.014**	10.195***
	(0.005)	(1.347)	(0.005)	(1.347)	(0.006)	(1.348)
Obs	23,580	23,580	23,580	23,580	23,580	23,580
R^2	0.253	0.054	0.261	0.054	0.124	0.054

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively, and the values in parentheses are robust standard errors of clustering in the firm–year dimension.

5. Conclusions

This paper examines whether and how climate change transition innovation affects firm default risk by the means of green and low-carbon patent inventory proposed by CNIPA between 2015 and 2021. The regression model used in this paper considers different low-carbon innovation measurements, robustness check, heterogenous analysis and endogeneity issues. Further, we construct several indicators of transition risk channels to investigate possible mechanism based on theory proposed by previous research. Our findings can be summarized as follows.

First, we find that low-carbon transition innovation significantly decreases default risk as measured by distance-to-default. This result is tested with three low-carbon innovation measurements, including quantity, generality and importance. Our work is robust when we use alternative normalization methods and default risk measurements. Furthermore, as a heterogeneous analysis, we find that firms under climate policy treatment will get lower innovation effects on default risks compared with other firms. Thirdly, we take innovation time costs as instrumental variables to test endogeneity and our results are robust under IV-2SLS model. Finally, we find that three mechanisms can explain how low-carbon innovations affect the default risk, including stakeholder attentions, productivity and technological spillovers.

Further, our results are of interest to corporate managers, investors and policymakers. From the perspective of managers, this work suggests that they should accelerate the process of low-carbon and carbon-neutral adaptation and transition, especially for enterprises in the industry out of the regulation coverage yet. Additionally, enforce the climate change transition information disclosure is an effective instrument for value management according to the mechanism of low-carbon innovation effects on default risks. As for investors, low-carbon innovations are verified as a good indicator for investing. However, it is noticed that firms under regulation do not have enough innovation effects as supposed. From the perspective of policymakers, climate finance barrier is an issue of high concern. Recognizing the effect of low-carbon innovations, it is necessary to propose policy to promote engagement in climate transition innovations. An effective method is developing a low-carbon technology inventory and give subsidies referring to it. There is incentive for stakeholders to take part in climate change transition by technological advances and financial supports.

Finally, this paper is the first to investigate the relationship between low-carbon innovations and default risk based on a more accurate low-carbon patent inventory. However, some limitations still exist in this study, providing possible suggestions for future research. First, our analysis concentrates on Chinese listed firms and patents, which are an important part of low-carbon innovations in the world. If the low-carbon patent inventory is expanded to the scope of global patents, the climate change risk driven from low-carbon innovations can be analyzed in the context of different national climate change transformation processes and objectives. Secondly, the mechanism tests in this work are still simple and coarse in terms of the method and theory. Although the existing theory of climate change transition risks give an illuminating framework for our mediation models [5], the economic theory can be developed for specific mechanisms, like technological spillovers. Last but not the least, we only formulated linear hypotheses and relationship. For further research, scholars can try to analyze nonlinear relationship, such as a U-shaped or inverted U-shaped curve between low-carbon innovations and default risk indicators. It is interesting to explore the positive effects and negative effects separately according to nonlinear relationship.

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