sustainability

MDPI

Article

The Impact of Climate Change Transition Innovations on the Default Risk

Yujun Huang and Zhihao Huang *

School of Data Science, Fudan University, Shanghai 200433, China; yjhuang19@fudan.edu.cn
* Correspondence: zhhuang20@fudan.edu.cn

Abstract: In the context of climate change mitigation and adaptation, climate risks stemming from climate transition innovations have garnered significant attention due to concerns about the inadequate climate finance. To shed light on the climate transition risk posed by innovations, this study constructed low-carbon innovation indicators of listed firms in China spanning 2015 to 2021. This study investigated the impact of climate transition innovations on the default risk, considering the mediation effect of investor attention, total factor productivity, and technology spillovers. The findings suggest that low-carbon innovations can mitigate the default risk of listed firms, as evidenced by three low-carbon innovation indicators. Additionally, the research reveals that the climate innovation effect on default risks was moderated when considering climate policy through heterogenous analysis. Furthermore, instrumental variable regressions using the time costs of innovation support the findings. Lastly, default risk was mitigated through lower levels of investor attention, greater total factor productivity, and technology spillovers.

Keywords: climate change transition; default risk; low-carbon innovations

check for updates

Citation: Huang, Y.; Huang, Z. The Impact of Climate Change Transition Innovations on the Default Risk. *Sustainability* **2024**, *16*, 4321. https://doi.org/10.3390/su16114321

Academic Editor: George Kyriakarakos

Received: 25 April 2024
Revised: 15 May 2024
Accepted: 17 May 2024
Published: 21 May 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

After the Paris Agreement was signed with the objective of limiting the increase in global temperatures, climate change has increasingly become a social issue of high concern. However, the sixth IPCC report identifies insufficient financing and a lack of incentives for finance as barriers for hindering climate mitigation and adaptation efforts with high confidence. The average annual investment requirements from 2020 to 2030, in scenarios aimed at limiting temperatures increases up to 2 °C or 1.5 °C, are estimated to be three to six times greater than the current levels across all sectors and regions with medium confidence. Achieving adequate decarbonization of production and consumption activities necessitates significant financial support and engagement, but there is neither enough confidence nor motivation to invest in due to uncertainty surrounding climate transition. Consequently, there is an urgent need for research on the impact of climate change transition and adaptation on economics and the financial markets before substantial financial involvement is pursued.

Climate change transition risks refer to the economic impact stemming from the changing valuation of carbon-intensive and low-carbon assets triggered by climate transition actions. These actions include drivers such as green technological advances, which usually indicated by patent applications. The Chinese National Intellectual Property Administration (CNIPA) has introduced the Green and Low-Carbon Technology Inventory in order to enhance the identification of low-carbon patents, ensuring relevance and accuracy in the transition towards a green development mode that promotes carbon dioxide peaking and carbon neutrality. This new inventory emphasizes the carbon-reducing capacity of technologies that facilitate carbon-reduction, zero-carbon, or even carbon-negative effects. With the help of the low-carbon inventory, it becomes possible to measure the climate change transition, while excluding pollution reduction technology. Leveraging the low-carbon

innovation identification, China has made significant advancements in climate change transition technology on a global scale. Figure 1 illustrates that Chinese low-carbon patent applications via the CNIPA have a significant global share, and that the trend of shares was on the rise from 2016 to 2022. By 2022, the quantity of low-carbon patents exceeded 80,000, with the global share surpassing 50%. Consequently, it is imperative and feasible to analyze the transition impact on default risk of low-carbon innovations in China.

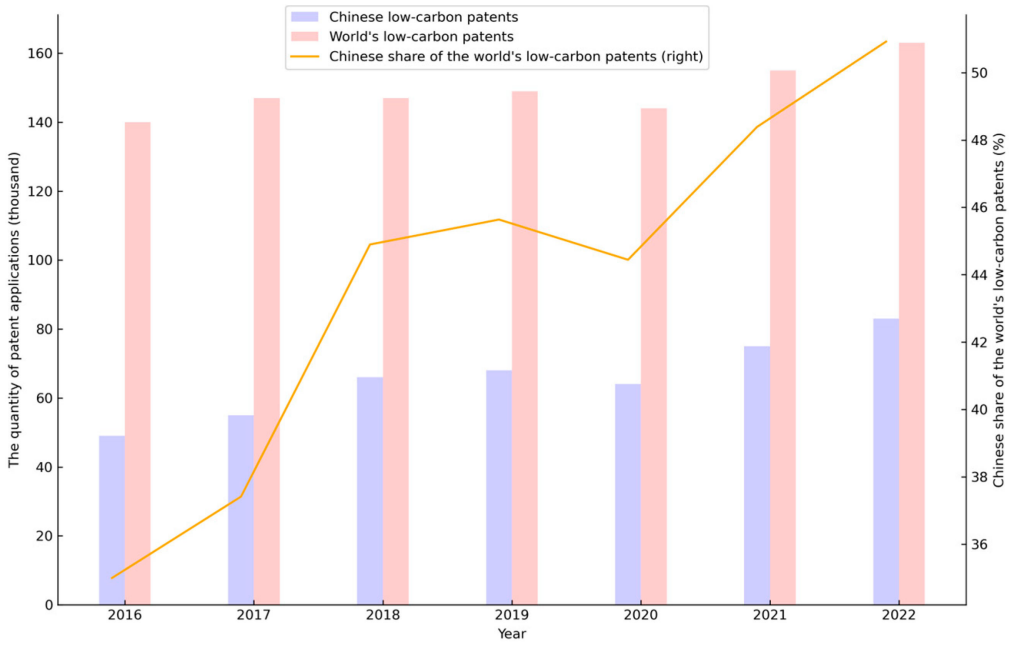


Figure 1. Chinese low-carbon patents and their global share from 2016 to 2022. Notes: In the figure, the quantity of Chinese and global low-carbon patents application is depicted by blue and red bars, respectively, on the left Y-axis. The global share of low-carbon patents is illustrated by an orange line on the right Y-axis.

With the transition towards innovation in a low-carbon economy, existing theory and evidence underscore the need for researching firms' default risks. Drawing from the production theory, productivity is shown to have a positive impact on corporate default risk in the framework of climate change transition risk [1]. Other theoretical models suggest that technological progress makes a net positive contribution through representing that the positive effect on the climate beta of uncertainty about exogenous, emission-neutral technological progress overwhelms the negative effect on the climate beta of uncertainty about the carbon climate response [2,3]. Empirical research further supports the proposition that technological innovations in climate change transition lead to improved enterprise performance [4,5]. Through stranded assets and innovation, firms transition towards low-carbon production that has a positive effect on the default risk [6,7]. However, there is limited research available to verify the impact on the default risks.

As the low-carbon innovations continue to progress, the primary objective of this paper was to analyze the impact of transitioning to low-carbon innovations on firms' credit and default risk, thereby addressing climate transition risks. To achieve this, this study initially proposes four hypotheses on the effect of climate transition innovations on the default risk. In order to verify the hypotheses, this study identified low-carbon patents held by Chinese-listed firms and constructed three low-carbon innovation metrics using the new inventory proposed by the CNIPA. Subsequently, this work examined the direct effect of low-carbon technological innovations on default risks. Finally, the study employed mediation analysis to investigate the mechanism through which low-carbon innovation affects default risk.

The remainder of this paper is presented as follows. Section 2 summarizes the related literature, Section 3 proposes the hypotheses, and Section 4 details the data and research method. Section 5 presents the empirical results, and Section 6 presents the conclusions.

2. Literature Review

There is already a substantial body of research in the existing literature on the relationship between innovation and firms' performance, encompassing aspects such as default risk. After a long period of research, a consensus has emerged on the positive effects of corporate innovation on business performance [8,9]. Innovations include products, processes, marketing, and the organization. Focusing on the technological innovations, the effect has heterogeneous results. For example, Wang [10] discovered that radical innovations are positively related to a firm's performance in SMEs, but the incremental innovation strategies have a negative impact on a firm's performance. Xu et al. [11] concluded that a direct positive effect of innovation inputs on return on assets (ROA) is significant, and technological innovations can be the mediator of different types of capital. Based on studies of firms' performance, the firms' risk is a natural focus for research on the effects of innovation. Most research has found that innovations, such as patents and R&D, can decrease a firms' risk in terms of bond defaults and stock price [12–14].

With the basis of innovation and firms' performance, when it turns to the climate change transition field, green or climate change innovations are represented by a number of studies [15]. One insight is that low-carbon technology can decrease costs with deployment [16]; however, the other side is that the implementation of low-carbon innovations can create investment difficulties because of the long development lead-in and high costs [17]. However, with the support of government policy, many countries have attained achievements in research and innovation for climate change transition, such as the renewable energy policies across Europe that were mentioned by Zhou et al. [18] and the policy drivers behind the development of photovoltaics and wind power in the European Union [19]. In China, Zhu et al. [20] found that an emission trading scheme increased low-carbon innovations by 5–10% without crowding out other technology. From the aspect of effectiveness, Acemoglu et al. [21] suggested that climate-friendly innovations can move away from reliance on carbon-intensive industries, and Davis et al. [22] proposed that the transition to new infrastructure using fossil fuels will be necessary for mitigation in the future. However, from short-term and empirical studies, climate change technology will not always decrease the level of carbon dioxide, especially in medium- and low-income countries [23]. At least it can be concluded that research into climate change innovations is growing with the effect of climate change, but currently the effectiveness remains ambiguous. It is time to focus on the effect of climate change transition on individual firms.

Before the analysis of the risks for firms, the effects of climate change innovation on firms' performance remain controversial. From the early 20th century to 2014, the study of Cheng et al. [24] illustrated that organizational innovations can promote business performance through eco-processes and eco-product innovation. As for positive effects, Liao [25] presented a theoretical model and tested the promotional effect of environmental innovations on a firm's financial performance through different types of culture. Huang and Li [26] tested the positive effects of green product and process innovation on environmental and organizational performance in the information and communication technology industry. Rezende et al. [27] proved a lagged positive relationship between green innovation intensity and financial performance, yet no significant effects in the immediate year were found. Li et al. [4] focused on low-carbon innovations in manufacturing companies. They presented that carbon reduction innovations can significantly and positively affect firms' performance via the mechanism of green competence and firm size.

On the other hand, studies that provide results illustrating negative effects are relatively less frequent than those illustrating the positive effects. From a broad perspective, the negative effects are associated with general innovations. The negative effects stem from complexity and risk during innovation [28], investment crowding out [29,30], and disruptive product innovation [31]. Aguilera-Caracuel and Ortiz-de-Mandojana [32] observed that green innovative firms do not show improved financial performance compared to non-green innovative firms. However, a positive effect exists when focusing on green innovative firms. Other studies tend to deliver ambiguous results. Aastvedt et al. [33] investigated a non-linear effect on the financial performance of oil and gas companies. The effect transformed from positive to negative in different areas and at different levels of innovation.

In summary, this study falls within the domain of innovation effects in corporate finance. Existing research has concentrated on and generated controversy around the impact of innovations on firm performance and default risks. However, empirical evidence regarding the impact of climate change transition innovations on default risk is still lacking. This study addresses this gap in the literature by examining the relationship and mechanism between low-carbon innovations and default risk.

3. Hypotheses Development

3.1. Hypothesis 1

Hypothesis 1: *Low-carbon innovation is positively or negatively associated with firm default risks.*

Based on the empirical results from the effects on firms' performance, company risks are positively associated with low-carbon innovations. A positive effect can originate from many different aspects. Gutiérrez-López et al. [7] empirically investigated that firms investing effort in low-carbon production operated more safely, with a moderating effect of stranded assets and innovation. A related analysis was presented by Bannier et al. [5]. They revealed that the higher a firm's level of corporate social responsibility, the lower the default risk in US and European firms. Another positive relationship was presented in the study of Safiullah et al. [6], with their hypothesis explaining pro-environmental orientation and information asymmetry.

Climate change transition can cause potential default risks, which come from 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 was highlighted in the study of Cahen-Fourot et al. [34]. The potential damage that stranded assets can cause are also presented in environment-related risk factors [35] and early obsolescence [36]. Chevallier et al. [37] proved 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 uncertainties surrounding low-carbon innovation may result in the devaluation of stranded assets.

3.2. Hypothesis 2

Hypothesis 2: *Investor attention acts as a mediator between low-carbon innovations and the default risk.*

With the existence of innovation effects on the default risks, the effects can be explained by instrumental stakeholder theory and information asymmetry. As firms expend effort in relation to green innovations, stakeholders tend to pay attention to other firms because of the disclosure effect of innovations. Significant relationships between investor attention and green innovations were supported in the work of He et al. [38] and Gao et al. [39]. Liu et al. [40] also proved that firms' green performance can affect the stock price via the mediation of investor attention. Specifically, firms with high pollution receive more attention on trading days, translating into stock prices. Deng et al. [41] posited that investor attention can affect energy-intensive enterprises negatively with spillovers, and sometimes

environmental events are significantly related with individual attention. Another research study conducted by Hao and Xiong [42] also confirmed the positive effect of investor attention on firms' risk in China through the Baidu search index. From the evidence previously obtained, it is assumed that investor attention should be a channel between low-carbon innovation and firm default risks, similarly with that in area of pollution performance [40].

3.3. Hypothesis 3

Hypothesis 3: *Total factor productivity acts as a mediator between low-carbon innovations and the default risk.*

The positive effect of corporate low-carbon innovations on firms' performance and default risk is abundant based on a comprehensive literature review [9] and representative research [4,7,12]. Investors consider a firm competitive when owning more and higher quality patents. 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 high-performance firms as an adaption for climate change. There are numerous empirical studies that reveal a positive correlation between climate change transition and total factor productivity, including transition policy [43] and innovations [44,45]. Better competitiveness indicates better firm performance and lower risks [46]. The theoretical mechanism is indirectly proven by the climate change risk theory model [1], Battiston et al. presented a systemic theory for climate change default risk in which the default probability is negatively related to firms total factor productivity.

3.4. Hypothesis 4

Hypotheses 4: *Technology spillover acts as a mediator between low-carbon innovations and the default risk.*

Research and innovation spillovers [1] can affect the performance and risks of firms. In the literature previously presented, innovations have an impact effect on the performance and risks of firms. Furthermore, the existence and effects of technological spillovers from innovation were widely recognized by de Faria and Lima [47], who argued that there was a positive spillover of innovation on firm values in different innovation types. Another study containing empirical evidence was that of Aiello and Cardamone [48]; they found a positive effect from R&D spillovers on firms' production. Yao et al. [49] revealed that the type of firm dual network structure has a positive influence on firms' performance, on the basis of social network theory. With the development of natural language processing, it can measure patent similarity, knowledge linkage, and technology spillovers through textual analysis [50,51]. Thus, as the effects from low-carbon innovations on firms' risks are proved in Hypothesis 1, it is assumed that innovation spillovers measured by centrality in the network are a mediator.

In brief, this study proposes four hypotheses for the transition impact on the default risks, as demonstrated in Figure 2. Hypothesis 1 plays a role as the baseline model for the relationship between the low-carbon innovations and the default risks. Hypotheses 2, 3, and 4 act as mediators to explain Hypothesis 1. Thus, this study needed to verify Hypothesis 1 at first, in order to estimate the impact of climate change innovations on the default risk. Then, other hypotheses were proven to demonstrate the potential mechanism of transition innovations to default risks.

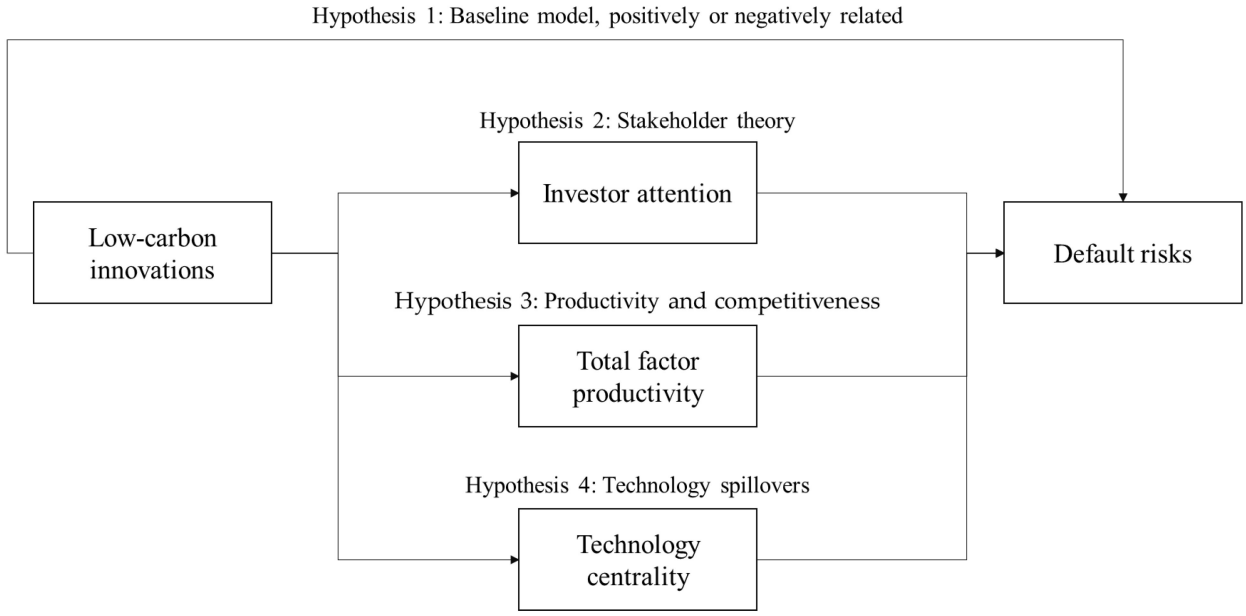


Figure 2. The hypotheses structure.

4. Data and Methods

4.1. Sample Selection and Data Source

Chinese A-share listed firms, excluding financial firms and special treatment firms, from 2015 to 2021 were selected as the samples in this study. These data were obtained after the carbon emissions trading market pilot, which is the most important policy for reducing carbon directly. The data used in this study can be divided into three parts. First, in addition to the patent data, patent citation data were collected for patent importance, with the patent data derived from the CCER [2]. This dataset collects daily patent application details for listed firms in China from 1990 to 2022, which consists of the applicant, application date, application number, patent classification, patent name, and patent abstract.

Measurement from CNRDS [3]. Secondly, the risk variables and covariates of Chinese listed firms were collected from CSMAR [4], including financial variables, such as distance-to-default, z-score, net ROA, ROE, and so on. Last, the Baidu search index with the stock code of listed firms was selected to represent investor attention, which was provided by CNRDS. In summary, daily data were transformed into yearly data, and the three parts of data based on the stock code of each dataset were merged. Then, the missing value of patent and investor attention were filled with zero. Finally, the panel data from 4474 firms from 2015 to 2021 was obtained in this study.

4.2. Dependent Variables

In this study, there was a need to measure firm default risks with the dependent variable. According to the research from Bannier et al. [5], Gutierrez-Lopez et al. [7], and Meles et al. [52], distance-to-default (DD) is taken as the main dependent variable. The distance-to-default measures credit default risks, meaning that firms with a higher DD have lower default risks. The value of DD can be negative according to the calculation as below. If a firm has a negative DD, it means that there is more than 50% probability to default in a specific time horizon, although it is rare [53]. Three types of DD [54,55] from CSMAR were used in this study for robustness tests. The Merton DD from Bharath and Shumway [55] was our main dependent variable, and two other dependent variables were used for the robustness test. The DD from Bharath and Shumway can be calculated as follows:

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

$$\sigma_V = \frac{E}{E+D}\sigma_E + \frac{D}{E+D}\sigma_D \quad (2)$$

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

where E means the market value of the firm's equity and D means the overall value of the firm's liquid liability and illiquid liability. Other notations are that of the risk-free interest rate r_f and the prediction range T. σ_V, σ_E, σ_D mean the volatility concerning the firm's asset value, equity, and debt, respectively, and approximation is calculated as $\sigma_D = 0.05 + 0.25\sigma_E$. Then, σ_E is calculated based on the variance in the logarithmic stock return.

4.3. 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 standards are based on the International Patent Classification (IPC) and a keyword search. In the IPC classification, the system takes IPC 2022 as the reference base to identify a patent as low-carbon technologies in 142 technological branches. In some branches, the IPC covers too many patents unrelated to 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 the IPC classification. In summary, this study classified all patents of Chinese listed firms into either low-carbon patent or non-low-carbon patent in order to correctly designate them. Then, this study calculated the quantity of green patents, their generality, and importance as the measurement for climate change transition. Low-carbon patent measurements are yearly for each listed firm, which are summarized from the 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 classifications in which the patent is classified in a year. Low-carbon importance is the green quantity weighted by the citation of each low-carbon patent. The quantity, generality, and importance measurements partly refer to the 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 the time costs of firms' low-carbon patenting activities [12].

Financial covariates are selected to control other financial measurements that would influence the default risk of listed firms. This study used the annual financial statements and financial indicators, describing solvency, operation, profitability, and growth. These constituents are the main elements deciding the default risk [6,7]. Investor attention is measured using the daily Baidu search index. In order to prove our hypothesis from annual panel data, this study grouped the search index by each listed firm and used an average and median index to describe the annual investor attention.

To measure technology spillovers, a patent network from their association needed to be built. A patent network is built from patent similarity between their claimants and abstracts, which is better than a traditional citation relationship for representing technology spillovers [50,51,56]. To build patent similarity, the Doc2vec model was used for this study. Each patent was transformed into a vector, and this study calculated cosine similarity. For the purpose of describing firms' technology spillovers, this research merged patent similarity into firm-level similarity and built a patent spillover network. Finally, this paper calculated degree centrality for testing potential mechanisms. In the end, the descriptions of our dependent variables and independent variables were as shown in Table 1.

Table 1. Variable definitions.

Variables	Definition
Distance-to-default (DD)	The measurement of default risks developed by the Merton model [55]; the more the DD is, the less is the 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.
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 of net sales divided by the average total assets, which measures the efficiency of generating revenue and sales.
Net return on assets (ROA)	The return on net assets is the ratio of net income divided by average net assets, which measures the profitability of the business.
Return on equity (ROE)	The return on equity is the ratio of 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 patents, denoting the number of climate change transition innovations.
Low-carbon patent generality	The generality measurement of low-carbon patents, 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.
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 with the generalized method of moments
Investor attention score	The annual median of daily Baidu search index for listed firms.
Patent centrality	The centrality degree of patent similarity network to describe the technology spillovers.

4.4. Empirical Method

To investigate the relationship between low-carbon innovations and default risks and prove the theoretical hypothesis, this study mainly built on the panel fixed effect empirical model. To test Hypothesis 1, regression models were constructed as the benchmark model:

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

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 in 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 $\beta_1 < 0$, a negative relationship is validated in H1. As for the robustness test, this study took different distance-to-default measurements and standardization methods to test.

To inspect the heterogeneous effect of climate change transition innovations on default risks, this study built a regression model with the introduction of intersection terms as Equation (5):

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

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 $H_{it} = 0$, Equation (5) is the same as Equation (4). If β_3 is significantly not equal to zero, there is a 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 presented in previous studies. This study took accurate low-carbon patent classifications to solve the measurement error and used control variables and individual fixed effect to mitigate the problem of missing variables. However, simultaneity occurs if firms with a lower risk have conditions for more low-carbon innovations. Therefore, the instrumental variable with the two-stage least squared (IV-2SLS) model was constructed for the endogeneity issue. Equation (6) is the first stage of the IV-2SLS model, and Equation (7) is the second stage, which uses the estimated low-carbon innovations in the regression model:

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

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

In Equation (6), IV_{it} denotes the instrumental variable, which is the time costs of the low-carbon patent, as demonstrated in Table 1. This study implemented the F-test, the 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 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 Equations (4) and (7) is in the same direction, the endogeneity will not have a significant influence on the effect.

To verify the mechanisms of innovation impact on default risks, this study constructed 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.

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

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

In 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.

5. Empirical Result and Discussion

5.1. Summary Statistics

Table 2 shows the descriptive statistics of the variables used in the empirical model. As shown in Table 2, the panel data had 23,580 observations and 4474 firms from 2015 to 2021. Firstly, the means of the main dependent variable, distance-to-default, was 8.683, with minimum and maximum values of 0.000 and 315.615, respectively. It is suggested that the default risk was diversified and thick-tailed among the listed firms. As for independent variables, this study built low-carbon innovation measurements, including quantity, generality, and importance. The means of quantity, generality, and importance were 0.790, 0.860, and 1.260, respectively, with standard deviations of 8.935, 9.621, and 15.255, respectively. The measurements of low-carbon innovations were more diversified and exhibited a thick-tailed distribution, primarily due to the concentration of low-carbon innovations within a small number of companies. Other control variables were selected and calculated from the financial statements of the sample listed firms. Most of them were similar within the same group of financial indicators. For example, current ratio and asset loan rate, which measure the solvency capability of firms, had similar average values, standard deviations, 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	8.683	5.953	0.000	315.615
Current ratio	CR	23,580	2.620	3.145	0.006	80.664
Debt-to-asset ratio	AL	23,580	0.428	1.201	0.008	178.346
Total asset turnover	TAT	23,580	0.643	0.529	−0.048	12.373
Net ROA	ROA	23,580	0.040	0.144	−9.117	12.211
ROE	ROE	23,580	0.043	1.229	−174.895	14.021
Total asset change	TAG	23,580	0.217	0.710	−0.961	37.029
ROA change	ROAG	23,580	−7.743	362.805	−36,205.561	7309.722
Low-carbon patent quantity	LCQ	23,580	0.790	8.935	0.000	417.000
Low-carbon patent generality	LCG	23,580	0.860	9.621	0.000	450.000
Low-carbon patent importance	LCI	23,580	1.260	15.255	0.000	750.000
Low-carbon patent time costs	LCT	23,580	23.446	73.606	0.000	1250.000
Total factor productivity	TFP	23,580	3.119	1.408	0.000	9.391
Investor attention score	IA	23,580	942.723	1422.728	0.000	44,965.000
Patent centrality	PC	23,580	0.033	0.070	0.000	0.888

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

The main result in this study was the effect of low-carbon innovations on default risks, which is presented in Hypothesis 1. With the help of regression, the baseline results and robustness checks in Section 5.2 are comprehensively illustrated in Figure 3. The impact of low-carbon innovations was assessed using indicators of quantity (LCQ), generality (LCG), and importance (LCI), as described in Table 1. As shown in Figure 3, the influence of low-carbon innovations on default risks was found to be significantly positive in both baseline results and robustness checks across all three indicators. Further detailed results are provided in the subsequent part in Section 5.2.

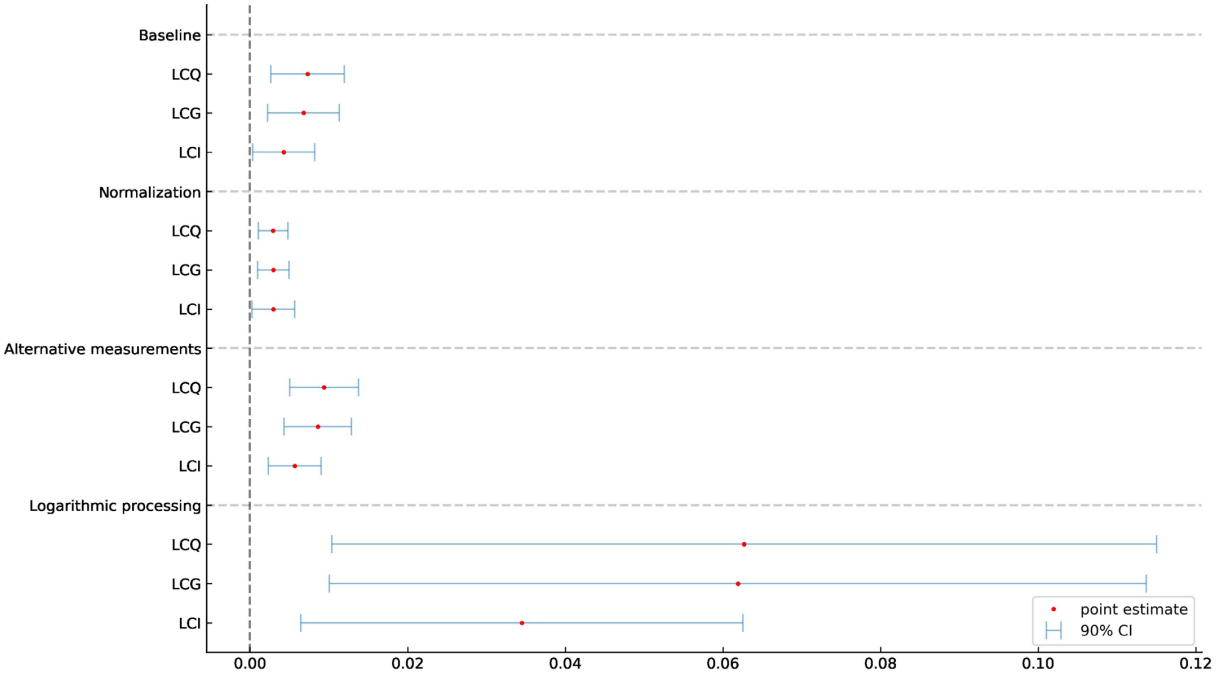


Figure 3. Baseline results and robustness checks. Notes: The dependent variable was the measurement of distance to default. Robustness checks were conducted using several methods, including normalization, alternative measurements, and logarithmic processing. Normalization means transformation using z-score and min–max techniques. Alternative measurements entail replacing the dependent variable by different calculation methods. Logarithmic processing was employed to transform heavy-tailed independent variables.

To test Hypothesis 1, Table 3 presents the baseline empirical result of innovation effects on the default risk based on Equation (4). As shown in Table 3, columns (1) and (2) report the results of model (4), with the low-carbon patent quantity representing the climate change transition measurement. They omitted and controlled the province fixed effect and industry fixed effect, respectively. Columns (3) and (4) present the results of the innovation effect, with the low-carbon patent generality representing the climate change transition measurement. Columns (5) and (6) show the low-carbon innovation effects on default risks, using low-carbon patent importance as the innovation measurement. First of all, the results were robust and similar, both with and without the control of the province fixed effect and industry fixed effect; in particular, the difference was concentrated on the constant terms. Secondly, three low-carbon innovation measurements all showed positive and significant effects on the default risk, and the effect of low-carbon patent importance was relatively smaller than the other two measurements. The effect of low-carbon patent quantity and generality was significantly positive and at the 5% level, and the coefficients of the low-carbon patent importance were significantly positive and at the 10% level.

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)
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: *, **, and *** 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.

The results of the baseline model support the negative relationship in H1 that low-carbon innovations have negative impacts on the default risk. Although this finding is similar to the innovation effect on default risks [9,12], it is a new result for climate change transition innovations. The baseline result suggests that low-carbon transitions can have a new and positive impact on the firm's situation. However, the empirical results could be influenced by the default risk indicator and data scale; therefore, the robustness check needs to be performed to verify the hypothesis.

As shown in Table 4, columns (1), (2), and (3) show the robustness check via normalization of the z-score, which transformed the low-carbon innovation indicator by

$n_i = (x_i - \mu(x_i))/\sigma_x$. n_i is the numeric data after normalization; x_i is the numeric data before 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 normalizes the low-carbon innovation indicators using $n_i = (x_i - \min(x_i))/(\max(x_i) - \min(x_i))$. After normalization, this study can compare the effects on the default risk from different innovation measurements [57]. All effects remained significantly positive as the baseline model. Further, the magnitude of the low-carbon innovation effect was almost the same between three measurements, with a 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	0.003 ***			0.001 ***		
	(0.001)			(0.000)		
LCG		0.003 **			0.001 **	
		(0.001)			(0.000)	
LCI			0.003 *			0.001 *
			(0.002)			(0.000)
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)
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: *, **, and *** 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 the method of Bharath and Shumway [55] to Merton [54], 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 are shown as being significantly positive for three measurements at the 1% level. The difference was the standard deviation of estimation for the low-carbon patent importance measurement. The hypothesis was verified by different default risk measurements, and the positive effect of low-carbon innovation showed robustness.

As displayed in Table 2, the standard deviation of independent variables, such as ROA, ROE, and low-carbon patent quantity, was much larger than the average value. It is indicated that independent variables were heavy-tailed and had outliers. This can be explained in two parts. Firstly, the financial performance was widely distributed among different industries. Another explanation is that only a few proportion firms have the ability to research and develop costly low-carbon patents. Table 6 shows the test of robustness by excluding the heavy-tailed characteristic through logarithmic processing. In columns (1), (2), and (3), LCQ, LCG, LCI, ROA, ROE, TAG, and ROAG were transformed with a

logarithmic function. The innovation effects on the distance to default were still significantly positive at the 5% level. Outliers did not have an impact on the result in this study.

Table 5. Robustness test for different default risk measurements.

	(1) Merton	(2) Merton	(3) Merton	(4) KMV	(5) KMV	(6) 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)
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: ** and *** 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.

Table 6. Robustness test for logarithm processing.

	(1) Logarithmic Processing	(2) Logarithmic Processing	(3) Logarithmic Processing
LCQ	0.063 **		
	(0.032)		
LCG		0.062 **	
		(0.032)	
LCI			0.035 **
			(0.017)
CR	0.271 ***	0.271 ***	0.272 ***
	(0.049)	(0.049)	(0.049)
AL	−0.022	−0.022	−0.021
	(0.022)	(0.022)	(0.022)
TAT	0.349 *	0.349 *	0.353 *
	(0.180)	(0.180)	(0.180)
ROA	−0.507 ***	−0.507 ***	−0.491 ***
	(0.187)	(0.187)	(0.188)
ROE	−0.010	−0.010	−0.010
	(0.009)	(0.009)	(0.009)
TAG	0.338 ***	0.338 ***	0.339 ***
	(0.091)	(0.091)	(0.091)
ROAG	0.000 ***	0.000 ***	0.000 **
	(0.000)	(0.000)	(0.000)

Table 6. *Cont.*

	(1) Logarithmic Processing	(2) Logarithmic Processing	(3) Logarithmic Processing
Cons	10.615 ***	10.611 ***	10.491 ***
	(1.383)	(1.382)	(1.374)
Obs	23,580	23,580	23,580
R^2	0.054	0.054	0.054

Note: *, **, and *** 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.

5.3. Heterogeneity Effects

After verifying 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, was introduced as a treatment assignment to explore the intergroup difference of innovation effects. This study used the first and second batches of LCCP projects by consulting governmental documents in 2010 and 2012 [58,59]. In Table 7, columns (1), (2), and (3) demonstrate the heterogeneous effects for three low-carbon innovation measurements, correspondingly, especially the coefficient of LCCP × Innovation. The low-carbon innovation effect was significant at −0.018 and −0.016 for quantity and generality measurements at the 10% level, respectively, but it was also significant at 0.006 for the innovation importance measurement at the 5% level. There was a different heterogeneous effect for different measurements. As for firms in the low-carbon city pilot, the significantly positive innovation effect on default risks was less than other firms for the average low-carbon patent quantity, and the innovation effect on default risks was more than other firms for the average low-carbon patent citation. It is suggested that high-quality low-carbon innovation does have a more significant effect on alleviating the default risks inherent to low-carbon regulations.

Table 7. Heterogeneous analysis from the 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)
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)

Table 7. *Cont.*

	(1)	(2)	(3)
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: *, **, and *** 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 came from the green credit policy shock in 2012, which may have impacted the effect on the default risk of firms [60]. This study selected heavily polluting industries, including the textile industry, paper industry, petrochemical industry, and metallic manufacturing and non-metallic manufacturing industries, as the group treated by green credit policy [61]. Based on columns (1), (2), and (3) in Table 8, firms in the green credit policy had significantly −0.067, −0.057, and −0.060 lower low-carbon innovation effects, respectively, compared with other firms without the support of green credit. This could be explained as the green credit policy acting to reduce firms' performance in these polluting industries [60]; thus, the improvement from low-carbon innovation to default risk could be weakened. Furthermore, the heterogeneous effects were similar in number and sign among the three low-carbon innovation measurements.

Table 8. Heterogeneous analysis from green credit policy shocks.

	(1)	(2)	(3)
Innovation=	Quantity	Generality	Importance
Policy × Innovation	−0.067 ***	−0.057 ***	−0.060 *
	(0.019)	(0.016)	(0.034)
Policy	0.921	0.921	1.088
	(0.886)	(0.887)	(0.845)
Innovation	0.008 *	0.007 *	−0.004
	(0.004)	(0.004)	(0.002)
CR	0.141 ***	0.141 ***	0.142 ***
	(0.020)	(0.020)	(0.020)
AL	−0.013	−0.013	−0.013
	(0.025)	(0.025)	(0.025)
TAT	−0.294 **	−0.294 **	−0.297 **
	(0.116)	(0.116)	(0.116)
ROA	−0.104	−0.104	−0.102
	(0.162)	(0.162)	(0.162)
ROE	−0.007	−0.007	−0.007
	(0.005)	(0.005)	(0.005)
TAG	−0.078 *	−0.078 *	−0.077 *
	(0.042)	(0.042)	(0.042)
ROAG	0.000 **	0.000 **	0.000 **
	(0.000)	(0.000)	(0.000)
Cons	10.768 ***	10.769 ***	10.792 ***
	(0.574)	(0.573)	(0.574)
Obs	23,580	23,580	23,580
R^2	0.206	0.206	0.206

Note: *, ** and *** 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.

5.4. Endogeneity Issues

The endogeneity issue was introduced in the previous Section 4.4, so this study constructed the IV-2SLS model to test the simultaneity issue. The low-carbon time costs were chosen as the instrumental variable for three low-carbon innovation measurements in the model, as shown in Table 1. This instrumental variable represents the time costs

of firms' patenting activities and should influence low-carbon innovation incentives to produce a significant number of innovations. On the other hand, it is exclusive because it is uncorrelated with the dependent variable, that is, distance-to-default, because a firm's relative patenting performance at the industry level has no effect on dependent variables. In addition to these conceptual arguments, we also conducted relevant statistical tests, including the F-test, the under-identification test, and the weak identification test, to empirically justify the validity of the instrumental variables in Table 9.

Table 9. Endogeneity issues in 2SLS without endogeneity.

	Quantity		Generality		Importance	
	First-Stage (1)	**Second-Stage (2)**	**First-Stage (3)**	**Second-Stage (4)**	**First-Stage (5)**	**Second-Stage (6)**
LCT	0.012 ***		0.013 ***		−0.008 ***	
	(0.002)		(0.003)		(0.003)	
Innovations		0.181 **		0.166 **		−0.271 **
		(0.073)		(0.066)		(0.131)
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 instrument in first stage						
Sanderson–Windmeijer F-test	25.04 ***		26.04 ***		9.15 ***	
(ii) Under-identification test						
Kleibergen–Paap LM statistic	24.94 ***		25.96 ***		9.17 ***	
(iii) Weak identification test						
Cragg–Donald–Wald F-statistic	331.74		339.62		57.05	
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: ** and *** 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.

In Table 9, columns (1) and (2) demonstrate the effect of low-carbon innovation quantity in two stages. Columns (3) and (4) present the innovation effects of low-carbon generality, and columns (5) and (6) present the innovation effects of low-carbon patent importance. For all innovation measurements, there were significant overall positive effects on default risks, indicating the validity of our verification of Hypothesis 1. In columns (1), (2), (3), and (4), the coefficient estimates of the instrument variable were significantly positive at the 1% and 5% levels. In columns (5) and (6), estimates for low-carbon patent importance were significantly negative at the 1% and 5% levels, respectively. As for statistic tests, the first-stage F-statistics for the excluded instrument were 25.04, 26.04, and 9.15, which were significant at the 1% level. Furthermore, the Kleibergen–Paap rank LM statistics were significant at the 1% level for under-identification, and the Cragg–Donald–Wald F-statistics for weak identification were 331.74, 339.62, and 57.05, which all exceeded the critical value of 16.38 at the 10% weak instrument bias level according to the Stock–Yogo weak instrument threshold.

5.5. Mechanism of Low-Carbon Innovation Effects

To test Hypotheses 2, 3, and 4, this study constructed three mediation models based on two-step regression. For Hypothesis 2, based on instrumental stakeholder theory and information asymmetry, this study took the investor attention of listed firms as the mediation variable, as shown in Table 1. In Table 10, columns (1), (3), and (5) display the first-stage results 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 were −6.275 and −0.001, respectively, significantly

at the 1% level, which shows incomplete mediation. In columns (3) and (4), the estimates were significant at −5.840 and −0.001, respectively, and significant at −5.397 and −0.001, respectively, in columns (5) and (6). The investor focus is a complete mediator for low-carbon patent generality and importance, owing to insignificant estimates of low-carbon indicators in columns (4) and (6). Overall, for three low-carbon innovation indicators, there was a significant path from low-carbon innovation to alleviate default risks through decreasing the investor focus.

Table 10. Mediator effects from investor attention.

	(1)	(2)	(3)	(4)	(5)	(6)
	Investor Attention	DD	Investor Attention	DD	Investor Attention	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)
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	2354.184 ***	8.646 ***	2354.560 ***	8.646 ***	2192.537 ***	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: *, **, and *** 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 Hypothesis 3, total factor productivity (TFP) was calculated by the general moment model [62]. With the TFP as the mediator, this study tried to argue that low-carbon innovations can improve the risk profile through overall production performance. In Table 11, 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 were significantly positive for low-carbon quantity and generality measurements. However, the mechanism was not significant for the low-carbon innovation importance based on columns (5) and (6). In conclusion, the TFP acted as a suppression mediator in the low-carbon innovation effects on default risks, and Hypothesis 3 was partly tested.

Table 11. Mediator effects from production efficiency.

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP	DD	TFP	DD	TFP	DD
TFP		0.183 ***		0.183 ***		0.973 ***
		(0.061)		(0.061)		(0.119)
LCQ	0.001 *	0.006				
	(0.001)	(0.004)				
LCG			0.001 *	0.005		
			(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)
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)
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: *, **, and *** 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 Hypothesis 4, this study tried to test the mediation effect through the technology spillovers. It is demonstrated in Table 12 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 were 0.003 and 2.488 at the 1% and 10% levels, respectively. In columns (3) and (4), the mediation effects were 0.003 and 2.500, significantly at the 1% and 10% levels, respectively, and columns (5) and (6) show significant mediation effects as 0.001 and 2.435 at the 1% and 5% levels, respectively. This study was able to test Hypothesis 4 with these complete mediation effects for all low-carbon innovation measurements. Low-carbon technology similarity network centrality acts as the influential 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 12. Mediator effects from technology spillovers.

	(1)	(2)	(3)	(4)	(5)	(6)
	Spillovers	DD	Spillovers	DD	Spillovers	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)

Table 12. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)
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)
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: *, **, and *** 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.

5.6. Discussion

In summary, analyzing the straightforward relationship of low-carbon technological innovations on default risks, it is concluded that low-carbon innovations positively affect a firm's distance-to-default, which is the indicator of default risks, and is also consistent with the 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 were tested with robustness and endogeneity issues. By means of several proxies for stakeholder attention, productivity, and technology spillovers, this study found that climate change transition innovations affected the credit risk through the mechanism of stakeholder theory and production theory, consistent with previous research [5,10]. Indeed, the positive relationship between low-carbon innovations and distance-to-default suggests that the positive effects of transition to the carbon-neutral economy overwhelm the negative effect of costs and stakeholder theory is the main channel. Firms should make an effort to embrace 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, this 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. Secondly, this study enriches the research on climate change transition risks from technological advances by empirically testing the relationship between innovations and default risks. Thirdly, this study focuses on the low-carbon technology advances by using a new patent inventory compared with the IPC Green Inventory of WIPO. This labeling of low-carbon innovations can accurately measure the technological driver of climate change risk and three low-carbon innovation measurements are constructed to make a robust and comprehensive evaluation of innovation effects on default risks. Lastly, results in this study demonstrate possible mechanisms from theories like stakeholder attention.

Further, our results are of interest to corporate managers, investors, and policymakers. From a managerial perspective, this study suggests that managers should expedite the adoption of low-carbon and carbon-neutral practices, particularly for enterprises operating in industries not subject to regulatory oversight. Additionally, the climate change transition information disclosure should be enforced as 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 was noticed that firms under regulation have insufficient innovation effects, as might be supposed. From the perspective of policymakers, the climate finance barrier is an issue of high concern. Recognizing the effect of low-carbon innovations, it is now necessary to propose policies that will promote engagement in climate transition innovations. An effective method is through the development of a low-carbon technology inventory and providing subsidies relating to its development.

To our knowledge, this is the first study to analyze a low-carbon innovation mediation channel of technological spillovers using patent similarity to measure low-carbon technology spillovers. However, some limitations still exist in this study, providing possible suggestions for future research. First, our analysis concentrated 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 unrefined in terms of the method and theory. Although the existing theory of climate change transition risks provide an illuminating framework for our mediation models [1], the economic theory can be developed for specific mechanisms, like technological spillovers. Last but not least, this study investigates the empirical effect based on the existing theory. Simulation results with climate transition scenarios can supplement the research about low-carbon innovations and firm's performance.

6. Conclusions

This study examined whether and how climate change transition innovation affects firms' default risk through the examination of the green and low-carbon patent inventory proposed by CNIPA between 2015 and 2021. The regression model used in this study considered different low-carbon innovation measurements, robustness checks, heterogenous analyses, and endogeneity issues. Further, three indicators of transition risk channels were constructed to investigate possible mechanisms based on theories that had been proposed in previous research. 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.

Findings in this study can be summarized as follows:

1. This study found that low-carbon transition innovation significantly decreased default risk as measured by distance-to-default. This result was tested with three low-carbon innovation measurements, namely, quantity, generality, and importance. The result was robust, with normalization methods and alternative default risk measurements.
2. As a heterogeneous analysis, it was concluded that firms under climate policy treatment will obtain lower innovation effects on default risks compared with other firms.
3. Innovation time costs were taken as instrumental variables to test endogeneity, and our results were robust under the IV-2SLS model.
4. This paper found that the three identified mechanisms can explain how low-carbon innovations affect the default risk, including stakeholder attention, productivity, and technological spillovers.

Author Contributions: Conceptualization, Y.H. and Z.H.; methodology, Y.H.; software, Y.H.; validation, Y.H. and Z.H.; formal analysis, Y.H.; data curation, Y.H.; writing—original draft preparation, Y.H.; writing—review and editing, Y.H. and Z.H.; visualization, Y.H. and Z.H.; supervision, Z.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

[1] In the technology and patent researches, spillovers mean the possibility, ability and extent that a technology diffused to other entities.

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

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

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

References

1. Battiston, S.; Mandel, A.; Monasterolo, I.; Roncoroni, A. Climate Credit Risk and Corporate Valuation. In *Climate Credit Risk and Corporate Valuation: Battiston, Stefano | uMandel, Antoine | uMonasterolo, Irene | uRoncoroni, Alan*; 2023. [CrossRef]
2. Lemoine, D. The Climate Risk Premium: How Uncertainty Affects the Social Cost of Carbon. *J. Assoc. Environ. Resour. Econ.* **2021**, *8*, 27–57. [CrossRef]
3. Dietz, S.; Gollier, C.; Kessler, L. The Climate Beta. *J. Environ. Econ. Manag.* **2018**, *87*, 258–274. [CrossRef]
4. Li, F.; Xu, X.; Li, Z.; Du, P.; Ye, J. Can Low-Carbon Technological Innovation Truly Improve Enterprise Performance? The Case of Chinese Manufacturing Companies. *J. Clean. Prod.* **2021**, *293*, 125949. [CrossRef]
5. Bannier, C.E.; Bofinger, Y.; Rock, B. Corporate Social Responsibility and Credit Risk. *Financ. Res. Lett.* **2022**, *44*, 102052. [CrossRef]
6. Safiullah, S.; Phan, D.H.B.; Kabir, M.N. Green Innovation and Corporate Default Risk. 2022. [CrossRef]
7. Gutiérrez-López, C.; Castro, P.; Tascón, M.T. How Can Firms' Transition to a Low-Carbon Economy Affect the Distance to Default? *Res. Int. Bus. Financ.* **2022**, *62*, 101722. [CrossRef]
8. Gunday, G.; Ulusoy, G.; Kilic, K.; Alpkan, L. Effects of Innovation Types on Firm Performance. *Int. J. Prod. Econ.* **2011**, *133*, 662–676. [CrossRef]
9. Naqbi, E.A.; Alshurideh, M.; AlHamad, A.; Al, B. The Impact of Innovation on Firm Performance: A Systematic Review. *Int. J. Innov.* **2020**, *14*, 31–58.
10. Wang, D.S. Association between Technological Innovation and Firm Performance in Small and Medium-Sized Enterprises: The Moderating Effect of Environmental Factors. *Int. J. Innov. Sci.* **2019**, *11*, 227–240. [CrossRef]
11. Xu, J.; Shang, Y.; Yu, W.; Liu, F. Intellectual Capital, Technological Innovation and Firm Performance: Evidence from China's Manufacturing Sector. *Sustainability* **2019**, *11*, 5328. [CrossRef]
12. Hsu, P.-H.; Lee, H.-H.; Liu, A.Z.; Zhang, Z. Corporate Innovation, Default Risk, and Bond Pricing. *J. Corp. Financ.* **2015**, *35*, 329–344. [CrossRef]
13. Ben-Nasr, H.; Bouslimi, L.; Zhong, R. Do Patented Innovations Reduce Stock Price Crash Risk? *Int. Rev. Financ.* **2021**, *21*, 3–36. [CrossRef]
14. Fernandes, A.M.; Paunov, C. The risks of innovation: Are innovating firms less likely to die? *Rev. Econ. Stat.* **2015**, *97*, 638–653. [CrossRef]
15. Matos, S.; Viardot, E.; Sovacool, B.K.; Geels, F.W.; Xiong, Y. Innovation and Climate Change: A Review and Introduction to the Special Issue. *Technovation* **2022**, *117*, 102612. [CrossRef]
16. Viardot, E. The Role of Cooperatives in Overcoming the Barriers to Adoption of Renewable Energy. *Energy Policy* **2013**, *63*, 756–764. [CrossRef]
17. Ghisetti, C.; Pontoni, F. Investigating Policy and R&D Effects on Environmental Innovation: A Meta-Analysis. *Ecol. Econ.* **2015**, *118*, 57–66. [CrossRef]
18. Zhou, S.; Matisoff, D.C.; Kingsley, G.A.; Brown, M.A. Understanding Renewable Energy Policy Adoption and Evolution in Europe: The Impact of Coercion, Normative Emulation, Competition, and Learning. *Energy Res. Soc. Sci.* **2019**, *51*, 1–11. [CrossRef]
19. Lacal Arantegui, R.; Jäger-Waldau, A. Photovoltaics and Wind Status in the European Union after the Paris Agreement. *Renew. Sustain. Energy Rev.* **2018**, *81*, 2460–2471. [CrossRef]
20. Zhu, J.; Fan, Y.; Deng, X.; Xue, L. Low-Carbon Innovation Induced by Emissions Trading in China. *Nat. Commun.* **2019**, *10*, 4088. [CrossRef]
21. Acemoglu, D.; Akcigit, U.; Hanley, D.; Kerr, W. Transition to Clean Technology. *J. Political Econ.* **2016**, *124*, 52–104. [CrossRef]
22. Davis, S.J.; Caldeira, K.; Matthews, H.D. Future CO_2 Emissions and Climate Change from Existing Energy Infrastructure. *Science* **2010**, *329*, 1330–1333. [CrossRef]
23. Du, K.; Li, P.; Yan, Z. Do Green Technology Innovations Contribute to Carbon Dioxide Emission Reduction? Empirical Evidence from Patent Data. *Technol. Forecast. Soc. Chang.* **2019**, *146*, 297–303. [CrossRef]
24. Cheng, C.C.J.; Yang, C.; Sheu, C. The Link between Eco-Innovation and Business Performance: A Taiwanese Industry Context. *J. Clean. Prod.* **2014**, *64*, 81–90. [CrossRef]

25. Liao, Z. Corporate Culture, Environmental Innovation and Financial Performance. *Bus. Strategy Environ.* **2018**, *27*, 1368–1375. [CrossRef]
26. Huang, J.-W.; Li, Y.-H. Green Innovation and Performance: The View of Organizational Capability and Social Reciprocity. *J. Bus. Ethics* **2017**, *145*, 309–324. [CrossRef]
27. de Azevedo Rezende, L.; Bansi, A.C.; Alves, M.F.R.; Galina, S.V.R. Take Your Time: Examining When Green Innovation Affects Financial Performance in Multinationals. *J. Clean. Prod.* **2019**, *233*, 993–1003. [CrossRef]
28. Saliba de Oliveira, J.A.; Cruz Basso, L.F.; Kimura, H.; Sobreiro, V.A. Innovation and Financial Performance of Companies Doing Business in Brazil. *Int. J. Innov. Stud.* **2018**, *2*, 153–164. [CrossRef]
29. Wagner, M. How to Reconcile Environmental and Economic Performance to Improve Corporate Sustainability: Corporate Environmental Strategies in the European Paper Industry. *J. Environ. Manag.* **2005**, *76*, 105–118. [CrossRef]
30. Misani, N.; Pogutz, S. Unraveling the Effects of Environmental Outcomes and Processes on Financial Performance: A Non-Linear Approach. *Ecol. Econ.* **2015**, *109*, 150–160. [CrossRef]
31. Trumpp, C.; Guenther, T. Too Little or Too Much? Exploring U-Shaped Relationships between Corporate Environmental Performance and Corporate Financial Performance. *Bus. Strategy Environ.* **2017**, *26*, 49–68. [CrossRef]
32. Aguilera-Caracuel, J.; Ortiz-de-Mandojana, N. Green Innovation and Financial Performance: An Institutional Approach. *Organ. Environ.* **2013**, *26*, 365–385. [CrossRef]
33. Aastvedt, T.M.; Behmiri, N.B.; Lu, L. Does Green Innovation Damage Financial Performance of Oil and Gas Companies? *Resour. Policy* **2021**, *73*, 102235. [CrossRef]
34. Cahen-Fourot, L.; Campiglio, E.; Godin, A.; Kemp-Benedict, E.; Trsek, S. Capital Stranding Cascades: The Impact of Decarbonisation on Productive Asset Utilisation. *Energy Econ.* **2021**, *103*, 105581. [CrossRef]
35. Muldoon-Smith, K.; Greenhalgh, P. Suspect Foundations: Developing an Understanding of Climate-Related Stranded Assets in the Global Real Estate Sector. *Energy Res. Soc. Sci.* **2019**, *54*, 60–67. [CrossRef]
36. Curtin, J.; McInerney, C.; Ó Gallachóir, B.; Hickey, C.; Deane, P.; Deeney, P. Quantifying Stranding Risk for Fossil Fuel Assets and Implications for Renewable Energy Investment: A Review of the Literature. *Renew. Sustain. Energy Rev.* **2019**, *116*, 109402. [CrossRef]
37. Chevallier, J.; Goutte, S.; Ji, Q.; Guesmi, K. Green Finance and the Restructuring of the Oil-Gas-Coal Business Model under Carbon Asset Stranding Constraints. *Energy Policy* **2021**, *149*, 112055. [CrossRef]
38. He, F.; Yan, Y.; Hao, J.; Wu, J.G. Retail Investor Attention and Corporate Green Innovation: Evidence from China. *Energy Econ.* **2022**, *115*, 106308. [CrossRef]
39. Gao, Y.; Li, Y.; Wang, Y. The Dynamic Interaction between Investor Attention and Green Security Market: An Empirical Study Based on Baidu Index. *China Financ. Rev. Int.* **2021**, *13*, 79–101. [CrossRef]
40. Liu, F.; Kang, Y.; Guo, K.; Sun, X. The Relationship between Air Pollution, Investor Attention and Stock Prices: Evidence from New Energy and Polluting Sectors. *Energy Policy* **2021**, *156*, 112430. [CrossRef]
41. Deng, C.; Zhou, X.; Peng, C.; Zhu, H. Going Green: Insight from Asymmetric Risk Spillover between Investor Attention and pro-Environmental Investment. *Financ. Res. Lett.* **2022**, *47*, 102565. [CrossRef]
42. Hao, J.; Xiong, X. Retail Investor Attention and Firms' Idiosyncratic Risk: Evidence from China. *Int. Rev. Financ. Anal.* **2021**, *74*, 101675. [CrossRef]
43. Zhang, H.; Huang, L.; Zhu, Y.; Si, H.; He, X. Does Low-Carbon City Construction Improve Total Factor Productivity? Evidence from a Quasi-Natural Experiment in China. *Int. J. Environ. Res. Public Health* **2021**, *18*, 11974. [CrossRef] [PubMed]
44. Su, T.; Chen, Y.; Lin, B. Uncovering the Role of Renewable Energy Innovation in China's Low Carbon Transition: Evidence from Total-Factor Carbon Productivity. *Environ. Impact Assess. Rev.* **2023**, *101*, 107128. [CrossRef]
45. Wu, J.; Xia, Q.; Li, Z. Green Innovation and Enterprise Green Total Factor Productivity at a Micro Level: A Perspective of Technical Distance. *J. Clean. Prod.* **2022**, *344*, 131070. [CrossRef]
46. İmrohoroğlu, A.; Tüzel, Ş. Firm-Level Productivity, Risk, and Return. *Manag. Sci.* **2014**, *60*, 2073–2090. [CrossRef]
47. de Faria, P.; Lima, F. Interdependence and Spillovers: Is Firm Performance Affected by Others' Innovation Activities? *Appl. Econ.* **2012**, *44*, 4765–4775. [CrossRef]
48. Aiello, F.; Cardamone, P. R&D Spillovers and Firms' Performance in Italy: Evidence from a Flexible Production Function. *Empir. Econ.* **2008**, *34*, 143–166. [CrossRef]
49. Yao, Y.; Gao, H.; Sun, F. The Impact of Dual Network Structure on Firm Performance: The Moderating Effect of Innovation Strategy. *Technol. Anal. Strateg. Manag.* **2020**, *32*, 1020–1034. [CrossRef]
50. Chen, L. Do Patent Citations Indicate Knowledge Linkage? The Evidence from Text Similarities between Patents and Their Citations. *J. Informetr.* **2017**, *11*, 63–79. [CrossRef]
51. Whalen, R.; Lungeanu, A.; DeChurch, L.; Contractor, N. Patent Similarity Data and Innovation Metrics. *J. Empir. Leg. Stud.* **2020**, *17*, 615–639. [CrossRef]
52. Meles, A.; Salerno, D.; Sampagnaro, G.; Verdoliva, V.; Zhang, J. The Influence of Green Innovation on Default Risk: Evidence from Europe. *Int. Rev. Econ. Financ.* **2023**, *84*, 692–710. [CrossRef]
53. Bellini, T. Chapter 2—One-Year PD. In *IFRS 9 and CECL Credit Risk Modelling and Validation*; Bellini, T., Ed.; Academic Press: Cambridge, MA, USA, 2019; pp. 31–89. ISBN 978-0-12-814940-9.
54. Merton, R.C. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *J. Financ.* **1974**, *29*, 449–470. [CrossRef]

55. Bharath, S.T.; Shumway, T. Forecasting Default with the Merton Distance to Default Model. *Rev. Financ. Stud.* **2008**, *21*, 1339–1369. [CrossRef]
56. Arts, S.; Cassiman, B.; Gomez, J.C. Text Matching to Measure Patent Similarity. *Strateg. Manag. J.* **2018**, *39*, 62–84. [CrossRef]
57. Liang, Y.; Rudik, I.; Zou, E.Y.; Johnston, A.; Rodewald, A.D.; Kling, C.L. Conservation Cobenefits from Air Pollution Regulation: Evidence from Birds. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 30900–30906. [CrossRef] [PubMed]
58. Li, S.; Zheng, X.; Liao, J.; Niu, J. Low-Carbon City Pilot Policy and Corporate Environmental Performance: Evidence from a Quasi-Natural Experiment. *Int. Rev. Econ. Financ.* **2024**, *89*, 1248–1266. [CrossRef]
59. Yang, G. Can the Low-Carbon City Pilot Policy Promote Firms' Low-Carbon Innovation: Evidence from China. *PLoS ONE* **2023**, *18*, e0277879. [CrossRef] [PubMed]
60. Yao, S.; Pan, Y.; Sensoy, A.; Uddin, G.S.; Cheng, F. Green Credit Policy and Firm Performance: What We Learn from China. *Energy Econ.* **2021**, *101*, 105415. [CrossRef]
61. Zhang, K.; Li, Y.; Qi, Y.; Shao, S. Can Green Credit Policy Improve Environmental Quality? Evidence from China. *J. Environ. Manag.* **2021**, *298*, 113445. [CrossRef]
62. Huang, J.; Cai, X.; Huang, S.; Tian, S.; Lei, H. Technological Factors and Total Factor Productivity in China: Evidence Based on a Panel Threshold Model. *China Econ. Rev.* **2019**, *54*, 271–285. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.