RESEARCH ARTICLE

Technological innovation and renewable energy consumption: a middle path for trading off financial risk and carbon emissions

Qiang Wang[1,2,3] · Zequn Dong[1,3]

Abstract

Global carbon dioxide emissions are on an upward trend, but there have been declines in carbon emissions during financial crises. The possible negative correlation between financial risks and carbon emissions will cause policy makers to face a dilemma when formulating carbon neutral policies. Therefore, it is crucial to find a middle path that can control financial risks while addressing carbon emission reduction, which can help achieve the dual goals of stable economic development and environmental protection. This empirical research studies the linear and non-linear relationships between financial risk and carbon emissions in Organization for Economic Cooperation and Development (OECD) countries, using a panel fixed effects model and a panel threshold regression model. The study further investigates the role of technological innovation and renewable energy consumption in the risk-emission relationship. Key results were as follows. First, the fixed effects model results verify that financial risk has a negative impact on carbon emissions. This relationship may be influenced by technological innovation and energy transition. Second, there is a significant single-threshold effect between financial risk and carbon emissions. When research and development (R&D) expenditures and renewable energy consumption exceed the threshold, there is a significant decrease in the contribution of financial stability to carbon emissions. Third, the slow growth of technological innovation in OECD countries compared to renewable energy consumption highlights that the potential of technological innovation for carbon reduction needs to be further explored. These empirical findings indicate that encouraging technological innovation and accelerating energy transitions would be productive new ways of thinking about the trade-off between controlling financial risk and carbon emission reduction.

Keywords Financial risk · Carbon emission · Renewable energy · Threshold panel data

Introduction

Global carbon dioxide emissions from fossil fuel combustion have been increasing since the 1990s. However, high upward trends have been followed by a sudden decline in carbon

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✉ Qiang Wang
  wangqiang7@upc.edu.cn

[1] School of Economics and Management, China University of Petroleum (East China), Qingdao 266580, People's Republic of China

[2] School of Economics and Management, Tiangong University, Tianjin 300387, People's Republic of China

[3] Institute for Energy Economics and Policy, China University of Petroleum (East China), Qingdao 266580, People's Republic of China

emissions during financial crises. For example, the Asian financial crisis in 1997 and the global financial crisis in 2008 were both accompanied by different abrupt short-term declines in CO_2 emissions. The carbon emissions gradually resumed their growth trend as the financial risks declined (Jalles 2019; Siddiqi 2000). This anomaly has been observed both broadly and at the individual country level.

For example, Venezuela's financial risk has recently been rising, with the Standard & Poor's (S&P) announcing a downgrade of its long-term foreign exchange sovereign credit rating from CC (high probability of default) to SD (selective default) in 2017. The Economist ranked the country as the most financially risky among emerging markets in 2020. At the same time, Venezuela's carbon emissions have been declining year by year; by 2018, they had fallen to levels close to year 2000 emission levels. These data indicate that CO_2 emissions may be sensitive to changes in financial risk, and that an unstable financial environment may lead

to significant fluctuations in carbon emissions. Few studies have systematically studied the impact of financial risk on carbon emissions at a micro-level.

From a theoretical perspective, financial risks may affect carbon emissions in different ways. There are three possible channels through which financial risks affect carbon emissions. First, financial risk directly hinders the mobilization and utilization of capital in economic operations and is detrimental to the smooth trading and monitoring of resources (Jalles 2019). This leads to a decline in GDP and a decrease in industrial production (Safi et al. 2021), leading to lower energy demands and consumption, and lower carbon emissions. Conversely, financial stability means that the average consumer has easy access to more favorable loans, increasing consumer willingness to purchase energy-intensive goods such as cars, large household appliances, and homes. This fundamentally increases energy demand and increases carbon emissions.

Second, financial risk may affect carbon emissions through technological innovation, and financial risk can somewhat reduce the economic viability of clean technology R&D innovations (Jalles 2019). A stable financial environment provides firms with better financial capital access lower-cost R&D capital and to improve the efficiency of technological innovation to reduce carbon emissions from their production activities (Sadorsky 2011).

Third, financial risk affects carbon emissions through renewable energy consumption. Countries with stable financial systems use tools such as tax breaks to encourage companies that actively adopt environmentally friendly technologies and help improve the environment and penalize companies that cause more air pollution by limiting access to easy credit (Nasreen et al. 2017). In addition, controlling risks may impose additional costs and regulatory burdens on governments, resulting in a lower level of political will to implement climate policies. This discourages the development of renewable energy industries that are dependent on policy subsidies to the detriment of carbon reduction (Wooders and Runnalls 2006).

Based on the discussion above, it is difficult to assess the impact of financial risk on carbon emissions, as the impact depends on a combination of mechanisms. Financial risk can disrupt a stable financial system and significantly slow down production activities, negatively affecting carbon emissions. However, financial risk can also hinder renewable energy consumption and technological innovation, increasing carbon emissions. This highlights the need for an empirical model to explore the relationship between financial risk and carbon emissions; this model could then be used to achieve carbon emission reduction targets.

In summary, this study explores the following questions. (1) Does financial risk significantly impact global CO_2 emissions? (2) Is this impact linear or non-linear?

(3) What role do technological innovation and renewable energy play in this impact? Answers to these questions contribute to the advancement of financial-carbon emissions research and provide an empirical basis for countries to control financial risks and achieve low-carbon development.

This study focuses on Organization for Economic Cooperation and Development (OECD) countries, which represent the world's largest economies and the highest carbon emitters. OECD countries enjoy energy-led growth, with a significant portion of energy coming from traditional fossil sources, such as oil, natural gas, and coal. These are the main sources of greenhouse gas CO_2 emissions. According to British Petroleum (BP) and the World Bank, OECD countries emitted 11,998.5 MT of CO_2 and consumed 5669 MT oil equivalent of energy in 2018, accounting for approximately 40.9% and 35.2% of the global total, respectively. These figures indicate that OCED's action to reduce emissions is likely to face enormous pressure. At the same time, OECD countries have well-developed financial systems and have built well-developed financial institutions. This background supports the choice to use OECD countries as a sample to explore the impact of financial risks on carbon emissions.

This study contributes to the existing body of knowledge in several ways. First, in contrast to studies examining the impact of overall financial development on carbon emissions, this paper focuses on the relationship between financial risk and carbon emissions. This topic has received little attention in the literature. This research summarizes the channels through which financial risk affects carbon emissions, improving knowledge about how financial risk may promote reductions in carbon emissions. Second, we consider the linear effect of financial risk on carbon emissions and include technological innovation and renewable energy consumption in the study of financial risk-carbon emissions. We also combine panel fixed effects models with interaction terms and panel threshold models (PTR) to systematically analyze the potential nonlinear relationships between variables. The PTR models can derive optimal research expenditures and renewable energy consumption thresholds to provide a foundation and guidance for policymakers to achieve emission reduction targets. Finally, we analyze the spatial and temporal dynamics of the thresholds over the study period, which can help different countries to develop more targeted carbon reduction policies.

The rest of this article is organized as follows: "Literature review" reviews the relevant literature. "Data and methodology" introduces the data and methodology. "Results and analysis" presents the data processing, display, and analysis of results. "Conclusions and policy implications" presents the conclusions and policy implications.

Literature review

The relationship between finance and carbon emissions

Finance plays a crucial role in modern economic and social development and is an important symbol of modernization. However, finance also significantly impacts environmental quality. The relationship between finance and carbon emissions has been widely studied, with most studies focusing on exploring the relationship between overall financial development and carbon emissions. However, scholars have not reached consensus on the conclusions. Some scholars have argued that financial development positively impacts carbon emissions. For example, Shen investigated the role of financial development in mitigating carbon emissions in 30 Chinese provinces using a cross-sectional augmented autoregressive distribution lag (CS-ARDL) approach. The results found that financial development increased carbon emissions (Shen et al. 2021). Acheampong analyzed the data from 46 sub-Saharan African countries between 2000 and 2015, examining the direct and indirect effects of financial development on CO_2 emissions. That study found that financial development contributes to an increase in CO_2 emissions, and that the effects may differ across financial development indicators (Acheampong 2019). Boutabba examined the long-term equilibrium and the presence and direction of causal relationships between carbon emissions, financial development, and energy consumption in India. That study showed that financial development has contributed to carbon emissions and energy use, exacerbating the deteriorating environmental quality in India (Boutabba 2014), This finding was confirmed by Bui (Bui 2020) and Fang (Fang et al. 2020). However, some scholars have argued that financial development has a dampening effect on carbon emissions. For example, Zaidi analyzed the panel data for APEC countries from 1990 to 2016, finding that financial development significantly reduced long- and short-term CO_2 (Zaidi et al. 2019), this finding was consistent with Kirikkaleli (Kirikkaleli and Adebayo 2021) and Umar (Umar et al. 2020). Umar found a long-term negative correlation between CO_2 emissions and financial development in China. Saidi and Mbarek reported that financial development had a negative long-term effect on carbon emissions, indicating that financial development minimizes environmental degradation (Saidi and Mbarek 2017). Moreover, other scholars argue there is no significant relationship between financial development and carbon emissions. Salahuddin used the time-series data for Kuwait and found that both short- and long-term relationships between financial development and carbon dioxide

emissions were not statistically significant (Salahuddin et al. 2018). Koshta also found no statistically significant effect of financial development on emissions when exploring the causal relationships between gross domestic product (GDP), financial development, agricultural value added, foreign trade, renewable and non-renewable energy consumption, and CO_2 (Köksal et al. 2021).

Recently, scholars have started to focus on the impact of different aspects of finance on carbon emissions, including financial efficiency (Köksal et al. 2021), financial deepening (Paramati et al. 2021), and financial technology (Croutzet and Dabbous 2021). Several studies have investigated the relationship between financial risk and CO_2 (Qin et al. 2021b); Zhao used a SYS-GMM approach to investigate the financial risk-emissions relationship; that study's findings identified a significant negative relationship between financial risk and carbon emissions, as well as an indirect effect by influencing technological innovation (Zhao et al. 2021). Safi used a CS-ARDL test to investigate the long- and short-term relationship between financial instability and carbon emissions in E-7 countries. That study's findings indicate that financial instability reduces consumption-based carbon emissions. This may be because an unstable financial system restricts the financial sector from financing firms' activities to improve production, leading to low energy consumption and reducing carbon emissions (Safi et al. 2021). Zhang and Chiu explored the non-linear effects of real income, energy use, and country risk on CO_2 emissions by applying a panel smoothed transition regression model. They found that a reduction in country risk amplifies CO_2 emissions; this effect increases monotonically (Zhang and Chiu 2020). Qin also confirmed the positive impact of the financial risk index on carbon emissions in China (Qin et al. 2021a).

The impacts of technological innovation and renewable energy on carbon emissions

Increasing R&D expenditures to improve technological innovation and encouraging renewable energy consumption for energy transition are essential for reducing carbon in most countries. However, no known studies have included R&D expenditures and renewable energy consumption when researching financial risk-carbon emissions. Previous studies have focused on the direct impact of research expenditures and renewable energy consumption on carbon emissions (Shao et al. 2021; Yu and Xu 2019) and have not considered the role of research expenditures and renewable energy consumption in financial risk-carbon emissions.

Some scholars argue that a higher level of R&D spending can be effective in reducing emissions and improving environmental quality. For example, Fernández and Fernández López found that technological innovation contributes positively to reducing CO_2 emissions in developed countries;

that study argued that R&D spending helps address CO_2 emissions through the rebound effects of innovation and spillover (Fernández et al. 2018). Shao and Zhong found that renewable energy technological innovation has a positive impact on achieving carbon neutrality targets (Shao et al. 2021). However, Su reached a different conclusion, finding that technological innovation can increase CO_2 emissions (Su et al. 2021).

With the heightened focus on energy transition strategies, there is also increasing interest in the impact of renewable energy on carbon emissions. Koengkan found that renewable energy consumption reduces environmental degradation by curbing carbon emissions (Koengkan et al. 2019). This is consistent with another study in Japan (Adebayo and Kirikkaleli 2021), which investigated the impact of renewable energy consumption on environmental degradation and found that renewable energy use mitigates CO_2 in the short and medium term.

The impacts of technological innovation and renewable energy on financial risk

Some studies have found that measures taken to improve climate have a potential unintended impact on financial system stability (Battiston et al. 2017; Dietz et al. 2016; D'Orazio and Popoyan 2019). First, to promote green structural change, significant investments are needed in sectors with high capital costs, such as R&D and renewable energy (WEF 2013); these sectors are subject to high levels of uncertainty and risk. At the same time, investments in low-carbon electricity generation, including renewables, would need to triple to comply with green transition scenarios, creating a "green finance gap" (Buchner et al. 2014). In other words, there is a lack of sufficient financial resources for green investments, which hurts the stability of the financial system. In addition, there is growing evidence that investment processes, accounting frameworks, and financial regulatory regimes contain an inherent "carbon bias" (Campiglio 2016). This creates barriers to aligning the financial sector with sustainable transition roadmaps and contributes to the risk that carbon assets may become stranded in a low-carbon economy (Chevallier et al. 2021). Technological innovation and the continued growth of renewable energy consumption may impact financial risk, hence, affecting the carbon reduction effect.

Together these studies provide important insights about the relationship among financial risk, R&D, renewable energy, and carbon emissions. However, there are gaps in the research. First, previous studies have concentrated on the impact of financial development on carbon emissions, but few papers have explored the relationship between financial risk and carbon emissions, especially for OECD countries. Second, previous studies indicate that R&D expenditures and renewable energy may have an important influence on the energy consumption-financial development nexus. However, most studies have examined the R&D-carbon emission and renewable energy-carbon emission

relationships, but have not deeply explored the role of research expenditures and renewable energy in the financial risk-carbon emission relationship. Finally, studies have explored the linear impact of financial risk-carbon emissions, but have not considered the non-linear impacts.

Data and methodology

Data

The sample for this empirical analysis includes balanced panel data for 38 OECD member countries from 2000 to 2018. The main indicators include carbon emissions intensity, financial risk index, technological innovation, renewable energy consumption, economic development level, total population, and urbanization. These data are from authoritative datasets, such as the World Development Indicators (WDI) and BP World Energy Statistics Yearbook. Some scholars use separate indicators such as national solvency to characterize financial risk, but have not considered its full complexity. We believe that financial risk is multifaceted, so referring to the existing literature, we choose the financial risk index from the International Country Risk Guide (ICRG) ratings published by the Political Risk Services (PRS) Group as the indicator to characterize the financial risk index consisting of five components: Foreign Debt as a Percentage of GDP, Foreign Debt Service as a Percentage of Exports of Goods and Services, Current Account as a Percentage of Exports of Goods and Services, Net International Liquidity as Months of Import Cover, and Exchange Rate Stability. It systematically measures a country's overall financial risk and the capacity of its financial system (Wang et al. 2022a). The financial risk index ranges from 0 to 50, where 0 indicates very high risk, and the financial risk index is an inverse indicator of financial risk, with higher scores representing lower financial risk. Detailed descriptions of all variables are presented in Table 1. Descriptive statistics for the above variables are presented in Table 2.

Model specification

Unit root test

The panel threshold model requires the variables to be stationary. If they are not stationary, a cointegration test is required, and if there is a cointegration relationship between the variables, then regression can be performed. To identify the random trend component in each variable, we used three unit root tests (Levin, Lin & Chu, ADF-Fisher, PP-Fisher) to ensure the accuracy of the results (Wang and Zhang 2021a). All the tests used the presence of a unit root as the null hypothesis (H_0). If the results indicate that the null hypothesis can be accepted, the

Table 1 Detailed description of variables

Variables	Name	Symbol	Definition	Units	Sources
Explained variable	Carbon emission intensity	CEI	Per capita carbon emissions	Metric tons per capita	WDI
Core explanatory variables	Financial risk	FRI	Financial risk index	-	RPS
Threshold variables	Technological innovation	RD	R & D expenditures account for a percentage of GDP	%	WDI
	Renewable energy	RE	Renewable energy consumption	Million tons oil equivalent	BP
Control variables	Economic development level	ECO	GDP per capita	constant 2010 US$	WDI
	Total population	TP	Number of total populations	-	WDI
	Urbanization level	UL	The proportion of urban population	%	WDI

Table 2 Descriptive statistics of variables

Variable	Obs	Mean	Sd	Min	P25	P50	P75	Max
CEI	722	8.213	4.384	1.249	5.153	7.729	9.871	25.669
FRI	722	37.499	4.442	19.000	34.917	37.542	40.000	49.042
RD	722	1.714	1.046	0.106	0.886	1.519	2.432	4.703
RE	722	3.854	9.578	0.0004	0.202	1.134	3.145	103.753
ECO	722	10.241	0.718	8.489	9.628	10.433	10.770	11.626
TP	722	16.443	1.406	12.986	15.477	16.167	17.665	19.605
UL	722	75.842	10.826	50.754	67.967	77.399	84.343	98.001

variable is not stationary; otherwise, the variable is stationary, regression can be performed directly.

The Levin, Lin and Chu unit root test uses the following regression form.

$$\Delta Y_{it} = u_i Y_{it-1} + \sum_{L=1}^{mn} v_{ip} \Delta Y_{it-L} + w_{pi} d_{pt} + z_{it}, \text{p} = 1, 2, 3 \tag{1}$$

The ADF-Fisher, PP-Fisher unit root test formula is as follows.

$$\text{Fisher} - ADF = -2 \sum_{m}^{p} \log(Qm) \rightarrow P \tag{2}$$

$$\text{Choi} - ADF = \frac{1}{\sqrt{U_{m-1}}} \sum_{m-1}^{K} \gamma^{-1}(Qm) \rightarrow K(0, 1) \tag{3}$$

where $m \cdot \gamma^{-1}$ denotes the reciprocal of the normal distribution function; and Qm denotes the P-value of the ADF unit root

Table 3 Results of panel unit root tests

Variable	LLC		Fisher-ADF		Fisher-PP	
	Horizontal sequence	First-order difference	Horizontal sequence	First-order difference	Horizontal sequence	First-order difference
CEI	1.070	− 8.8071***	32.282	245.175***	34.414)	245.175***
	(0.858)	(0.000)	(1.000)	(0.000)	(1.000)	(0.000)
FRI	− 0.286	− 13.786***	41.8254	299.850***	34.1023	723.348***
	(0.3874)	(0.000)	(0.9995)	(0.000)	(1.000)	(0.000)
RD	− 0.347	− 6.7757***	49.4590	213.091***	64.091	673.562***
	(0.3641)	(0.000)	(0.9921)	(0.000)	(0.833)	(0.000)
RE	9.299	− 2.05856**	8.27079	98.4115***	3.15945	207.878***
	(1.000)	(0.019)	(1.0000)	(0.042)	(1.000)	(0.000)
ECO	8.727	− 10.306***	5.388	230.576***	2.83737	279.025***
	(1.000)	(0.000)	(1.000)	(0.000)	(1.000)	(0.000)
TP	2.067	− 3.876***	55.688	114.210***	92.907	128.802***
	(0.981)	(0.000)	(0.961)	(0.003)	(0.910)	(0.000)
UL	3.009	− 17.986***	94.3350*	265.896***	55.6963	190.484***
	(0.999)	(0.000)	(0.076)	(0.000)	(0.961)	(0.000)

***, **, and * indicate that they passed the test at the significant levels of 10%, 5%, and 1%, respectively

test. The null hypothesis is $a_i = 0$; there is a unit root; if $a_i < 0$, there is no unit root.

Co-integration test

The cointegration test determines whether the variables have a stable cointegration relationship over the study period. If the variables are not stationary, a cointegration test is required, and if there is a cointegration relationship, there is no "pseudo regression" problem, and the regression is accurate using the original data, otherwise the regression is performed using first-order difference data. The Pedroni cointegration test includes two alternative hypotheses: the panel statistical hypothesis and the outlier statistical hypothesis. The specific statistical formula is as follows.

A. Panel-ρ

$$Y\sqrt{AB_{\widehat{\rho}A,Y-1}} \equiv Y\sqrt{A}\left(\sum_{\delta=1}^{A}\sum_{\eta=1}^{Y}\widehat{L}_{11\delta}^{-2}\varepsilon_{\delta,\eta-1}^{2}\right)^{-1}\sum_{\delta=1}^{A}\sum_{\eta=1}^{Y}\widehat{L}_{11\delta}^{-2}(\widehat{\varepsilon}_{\delta,\eta-1}\Delta\widehat{\varepsilon}_{\delta,\eta} - \widehat{\theta}_{\delta}) \tag{4}$$

B. Panel-β

$$B_{\delta A,Y}^{*} \equiv (S_{A,Y}^{*2}\sum_{\delta=1}^{A}\sum_{\eta=1}^{Y}\widehat{L}_{11\delta}^{-2}\varepsilon_{\delta,\eta-1}^{2})^{-\frac{1}{2}}\sum_{\delta=1}^{A}\sum_{\eta=1}^{Y}\widehat{L}_{11\delta}^{-2}\varepsilon_{\delta,\eta-1}\Delta\widehat{\varepsilon}_{\delta,\eta} \tag{5}$$

C. Group-ρ

$$Y\widetilde{B}_{\widetilde{\rho}A,Y-1} \equiv YA^{-\frac{1}{2}}\sum_{\delta=1}^{A}\left(\sum_{\eta=1}^{Y}\varepsilon_{\delta,\eta-1}^{2}\right)^{-1}\sum_{\eta=1}^{Y}(\widehat{\varepsilon}_{\delta,\eta-1}\Delta\widehat{\varepsilon}_{\delta,\eta} - \widehat{\theta}_{\delta}) \tag{6}$$

D. Group-β

$$A^{-\frac{1}{2}}\widetilde{B}_{\widetilde{\rho}A,Y} \equiv A^{-\frac{1}{2}}\sum_{\delta=1}^{A}\left(\sum_{\eta=1}^{Y}S_{\delta}^{*2}\varepsilon_{\delta,\eta-1}^{2}\right)^{-\frac{1}{2}}\sum_{\beta=1}^{Y}\widehat{\varepsilon}_{\delta,\eta-1}\Delta\widehat{\varepsilon}_{\delta,\eta} \tag{7}$$

where

$$\widehat{\theta}_{\delta} = \frac{1}{2}\left(\widehat{\mu}_{\delta}^{2} - \widehat{s}_{\delta}^{2}\right); s_{A,Y}^{*2} = \frac{1}{A}\sum_{\delta}^{A}s_{\delta}^{*2} \tag{8}$$

0. Introducing the dummy variable facilitates a preliminary comparison of the impact of financial risk on carbon emissions at different levels of R&D expenditures. The specific model is as follows.

$$CEI_{it} = \alpha_0 + \beta_0 FRI_{it} + \beta_1 FRI_{it} \times dRD + \beta_2 dRD + \beta'X_{it} + \mu_i + \varepsilon_{it} \tag{10}$$

The process is completed for renewable energy, where the dummy variable is dRE, modeled as follows.

$$CEI_{it} = \alpha_0 + \beta_0 FRI_{it} + \beta_1 FRI_{it} \times dRE + \beta_2 dRE + \beta'X_{it} + \mu_i + \varepsilon_{it} \tag{11}$$

Artificially dividing the "high R&D expenditure group" and the "low R&D expenditure group" by comparing them with the mean value can help identify a trend. However, the artificial grouping method is inevitably subjective. Therefore, we directly generate an interaction term between financial risk and R&D expenditures. This facilitates a discussion about the relationship between R&D expenditures, renewable energy, financial risk, and carbon emissions. Some studies artificially include interaction terms in the regression, after the main term is correlated with the

Panel fixed effects model

This paper begins by preliminarily exploring the impact of financial risk on carbon emission intensity (CEI) using a panel data regression approach. The baseline regression model is as follows.

$$CEI_{it} = \alpha_0 + \beta_0 FRI_{it} + \beta'X_{it} + \mu_i + \varepsilon_{it} \tag{9}$$

where i and t denote each cross-Sect. (38 OECD countries) and year of the time series (2000–2018), respectively. β_0 are the coefficients of the core explanatory variables, and β' is a set of control variables X of coefficients, which means that, assuming other variables remain constant, each unit increase in an explanatory variable increases (or decreases) carbon emissions by β unit. μ_i is the individual effect, and ε_{it} is the estimated residual.

To investigate whether the impact of financial risk on carbon emissions differs across levels of R&D expenditures, we introduce a dummy variable dRD and an interaction term between FRI and dRD. When introducing an interaction term, each variable that usually constitutes the interaction term needs to be included in the model. The dummy variable is used to reflect the qualitative properties of R&D expenditures: when the R&D of a country exceeds the sample mean, the country belongs to the high R&D expenditure group, and the dummy variable has a value of 1; otherwise, the value is

interaction term. However, this may lead to collinearity problems. Some scholars have found this collinearity is not serious in interaction models (Balli and Srensen 2013). Out of rigor, we apply a centralized (Dalal and Zickar 2011) treatment to mitigate the collinearity problem, as modeled below.

$$CEI_{it} = \alpha_0 + \beta_0 FR_{it} + \beta_1 FR_{it} \times RD + \beta_2 RD + \beta' X_{it} + \mu_i + \varepsilon_{it} \tag{12}$$

Similarly, renewable energy, financial risk, and carbon emissions are modeled as follows.

$$CEI_{it} = \alpha_0 + \beta_0 FR_{it} + \beta_1 FR_{it} \times RE + \beta_2 RE + \beta' X_{it} + \mu_i + \varepsilon_{it} \tag{13}$$

Panel threshold model

The fixed effects model above initially explores the potential non-linear characteristics of the impact of financial risk on carbon emission intensity, by adding dummy variables and interaction terms, and artificially dividing the groups for regression in the classical method. This approach does have some limitations, as artificially dividing the groups

$$CEI_{it} = \alpha_0 + \beta_0 FRI_{it} \cdot I(thr \leq \gamma) + \beta_1 FRI_{it} \cdot I(thr > \gamma) + \beta' X_{it} + \mu_i + \varepsilon_{it}$$

$$\tag{14}$$

$$CEI_{it} = \alpha_0 + \beta_0 FRI_{it} \cdot I\left(thr \leq \gamma_1\right) + \beta_1 FRI_{it} \cdot I\left(\gamma_1 < thr \leq \gamma_2\right) + \beta_2 FRI_{it} \cdot I\left(thr > \gamma_2\right) + \beta' X_{it} + \mu_i + \varepsilon_{it} \tag{15}$$

In the equation, the *thr* is the threshold variable; γ is the threshold value, and $I(*)$ is the indicator function, such that the dummy variable $I_{it}(\beta) = \{thr \leq \gamma\}$, When $thr \leq \gamma$ when $I = 1$, otherwise $I = 0$. The coefficients $\beta_0, \beta_1, \beta_2$ are the coefficients of the effect of the explanatory variables on the explanatory variables when the threshold variables are at different threshold intervals, respectively.

cannot generate confidence intervals for the threshold values. This may lead to errors in the regression. To explore in more detail the impact of financial risk on carbon emission intensity, and the non-linearity of the impact of financial risk on carbon emission intensity, we develop a panel threshold model based on the theory of panel threshold model proposed by Hansen (Hansen 1999). R&D expenditures and renewable energy are used as threshold variables for empirical testing.

The advantages of this model are that the user is not required to provide the form of the non-linear equation when studying the non-linear relationship between the independent and dependent variables. The count of thresholds and threshold values is endogenously determined by the sample data. This avoids the errors caused by artificial sample division. This method provides an asymptotic distribution approach to establish the confidence intervals of the parameters to be estimated (Wang et al. 2022c), and the bootstrap method can also be applied to estimate the threshold values of statistical significance, and the conclusion is more reliable. On the basis of Eq. (1), we develop single panel threshold regression models and double threshold regression models.

Results and analysis

Unit root test results

Table 3 shows that the results of the three unit root tests are consistent and indicate that all variables are smooth after first-order difference. This leads to the next step of the co-integration test.

Table 4 Pedroni cointegration test results (with RD variable)

Pedroni cointegration test	Value	P-value
Panel PP-statistic	−7.3346***	0.0000
Panel ADF-statistic	−8.1437***	0.0000
Group PP-statistic	−21.719***	0.0000
Group ADF-Statistic	−5.9739***	0.0000
Kao cointegration test	Statistic	P-value
ADF	1.5210*	0.0641
Residual variance	0.2103	
HAC variance	0.1778	

***, **, and * indicate that they passed the test at the significant levels of 10%, 5%, and 1%, respectively

Table 5 Pedroni cointegration test results (with RE variable)

Pedroni cointegration test	Value	P-value
Panel PP-statistic	−12.9862***	0.0000
Panel ADF-statistic	−9.4909***	0.0000
Group PP-statistic	−20.4460***	0.0000
Group ADF-statistic	−6.2080***	0.0000
Kao cointegration test	Statistic	P-value
ADF	1.5439*	0.0613
Residual variance	0.2080	
HAC variance	0.1709	

***, **, and * indicate that they passed the test at the significant levels of 10%, 5%, and 1%, respectively

Co-integration test results

The results of the Pedroni co-integration test and Kao co-integration test (Kao 1999) (see Tables 4 and 5) show that both data sets pass the co-integration test, which means that there is a stable equilibrium relationship between the variables over time. Therefore, the original equation can be regressed directly on the basis of using the original data, and the regression results are accurate at this point.

Panel fixed effects model

In this section, the direct effect of FRI on CEI (Model 1), and the mediating effect of RD and RE are investigated using a fixed effects model and a fixed effects model with an interaction term, respectively. Table 6 presents the results.

Models 2–3 add RD and its interaction term as control variables; Models 4–5 add RE and its interaction term as control variables, based on Model 1.

Model 1 indicates that the coefficient of FRI on CEI is 0.0996, meaning that the financial risk index has a significant positive effect on carbon emissions. In other words, reducing financial risk positively impacts carbon emissions, confirming a negative correlation between financial risk and carbon emissions. However, a simple regression of the two variables may not consider the heterogeneity of the variables, and FRI may have a different impact on CEI at different levels of RD and RE. As such, we introduce different dummy variables and interaction terms between the dummy variables and the dependent variable in different models for regression analysis.

When introducing a discrete dummy variable for research expenditures (dRD) and an interaction term between FRI

Table 6 Results of the panel fixed effect regression models

	Model 1	Model 2	Model 3	Model 4	Model 5
FRI	0.0996***	0.1276***	0.101***	0.0997***	0.0889***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FRI×dRD		−0.0589***			
		(0.009)			
dRD		2.2433***			
		(0.008)			
FRI×RD			−0.0522***		
			(0.000)		
RD			2.1555***		
			(0.000)		
FRI×dRE				−0.0564*	
				(0.059)	
dRE				1.6253	
				(0.168)	
FRI×RE					−0.001
					(0.455)
RE					−0.0194
					(0.692)
ECO	1.2880***	1.3638***	1.2082***	1.3756***	1.5252***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TP	−10.2347***	10.244***	10.0665***	−8.9902***	8.6184***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UL	−0.0566***	−0.0601***	−0.0752***	−0.0537***	−0.0455***
	(0.006)	(0.004)	(0.000)	(0.009)	(0.020)
Constant	162.8429***	161.4387***	162.3197***	141.482***	133.5461***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hausman test	117.8***	116.22***	114.34***	51.64***	82.2***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.3154	0.3225	0.3393	0.3355	0.3921
Obs	722	722	722	722	722

***, **, and * indicate that they passed the test at the significant levels of 10%, 5%, and 1%, respectively

and dRD (FRI×dRD) in Model 2, the results show that the coefficient of effect of FRI on CEI is 0.1276, while the coefficient of effect of FRI×dRD on CEI is −0.0589. This indicates that research expenditures may influence the relationship between financial risk index and carbon emissions. Changes in research expenditures lead to changes in the effect of financial risk on carbon emissions. Model 3 further improves upon Model 2. Introducing the continuous variable of research and development expenditure RD to replace the dummy variable dRD and including the interaction terms of FRI and FD (FRI×RD), yield the following results: the coefficient of FRI is positive and the coefficient of FRI×RD is negative and significant at the 1% level. This implies that an increase in research expenditure investments weakens the promoting effect of the financial risk index on carbon emissions. It may even produce a carbon reduction effect. Similar to the research approach for research expenditures, we construct Models 4 and 5, which contain the discrete dummy variable dRE for renewable energy and interaction term FRI×dRE (Model 4) and continuous variable RE and interaction term FRI×RE (Model 5). The results indicate that the coefficient of FRI is positive, and the coefficient of the interaction term on carbon emissions is negative. This implies that renewable energy may have a potential impact on reducing carbon emissions.

To further illustrate the relationship between the variables, graphs show the effect of each unit increase in FRI on CEI at different levels of research expenditures and renewable energy. Figure 1–a b cd correspond to the marginal effects of the interaction terms of Models 2, 3, 4, and 5, respectively.

Figure 1(a) shows the effect of FRI on CEI changes from positive to negative with increasing research expenditures under different research expenditure group classifications. More specifically, in the low research expenditure interval, increasing FRI promotes carbon emissions. In contrast, in the high research expenditure interval, increasing FRI has a dampening effect on carbon emissions. Furthermore, to further explore the relationship between research expenditures, financial risk, and carbon emissions, Fig. 1(b) depicts the effect of financial risk on carbon emissions as research expenditures successively increase, based on Model 3. Figure 1(b) shows that the positive effect of the financial risk index on carbon emissions diminishes as research expenditures increase. The financial risk index produces a carbon reduction effect when research expenditures reach a certain level. Similarly, to illustrate the impact of renewable energy, Fig. 1(c) shows the effect of FRI on CEI decreases, with an increasing coefficient of renewable energy consumption under different renewable energy consumption group classifications. This implies that high renewable energy consumption intervals more effectively reduce carbon emissions compared to low renewable energy consumption intervals. This is also confirmed by Fig. 1(d), on the marginal effects of continuous renewable energy consumption variables.

To avoid endogeneity problems, due to the possible two-way causality between FRI and CEI, we use the first-order lagged term of FRI as an instrumental variable to replace the original variables for estimation. This yields relatively robust conclusions. The estimation results are presented in Appendix Table 10; it shows that the magnitude and

Fig. 1 Marginal effect of the interaction term generated by FRI with different RD and RE variables on CEI
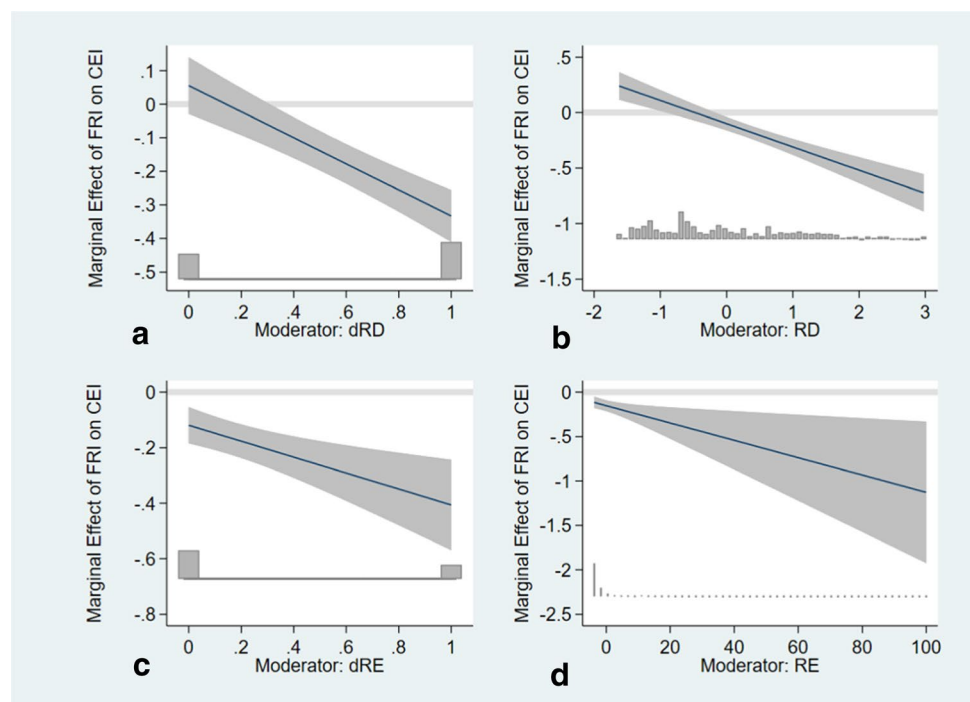
direction of the variable coefficients remain largely consistent with the results above. In addition, Appendix Fig. 3 displays the instrumental variables (FRI) $_{-1}$ marginal utilities. These graphs are also consistent with the graphs above, indicating that the conclusions presented graphically continue to hold. This again confirms the robustness of the estimates.

The estimation results of the above panel fixed effects model suggest that FRI has a positive impact on CEI, i.e., carbon emissions increase when financial risk is reduced, which is consistent with the results of Zhao (Zhao et al. 2021). Moreover, the positive effect of FRI on CEI is weakened as research expenditures and renewable energy consumption increase. All of the above results suggest that the impact of FRI on CEI varies due to different levels of RD and RE, so this paper uses a panel threshold model to explore the impact of financial risk on carbon intensity in more depth from a non-linear perspective.

Panel threshold model results

A threshold effect is an event which causes a change in the trend of another variable of interest, after one variable reaches a specific value. The threshold model consists of two parts: the threshold presence test and the threshold regression analysis.

Threshold presence test

A threshold presence test is conducted before a threshold regression analysis to determine whether there is a threshold effect. This study applies the Hansen method, using stata16 software. The number of self-iterations for the Bootstrap method is set to 300. The sampling results indicate that the RD and RE threshold variables pass the single threshold model test. However, the second threshold value is not significant. Specifically, the threshold value in the threshold regression model is RD = 2.677 when RE is used as the threshold variable; the threshold value is RE = 2.879 when RE is used as the threshold variable. Table 7 shows the sampling results and threshold estimates. In summary, there is a non-linear threshold effect of financial risk on carbon emissions when RD expenditure or RE is set as the threshold variable.

Threshold regression analysis

Table 8 shows the results of the threshold regression analysis. With RD as the threshold variable and a threshold value of 2.667, when RD < 2.667, the regression coefficient of FRI on CEI is 0.116. In other words, a one-unit increase in FRI increases carbon emission intensity by 0.116. An increase in FRI is associated with a decrease in financial risk; as such, reducing financial risk has a positive impact on carbon emissions (e.g., emissions increase). As R&D expenditures exceed the threshold of 2.667, the regression coefficient of FRI on CEI decreases to 0.0881. This indicates that an increase in R&D expenditure investments can significantly reduce the positive impact of FRI on carbon emissions. Specifically, the financial risk index has a significant positive effect on carbon emissions. This indicates that a lower financial risk increases carbon emissions. This result is consistent with a previous study (Zhang and Chiu 2020), which also found that a reduction in financial risk increases

Table 8 Results of threshold regression analysis

Variable	Threshold variable	
	RD	RE
FRI	0.116*** (*thr* < 2.677)	0.0971***(*thr* < 2.879)
	(8.84)	(7.42)
	0.0881***(*thr* > 2.677)	0.0763***(*thr* > 2.879)
	(6.63)	(5.53)
ECO	1.506***	1.537***
	(5.10)	(5.19)
TP	−9.580***	−7.880***
	(−12.43)	(−9.29)
UL	−0.0637***	−0.0561***
	(−3.12)	(−2.76)
Constant	151.0***	122.9***
	(12.81)	(9.25)
R-squared	0.350	0.350
Obs	703	703
F-test	71.27	71.14

***, **, and * indicate that they passed the test at the significant levels of 10%, 5%, and 1%, respectively

Table 7 Results of the threshold existence test

Threshold variable	Model	*F*-value	*P*-value	BS time	Estimated thresholds	95% confidence interval	Critical value		
							10%	5%	1%
RD	Single	39.724**	0.017	300	2.677	[2.626,2.725]	17.158	23.269	49.134
	Double	18.34	0.333	300	-				
RE	Single	41.582**	0.033	300	2.879	[2.555,3.536]	24.612	31.937	64.148
	Double	16.666	0.220	300	-				

***, **, and * indicate that they passed the test at the significant levels of 10%, 5%, and 1%, respectively

national carbon emissions. This outcome may be because a reduction in risk reduces the cost of capital mobilization and enables smooth resource transactions. This increases the incentive for industrial production, leading to further increases in energy consumption and increases in carbon emissions. In addition, reducing financial risk leads to easier access to loans and subsidies for energy-intensive goods for consumers, increasing carbon emissions on the consumption side. These results suggest that technological innovation plays a positive role in reducing carbon emissions despite low financial risk. Increasing R&D expenditures above the threshold significantly reduces the boosting effect of financial stability on carbon emissions. Increased R&D expenditures encourage the generation of new and more productive energy-efficient technologies, thereby increasing the level of efficiency in the use of energy and other resources to reduce CO_2 emissions. Furthermore, the unpredictability of technological innovation and long payback cycles increases financial risk. In addition, in terms of bond risk, R&D investment is positively associated with a high risk of bond default (Shi 2003). In terms of stock risk, R&D investment increases the volatility of investments in corporate stock returns (Gharbi et al. 2014). When there is a high level of information asymmetry, executives are less likely to disclose too much about corporate R&D to protect innovation and competitive advantage. This may be associated with a higher risk of stock price collapse (Kim and Zhang 2016), leading to investor apprehension and the discouragement of environmentally productive activities.

Based on the regression results with RE as the threshold variable, the regression coefficient of FRI on CEI varies with increasing RE. When RE is below the threshold value of 2.879, the regression coefficient of FRI on CEI is 0.0971. When RE exceeds the threshold value, the regression coefficient of FRI on CEI is 0.0763. All the results are significant at the 1% level. This indicates that as RE increases, the financial risk index is non-linearly positively related to carbon intensity; as the threshold interval changes, the promotion of the carbon intensity effect decreases. This may be because an increase in renewable energy consumption can directly impact carbon emissions by improving the energy mix. Increasing the share of renewable energy consumption significantly reduces energy intensity and diminishes dependence on fossil energy sources, reducing carbon emissions. Furthermore, RE can indirectly impact carbon emissions by adjusting financial risk. Short-term targeting pressures on the energy transition have led many countries to have a preference for renewable energy consumption. This preference has created a green investment gap, creating new sources of risk for asset price volatility and financial stability (Monasterolo et al. 2017). In addition, climate policies related to renewable energy can also affect financial risk, with the disorderly introduction of climate policies leading to a sudden revaluation of entire asset profiles. This can leave investors without adequate expectations and create transition risks, reducing carbon emissions.

To effectively address the possible endogeneity problem in the estimation process, this study uses the first-order lagged term of the financial risk index instead of the financial risk index for the specific estimation (Wang et al. 2022b). The results are in Appendix Table 11 and show similar results as in Table 9. This indicates that the results remain robust, even after accounting for possible endogeneity issues. To further test the robustness of the benchmark results, we exclude an additional control variable: urbanization. The empirical results are shown in Appendix Table 12; overall, the results remain robust after excluding urbanization. In particular, the threshold remains unchanged, similar to the results of the benchmark test. This again supports the robustness of the study's conclusions.

Dynamics of the number of countries in the threshold range

To analyze the dynamic impact of research expenditures and renewable energy consumption on financial risk and carbon emissions during the study period, we construct three-dimensional (country, time, threshold value) curve

Table 9 OECD countries and their corresponding numbers

No.	Country	No.	Country	No.	Country	No.	Country
1	Australia	11	Finland	21	Korea, DPR	31	Slovakia
2	Austria	12	France	22	Latvia	32	Slovenia
3	Belgium	13	Germany	23	Lithuania	33	Spain
4	Canada	14	Greece	24	Luxembourg	34	Sweden
5	Chile	15	Hungary	25	Mexico	35	Switzerland
6	Colombia	16	Iceland	26	Netherlands	36	Turkey
7	Costa Rica	17	Ireland	27	New Zealand	37	UK
8	Czech Republic	18	Israel	28	Norway	38	USA
9	Denmark	19	Italy	29	Poland		
10	Estonia	20	Japan	30	Portugal		
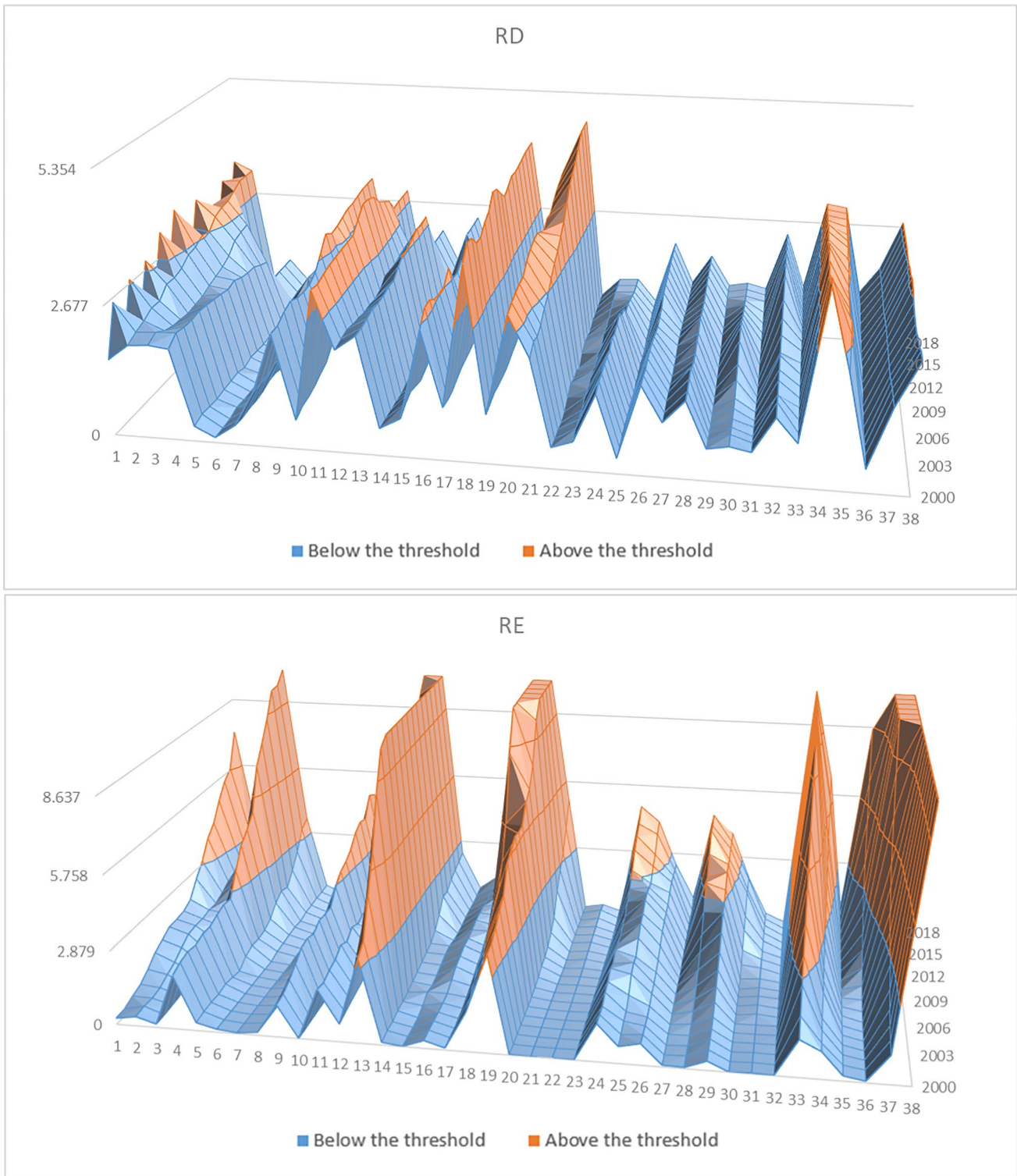
Fig. 2 Threshold interval and its 3D dynamic change

plots to reflect the dynamics of the threshold variables in 38 OECD countries. The blue area indicates the range interval below the threshold, and the orange area indicates the range interval above the threshold. Table 9 shows the corresponding numbers of the 38 countries. The following conclusions can be drawn based on the three-dimensional dynamics in Fig. 2, combined with the panel threshold model results.

1. The number of countries crossing both the research expenditure and renewable energy thresholds in OECD countries increases from 2000 to 2018. For the technological innovation threshold variable, the number of countries above the threshold increases from 4 to 10. For the renewable energy consumption threshold, 3 countries are in the high technological innovation range in 2000. However, by 2018 this number increases to 20. Renewable energy is growing very rapidly compared to research spending, which indicates that renewable energy has received attention from most countries in recent years. This indicates that some countries have placed energy transition on the agenda, perhaps due to conferences and climate constraints. The low growth in research expenditures indicates that area may need more attention.

2. In terms of countries crossing the threshold, no country had crossed both thresholds in 2000. Four countries (Finland, Israel, Japan, and Sweden) have a "first-mover" advantage in technological innovation and remain in the high R&D spending range for all 18 study years. Germany, Italy, and the USA are uniquely positioned to develop renewable energy. As of 2018, seven countries crossed both the R&D expenditure and renewable energy consumption thresholds: Australia, Denmark, Finland, Israel, Japan, Sweden, and the USA. The 15 countries not crossing either threshold during the study period are: Colombia, Costa Rica, Czech Republic, Estonia, Greece, Hungary, Iceland, Ireland, Latvia, Lithuania, Netherlands, New Zealand, Portugal, Slovakia, and Slovenia. These countries may need more policy guidance and attention.

Conclusions and policy implications

This case study analysis applies balanced panel data of OECD countries from 2000 to 2018, constructs a panel fixed effects model and a panel threshold model, focuses on the non-linear relationship between financial risk and carbon emissions, and includes technological innovation and renewable energy consumption in the research framework of financial risk and carbon emissions. This helps explain the mechanism of the impact of financial risk on carbon emissions and the important role of technological innovation and renewable energy in reducing carbon emissions. This provides a realistic basis for alleviating the global environmental pressure caused by greenhouse gas emissions. Study conclusions are as follows.

1. The results of the fixed effects model show that reducing financial risk increases carbon emissions. This relation-

ship may be influenced by technological innovation and renewable energy consumption.

2. There is a significant technological innovation and renewable energy single threshold effect in the relationship between financial risk and carbon emissions. Increasing R&D expenditures and renewable energy consumption above the threshold significantly reduces the positive impact on carbon emissions.

3. The number of countries crossing the threshold for renewable energy and technological innovation increases over the study period. This indicates that financial risks have an enhanced impact on reducing carbon emissions. However, the slow growth in technological innovation compared to renewable energy consumption in OECD countries highlights the need to further explore the potential of technological innovation for carbon reduction.

The results and discussion above lead to the following policy recommendations.

First, our analysis shows that controlling financial risks and reducing carbon emissions do not go hand-in-hand. This means policymakers need to control financial risks within reasonable limits, while finding effective measures to weigh the negative correlation between such financial risks and carbon emissions, because policymakers are unlikely to sacrifice the roots of national stability and economic development for solely to reduce carbon emissions. Second, we find that increasing technological innovation and renewable energy consumption provide a solution to achieve the dual goals of stable and orderly economic development and carbon emission reduction, because the coefficient of financial risk index on carbon emission becomes smaller when increasing technological innovation or renewable energy consumption, which means that the increase of these two has a positive impact on carbon emission reduction, and they will weaken the contribution of financial stability to carbon emissions.

Given this, country governments should incentivize energy-intensive industries to expand R&D investments. For example, the government should set industry R&D investment standards and give corresponding tax breaks or financial subsidies to enterprises whose R&D investment exceeds the prescribed standards, and increase the tax levy percentage for enterprises whose R&D investment does not meet the standards.

In addition, a reasonable renewable energy investment policy is also vital for promoting energy conservation and emission reduction. Policies should be aligned with the real-world situation of each country to effectively coordinate technology promotion policies, energy fiscal policies, financing policies, and other incentive policies. This would stimulate the development of renewable energy industries. Countries should combine their resource and technology endowments to develop renewable energies that

have comparative advantages and to transform and achieve sustainable energy structures.

Moreover, the government, while controlling financial risks, should encourage financial institutions to innovate consumer credit products and services, increase the motivation to provide credit support for residents to purchase new energy vehicles, energy-efficient home appliances, and other green and smart products, and encourage green consumption and green lifestyles among residents.

The path dependence on fossil energy is a reality, so the energy transition will need to occur over time. This highlights the importance of avoiding a disorderly transition as much as possible. Green macroprudential tools can be effectively applied to guide financial flows, to maintain a smooth transition, and avoid financial systemic risks.

Appendix

Table 10 Results of the panel fixed effect regression models

	Model 1	Model 2	Model 3	Model 4	Model 5
$(FRI)_{-1}$	0.1116***	0.1444***	0.1122***	0.1108***	0.1004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$(FRI)_{-1} \times dRD$		−0.0688***			
		(0.002)			
dRD		2.6086***			
		(0.002)			
$(FRI)_{-1} \times RD$			−0.0600***		
			(0.000)		
RD			2.404***		
			(0.000)		
$(FRI)_{-1} \times dRE$				−0.0446	
				(0.128)	
dRE				1.1679	
				(0.315)	
$(FRI)_{-1} \times RE$					−0.0015
					(0.277)
RE					0.0013
					(0.979)
ECO	1.3697***	1.4549***	1.3237***	1.4621***	1.6184***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TP	−11.2027***	−11.2119***	−11.0998***	−9.8755***	−9.6394***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UL	−0.0687***	−0.0728***	−0.0887***	−0.0652***	−0.0564***
	(0.002)	(0.001)	(0.000)	(0.003)	(0.008)
Constant	178.3120***	176.6786***	178.6498***	155.5411***	149.6875***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hausman Test	129.31***	128.38***	128.49***	55.31***	96.15***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.3545	0.3644	0.3812	0.3730	0.4211
Obs	684	684	684	684	684

***, **, and * indicate that they passed the test at the significant levels of 10%, 5%, and 1%, respectively

Fig. 3 Marginal effect of the interaction term generated by $(FRI)_{-1}$ with different RD and RE variables on CEI
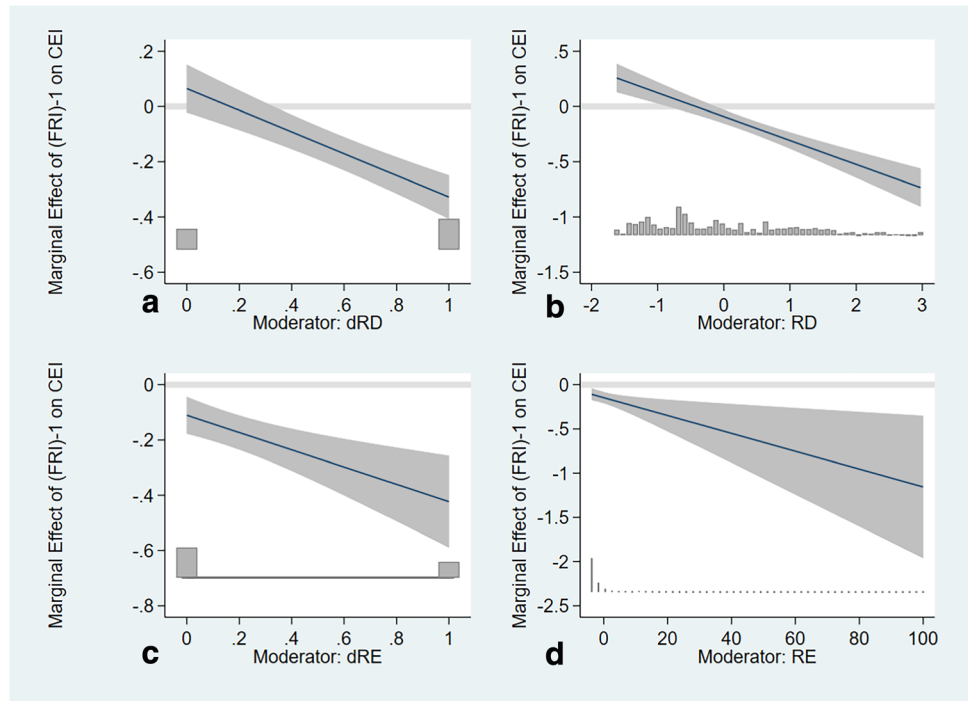
Table 11 Results of robustness tests: by considering the problem of endogeneity

Variable	Tthreshold variable	
	RD	RE
$FRI)_{-1}$	0.125*** (thr < 2.677)	0.105*** (thr < 2.879)
	(5.80)	(8.40)
	0.0978*** (thr > 2.677)	0.0856*** (thr > 2.879)
	(4.56)	(6.48)
ECO	1.527	1.603***
	(1.60)	(5.07)
TP	−11.06***	−9.109***
	(−3.77)	(−10.54)
UL	−0.0694	−0.0655***
	(−1.11)	(−3.02)
Constant	174.2***	141.9***
	(3.92)	(10.62)
R-squared	0.392	0.387
Obs	684	684
F-test	9.274	81.08

***, **, and * indicate that they passed the test at the significant levels of 10%, 5%, and 1%, respectively

Table 12 Results of robustness tests: by excluding an additional control variable

Variable	Threshold variable	
	RD	RE
FRI	0.113***(thr < 2.677)	0.0952***(thr <2.879)
	(8.85)	(7.56)
	0.0891***(thr > 2.677)	0.0747***(thr >2.879)
	(6.95)	(5.62)
ECO	1.244***	1.332***
	(4.36)	(4.67)
TP	−10.93***	−9.580***
	(−16.18)	(−11.87)
Constant	170.1***	137.9***
	(16.34)	(11.55)
R-squared	0.338	0.345
Obs	722	722
F-test	86.93	89.66

***, **, and * indicate that they passed the test at the significant levels of 10%, 5%, and 1%, respectively

Declarations

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable

Competing interests The authors declare no competing interests.

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