



Threshold effects of credit risk on renewable energy consumption and green financial policies nexus: evidence from OECD countries

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Abstract

Previous research on renewable energy financing has often underestimated or neglected the important impact of credit risk on the energy transition process. The study addresses this gap by exploring the threshold effect of credit risk on renewable energy consumption (REC) and green financial policies (GFP) nexus in 47 OECD countries from 2000 to 2020. Using a Panel Smooth Transition Regression (PSTR) model, we find a positive relationship between GFP and REC. However, exceeding a specific threshold of credit risk significantly decreases the effectiveness of bank financing for renewable energy projects. The threshold is approximately 74% for the entire sample, with slight variations between developed (77%) and developing countries (72%). Despite the risk, banks in developed countries are more involved in financing green projects than their counterparts in developing nations. These results remain consistent after adding control variables and employing an alternative model and estimation method. The findings highlight the importance of credit risk management in optimising banks' green lending policies and facilitating the transition towards renewable energy sources.

Keywords Renewable energy consumption · Green finance policies · Credit risk · Panel smooth transition regression model

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1 Introduction

The global imperative to transition towards sustainable energy sources has now become imminent and rendering investments in renewable energy an undeniable obligation for nations. This shift is crucial not only for mitigating the detrimental impacts of fossil fuels on the environment but also for combating climate change, preserving water resources, managing pollution, and navigating the challenges of escalating oil prices. In response to the urgent need for action on climate change, leading international organizations have made limiting global warming a top priority. The International Energy Agency (IEA), the International Renewable Energy Agency (IRENA), and the United Nations Climate Change Conferences (COP) are all focused on achieving the critical target of restricting global temperature increases to 1.5 °C by 2030. Their focus extends to facilitating a smooth and cost-effective transition towards clean and accessible energy solutions. Aligning with the Sustainable Development Goals for Energy and Climate (SDGs 7 and 13), these objectives advocate for a shift away from reliance on fossil fuels such as oil, carbon dioxide, and coal, towards harnessing the potential of abundant and diverse renewable energy sources.

To achieve this vision, the IEA, IRENA, and COP conferences have strongly supported the adoption of stringent and impactful environmental policies, relevant green financial policies, and efficient green technologies. These actions aim at climate change mitigation and adaptation, sustainable resource use, environmental protection, biodiversity, natural habitat rehabilitation, and the promotion of green credits.

The implementation of such policies and actions empowers countries to ensure a successful energy transition while safeguarding themselves against environmental uncertainty and polluting technologies (Lee et al., 2024; Shvydanenko et al., 2023; Flammer, 2023; Su & Lee, 2023; Sun et al., 2023; Tang & Zhou, 2023; Yan et al., 2023; Ao et al., 2023; Sadiq et al., 2022; Li et al., 2022; Kruse et al., 2022; Abid et al., 2022; Nawaz et al., 2021; Taskin et al., 2020; Lui et al., 2020; Su et al. 202); Bhat & Mishra, 2019; Bai et al., 2019).

Within this framework of global concern, governments, national and international financial institutions, and relevant organizations bear a critical responsibility to collaborate and coordinate their efforts in terms of energy optimization and efficiency. Their collective aim is to strategically direct financial flows towards green projects, foster the implementation of green technologies, progressively reduce reliance on coal-based electricity generation, phase out inefficient fossil fuel subsidies in a just and equitable manner, and stimulate job creation.

It is acknowledged that the transition to renewable energy and the fight against global warming necessitate substantial technical and technological assistance, coupled with specialized funding for developing nations grappling with a significant scarcity of Green Climate Fund (GCF) and limited public–private partnerships. However, according to the UN (2023), financial commitments pledged for 2024 (\$100 million per year) by donor countries and funding entities towards climate change mitigation, clean energy transition, and the execution of adaptation action plans in developing countries fall short of expectations. Consequently, the pursuit of novel funding sources and the reform of financial and banking systems at the national level have emerged as paramount concerns for financing green projects and technologies. This reform entails the modernization of financial laws and regulations, promoting a more flexible financial and monetary regulatory environment. Financial incentives, tax avoidance, streamlined administrative processes, information disclosure, green technology and green finance represent key instruments for a successful energy transition policy.

While banks and relevant financial institutions are inherently obligated to embrace sustainability activities that promote the financing of green investments, their engagement is also contingent upon the risk-return principle, and default risk (Chen et al., 2023a, 2023b, 2023c; Belloni et al., 2022; Zhou et al., 2022; Park and Kim, 2020). However, the rise in green credit lending improves the social reputation of banks, increases their performance (Feng et al., 2024; Huang et al., 2023; Liu & Huang, 2022), and subsequently strengthens their risk management, particularly in mitigating credit risk (Al-Qudah et al., 2023; Cui et al., 2018).

A central challenge lies in the inherent cautiousness, reluctance, and uncertainty that banks often exhibit when confronted with the decision to fulfill their environmental commitments and responsibilities by financing green projects, which can be perceived as inherently risky and uncertain. The complexity of granting green loans has been further amplified by factors such as liquidity availability. Additionally, substantial risks impact the financial performance of companies operating within the renewable energy sector. The unwavering support and environmental policy stringency, coupled with the commitment of companies and public authorities to reimburse GCF, serve as crucial incentives for banks to increase their financing of green projects.

In response to this dynamic landscape, central banks, conventional banks, and specialized financial institutions have embarked on a novel approach encompassing various facets, including green prudential regulation, green loans, green bonds and green financial principles. This comprehensive approach is geared towards fostering sustainable development and stimulating economic growth.

In this context, we aim to investigate the relationship between green financial policies (GFP), renewable energy consumption (REC), and credit risk, focusing on the threshold effect of credit risk on the GFP-REC nexus. This study analyzes the dynamic interplay between these factors to provide insights into optimal financing strategies for green projects across diverse economic landscapes.

Based on a PSTR model of 47 OECD countries for the period 2000 to 2020, the expected results show that when credit risk exceeds the specified threshold, green projects are perceived as increasingly risky, which in turn makes banks reluctant to engage in such projects. The consistency and robustness of the initial findings were confirmed by robustness tests that included a control variable (Bank Deposits to GDP) and an alternative model (Panel Threshold Regression) with different estimation methods.

Our contributions to the existing literature are threefold:

Firstly, We examine the underexplored issue of banks' reluctance to engage in complex and risky environmental financing. By analyzing the GFP-REC relationship and identifying critical credit risk thresholds within OECD countries, we highlight the challenges of promoting green investments in the face of perceived financial risks.

Secondly, We demonstrate that credit risk, beyond a certain threshold, hinders the effectiveness of GFP in promoting REC. Utilizing a PSTR model, we pinpoint critical credit risk levels beyond which banks are less likely to engage in green financing. This approach underscores the dynamic and potentially limiting impact of credit risk on green finance initiatives.

Thirdly, We reveal that banks in developed OECD countries exhibit a higher threshold for credit risk tolerance compared to their counterparts in developing countries. This finding emphasizes the importance of considering specific financial contexts and regulatory environments when evaluating the effectiveness of green financial policies.

Our results also reveal that profitability, liquidity, and stability of banks, coupled with the current account balance, the level of economic development, and the environmental

policy stringency, appear to be decisive factors in fostering the emergence of clean energy solutions. However, the substantial size of allocated funds and the extended repayment periods, often exceeding 20 years, pose challenges to financing green projects. These projects are traditionally riskier and have lower short-term profitability compared to conventional alternatives.

The study provides valuable insights for policymakers and financial institutions, emphasizing the importance of managing credit risk and developing strategies to reduce risk perceptions associated with green projects. It also highlights the need for specific financial support mechanisms and incentives to encourage banks in developing countries to engage more actively in green financing.

The remainder of the study is structured as follows: Sect. 2 provides a relevant literature review and research hypotheses. Section 3 describes the data and sample selection. Section 4 extends the model specification, methodology and empirical results. Section 5 discusses the results. Finally, Sect. 6 concludes the paper by summarizing avenues for future research.

2 Literature review and research hypothesis

This section explores the existing literature on the dynamic relationships between renewable energy consumption, green finance instruments, and credit risk exposure within the financial sector.

Green finance is vital for attaining sustainable development targets through increased investment in renewables and energy efficiency, mitigating the risks associated with new technologies, and offering potentially higher returns (Sachs et al. 2019). Several studies highlight the positive correlation between green finance and renewable energy development. For instance, Shvydanenko et al. (2023) discovered a substantial association between renewable energy consumption and green financing in developing nations. Similarly, Chen et al., (2023a, 2023b, 2023c) found that green finance and renewable energy have a dynamic interaction that contributes to sustainable development in China, a finding echoed by Zhang and Wang (2021).

Beyond this general positive trend, research suggests that green finance instruments can play a significant role in specific areas, such as environmental sustainability and CO₂ emissions reduction. Khan et al. (2022) argued that green finance and investments in renewable energy sources are key drivers in enhancing environmental sustainability and reducing CO₂ emissions. Alharbi et al. (2023) further emphasized the substantial impact of green finance on supporting renewable energy in both the short and long term.

Green bonds, in particular, have emerged as a key instrument for promoting sustainable investments. According to Tolliver et al. (2019), green bonds are experiencing rapid growth in their allocation to renewable energy projects. By providing specialized financing for environmentally sustainable endeavors, encompassing solar, wind, and hydroelectric projects, green bonds play a pivotal role in diminishing the cost of financing and enhancing the accessibility of funding for renewable energy ventures. The European Investment Bank (EIB) launched green bonds in 2007, which share similarities with conventional corporate bonds. However, the funds raised are exclusively earmarked for environmentally friendly initiatives, ensuring a targeted allocation towards sustainability (Naeem et al., 2022). This targeted approach has yielded promising results, as demonstrated by Taghizadeh-Hesary et al. (2023) who showed that green bonds effectively encourage green energy projects and

significantly reduce CO₂ emissions. Similarly, Ye and Rasoulinezhad (2023) found that green bonds positively impact the efficiency of green resource usage.

Green finance has emerged as a powerful tool for improving environmental sustainability, notably by influencing the credit risk associated with lending practices. Numerous studies have explored this complex relationship. Cui et al. (2018) investigated the impact of China's green credit policy on credit risk. Based on data from 24 Chinese banks over five years, they found that a higher percentage of green loans reduced a bank's non-performing loan. This finding suggests that expanding green loans can potentially improve bank performance.

Zhou and al. (2022) examined a sample of 41 Chinese banks throughout 2007–2018. The results of the study indicate that China's green credit policy (GCP) has effectively decreased credit risk for major state banks. However, the opposite effect has been observed in municipal and regional commercial banks, where an increase in credit risk has been noted due to information and knowledge imbalances. The findings may assist authorities in modifying their green finance strategies for banks. Cao et al. (2021) posit that China's GCP reduces the risk of deadline asymmetry in polluting companies, stimulates environmental behavior, and helps mitigate capital chain risks by balancing environmental protection and economic development.

Wang (2022) further explored the potential of green credit to mitigate credit risk and enhance business performance within Chinese commercial banks. This potential, he argues, lies in the promotion of sustainable development and environmentally-friendly financial practices. In fact, green credit has the potential to become a driving force in future financial progress, shaping both the risks and business performance of banks.

Research beyond China further supports the positive impact of GCP. Al-Qudah et al. (2023) found that in the United Arab Emirates, a higher ratio of green loans correlated with a lower ratio of non-performing loans. This suggests that GCPs can contribute to a healthier financial sector. Their study also highlighted the positive impacts of credit quality, bank efficiency, and bank size, aligning with findings by Liu and Huang (2022) and Feng et al. (2024) which demonstrate that increased green credit activity can enhance a bank's social reputation, operating performance, and risk management.

It is crucial to utilize renewable energy sources and replace fossil fuels to support environmental health and attain a carbon-neutral ecosystem. Financial institutions play a crucial role, as they seek incentives to accelerate green finance (Chen et al., 2023a). Amuakwa-Mensah and Näsström (2022) demonstrate that higher performance in the banking sector increases the use of renewable energy. Chen et al. (2023b) illustrate that a rise in loans towards renewable energy enhances a bank's profit margin. Ünlü et al. (2022) suggest that increased demand for renewable energy can help reduce credit gap risk, a reliable predictor of widespread banking crises.

The study conducted by Umar et al. (2021) examines the effects of carbon-neutral lending on credit portfolios. The findings indicate that the decrease in credit risk can be attributable to the decreased volatility of borrowers' income and cash flows resulting from their environmentally friendly operations. In their study, Choudhury et al. (2023) examined the association between renewable energy growth and the level of risk in the banking sector. They discovered that enhancing the amount of renewable energy in a country's entire energy supply significantly decreases banks' default risk.

Alonso (2020) indicates that commercial banks play a vital role in clean energy funding by offering non-recourse lending and lowering credit risk. Improving credit risk management and access to finance in green energy projects can boost the profitability and feasibility of clean energy initiatives (Dhruba, 2018).

Non-performing loans (NPLs) represent a significant indicator of credit risk for lenders and financial institutions, providing insight into the potential for borrower default and the quality of assets. According to Ozili (2023), There is a positive link between sustainable development and NPLs in the banking sector, especially in European and American nations. In contrast, there is a negative association between SDG3 and SDG7 achievement in European and African nations. Ntarmah et al. (2020) demonstrated that countries with low environmental sustainability are more susceptible to environmental issues resulting from rising NPLs than those with high environmental sustainability.

Iqbal and Nosheen (2023) examine the moderating effect of NPLs on adopting sustainable development targets and banks' financial performance. They find that when banks adopt sustainable development targets, they may generate lower earnings if they have a high ratio of NPL. Indeed, some studies highlighted a reluctance among banks and financial institutions, particularly in developing countries, to finance green projects. This reluctance can be attributed to the elevated perception of credit and default risks in this sector (Chen et al., 2023a, 2023b, 2023c; Belloni et al., 2022; Zhou et al., 2022; Park and Kim, 2020).

On the corporate side, the relationship between financial performance and environmental initiatives is complex. While some studies highlight the positive impact of responsible environmental practices on corporate financial performance, others emphasize the importance of strategic implementation and the role of external factors. The study of Ao et al. (2023) shows that environmental uncertainty and digital technology applications moderate the link between corporate green behavior and tax avoidance in Chinese firms, suggesting that responsible practices can benefit both the environment and financial performance. Qing et al. (2023) further explore the financial implications of green technology innovations in the semiconductor industry. Their findings demonstrate the importance of proactive implementation, aligning green technology with environmental sustainability goals, for achieving improved financial performance. Conversely, reactive green technology innovations, adopted due to external pressure, negatively impact firm finances; furthermore, their research shows that print media strengthens the positive link between green technology innovations and financial performance, while new media weakens it.

In the same vein, Chen and Dagestani (2023) found that circular economy practices, using data from Chinese-listed firms between 2009 and 2019, are a powerful tool for achieving corporate sustainability. Their research reveals that innovation and digital transformation further enhance the positive effects of these practices. However, the negative consequences of climate change on both financial and energy sectors are irrefutable (Qing et al., 2024).

On a more positive note, corporate social responsibility has been shown to significantly boost green innovation (Chen et al., 2023a, 2023b, 2023c) and improve environmental performance (Dagestani et al., 2024a, 2024b). Furthermore, third-party environmental information disclosure significantly enhances both financial performance (Dagestani and Qing, 2024) and green innovations of Chinese companies (Luo et al., 2021).

The literature review highlights the complexity and multifaceted nature of environmental challenges. Protecting the environment and combating pollution are significant issues demanding collaboration from all stakeholders, including corporations and banks.

Companies face the challenge of balancing environmental responsibility with maintaining their economic and financial performance. Meanwhile, banks must reconcile their commitment to funding green investments, particularly renewable energy projects, with the inherent credit risk associated with such ventures.

This research aims to identify the credit risk threshold at which banks cease to provide green loans for projects promoting renewable energy and reducing harmful emissions. This issue, not yet explored by relevant literature, will allow us to evaluate the impact of GFP on REC and calculate the associated critical credit risk threshold.

This credit risk threshold serves as a valuable tool for banks, enabling them to make informed decisions about financing green projects. It also provides environmental policymakers with a clear understanding of the economic and financial challenges associated with green projects, thereby facilitating the development of solutions to mitigate default risks.

To address this issue, we have formulated the following hypotheses:

H1 Green financial policies positively influence the consumption of renewable energy.

H2 The relationship between GFP and REC is contingent upon the threshold of credit risk beyond which banks are unwilling to finance green projects.

3 Data and sample selection

3.1 Data

3.1.1 Dependent variable: renewable energy consumption

This refers to the proportion of low-carbon energy produced from naturally renewable sources such as solar, wind, biomass, and hydro in a country's total primary energy consumption.

3.1.2 Independent variable

3.1.2.1 Green financial policies Green financial policies, the main pillar of a successful environmental policy, is measured by the D'Orazio (2023) composite index, applied to data from the Climate-Related Financial Policy Index (CRFPI). This index encompasses five key policy areas: green prudential regulations, green credit allocation policies, green financial principles, environmental disclosure requirements, and issuance of green bonds. Each policy receives a value of 1 if adopted and 0 otherwise. A higher CRFPI index score indicates a greater level of effectiveness in financial policies supporting green projects and renewable energy development. We opted for index number one, where the policy areas are equally weighted, and the level of commitment to each policy is considered.

3.1.2.2 Credit risk To assess credit risk, we use the Bank Non-Performing Loans to Gross Loans. This ratio is calculated as doubtful and lost loans past due by 90 days or more divided by total loans.

3.1.3 Control variables

3.1.3.1 Bank-specific variables *Bank performance:* Return on assets (ROA) is employed in this analysis to evaluate financial performance as it reflects the bank's ability to generate

income from its asset base, which is a crucial aspect of our evaluation (Ruslan et al., 2019; Robin et al., 2018).

Bank stability: To assess bank stability, we incorporate a banking crisis dummy variable. This binary variable takes a value of 1 for years experiencing a systemic banking crisis, characterized by significant financial distress, widespread bank failures, and substantial policy interventions in response to major losses within the banking system, and 0 otherwise.

Bank liquidity: To assess bank liquidity, we use two key indicators:

- **Liquid Assets to Deposits and Short-Term Funding Ratio:** This ratio measures the proportion of easily convertible assets (e.g., cash, central bank reserves, marketable securities) to short-term liabilities and total deposits. A higher ratio signifies a greater ability to meet immediate financial obligations and withstand liquidity shocks.
- **Bank Deposits to GDP Ratio:** As a robustness check, we employ this indicator that represents the overall size of the banking sector relative to the national economy. A higher ratio suggests a larger and potentially more liquid banking sector.

3.1.3.2 Macroeconomic variables **Environmental policy stringency:** To measure the stringency of environmental policies, we utilize the index developed by Kruse et al. (2022). This index quantifies the degree to which policies, either directly or indirectly, impose a cost on environmentally damaging activities. Ranging from 0 (not stringent) to 6 (most stringent), the index considers 13 policy instruments related to climate change and air pollution. These include measures such as CO₂ emission quotas, renewable energy quotas, taxes on harmful emissions, and investments in clean technology research and development.

Current Account Balance as % of GDP: This ratio measures the strength of a country's international trade and reflects its dependence on foreign trade and potential vulnerability to external shocks.

GDP per capita growth rate: This variable reflects a country's annual economic growth, adjusted for population changes, by measuring the percentage change in GDP per person (Table 1).

Table 1 Variables, proxy and sources

Variable	Proxy	Source
Renewable Energy Consumption	REC	World bank database
Green Financial Policies	GFP	D'Orazio (2023)
Bank nonperforming loans to gross loans	Credit_Risk	IMF, Database
Banking Crisis Dummy	Crisis	Laeven & Valencia (2020)
Return on assets (ROA)	ROA	Bankscope (2000–14) and Orbis (2015–21)
Liquid Assets to Deposits and Short-Term Funding Ratio	Liquidity	Bankscope (2000–14) and Orbis (2015–21)
Bank Deposits to GDP Ratio	Deposits	IMF, Database
Environmental Policy Stringency	EPS	Kruse et al. (2022)
Current Account Balance as % of GDP	CAB	World Bank Database
GDP per capita growth rate (annual %):	GDP	World Bank Database

3.2 Sample description

Our study examines 47 OECD countries over a two-decade span, from 2000 to 2020. This timeframe was chosen due to the consistent availability of data and its coincidence with the rise of green financial policies designed to address environmental concerns.

Developed OECD countries have been relatively successful in their energy transition due in part to their adoption of effective green financial policies that address energy efficiency and manage the credit risks associated with green loans. Except India, China, and Brazil stand out among developing countries, having made notable progress in their energy transitions. However, other developing countries still face challenges, including a lack of financing to access renewable energy, environmental policies weakened by cumbersome procedures and administrative burdens, and vulnerable technical and technological infrastructure. These factors leave them stuck in a situation of energy deficit highlighting the need for comprehensive strategies that address financing gaps, streamline policy frameworks, and strengthen infrastructure to facilitate a successful transition towards sustainable energy solutions. For this reason, we have divided our sample into two distinct sub-sample countries. The first sub-sample comprises 32 developed countries (Australia, Austria, Belgium, Canada, Croatia, Cyprus, Czechia, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States), while the second encompasses 15 developing countries (Argentina, Brazil, China, Chile, India, Indonesia, Malaysia, Mexico, Philippines, Russia, Singapore, South Africa, Thailand, Turkey, Ukraine).

This division allows us to investigate the influence of green financial policies on renewable energy uptake while simultaneously examining the potential effect of credit risk within this relationship. By analyzing these sub-samples, we aim to gain deeper insights into how varying economic contexts and financial systems may influence the effectiveness of green financial initiatives in promoting the transition towards sustainable energy sources.

4 Model and methodology

4.1 Model specification

In order to explore the nonlinear impact of credit risk on the relationship between Renewable Energy Consumption (REC) and Green Financial Policies (GFP) we use Panel threshold models. In the econometric literature we found the panel threshold regression models (PTR) of Hansen (1999) and the panel smooth transition regression model (PSTR) proposed by Gonzales et al. (2005). The PTR, is used to identify different regimes in the data based on the value of a threshold variable. It involves sharp switching between regimes. When the threshold variable crosses a certain value, the model switches from one regime to another. The threshold value is estimated by minimizing the sum of squared residuals (SSR). The PSTR model extends the PTR by allowing smooth transitions between regimes rather than abrupt switches. The transition between regimes is smooth, governed by a continuous function (usually logistic or exponential). Regimes allow for a continuum of regimes, providing a more flexible and realistic modeling of transitions. The estimation method involves nonlinear least squares methods to estimate the parameters of the transition function along with other

model parameters. The key differences between a PTR and a PSTR depend on the nature of the regime changes in the data. If the transitions are believed to be abrupt, a panel threshold model may be appropriate. If the transitions are smooth and gradual, a PSTR model would be more suitable. In this study, we will proceed to use the two above-presented models. We use, in the first step the PSTR model to estimate the threshold parameters at coefficients in different regimes. In the second step, we check the robustness of our work by using the PTR.

4.1.1 The PSTR model

The basic PSTR model with two regimes can be represented as follows:

$$y_{i,t} = \alpha_i + \mu_t + \beta_0 x_{i,t} + \beta'_1 x_{i,t} g(q_{i,t}, \gamma, c) + \varepsilon_{i,t} \quad (1)$$

where.

- $i = 1, \dots, N$ and $t = 1, \dots, T$, N and T are the cross-sectional (CS) and time dimensions respectively of the panel.
- α_i and μ_t are respectively fixed individual effects and time effects.
- The coefficients $\beta_{0,1}, \beta_{0,2}, \dots, \beta_{0,8}$ are those of the first linear regime and $\beta_{1,1}$ and $\beta_{1,2}$ are the coefficient of the second linear regime.
- $g(q_{i,t}, \gamma, c)$ is the transition function and depends on the threshold variable ($q_{i,t}$), threshold parameter (c) and the slope transition function parameter (γ).
- $x_{i,t}$ is the vector of explanatory and control variables
- $y_{i,t}$ is the dependent variable.
- $\varepsilon_{i,t}$ represents the error term.

Investigating the impact of credit risk on the REC/GFP relationship requires considering the potential non-linearity of this nexus. We expect that the effect of credit risk on the REC/GFP nexus might vary at different levels of credit risk, potentially exhibiting a threshold effect. To capture this non-linearity, we employ the PSTR model. This technique is well-suited for identifying thresholds and smooth transitions between different regimes, allowing us to analyze how the relationship between credit risk and REC/GFP nexus changes as credit risk surpasses a certain level. The PSTR model is specified as follows:

$$\begin{aligned} \Delta REC_{it} = & \alpha_i + \mu_t + \beta_{0,1} \Delta GFP_{i,t} + \beta_{0,2} Credit_{Risk_{i,t}} + \beta_{0,3} EPS_{i,t} \\ & + \beta_{0,4} ROA_{i,t} + \beta_{0,5} CAB_{i,t} + \beta_{0,6} Crisis_{i,t} + \beta_{0,7} Liquidity_{i,t} + \beta_{0,8} GDP_{i,t} \\ & + (\beta_{1,1} \Delta Green_Finance_{i,t} + \beta_{1,2} Credit_Risk_{i,t}) g(q_{i,t}, \gamma, c) + \varepsilon_{i,t} \end{aligned} \quad (2)$$

View that PSTR model requires stationary variables, ΔREC and ΔGFP are respectively the first difference of REC and GFP, which are non-stationary in level. ΔREC is the dependent variable. Credit_Risk and ΔGFP are the exogenous variables. EPS, ROA, CAB, Crisis, Liquidity and GDP are the control variables.

The transition function $g(q_{i,t}, \gamma, c)$ is a continuous and bounded function of the threshold variable $q_{i,t}$. According to Gonzales et al. (2005), the transition function is given as follows:

$$g(q_{i,t}, \gamma, c) = \left[1 + \exp \left(-\gamma \prod_{j=1}^m (q_{i,t} - c) \right) \right]^{-1} \quad (3)$$

With $\gamma > 0$, and $c_1 < c_2 < \dots < c_m$, γ is the slope parameter and indicates the smoothness of the transition, and $c(c_1, \dots, c_m)'$ is a vector of location parameters.

When $m = 1$, the PSTR model simplifies into a two-regime model. In this scenario, the coefficients of the regressors change monotonically as the threshold variable increases. These two regimes represent periods of low and high values of the threshold variable, while the transition point occurring at c_1 .

According to Gonzalez et al. (2017), the PSTR modeling cycle consists of three stages: specification, estimation and evaluation.

- Homogeneity (linearity) test: Before specifying a model, it's crucial to examine the homogeneity of the data-generating process. This means checking if the relationship between variables remains consistent across the data or if it changes under different regimes. One way to test for homogeneity is by comparing a linear model against a regime-changing alternative, such as a Panel Smooth Transition Regression (PSTR) model.

The null hypothesis states that, $H_0: \gamma = 0$ or $H_0: \beta_1 = 0$. A standard hypothesis test may not be adequate for this situation because of the unidentified nuisance parameters the PSTR model can contain under H_0 (Gonzalez et al., 2017). To bypass the identification issue, the logistic transition function $g(q_{it}; \gamma, c)$ is replaced by its first-order Taylor expansion around $\gamma = 0$.

The null hypothesis $H_0: \gamma = 0$ is equivalent to $H_0: \beta_0^* = \beta_1^* = \dots = \beta_m^*$, where $\beta_0^*, \beta_1^*, \dots, \beta_m^*$ are multiples of γ . The linearity test can be conducted using three different tests, that is, Lagrange Multiplier (LM) test, Fischer-version LM test, Wild Bootstrap (WB) and Wild Cluster Bootstrap (WCB) LM tests.

- Parameter estimation: To simplify the estimation procedure, time effects (λ_t) and individual effects μ_i are eliminated by removing individual-specific means. The estimated parameters $\theta(\beta_0', \beta_1', \gamma, c')$ may be simply obtained via the application of nonlinear least squares (NLS) to a fixed effects panel. This relationship is linear in β conditional on γ and c .
- No remaining nonlinearity test: As aforementioned, a two-regime PSTR model can sufficiently capture the heterogeneity of a panel data-generating process. The null hypothesis of the no-remaining linearity test can be stated as $H_0: \gamma_2 = 0$. Again, we face the unidentified nuisance parameters presence issue under the null hypothesis. To mitigate the identification problem, we replace $g_2(g_{it}^{(2)}; \gamma_2, c_2)$ by its first-order Taylor expansion around $\gamma_2 = 0$.

4.1.2 The panel threshold model

The PTR model proposed by Hansen (1999) is based on the following form:

$$y_{it} = \alpha_i + \beta'_1 x_{it} + \beta'_2 x_{it} h(q_{it}; \gamma) + \varepsilon_{it} \quad (4)$$

where y_{it} is the dependent variable, x_{it} is the independent variable, ε_{it} is error term, $h(\cdot)$ is a transition function, q_{it} is the threshold variable, and γ is the threshold value.

If the transition variable is binary such that

$$h(q_t; \gamma) = \begin{cases} 1 & \text{if } q_t \geq \gamma \\ 0 & \text{if } q_t < \gamma \end{cases} \quad (5)$$

then the model is simply defined by:

$$y_{it} = \alpha_i + \beta'_1 x_{it} + \beta'_2 x_{it} I(q_t \geq \gamma) + \varepsilon_{it} \quad (6)$$

where $I(\cdot)$ is the indicator parameter function.

If the transition function is a binary function, we have a regime-switching mechanism for the slope parameters that dependent on the threshold variable location parameter γ :

$$y_{it} = \begin{cases} \alpha_i + (\beta'_1 + \beta'_2)x_{it} + \varepsilon_{it} & \text{if } q_t \geq \gamma \\ \alpha_i + \beta'_1 x_{it} + \varepsilon_{it} & \text{if } q_t < \gamma \end{cases} \quad (7)$$

In this case, we have two regimes for the slope parameter β'_1 and $(\beta'_1 + \beta'_2)$.

For a given threshold γ , the slope coefficient β can be estimated by ordinary least squares:

$$\hat{\beta}(\gamma) = (X^*(\gamma)' X^*(\gamma))^{-1} X^*(\gamma)' Y \quad (8)$$

The vector of the residuals is given by:

$$\hat{\varepsilon}(\gamma) = Y^* - X^*(\gamma) \hat{\beta}(\gamma) \quad (9)$$

And the sum of squared residuals is

$$SSR(\gamma) = \hat{\varepsilon}^*(\gamma)' \hat{\varepsilon}^*(\gamma) \quad (10)$$

The PSTR estimation process involves several crucial steps. Before estimating the model itself, we conduct a series of statistical tests. First, we perform a cross-sectional dependence (CS) test using Pesaran's (2004) method. This is followed by an assessment of the stationarity of all variables in the model, which is done by applying appropriate unit root tests.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \right) \quad (11)$$

where $\hat{\rho}_{ij}$ represents the sample estimate of the pairwise correlation of the residuals, and under the null hypothesis of no CS dependence $CD \rightarrow N(0,1)$ for $N \rightarrow \infty$ and T sufficiently large. In cases of unbalanced panels, Pesaran (2004) proposed the following statistic:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \sqrt{T_{ij}} \hat{\rho}_{ij} \right) \quad (12)$$

where T_{ij} is the number of common time series observations between units i and j .

The above Pesaran (2004) CS dependence test informs us about the generation of unit root tests (first or second generation). According to the results of the Pesaran CD test, we apply the Im-Pesaran-Shin (IPS, 2003) unit root test for independence cases. These tests have as the null hypothesis that all the panels contain a unit root. For the dependence case, we use Pesaran's (2004) unit root test.

4.2 Results and preliminary analysis

The PSTR model assumes that all variables are stationary. To mitigate the risk of spurious regressions, we perform a unit root test for each variable to assess its stationarity. The choice of the unit root test depends on the CS dependence or independence of the data generation process. There are two generations of unit root tests for panel data (Pesaran, 2015). The first-generation unit root tests, applicable in the presence of CS independence, include Harris and Tzavalis (1999), Choi (2001), Levin et al. (2002), and Im et al. (2003). On the other hand, the second-generation unit root tests allow for CS dependence and include Breusch and Pagan (1980) and Pesaran (2007), among others. The CS dependence test is a crucial diagnostic step that researchers should undertake before embarking on a panel data investigation, particularly when establishing a panel threshold model. To assess whether our variables exhibit CS dependence, we employed Pesaran's (2007) CS dependence test.

The findings in Table 2 indicate that our results are mitigated. Only Credit_Risk and Crisis variables present a CS independence. However, for the remaining variable, we found a strong rejection of the null hypothesis of no CS dependence. Consequently, we must proceed with the two generations of unit root test that accommodates CS dependence and CS independence in the variables.

The panel unit root tests, as presented in Table 3, confirm the stationarity of all variables at their level, except for REC and GFP. Applying unit root tests to the first difference of REC and GFP reveals that these two variables are integrated into order one. Consequently, within the PSTR model, we substitute REC and GFP with their first differences, Δ REC and Δ GFP, respectively.

Before performing the PSTR model, we need to ensure that the relationship between the dependent variable and the transition variable should be nonlinear. To do this, we test the null hypothesis of homogeneous panel data against a PSTR regression. From the results reported in Table 4, it can be seen that the linearity assumption is strongly rejected at the 1% significance level across the six applied tests. This implies that credit risk exerts a significant nonlinear impact on REC. Therefore, PSTR modeling is suitable for our investigation with credit risk as the transition variable.

Having confirmed the presence of nonlinearity from the above tests, we must now determine the optimal number of parameters 'r' within the logistic function. This involves conducting a no-remaining nonlinearity test. As shown in Table 5, the p-values for both the Wald (WB) and Wald-corrected bootstrap (WCB) statistics approach

Table 2 Cross-section dependence test

Variable	CD test	P-value	Accepted hypothesis
REC	10.42	0.0000	Dependence
GFP	95.10	0.0000	Dependence
Credit_Risk	0.25	0.5470	Independence
EPS	96.82	0.000	Dependence
ROA	20.66	0.0000	Dependence
CAB	83.20	0.0000	Dependence
Crisis	0.054	0.6321	Independence
Liquidity	7.44	0.0000	Dependence
GDP	89.98	0.0000	Dependence

Table 3 Unit root test results

Variable	Pesaran CD tests			IPS (2003) tests			
	t-bar	Z[t-bar]	p-value	t-bar	t-tilde-bar	Z-t-tilde-bar	p-value
REC	-0.756	8.453	1.000	...	...	...	...
GFP	-1.212	3.705	1.000	...	...	...	...
Credit_Risk	...	...	...	-2.568	-2.236	-7.792	0.000
EPSI	2.328	3.705	0.000			...	
ROA	...	-2.685	0.004	...	...	...	...
CAB	...	3.244	0.000	...	...	...	...
Crisis	...	...	...	...	...	-6.584	...
Liquid	5.235	12.546	0.000	-2.021	-3.625	...	0.000
GDP	-2.040	-1.979	0.024	...	...	...	...

H0: variable present unit root, Ha: variable is stationary

Table 4 Results of the linearity test

Variable transition	LM_{χ}	LM_F	HAC_{χ}	HAC_F	WB_PV	WCB_PV
Credit_Risk	25.65	3.002	12.02	1.407	0	0
	0.0012	0.0024	0.1503	0.1895		

H0: linear model against Ha: PSTR model with at least one threshold

Table 5 Results of no remaining linearity test

Transition m	LM_{χ}	LM_F	HAC_{χ}	HAC_F	WB_PV	WCB_PV
1	20.89	1.201	16.25	0.9344	1	1
p-value	0.1829	0.2604	0.4355	0.5288		

H0: linear model against Ha: PSTR model with at least one threshold

unity. Consequently, we can no longer reject the null hypothesis and we admit both the existence of one transition function and a model with a single estimated threshold.

A grid search is employed to identify the slope parameter (γ) and the threshold (c) for our PSTR model. According to Table 6, the results suggest that the estimated threshold values (c) of the global panel, developed and developing countries panels are respectively 74.32%, 76.81 percent, and 72.24 percent and the slope parameters γ , which measures the smoothness of the transition process, are respectively 0.570, 0.8407, and 0.6717.

Figures 1, 2, and 3 illustrate the transition function curves for each panel, showing the relationship between the transition variable (q), the estimated threshold (c), and the slope parameter (γ). The graphs suggest a relatively smooth transition from the low credit risk regime to the high credit risk regime. In the first regime, where the credit risk level is below or equal to the threshold (c), the coefficients (β) capture the direct marginal effect of both the credit risk variable and the control variables. In the second regime, where credit risk exceeds the threshold, the coefficients reflect the marginal effect of all explanatory variables.

Table 6 PSTR model estimation results

Panel	Variable	Parameter estimates in the linear part (first extreme regime)	Parameter estimates in the non- linear part	Parameter estimates in the linear part (second extreme regime)
Global panel	Δ GFP	0.0488***	0.0147*	0.0057
	Credit_Risk	-0.0019*	-0.0425**	-0.0335***
	EPSI	0.0749**	0.0845**	0.1125***
	ROA	0.1265**	0.2259***	0.1856**
	CAB	0.1453**	0.1956**	0.1354**
	Crisis	-1.2451***	-1.6221***	-1.7456***
	Liquidity	0.0459**	0.3540***	0.0245
	GDP	0.1362***	0.1105***	0.1321***
	Threshold (c)	74.32		
	Slope parameter (γ)	0.570		
Developed countries	Δ Green_Finance	0.0211***	0.0437*	0.00254
	Credit_Risk	-0.055**	-0.0602**	-0.052***
	EPSI	0.0126**	0.0523**	0.0650***
	ROA	0.3771***	0.8238***	0.4467***
	CAB	0.1182**	0.2017**	0.3199**
	Crisis	-1.353**	-1.491***	-0.1383*
	Liquid	0.0395**	0.0259*	0.0655**
	GDP	0.01405**	0.3220***	0.3361***
	Threshold (c)	76.81		
	Slope parameter (γ)	0.8407		

Table 6 (continued)

Panel	Variable	Parameter estimates in the linear part (first extreme regime)	Parameter estimates in the non- linear part	Parameter estimates in the linear part (second extreme regime)
Developing countries	$\Delta Green_Finance$	0.0667***	0.2592**	0.00228
	Credit_Risk	-0.04497**	-0.0351**	-0.0980***
	EPSI	0.03001**	0.3413***	0.3113***
	ROA_B	0.1835**	0.3309**	0.1474*
	CAB	0.1509**	0.3161**	0.1652**
	Crisis	-2.525***	-6.463***	-3.938***
	Liquid	0.0298**	0.0850***	0.05521**
	GDP	0.0790***	0.0649**	0.01179**
	Threshold (c)	72.24		
	Slope parameter (γ)	0.6717		

***, **, * denote levels of statistical significance at 1%, 5%, and 10%, respectively

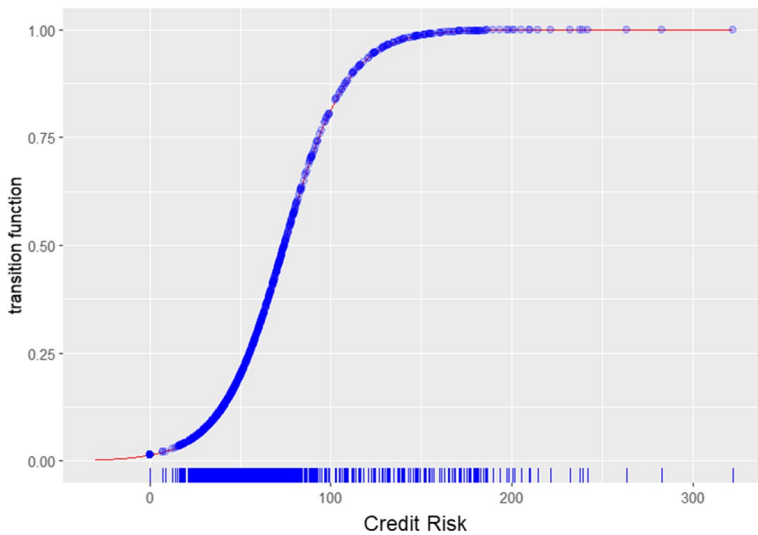


Fig. 1 Estimated transition function of global panel

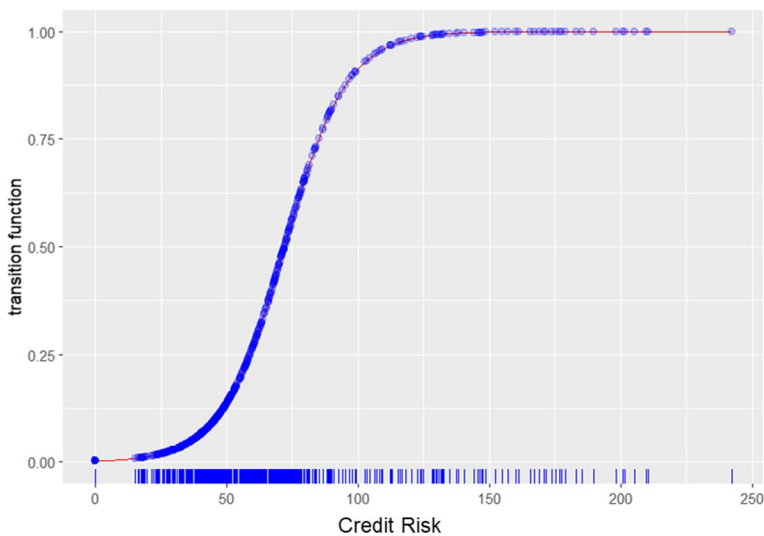


Fig. 2 Estimated transition function of developed countries panel

PSTR estimation results indicate a significant negative relationship between credit risk and the $\Delta\text{GFP}/\Delta\text{REC}$ ratio in both the linear (first regime) and nonlinear parts of the model. In the first regime, characterized by lower credit risk levels, the estimated ΔGFP coefficients are 0.0488 for the global panel, 0.0211 for developed countries, and 0.0667 for developing countries, all statistically significant at the 1% level. In the nonlinear portion, the estimated ΔGFP coefficients are 0.0147, 0.0437, and 0.2592 for the global panel, developed, and developing countries, respectively. These coefficients are statistically

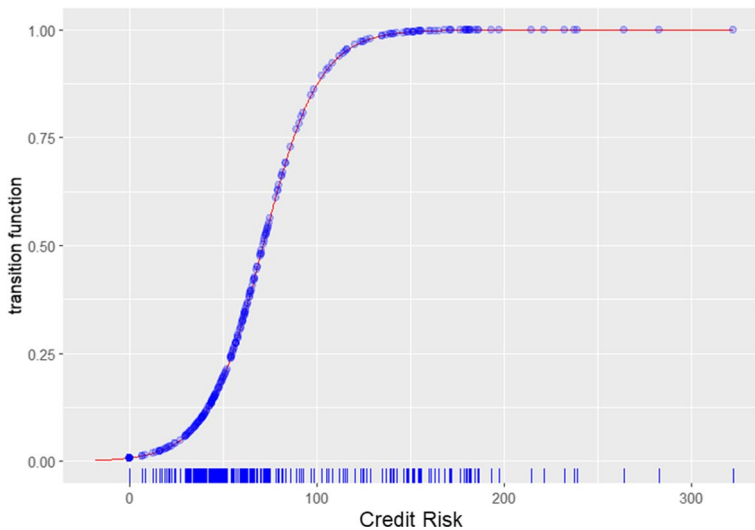


Fig. 3 Estimated transition function of developing countries panel

significant at the 10% level for the global and developed country panels and at the 5% level for the developing countries panel. In contrast, in the second regime, characterized by higher credit risk levels, the Δ GFP coefficients are not statistically significant.

These findings suggest the existence of a credit risk threshold, along with a corresponding slope inflection point, beyond which the positive impact of green finance on renewable energy consumption diminishes. The estimated threshold and slope inflection point are 0.7432 and 0.570 for the global panel, 0.7681 and 0.8407 for developed countries, and 0.7224 and 0.6717 for developing countries, respectively. This suggests that when credit risk is below the threshold, banks may be more willing to finance green projects. However, as credit risk surpasses its threshold, green projects likely become less attractive to banks due to increased risk.

4.2.1 Robustness tests

Robustness checks were conducted to assess the sensitivity of the relationship between REC and GFP to various factors. We extend our empirical work by estimating the main model including the control variable. We also check whether the results change when we add a new variable "bank deposits to GDP". Finally, we check the relationship with an alternative model and an alternative estimation method.

4.2.1.1 Robustness test with added variable To test the consistency of our findings, we enhance the main PSTR model by incorporating a control variable such as "Bank deposit to GDP". This indicator is chosen due to its established positive and significant influence on the REC, ensuring a more robust and nuanced analysis.

Results presented in Table 7 show that, in the cases of three defined panels, the above results of the relationship between REC and GFP and its sensitivity to credit risk threshold value are consistent. By adding a new variable in the main PSTR model, the coefficient of

Table 7 PSTR model estimation results with added control variable

Panel	Variable	Parameter estimates in the linear part (first extreme regime)	Parameter estimates in the non-linear part	Parameter estimates in the linear part (second extreme regime)
Global panel	ΔGFP	0.05028***	0.0122*	0.00195
	Credit_Risk	-0.0021*	-0.0450**	-0.0622***
	EPSI	0.0705**	0.0794**	0.1008***
	ROA	0.1434**	0.2509**	0.1688**
	CAB	0.1543**	0.1977**	0.1542**
	Crisis	-1.2611***	-1.5955***	-1.7756***
	Liquidity	0.0468**	0.3490***	0.02541
	GDP	0.1292***	0.1323***	0.1385***
	Deposits	0.1544**	0.1188**	0.08447*
	Threshold (c)	74.69		
	Slope parameter (γ)	0.5681		
Developed countries	ΔGFP	0.0261***	0.0457*	0.00204
	Credit_Risk	-0.057**	-0.0600**	-0.0541***
	EPSI	0.0186**	0.0533**	0.0652***
	ROA	0.3761***	0.8212***	0.4466***
	CAB	0.1182**	0.2017**	0.3105**
	Crisis	-1.355**	-1.495***	-0.1344*
	Liquidity	0.0405**	0.0261*	0.0665**
	GDP	0.01411**	0.3241***	0.3351***
	Deposits	0.1466**	0.2551***	0.3022***
	Threshold (c)	76.55	s	
	Slope parameter (γ)	0.8172		
Developing countries	ΔGFP	0.0677***	0.2511**	0.00221
	Credit_Risk	-0.04504**	-0.0362**	-0.0987***

Table 7 (continued)

Panel	Variable	Parameter estimates in the linear part (first extreme regime)	Parameter estimates in the non-linear part	Parameter estimates in the linear part (second extreme regime)
	EPSI	0.03102**	0.3443***	0.3153***
	ROA	0.1835**	0.3309**	0.1214*
	CAB	0.1529**	0.3361**	0.1655**
	Crisis	-2.566***	-6.443***	-3.898***
	Liquidity	0.0298**	0.0860***	0.05491**
	GDP	0.0791***	0.0640**	0.01165**
	Deposits	0.3220***	0.1145**	0.2875***
	Threshold (c)	72.44		
	Slope parameter (γ)	0.6736		

***, **, * denote levels of statistical significance at 1%, 5%, and 10%, respectively

GFP is still positive and significant below the threshold value and not significant above the credit risk location parameters (c).

4.2.1.2 Robustness test with an alternative model and alternative estimation method To ensure the reliability of our findings, we conduct a robustness check using the fixed-effect panel threshold model developed by Hansen (1999).

$$\Delta REC_{it} = \mu + \Delta GF_{it}(q_{it} < \gamma)\beta_1 + \Delta GF_{it}(q_{it} > \gamma)\beta_2 + \text{control variables} + u_i + e_{it} \quad (6)$$

With.

- q_{it} is the threshold variable.
- γ is the threshold parameter that divides the equation into two regimes with coefficients β_1 and β_2
- u_i is the individual effect, while e_{it} is the disturbance.

As shown in Table 8, F-stat tests strongly accept a single threshold. The values of the credit risk thresholds (γ) of our three panels are respectively 75.114%, 77.01%, and 72.53%. Moreover, these threshold values are much closer to those estimated with PSTR model. The coefficients of green financial policies are always positive and significant below the threshold's values and positive and insignificant in the second regime. So, our results with the alternative model are consistent with the above main findings.

5 Discussion

Our analysis reveals that the effectiveness of GFP in promoting REC is inversely related to credit risk. Specifically, these policies demonstrate a strong and statistically significant positive impact when credit risk is low (as depicted by the linear portion of the first regime). However, as credit risk rises to a moderate level (a nonlinear portion of the first regime), the impact of these policies weakens and becomes less statistically significant. Ultimately, when credit risk reaches a high level (a linear portion of the second regime), the influence of GFP on REC becomes statistically insignificant. This observation consistently holds true across all three samples.

Furthermore, we observe that the threshold for credit risk tolerance is higher in developed countries than in developing ones. In other words, banks and relevant financial institutions in developed countries are more willing to take risks and engage in sustainable project financing, despite the credit risk, compared to their counterparts in developing countries. Indeed, green financial policies remain effective and have a significant impact on renewable energy financing until the non-performing loan ratio reaches 76.84% of total loans in developed countries. In contrast, this threshold does not exceed 72.24% in developing countries.

In summary, the relationship between GFP and REC depends on the credit risk threshold. Below this threshold, the effect of green financial policies on renewable energy consumption is more pronounced. However, above the threshold, green financial policies in terms of green prudential regulations, green credit allocation policies, green financial guidelines, and green bond issuance become less effective and may not promote the consumption of clean energy.

Table 8 The estimation results of the threshold panel model with CR as transition variable

Panel	Variable	Coefficients	Fisher statistics of global significance	F_Stat of single threshold
Global panel	ΔGFP_0	0.0613***	234.41 (0.000)	1.3502 (0.6600)
	ΔGFP_1	0.0039		
	Credit_Risk	-0.0411**		
	EPSI	0.0654**		
	ROA	0.1721***		
	CAB	0.3522***		
	Crisis	-1.4150**		
	Liquidity	0.0447***		
	GDP	0.2105**		
	Threshold (c)	75.114		
Developed countries	ΔGFP_0	0.0623***	198.25 (0.000)	0.9521 (0.5890)
	ΔGFP_1	0.00112		
	Credit_Risk	-0.0371**		
	EPSI	0.0662**		
	ROA	0.1801***		
	CAB	0.3223***		
	Crisis	-1.4681**		
	Liquidity	0.0455***		
	GDP	0.2262**		
	Threshold (c)	77.01		
Developing countries	ΔGFP_0	0.0622***	174.23 (0.000)	0.7395 (0.7122)
	ΔGFP_1	0.00205		
	Credit_Risk	-0.0409**		
	EPSI	0.0673**		
	ROA	0.1788***		
	CAB	0.3675***		
	Crisis	-1.4500**		
	Liquidity	0.0325***		
	GDP	0.1925**		
	Threshold (c)	72.53		

***, **, * denote levels of statistical significance at 1%, 5%, and 10%, respectively

Value in (..) are the *p*-value

Furthermore, we highlight that renewable energy financing is also influenced by other crucial variables. These encompass factors related to the banking sector's health, such as performance (ROA), financial crisis and liquidity, as well as macroeconomic indicators like the stringency of environmental policies (EPS), the current account balance (CAB) and gross domestic product (GDP). Our analysis reveals a consistently positive and significant impact of ROA, liquidity, EPS, CAB, and GDP on renewable energy consumption across all regimes (first regime, non-linear part, and second regime). Conversely, we find evidence that during wars, renewable energy consumption decreases.

5.1 A comparative analysis with previous studies

Our findings, which appear to be innovative in this field, align with other studies exploring the relationship between green finance and renewable energy in all their complexity (Shvydanenko et al., 2023; Chen et al., 2023a, 2023b, 2023c; Alharbi et al., 2023; Ye & Rasoulinezhad, 2023; Khan et al., 2022; Taghizadeh-Hesary et al., 2023; Zhang et al., 2022; Zhang & Wang, 2021; Tolliver et al., 2019). Additionally, our conclusions are relatively consistent with research on the link between green finance and credit risk (Al-Qudah, et al., 2023; Cao et al., 2021; Cui et al., 2018; Feng et al., 2024; Liu & Huang, 2022; Wang, 2022; Zhou et al., 2022), as well as those examining the relationship between credit risk and renewable energy (Choudhury et al., 2023; Chen et al., 2023a, 2023b, 2023c; Belloni et al., 2022; Zhou et al., 2022; Alonso, 2020; Park and Kim, 2020).

Our study distinguishes itself from previous relevant studies by identifying a major obstacle that can hinder the financing process of renewable energies through the change in banks' behavior toward green finance. Calculating the critical threshold of credit risk beyond which OECD developed and developing country banks cease financing green projects is crucial. Moreover, defining critical credit risk thresholds is a decision-making tool that enables banks to pay particular and proactive attention to non-performing loans in the renewable energy sector.

5.2 Theoretical implications

The theoretical implications of our study highlight that the success of the energy transition is intrinsically linked to a financial system that is both developed and adapted to environmental requirements, and capable of mobilizing substantial green investments. However, this system sometimes faces a dissuasive level of credit risk, generating uncertainty and reluctance to finance costly and potentially unprofitable green projects. Consequently, knowledge of the critical credit risk threshold becomes crucial for banks, allowing them to determine the inflection point of their green financing policies.

Furthermore, awareness of the credit risk threshold in the renewable energy sector provides greater visibility for all stakeholders, highlighting their commitments and interests, thereby contributing to the energy transition process. This threshold enables banks to rationalize their green financing policies and decisions, companies to optimize their green investment decisions and governments to refine and strengthen their environmental policies.

5.3 Practical implications

The practical implications highlight the urgent need for collaborative action from all stakeholders to achieve a low-carbon economy and successful energy transition. This shared responsibility demands a concerted effort from banks through managing credit risk associated with green projects, governments through incentive policies and risk-sharing mechanisms to encourage banks to finance green projects, especially in developing countries, and firms through their commitment to environmental protection and green investment without compromising their creditworthiness.

5.4 Policy recommendations

To achieve a smooth energy transition, active participation from all stakeholders is crucial. This includes raising awareness about green projects, streamlining administrative and legal processes, and increasing transparency in green project financing. Clear risk disclosures can build trust among investors and mitigate risk perceptions. These actions are vital to mitigating default risks and ensuring bank confidence in green financing, ultimately paving the way for a sustainable future. Likewise, environmental policymakers should urgently implement measures and mechanisms that mitigate default risk and facilitate a smooth energy transition, a process requiring significant time, technology, and financial resources.

5.5 Limitations of the study

As with any scientific research, our study has certain limitations, particularly regarding data availability, especially for the green finance index and the credit risk associated with green projects. Expanding the sample size and including additional variables, such as climate risk, geopolitical risk, and ESG risk, could enrich the analysis and offer more comprehensive perspectives on the nexus between GFP and REC.

6 Conclusion and future research perspectives

The transition to renewable energy is imperative to protect our planet from the harmful effects of fossil fuels and combat climate change. This objective requires considerable efforts in terms of sustainable financing, stakeholder engagement, green technologies, and international cooperation.

Within a global environmental context characterized by uncertainty, our study investigates the nuanced relationship between GFP and REC, specifically focusing on the often-overlooked threshold effect of credit risk. Considering this indicator is essential to ensure the success of green financial policies in promoting renewable energy and to design pro-environmental financing strategies that are more ambitious and effective in terms of energy impact.

The development of green finance, a fundamental pillar of renewable energy and its infrastructure, presents a major challenge, particularly for developing countries. The credit risk associated with these projects can hinder investment. It is therefore crucial that green financial policies, including prudential regulations and environmental disclosure requirements, are carefully designed and implemented progressively and adaptively. State guarantees, bank commitments, and central bank involvement are also essential to strengthen the effectiveness of green finance and direct credit towards sustainable investments, without incurring excessive default risk.

In this context, we explore an issue that has not yet been fully addressed by the existing literature: the threshold effect of credit risk on the relationship between GFP and REC. In other words, we seek to determine the critical threshold of credit risk beyond which banks hesitate to finance green projects.

Using a PSTR model applied to a global panel of 47 OECD countries, divided into sub-sample countries, over 21 years (2000–2020), our analysis reveals a significant

threshold effect of credit risk. The results show that the effectiveness of GFP on the development of REC is contingent upon specific credit risk thresholds: 74.32% for the total sample, 76.81% for developed countries, and 72.24% for developing countries.

Furthermore, our results demonstrate that the impact of green financial policies on renewable energy consumption is inversely proportional to the level of credit risk. This impact is at its peak and highly significant when credit risk is low, corresponding to the linear part of the first regime. As credit risk increases and enters the non-linear part, the impact of green policies decreases and becomes less significant. Finally, in the second regime, characterized by high credit risk, the effect of GFP on REC becomes statistically insignificant.

Our empirical analysis also reveals a disparity in the commitment of banks towards financing sustainable projects. Banks in developed countries demonstrate a greater propensity to finance such projects despite credit risk, compared to those in developing countries. Indeed, the mobilization of green credit to finance renewable energy remains viable in developed countries until the non-performing loan ratio reaches 76.84% of total loans. In contrast, in emerging countries, the mobilization of green credit loses momentum as soon as this ratio reaches 72.24%.

The energy transition proves to be a challenging path. Our results demonstrate that its success relies not only on robust green financing policies and a stable banking environment with low credit risk but also on stringent environmental policies, a minimum level of economic development, a sustainable current account balance, and increased performance, stability, and liquidity within the banking sector.

Overall, this article makes an important contribution to the field by empirically demonstrating the critical role of credit risk in shaping the effectiveness of green financial policies. Its findings provide valuable insights for decision-makers, financial institution managers, and other stakeholders seeking to promote a sustainable energy future.

Future research could expand upon this analysis by incorporating financial market sentiment and climate change as explanatory variables when examining the impact of green finance on renewables development. Moreover, investigating strategies to ease administrative and legal constraints and promote the development of dedicated green banks or specialized green financial units within existing institutions would be valuable. These avenues could accelerate green investments and stimulate job growth in this vital sector.

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Data availability Not applicable.

Declarations

Conflict of interest The authors, Hamdi Khalfaoui, Hassan Guenichi, Mohamed Amine Nabli, Housseem Belghouthi and Mouna Guesmi have no relevant financial or non-financial interests to disclose.

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