

Article

The Impact of Media-Based Transition and Physical Climate Risks on Banks' Credit Risk: Evidence from a Dynamic Panel Threshold Model

Mariem Turki ¹ , Imed Chkir ^{2,*} and Kamel Naoui ¹ 

¹ Department of Finance and Accounting, ESCT-Business School of Tunis, LARIMRAF LR21ES29, University of Manouba, Manouba 2010, Tunisia; turkimariem10@gmail.com (M.T.); kamel.naoui@esct.uma.tn (K.N.)

² Telfer School of Management, University of Ottawa, 55 Laurier E., Ottawa, ON K1C5C7, Canada

* Correspondence: chkir@telfer.uottawa.ca

Abstract

This paper examines the threshold impact of media-based attention to transition and physical climate risks on banks' credit risk among the 230 largest US commercial banks from 2011 to 2022. Using a dynamic panel threshold model, our analysis reveals a non-linear relationship between media-based climate risk and banks' credit risk. The empirical results indicate the existence of a significant threshold dividing the data into lower and upper regimes for both climate transition risks and physical climate risks. More specifically, the estimated threshold levels are 0.500 for the transition risk index and 0.571 for the physical climate risk index. Below these critical thresholds, banks appear resilient to increased media attention to climate risks; however, once these thresholds are exceeded, growing concern about climate risks significantly increases banks' vulnerability to credit risk. These findings highlight the critical implications of physical and transition risks for financial stability. Our results are robust to a range of alternative measures and model specifications, providing valuable insights for bank managers, regulators, and policymakers, while emphasizing the need to integrate media-based climate risk considerations into credit risk assessments and policy frameworks to strengthen the banking sector's resilience.

Keywords: media-based transition climate risk; media-based physical climate risk; credit risk; non-performing loans; dynamic panel threshold model

1. Introduction

Globally, climate change poses a significant threat to sustainable development (Zhen-min & Espinosa, 2019). According to the World Economic Forum's Global Risks Report 2022 (World Economic Forum, 2022), climate action failure, extreme weather events, and biodiversity loss are the three most serious risks for the coming decade, creating one of the most complex challenges of our time. Climate change is fundamentally altering the ecological balance, socio-economic frameworks, and strategic decision-making at all levels of human activity (Y. Zhang et al., 2026). A crucial aspect of this challenge is assessing its economic impact, which will have far-reaching implications across society, from environmental sustainability to the stability of the global economy. Recent studies (Bernstein et al., 2019; Painter, 2020; Seltzer et al., 2022) have highlighted the impact of climate risk on the valuation of stocks, bonds, and real estate. Additionally, most institutional investors recognize climate risk as a significant concern (Krueger et al., 2020). It is essential to emphasize that climate change not only disrupts the natural environment and human well-being but



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also significantly impedes economic development and the foundations of financial stability (Liddle, 2018). Global climate change will ultimately impact socioeconomic systems, including natural resources, infrastructure services, physical assets, food systems, and quality of life and work. In the short term, significant catastrophic climate events will damage the physical assets of businesses and households, affecting the total financial and economic capital. They may also lead to currency instability, which can impact financial stability (Wu et al., 2023).

Among economic actors, financial institutions, especially banks, are under increasing pressure to fully assess and effectively manage the risks associated with climate change. They are increasingly exposed to the challenges of climate change by providing capital to firms facing physical and transition risks; therefore, the banking sector urgently needs to consider climate exposures (Battiston et al., 2017). These climate-related risks, whether tangible physical events or regulatory and policy transitions, have moved to the top of the agenda for regulators, policymakers, and financial market participants. Incorporating climate risk into central bank policies has been proposed to maintain financial stability (Campiglio et al., 2018). This focus on the financial system stems from recognizing that the credit channel is an essential mechanism for propagating climate risk (Basel Committee on Banking Supervision [BCBS], 2021b).

For example, natural disasters resulting from climate change can reduce borrowers' ability to repay their loans, ultimately forcing banks to sell assets and ration credit (Faiella & Natoli, 2018). These types of events represent the physical risks of climate change. Indeed, natural disasters caused by climate change can reduce borrowers' ability to repay their loans and impact loan quality (D. Zhang et al., 2024). Furthermore, physical climate risks could revalue many of a company's assets (such as plants, land, and equipment) and increase operating costs (e.g., relocation and insurance), thereby lowering profits and reducing solvency. In addition, banks are also exposed to transitional climate risks, which arise from the likelihood that an ungoverned transition to a low-carbon economy could reduce the value of the assets of borrowers engaged in this process and thus affect the bank's financial performance (Basel Committee on Banking Supervision [BCBS], 2021a; Task Force on Climate-related Financial Disclosures [TCFD], 2017; European Central Bank [ECB], 2020). Conversely, firms facing higher climate risk can implement mitigation strategies, such as reducing leverage, to reduce potential default risk (Ginglinger & Moreau, 2023). While increased climate risk increases default and operating costs, these firms can reassess their financial structure to reduce debt. Debt reduction lowers the risk of bankruptcy and can potentially reduce the risk of bank failure. On the other hand, the Creative Destruction Theory suggests that banks can mitigate risk by financing the replacement of high-carbon polluting technologies with low-carbon alternatives (Aghion et al., 2021). This risk reduction can be achieved by protecting the revenues of existing firms and promoting sustainable profits through financial support for the adoption of new low-carbon technologies, thereby reducing firms' financial risk.

This article aims to contribute to the existing literature in several ways. First, while D. Zhang et al. (2024) focus on climate impacts on the loan quality of Chinese regional commercial banks, Birindelli et al. (2022) focus on international banks. Our study focuses on systemically important banks in the United States. By focusing on this specific context, we gain insight into the challenges that the intensity of media attention on climate risks poses to the banking sector, as well as the uncertainties surrounding physical climate risk and transition climate risk news coverage. Second, we emphasize the importance of incorporating media-conveyed climate change risks in business decisions, aiming to mitigate their negative impact by strengthening the financial health of their institutions. Finally, we assess two media-based climate risk factors developed by Faccini et al. (2023).

These factors are derived from a textual analysis of news articles addressing physical climate risks (e.g., disaster-related media attention) and transition climate risks (e.g., US climate-policy media attention), as well as their potential impact on banks' credit risk, as measured by non-performing loans (NPLs).

Figure 1 presents the conceptual framework linking media-conveyed physical climate risk and transition climate risk to bank credit risk. It illustrates how the intensity of media-conveyed physical climate risk (proxied by the Physical Climate Risk Index, PRI) and media-conveyed transition climate risk (proxied by the Transition Climate Risk Index, TRI) can influence bank credit risk through threshold effects, leading to distinct dynamics between the lower and upper regimes.

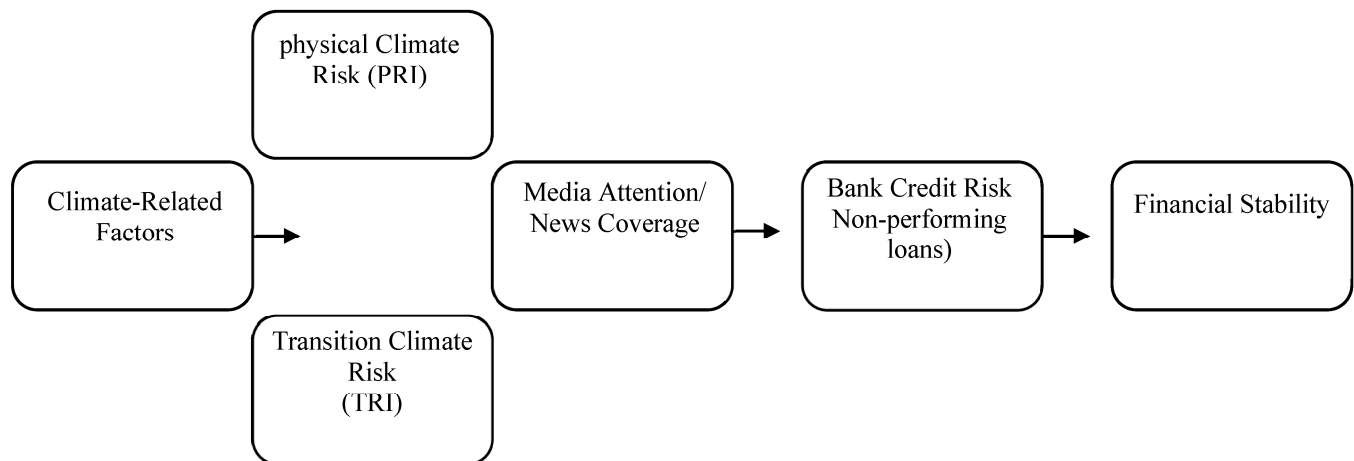


Figure 1. Conceptual framework of climate-related risks transmission to bank credit risk and financial stability.

Furthermore, this study is the first to examine whether media-based climate risk indicators, including the Physical Climate Risk Index (PRI) and the Transition Climate Risk Index (TRI), have a threshold-dependent impact on non-performing loans using a dynamic threshold regression model in the United States.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 describes the research design, including the data, variable measurement, and methodology. Section 4 presents the empirical results, while Section 5 reports the robustness checks. Section 6 discusses the findings. Finally, Section 7 concludes the study and presents its implications and limitations.

2. Literature Review

The banking system is a key sector in any economy, and its ability to encourage investment and stimulate economic growth is crucial. The stability of the banking sector reflects an economy's ability to withstand internal and external shocks. Saliba et al. (2023) examine whether country-specific risks, including financial, economic, and political risks, have a significant impact on non-performing loans in the banking sectors of BRICS countries, and identify which risk has the most substantial effect on credit risk. They find that country risk significantly increases the credit risk of the banking sector, particularly for countries with higher non-performing loan ratios. In addition, credit risk is influenced by financial market development, interest rates, and global risk factors.

Previous research has suggested that a country's vulnerability plays a key role in reducing banking sector stability. However, the impact of country-specific risks on banking sector stability remains largely unknown. To better understand how this relationship varies across groups of countries classified by their income and risk levels, Athari et al.

(2023) adopt a global perspective to examine the impact of country risk, including political, economic, and financial risks, on banking sector stability. Their results suggest that reducing a country's vulnerability to specific political, economic, and financial risks contributes to greater stability in the banking sector. Their results show a positive relationship between a country's stability and its reduced vulnerability to specific political, economic, and financial risks. This positive relationship is particularly pronounced when countries transition from a low-income to a middle- or high-income level. Furthermore, a decline in country risk leads to greater banking sector stability in both low-risk and high-risk countries, although the effect is more pronounced in low-risk environments. They also emphasize that factors specific to the banking sector and country-level determinants significantly influence the magnitude and direction of these effects, which depend on countries' income and risk levels. Country-specific risks clearly influence credit risk and banking sector stability; however, recent literature has highlighted the emerging role of climate-related risks.

2.1. Physical Climate Risk and Bank Credit Risk

Climate change and catastrophic weather events have long-term global structural characteristics. These characteristics allow the disruptions caused by these events to propagate through the real economy and affect the global financial environment. Recently, scholars have identified climate risk as a new type of systemic risk and a significant threat to the stability of the entire financial sector (Birindelli et al., 2022).

Commercial banks are among the most exposed in the financial sector to these climatic events. Climate change affects the quality of credit assets directly through physical risk (Battiston et al., 2021; Ciccarelli & Marotta, 2024). This direct influence means climate change directly affects the value of the borrower's products, real estate, land, fixed assets, and other physical assets (Diaz & Moore, 2017). Physical climate risks, such as extreme weather events, can cause direct property damage, disrupt business activities, and generate corporate losses. This increases the probability of default and reduces the quality of loans, subsequently affecting the borrower's ability to repay the loan (Klomp, 2014). For example, climate change threatens the yield, quality, and price stability of the food industry (Chakraborty & Newton, 2011), which directly affects the repayment capacity of related firms or individuals and leads to a deterioration in the quality of credit assets associated with banks (Ascui & Cojoianu, 2019).

Furthermore, climate change directly affects real estate prices. First, gradual environmental changes, such as rising sea levels, lead to a long-term decline in real estate values, and anticipation of these events further depresses real estate market values (Shahid et al., 2017). Second, adverse events such as extreme storms, floods, wildfires, or disasters, including landslides, directly impact property values (Kellenberg & Mobarak, 2011; Mueller et al., 2009). When borrowers have assets that are more likely to depreciate, banks worry that the value of the collateral may not be sufficient to cover the debt. Borrowers may abandon collateral and default, which results in heightened credit risk for banks. In general, high levels of physical climate risks lead to unfavorable financing conditions, a deterioration in companies' financial performance, and an increased risk of default, which results in tighter credit conditions (Huang et al., 2022).

To broaden this perspective beyond local contexts, recent international data presented by Adeyemi et al. (2025) highlight the systemic and transnational scope of these vulnerabilities. Drawing on the Global Financial Stress Index (GFSI), their study confirms that physical and transition risks significantly exacerbate global financial stress. In particular, they note that the destabilizing impact is more pronounced for physical risks due to the immediate and tangible destruction of assets, whereas transition risks manifest over a longer time

horizon. These empirical data underscore that climate-induced financial disruptions are not isolated anomalies, but global threats requiring a macroprudential approach.

In addition to general frameworks covering multiple countries, empirical data from key emerging markets provide nuanced insights into size-related vulnerabilities. For example, [X. Liu et al. \(2024\)](#) examine Chinese commercial banks by using local temperature fluctuations to model physical climate shocks and find that temperature increases significantly raise credit risk. It is interesting to note that their heterogeneity analysis reveals that small banks and rural institutions are significantly more sensitive to these climatic variations. However, although their results suggest a linear transmission mechanism, they emphasize that no obvious non-linear relationship was identified within their specific dataset.

In a more in-depth analysis of these mechanisms within emerging economies, [Luangaram et al. \(2026\)](#) examine systemic banking risk in Thailand using a market-based CoVaR measure and a mediation analysis. Their results reveal that, while transition risk operates primarily through the credit channel by accelerating the rise in non-performing loans, physical climate risks significantly amplify systemic vulnerabilities through asset price volatility. However, although they track these distinct transmission channels and identify size-related heterogeneities, their empirical strategies remain limited to continuous linear specifications. This highlights a major gap in the current empirical literature and underscores the need to adopt more advanced regime-switching specifications, such as threshold models, to robustly capture potential non-linear tipping points that traditional linear frameworks might overlook.

2.2. Transition Climate Risk and Bank Credit Risk

While the impact of physical climate risks on bank loans is direct, the mechanisms through which climate risks related to the transition influence the quality of bank loans are, from a structural perspective, more complex. The uncertainties associated with climate change pose a significant challenge to the sustainability of economic and financial systems ([Apergis & Payne, 2012](#)). The transition to a low-carbon economy suggests that industries such as coal mining, power generation, oil, and gas may be subject to stricter regulation, disruptive technologies, and changes in consumer behavior. These potential changes could generate “transition risks” that threaten financial stability ([Lu et al., 2021a, 2021b, 2022](#)).

This risk stems primarily from policies aimed at controlling carbon emissions. With the global warming trend, there has been an increase in extreme weather events, highlighting the urgent need to transform the national economy into a low-carbon economy for sustainable development ([Masson-Delmotte et al., 2018](#)). These policies are expected to increase investment in low-carbon technologies and reduce investment in carbon-intensive sectors ([Fried et al., 2021](#)). Conversely, the rise of low-carbon industries (e.g., the new energy sector) may create new investment opportunities and promote sustainability within the financial industry through carbon-neutral loans that lower credit risk and reduce emissions ([Semieniuk et al., 2021; Umar et al., 2021](#)). However, the implementation of climate policies could be overly aggressive, delayed, or even reversed (as seen in Trump’s withdrawal from the Paris Agreement), leading to sudden asset repricing (e.g., stranded physical assets) and increasing the likelihood of debt defaults. Such risks could disrupt established high-carbon industries and threaten financial stability ([Battiston et al., 2021](#)).

The scale of this transition depends heavily on the banking system’s level of exposure to these declining sectors ([Giuzio et al., 2019](#)). For example, [Aiello and Angelico \(2023\)](#) assess the potential impact of different carbon taxes (€50, €100, €200, and €800 per metric ton of CO₂) on the short-term default rates of Italian banks using a counterfactual analysis. They find that, although corporate default rates increase following the introduction of a

carbon tax, the impact on short-term credit risk remains modest if the initial default rate is low. Higher rates of non-performing loans could harm the profitability of lending banks, impact their market valuation, and, if substantial enough, lead to a banking panic and bank default (Dafermos & Nikolaidi, 2019; Diamond & Dybvig, 1983).

Climate change and the challenges associated with the transition to a zero-carbon economy pose significant financial risks, which indirectly impact banks through their loan portfolios. Expanding on this perspective, Redondo and Aracil (2024) provide a comprehensive review of the academic and institutional literature, identifying four main thematic areas: climate risk factors, tools, data, and pricing. In particular, they emphasize that inherent uncertainty, non-linearity, and geographic or sectoral dependencies considerably complicate the assessment of climate-related credit risks. This highlights the limitations of traditional linear frameworks in fully capturing global climate and financial vulnerabilities.

In addition to these international frameworks, empirical data from advanced banking sectors confirm the existence of these transmission channels. For example, Bellinvia et al. (2025) analyze a large sample of European financial institutions using an innovative exposure-based approach that weights bank loans according to the vulnerabilities of countries and economic sectors. Their results show that both climate transition risk and physical climate risk significantly exacerbate bank credit risk across several indicators. These cross-border European data underscore that asset quality is systematically linked to macro-climate exposures, thereby reinforcing the structural arguments in favor of integrating global risk dimensions into macroprudential oversight.

To complement these analyses, Ali et al. (2026) use a dynamic panel dataset on European financial institutions to examine how climate risk threatens capital resilience. Although their results incorporate environmental and cultural moderators to account for changes in capital adequacy, their empirical framework relies on continuous linear panel designs. This highlights a persistent methodological shortcoming in studies using similar dynamic panel methodologies, which often assume constant parameter behavior and fail to explicitly model threshold mechanisms. Consequently, traditional frameworks remain limited in their ability to isolate the discrete dynamics of regime shifts and the non-linear tipping points that characterize the links between climate and finance across different financial conditions.

To support this perspective from a macroeconomic policy standpoint, Andrieş et al. (2026) assess the macro-financial implications of climate-related financial policies (CRFPs) using a cross-national sample of 458 banks. Their decomposition analysis indicates that higher climate policy-related media attention exacerbate systemic risk by increasing the vulnerability of individual banks, particularly by reducing their profitability and capital adequacy. Although they note that the severity of this impact is mitigated, under certain conditions, by banks' ESG commitments and macro-climate contexts, their macro-financial models rely on linear systems with constant parameters. This reliance on continuous linear specifications overlooks the structural changes that occur when financial systems reach critical stress thresholds, thereby leaving a clear empirical gap that only non-linear threshold frameworks can adequately fill.

Taking this methodological debate a step further, Giacchetta et al. (2026) examine the European financial system using a scenario-based framework, drawing on NGFS trajectories and vine copulas to capture complex systemic dependencies at the tails of the distribution. In particular, they emphasize that traditional econometric methods often prove insufficient to capture the long-term systemic implications across the various dimensions of climate risk. However, although their copula-based multi-scenario analysis offers great flexibility, it remains structurally dependent on hypothetical trajectories predetermined ex ante. This operational strategy leaves a significant empirical gap, as it does not allow for

the endogenous identification of exact, data-driven thresholds or structural tipping points triggered by actual macro-financial and climate fluctuations. Consequently, an explicit non-linear threshold model is needed to capture these tipping points in real time without relying on assumptions derived from simulated scenarios.

To better understand these dynamic interdependencies in the US political context, [Gaies and Bruna \(2026\)](#) examine the global spillover effects of physical and transition climate risks in the United States using a time-varying parameter VAR (TVP-VAR) model and local projection causality methods. However, although their framework accounts for continuous variations in parameters, it remains limited to continuous-time specifications. This operational approach entails a major empirical omission, as it does not model the structural regime-switching dynamics triggered endogenously when specific indicators of macro-financial uncertainty or climate policy cross discrete thresholds. Consequently, continuous time-varying-parameter frameworks remain limited in their ability to identify distinct tipping points that alter macro-financial behavior across different financial states.

Based on the joint effect of these processes, we formulate our research hypothesis, dividing it into two hypotheses:

H1 *Increased media attention to US climate policy, proxied by the Transition Climate Risk Index (TRI), increases banks' credit risk.*

H2. *Increased media attention to natural disasters, proxied by the Physical Climate Risk Index (PRI), increases banks' credit risk.*

3. Research Design

3.1. Sample and Data Collection

To test our hypotheses, we conduct a study involving very large banks that have a protective effect on other smaller financial institutions and the broader financial system. We restricted our analysis to the period during which information on our variables was available, specifically from 2011 to 2022. The year 2011 was chosen as the starting point, as it corresponds to the period following the peak of the financial crisis's impact. Using these criteria, our final sample consists of 230 major US commercial banks. Due to its significant economic influence and environmental impact, the United States is chosen because it plays a crucial role in the global effort to combat climate change. As the second largest emitter of greenhouse gases after China, it has emitted more greenhouse gases than any other country, including the European Union. It has been responsible for approximately a quarter of global CO₂ emissions since the Industrial Revolution began ([Ritchie et al., 2023](#)). Furthermore, the United States is the world's largest economy and one of the biggest producers and consumers of fossil fuels and energy. The country is particularly exposed to the impacts of climate change due to its massive industrial activity, extensive infrastructure, and large population ([Reidmiller et al., 2019](#)). However, we did perform robustness checks to confirm our results (see Section 5).

For our analysis, we use a merged dataset that includes data from DataStream, Orbis BankFocus, and the World Bank. Media-based climate-risk indicators, disaggregated into Transition Climate Risk Index (TRI) and the Physical Climate Risk Index (PRI), are constructed using the methodology outlined by [Faccini et al. \(2023\)](#). Financial data (credit risk, profitability, bank size, capital adequacy, diversification, inefficiency, and credit growth) are collected from BankFocus and the DataStream database. Finally, we utilize country-level variables, including gross domestic product (GDP) per capita and domestic credit to the private sector, both of which are obtained from the World Bank. To enhance transparency, Figure 2 outlines the data collection and integration process. It shows how bank-specific

variables, media-based climate risk variables, and macroeconomic variables were collected from various sources, merged using bank identifiers and the year, validated, and then combined to form the final balanced panel used in the empirical analysis.

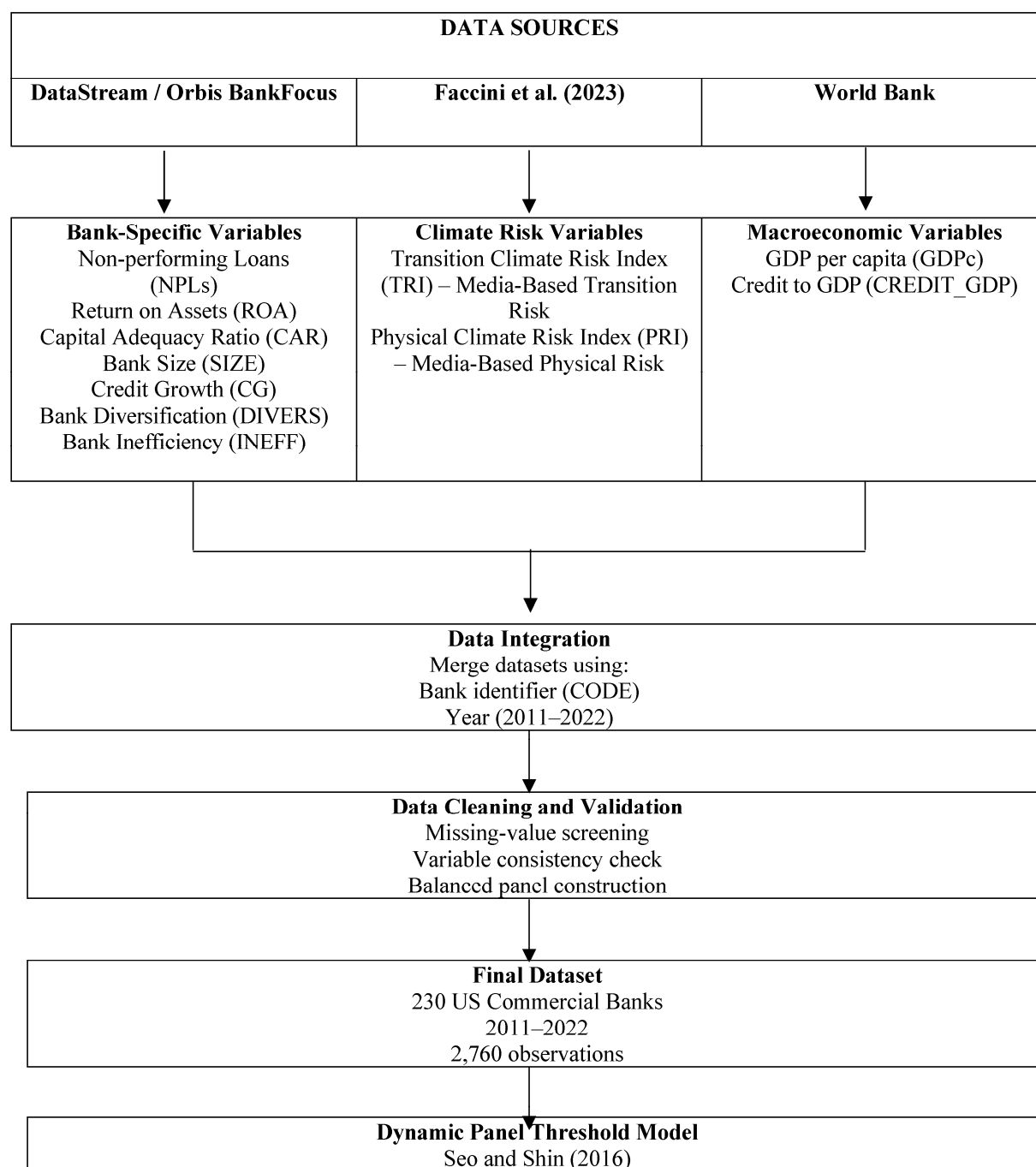


Figure 2. Data Collection and Integration Process (Faccini et al., 2023; Seo & Shin, 2016).

3.2. Variables

Our dependent variable in this research is the banks' credit risk, expressed by the ratio between non-performing loans and total loans (NPLs) (Kryzanowski et al., 2023; Naili & Lahrichi, 2022). Following Reinhart and Rogoff (2011), the non-performing loans (NPLs) can be used to indicate the beginning of banking crises. We use NPLs to measure loan quality because they are commonly employed as a proxy for banks' loan quality and associated credit risk (D. Zhang et al., 2024). The lower this variable, the better the quality of the loans (Chaibi & Ftiti, 2015; Chen et al., 2016).

As a key explanatory variable, we utilize two of the four climate risk factors developed by Faccini et al. (2023) to investigate how media-conveyed climate risk impacts banks' credit risk. These risk indices are media-based text-analysis indicators derived from a textual analysis of a large corpus of news articles from 2000 to 2018. The authors update the series for the four climate change risk factors and extend it from 2000 to 2025. The authors employ an unsupervised machine learning method known as Latent Dirichlet Allocation (LDA) to categorize news articles into different topics. From these topics, Faccini et al. (2023) select four topics that reflect natural disasters, global warming, US climate policy, and international summits. We analyze only physical climate risk (PRI), proxied by natural disaster-related media attention, and transition climate risk (TRI), proxied by US climate-policy media attention to assess their potential impact on banks' credit risk.

Here is the approach followed for each variable: For TRI, the index captures media attention related to US climate-policy developments. For PRI, the index captures media attention related to climate-related natural disasters, including floods, droughts, wildfires, and other extreme events, as identified by Faccini et al. (2023) in the context of climate change. To align with the characteristics of the other variables, we calculate the annual averages of the daily physical and transition indices, resulting in annual physical and transition risk indices.

To highlight the underlying structure of these continuous time series, their text mining framework is based on a bottom-up construction process. More specifically, Faccini et al. (2023) apply the LDA algorithm, which uses an initial filtering matrix derived from a vast corpus of over 13 million Reuters articles, which is then reduced to 33,735 climate-specific texts using targeted bigrams ("climate change" and "global warming"). With $K = 25$ latent themes, the model estimates a document-theme distribution matrix where θ_d^k denotes the specific thematic share (or probability weight) of theme k within a given news article d . Aggregating these individual weights θ_d^k across all articles published on a given day t yields the continuous daily indices. To further improve the reliability of the resulting climate risk measures, Faccini et al. (2023) supplement the automated LDA procedure with a manual classification of each climate-related article's content. Unlike standard dictionary-based approaches (e.g., Engle et al., 2020; Ardia et al., 2023) this manual classification enables distinguishing whether climate-related news reflects climate concerns or positive economic developments, thereby generating sentiment-adjusted climate risk factors and improving interpretability and thematic consistency.

Among other variables, we use bank- and country-specific macroeconomic variables to examine their impact on banks' credit risk, in line with the literature. Starting with bank-specific variables, we control for banks' performance, specifically profitability, measured by return on assets (ROA). The inverse relationship between bank performance (measured by profitability) and credit risk is validated by Godlewski (2004). Poor corporate performance can be attributed to managerial characteristics that lead to lower profitability, as measured by a low return on assets or equity (Berger & DeYoung, 1997). Good management should lead to a reduction in non-performing loans. We also control for a bank's size (SIZE), measured by the natural logarithm of its total assets. Several studies have examined the relationship between bank size and the level of non-performing loans (NPLs). Empirical evidence of the impact of bank size on NPLs is mixed. Some studies have found a negative relationship between NPLs and bank size, while others have found a positive one (Naili & Lahrichi, 2022). Also, we control for bank capitalization (CAR). The literature has provided evidence that the capital adequacy ratio (CAR, short for "Capital Adequacy Ratio") has a significant effect on loan loss rates (Naili & Lahrichi, 2022). This capital is generally employed as a precaution against excessive risk. We also control for bank diversification (DIVERS). Researchers have found that bank diversification has a significant influence on

risk-taking behavior. In recent years, the importance of non-interest income as a source of banking revenue has grown considerably. This is reflected in the fact that many banks have expanded their activities into non-traditional areas such as investment banking, asset management, insurance underwriting, fee- and commission-based services, as well as trading and derivatives, thus generating income in the form of fees rather than interest. Greater diversification in banks' business models improves loan quality and reduces credit risk (Ghosh, 2015). For bank inefficiency (INEFF), the correlation between this variable and credit risk can be negative or positive: on the one hand, banks that devote fewer resources to loan quality control may be efficient, but suffer from an increase in non-performing loans in the medium and long term; on the other hand, inefficient banks may have difficulty assessing risky loans, which could lead to an increase (Berger & DeYoung, 1997). The last bank-specific variable is credit growth (CG), which is the ratio of net loans to total assets. Credit growth can have a mixed effect on credit risk, depending on the credit standards implemented by banks over time (Birindelli et al., 2022). Finally, for country-specific variables, we used two variables: the first is the GDP per capita. As GDP increases, so does the income level, which could contribute to a reduction in loan defaults (Birindelli et al., 2022). The second variable is Credit-to-GDP (CREDIT_GDP). Research indicates that increased credit to the private sector is associated with a deterioration in loan quality (Birindelli et al., 2022).

Table 1 summarizes our variables, with a description and data source for each.

Table 1. Description of variables.

Variable	Description	Symbol	Source
Dependent variable			
Credit risk	$\frac{\text{Non – performing loans}}{\text{Total loans}}$	NPLs	DataStream Orbis BankFocus
Independent Variables			
US Climate Policy	Developed by Faccini et al. (2023)	TRI	Faccini et al. (2023). Dissecting climate risks: Are they reflected in stock prices? Journal of Banking & Finance, 155, 106948.
Natural Disasters	Developed by Faccini et al. (2023)	PRI	Faccini et al. (2023). Dissecting climate risks: Are they reflected in stock prices? Journal of Banking & Finance, 155, 106948.
Control variables			
Capital adequacy ratio	$\frac{\text{Tier1} + \text{Tier2}}{\text{RWAs}}$	CAR	DataStream Orbis BankFocus
Return on assets ratio	$\frac{\text{Net income}}{\text{Total assets}}$	ROA	DataStream Orbis BankFocus
Bank size	Natural log of total assets	SIZE	DataStream Orbis BankFocus
Bank diversification	Non-interest income to net income	DIVERS	DataStream Orbis BankFocus
Bank inefficiency	$\frac{\text{Operating expenses}}{\text{Operating income}}$	INEFF	DataStream Orbis BankFocus
Credit growth	Net loans to total assets	CG	DataStream Orbis BankFocus

Table 1. *Cont.*

Variable	Description	Symbol	Source
Independent country-level variables			
Log GDP per capita	The logarithm of Gross Domestic Product divided by midyear	GDPc	The World Bank
Credit to GDP	Financial resources provided to the private sector by financial corporations	CREDIT_GDP	The World Bank

Notes: This table presents the description and source for each variable used.

We rely on a balanced panel of 2760 observations throughout our investigation, using data for 230 major commercial banks in the United States. Table 2 presents the descriptive statistics of our main variables. Regarding our dependent variable, in our sample, credit risk (NPLs) ranges from a maximum of 20.790 to an average of 1.455, indicating that some major commercial banks experience significant difficulty in collecting loan repayments. However, the Transition Climate Risk Index (TRI) has a maximum value of 2.708 and an average of 0.938. On the other hand, the Physical Climate Risk Index (PRI) has an average of 0.839 and a maximum of 2.089. This suggests that there is considerable variation in the intensity of media coverage concerning climate policies and natural disasters.

Table 2. Descriptive statistics of main variables.

	Mean	Min	Max	SD	CV	Skewness	Kurtosis
NPLs	1.455	0	20.790	1.481	1.018	3.615	26.656
TRI	0.938	0.287	2.708	0.644	0.687	1.578	4.959
PRI	0.839	0.43	2.089	0.479	0.571	1.555	4.371
ROA	1.148	−4.2	7.360	0.552	0.481	0.315	27.606
SIZE	15.232	11.019	19.311	1.366	0.09	0.224	3.143
CAR	14.963	7.1	52.700	3.319	0.222	3.511	26.816
DIVERS	1.314	−485.379	1077.253	22.662	17.249	35.191	1919.429
INEFF	3.203	0.384	355.629	11.546	3.604	23.581	652.595
CG	0.669	0	3.450	0.144	0.215	4.437	85.687
GDPc	10.999	10.821	11.244	0.121	0.011	0.425	2.345
CREDIT_GDP	51.277	49.19	53.919	1.308	0.026	0.21	2.316

Notes: This table presents descriptive statistics for the variables used in empirical analysis.

It would be relevant to consider non-linear models due to the strong asymmetry and leptokurticity observed in several key variables (such as NPLs, TRI, PRI, CG, DIVERS, INEFF, and CAR).

Table 3 presents the correlation matrix between the variables. The correlation matrix is computed to detect multicollinearity problems to ensure the model's robustness (Table 3).

There appear to be significant correlations between some of the explanatory variables: TRI and PRI (0.689), GDPc and PRI (0.763), and GDPc and TRI (0.749).

These results indicate the possibility of multicollinearity problems, which can be verified by applying the variance inflation factor (VIF) test. Miles (2014) reported that a multicollinearity problem exists when the Variance Inflation Factor (VIF) exceeds 10. We therefore calculated the VIF statistics (Table 4). In our study, they range from 1.06 to 5.18, confirming that our data do not suffer from multicollinearity problems.

Table 3. Pearson correlation matrix.

Variables	NPLs	TRI	PRI	ROA	SIZE	CAR	DIVERS	INEFF	CG	GDPc	CREDIT_GDP
NPLs	1.000										
TRI	−0.186 *	1.000									
PRI	−0.126 *	0.689 *	1.000								
ROA	−0.080 *	0.140 *	0.124 *	1.000							
SIZE	−0.114 *	0.204 *	0.178 *	0.135 *	1.000						
CAR	0.135 *	−0.041 *	−0.041 *	0.068 *	−0.078 *	1.000					
DIVERS	−0.010	−0.019	−0.013	−0.014	0.000	−0.014	1.000				
INEFF	0.119 *	−0.068 *	−0.044 *	−0.136 *	−0.072 *	0.040 *	−0.227 *	1.000			
CG	−0.143 *	−0.024	−0.041 *	−0.014	−0.043 *	−0.242 *	−0.003	−0.011	1.000		
GDPc	−0.295 *	0.749 *	0.763 *	0.184 *	0.251 *	−0.118 *	−0.025	−0.098 *	0.096 *	1.000	
CREDIT_GDP	−0.203 *	0.217 *	0.077 *	0.008	0.151 *	−0.099 *	−0.038 *	−0.043 *	0.165 *	0.459 *	1.000

Notes: This table presents the Pearson correlation matrix for the variables. * denotes statistical significance at the 5% level.

Table 4. Variance inflation factor (VIF).

Variable	VIF	1/VIF
GDPc	5.18	0.193118
PRI	3.29	0.303794
TRI	2.52	0.397082
CREDIT_GDP	1.69	0.592640
CG	1.12	0.893774
SIZE	1.09	0.913832
CAR	1.09	0.916357
INEFF	1.09	0.918551
ROA	1.09	0.920919
DIVERS	1.06	0.943872
Mean VIF	1.92	

Notes: In our study, we confirmed that our data do not suffer from multicollinearity concerns.

3.3. Model and Empirical Strategy

We employ a panel threshold regression model, which is particularly suitable for analyzing non-linear problems. The potential dynamics between the variables examined in this model, capturing the heterogeneity of banks and addressing any endogeneity issues:

$$\text{NPLs}_{i,t} = \alpha + \varphi \text{NPLs}_{i,t-1} + \vartheta \text{TRI}_{i,t} + \delta \text{TRI}_{i,t}^2 + \theta \text{ROA}_{i,t} + \sigma \text{SIZE}_{i,t} + \rho \text{CAR}_{i,t} + \tau \text{DIVERS}_{i,t} + \beta \text{INEFF}_{i,t} + \gamma \text{CG}_{i,t} + \lambda \ln \text{GDPc}_{i,t} + \mu \text{CREDIT_GDP}_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$\text{NPLs}_{i,t} = \alpha + \varphi \text{NPLs}_{i,t-1} + \vartheta \text{PRI}_{i,t} + \delta \text{PRI}_{i,t}^2 + \theta \text{ROA}_{i,t} + \sigma \text{SIZE}_{i,t} + \rho \text{CAR}_{i,t} + \tau \text{DIVERS}_{i,t} + \beta \text{INEFF}_{i,t} + \gamma \text{CG}_{i,t} + \lambda \ln \text{GDPc}_{i,t} + \mu \text{CREDIT_GDP}_{i,t} + \varepsilon_{i,t} \quad (2)$$

where $\text{NPLs}_{i,t-1}$ represents lagged NPLs, i represents banks under consideration, t represents time, and $\varepsilon_{i,t}$ represents the error term.

Seo and Shin (2016) propose the dynamic panel threshold model, estimated by the first-differenced GMM technique. Seo et al. (2019) later refined this approach to extend Hansen's (1999) panel threshold regression (PTR) model. The model in Equations (1) and (2) is specified to consider possible threshold effects in estimating the impact of the intensity of transition climate risk (TRI) and physical climate risk (PRI) on banks' credit risk (NPLs), with a focus on the dynamic panel threshold model.

To reduce the potential for omitted-variable bias, our empirical specification includes a comprehensive set of bank-specific control variables (return on assets, bank size, credit growth, capital adequacy ratio, bank diversification, and bank inefficiency), as well as macroeconomic control variables (GDP per capita and Credit to GDP), which are widely recognized in the banking literature as important determinants of credit risk. Furthermore, the dynamic panel threshold model by Seo and Shin (2016), estimated using the first-

differenced GMM estimator, mitigates endogeneity by employing internal instruments and eliminates time-invariant unobserved heterogeneity through first differences. Although these methodological features significantly reduce the potential for omitted-variable bias, the possibility of bias resulting from unobserved factors that vary over time cannot be completely ruled out.

Therefore, the dynamic panel threshold regression approach is used to assess if the impact the intensity of US climate-policy and disaster-related media attention on banks' credit risk depends on a given threshold γ (which will be calculated). This type of analysis makes it possible to estimate the impact of these media-based climate-risk indicators (Transition Climate Risk (TRI) and the Physical Climate Risk Index (PRI) on banks' credit risk both below and above the threshold. Considering the media-based climate-risk threshold γ , Equations (1) and (2) can be rewritten as follows:

Lower regime

$$\text{NPLS}_{i,t} = \alpha_i + \varphi_{11}\text{NPLS}_{i,t-1} + \vartheta_{11}\text{TRI}_{i,t} + \delta_{11}\text{TRI}_{i,t}^2 + \theta_{11}\text{ROA}_{i,t} + \sigma_{11}\text{SIZE}_{i,t} + \rho_{11}\text{CAR}_{i,t} + \tau_{11}\text{DIVERS}_{i,t} + \beta_{11}\text{INEFF}_{i,t} + \gamma_{11}\text{CG}_{i,t} + \lambda_{11}\ln\text{GDP}_{i,t} + \mu_{11}\text{CREDIT_GDP}_{i,t} + \varepsilon_{i,t} \text{ if } \text{TRI}_{i,t} \leq \gamma \quad (3)$$

$$\text{NPLS}_{i,t} = \alpha_i + \varphi_{11}\text{NPLS}_{i,t-1} + \vartheta_{11}\text{PRI}_{i,t} + \delta_{11}\text{PRI}_{i,t}^2 + \theta_{11}\text{ROA}_{i,t} + \sigma_{11}\text{SIZE}_{i,t} + \rho_{11}\text{CAR}_{i,t} + \tau_{11}\text{DIVERS}_{i,t} + \beta_{11}\text{INEFF}_{i,t} + \gamma_{11}\text{CG}_{i,t} + \lambda_{11}\ln\text{GDP}_{i,t} + \mu_{11}\text{CREDIT_GDP}_{i,t} + \varepsilon_{i,t} \text{ if } \text{PRI}_{i,t} \leq \gamma \quad (4)$$

Upper regime

$$\text{NPLS}_{i,t} = \alpha_i + \varphi_{21}\text{NPLS}_{i,t-1} + \vartheta_{21}\text{TRI}_{i,t} + \delta_{21}\text{TRI}_{i,t}^2 + \theta_{21}\text{ROA}_{i,t} + \sigma_{21}\text{SIZE}_{i,t} + \rho_{21}\text{CAR}_{i,t} + \tau_{21}\text{DIVERS}_{i,t} + \beta_{21}\text{INEFF}_{i,t} + \gamma_{21}\text{CG}_{i,t} + \lambda_{21}\ln\text{GDP}_{i,t} + \mu_{21}\text{CREDIT_GDP}_{i,t} + \omega_{i,t} \text{ if } \text{TRI}_{i,t} > \gamma \quad (5)$$

$$\text{NPLS}_{i,t} = \alpha_i + \varphi_{21}\text{NPLS}_{i,t-1} + \vartheta_{21}\text{PRI}_{i,t} + \delta_{21}\text{PRI}_{i,t}^2 + \theta_{21}\text{ROA}_{i,t} + \sigma_{21}\text{SIZE}_{i,t} + \rho_{21}\text{CAR}_{i,t} + \tau_{21}\text{DIVERS}_{i,t} + \beta_{21}\text{INEFF}_{i,t} + \gamma_{21}\text{CG}_{i,t} + \lambda_{21}\ln\text{GDP}_{i,t} + \mu_{21}\text{CREDIT_GDP}_{i,t} + \omega_{i,t} \text{ if } \text{PRI}_{i,t} > \gamma \quad (6)$$

Equations (3)–(6) show two different regimes, based on the endogenously determined climate risk threshold variable. For a regime below or above the threshold γ , the impact of climate risk on banks' credit risk and the control variables is estimated.

4. Empirical Results

This study aims to assess whether the impact of the intensity of transition climate risk (TRI) and disaster-related media attention (PRI) on banks' credit risk (NPLs) depends on a particular threshold, by applying the estimator developed by [Seo and Shin \(2016\)](#). The results for both regimes are presented in Table 5.

The threshold model enables the evaluation of the impact of transition climate risk (TRI) and physical climate risk (PRI) on banks' credit risk, as a non-linear relationship is evident between the variables, as shown in Table 5. The lagged dependent variable (NPLS_{t-1}) is significant in both regimes, demonstrating the importance of dynamic specification. The findings reveal thresholds for the media-based TRI and PRI variables that split the sample into lower and upper regimes. The threshold of 0.50 for TRI and 0.57 for PRI classifies the effects according to the presence and intensity of climate-policy and disaster-related media attention. For TRI, the estimated threshold value ($\gamma = 0.500$) divides the sample into two regimes: the lower regime ($\text{TRI} \leq \gamma$) contains 920 observations, representing 33.33% of the total sample, while the upper regime ($\text{TRI} > \gamma$) includes 1840 observations, corresponding to 66.67% of the observations. Similarly, for PRI, the estimated threshold value ($\gamma = 0.571$) separates the sample into a lower regime containing 1150 observations (41.67%) and an upper regime containing 1610 observations (58.33%). This distribution indicates that both regimes are sufficiently represented, supporting the empirical relevance of the estimated threshold effects. The regime analysis reveals the non-linear impacts of US climate-policy and disaster-related media attention intensity on banks' credit risk. In this table, we show the estimated coefficients for testing H1 and H2.

Table 5. Panel threshold model results using TRI (Transition Climate Risk) and PRI (Physical Climate Risk) indices.

	Lower Regime		Upper Regime	
	Transition Climate Risk (TRI)	Physical Climate Risk (PRI)	Transition Climate Risk (TRI)	Physical Climate Risk (PRI)
	$\gamma \leq 0.500$	$\gamma \leq 0.571$	$\gamma > 0.500$	$\gamma > 0.571$
NPLs _{t-1}	0.672 *** (0.000)	0.678 *** (0.000)	−0.090 *** (0.000)	−0.0283 *** (0.005)
TRI	−9.530 *** (0.000)	-	9.547 *** (0.000)	-
PRI	-	−2.464 *** (0.000)	-	2.228 *** (0.000)
ROA	−0.096 *** (0.003)	0.0271 (0.298)	0.034 (0.302)	−0.132 *** (0.000)
SIZE	0.181 *** (0.000)	−0.0822 ** (0.051)	−0.133 *** (0.000)	0.0343 (0.153)
CG	−1.494 *** (0.000)	−1.268 *** (0.000)	1.165 *** (0.000)	0.893 *** (0.000)
DIVERS	−0.000691 *** (0.000)	−0.000116 (0.983)	−0.00532 *** (0.000)	−0.0774 *** (0.000)
CAR	0.071 *** (0.000)	−0.00309 (0.610)	−0.065 *** (0.000)	0.0516 *** (0.000)
GDP _c	26.62 *** (0.000)	−0.979 *** (0.001)	−27.20 *** (0.000)	1.659 *** (0.000)
CREDIT_GDP	−1.566 *** (0.000)	−0.0113 (0.416)	1.629 *** (0.000)	0.0657 *** (0.000)
INEFF	−0.003 * (0.096)	−0.000351 (0.552)	−0.00497 ** (0.017)	0.00409 *** (0.044)
Threshold level (<i>p</i> -value)	0.500 *** (0.000)	0.571 *** (0.000)	0.500 *** (0.000)	0.571 *** (0.000)

Note: This table reports the impact of climate risk on banks' credit risk. Banks' credit risk, measured by the ratio of non-performing loans (NPLs) to total loans, is the dependent variable in our model. TRI and PRI represent the Transition Climate Risk Index and the Physical Climate Risk Index, respectively, based on media-conveyed indicators developed by Faccini et al. (2023). The remaining variables are control variables. Detailed variable definitions are provided in Table 1. The results are estimated using the panel threshold model developed by Seo and Shin (2016). γ denotes the estimated threshold level. *p*-values are reported in parentheses. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

To visually confirm the presence of threshold effects and illustrate the regime-dependent nature of media-based climate risk, Figures 3 and 4 present the estimated marginal effects of climate-policy and disaster-related media attention across their respective ranges. The vertical red dashed line indicates the estimated threshold values ($\gamma = 0.50$ for TRI and $\gamma = 0.57$ for PRI), while the gray horizontal dashed line represents the zero-effect baseline.

Concerning H1, the intensity of US climate-policy media attention (TRI) has a significant and negative effect in the lower regime, meaning that it decreases credit risk. This result suggests that when media attention to climate policies remains relatively low, climate-related regulatory changes are perceived as gradual and manageable by both banks and borrowers. Under these conditions, banks have sufficient time to strengthen their credit screening and risk management practices, while firms can gradually adapt their business models and investment decisions to the evolving regulatory environment. As a result, borrowers' repayment capacity remains relatively stable, contributing to lower non-performing loans and improved loan portfolio quality. However, above the threshold (upper regime), the effect becomes positive and significant (9.547, *p*-value (0.000)), indicating that higher

climate policy-related media attention increases credit risk. Our dependent variable is the ratio of non-performing loans to total loans, where an increase (or decrease) indicates a deterioration (or improvement) in the banks' loan quality. Thus, this evidence can be interpreted as follows: This non-linear effect, which is also illustrated in Figure 3, indicates that banks may be resilient to low levels of climate-policy media attention but become vulnerable once the intensity of this news coverage exceeds the threshold. This means that once climate-policy media attention exceeds the estimated threshold, further increases in media attention are associated with higher bank credit risk. H1 is therefore confirmed in terms of the intensity of climate-policy media attention (representing transition climate risk), which exhibits a threshold-dependent positive impact on credit risk for banks.

Regarding H2, the effect of disaster-related media attention (PRI) is significantly negative in the lower regime, indicating that low levels of disaster media exposure decrease credit risk (NPLs). This result indicates that relatively low levels of disaster-related media attention may reflect periods in which physical climate risks remain limited and localized, generating only modest disruptions to economic activity. Under such conditions, households and firms are generally better able to maintain their repayment capacity, while banks experience limited deterioration in loan quality. Consequently, lower levels of disaster-related media attention are associated with reduced credit risk in the banking sector. On the other hand, the effect becomes positive and significant, indicating that high intensity of disaster-related media attention increases credit risk above the threshold (upper regime). As shown in Figure 4, this regime-dependent relationship confirms the existence of a non-linear effect of physical climate risk on banks' credit risk. Therefore, our findings also support H2. This shift suggests that as the intensity of natural disasters increases, borrowers face greater financial stress, leading to higher loan defaults.

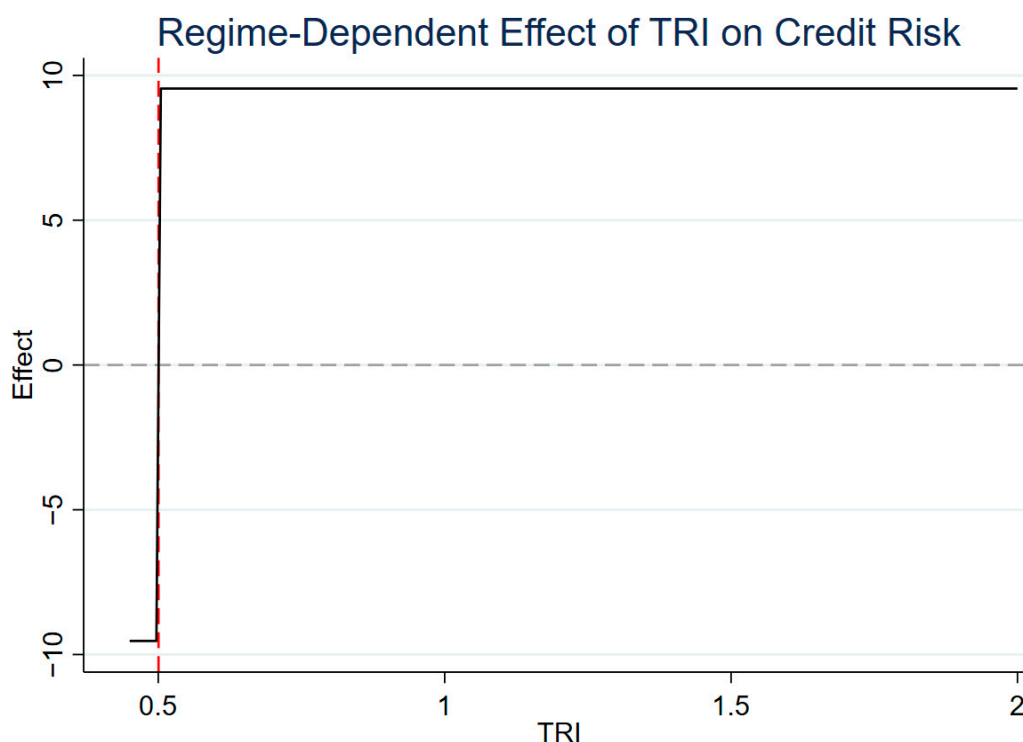


Figure 3. Regime-dependent effect of transition climate risk (TRI) on NPLs. *Notes:* The black solid line represents the estimated regime-dependent effect of Transition Climate Risk (TRI) on credit risk, while the red dashed vertical line indicates the estimated threshold value ($\gamma = 0.500$).

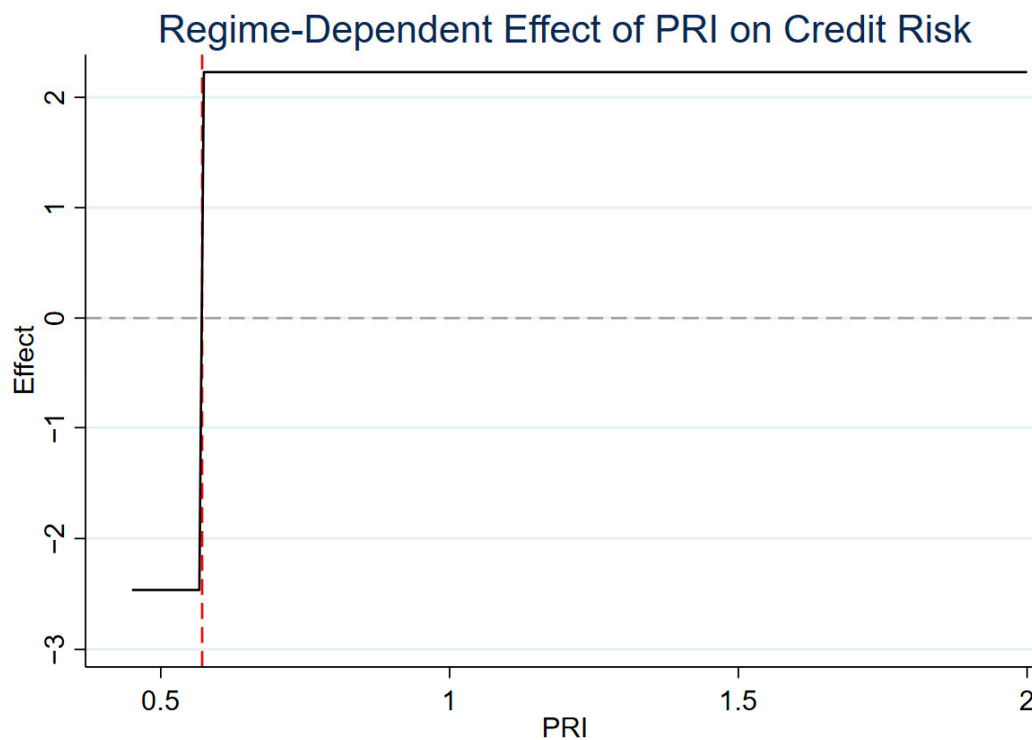


Figure 4. Regime-dependent effect of physical climate risk (PRI) on NPLs. *Notes:* The black solid line represents the estimated regime-dependent effect of Physical Climate Risk (PRI) on credit risk, while the red dashed vertical line indicates the estimated threshold value ($\gamma = 0.571$).

Beyond the main media-based climate risk variables, the control variables provide additional insights into the determinants of banks' credit risk. Bank profitability (ROA) has heterogeneous effects across the two threshold models. In the transition climate risk (TRI) model, ROA has a negative and significant effect in the lower regime (-0.096 , p -value 0.003), suggesting that the most profitable banks are better able to absorb moderate transition-related media shocks and maintain the quality of their loans. However, its effect becomes statistically insignificant as soon as transition-policy media attention threshold is exceeded. In contrast, in the physical climate risk (PRI) model, ROA is not significant in the lower regime but becomes negative and highly significant in the upper regime (-0.132 , p -value 0.000), indicating that profitability strengthens banks' resilience as disaster-related media attention intensifies.

Bank size (SIZE) also exhibits regime-dependent effects. Under conditions of moderate transition-policy media attention, SIZE is positively correlated with non-performing loans (0.181 , p -value 0.000). This suggests that larger banks may assume higher credit risk under moderate transition-related media intensity, possibly reflecting "too-big-to-fail" incentives or higher risk-taking behavior. However, once the TRI threshold is exceeded, the coefficient becomes negative (-0.133 , p -value 0.000), indicating that larger institutions benefit from greater diversification, more advanced risk management practices, and greater financial capacity to withstand heightened transition-related media attention. In the PRI model, SIZE reduces NPLs in the lower regime (-0.082 , p -value 0.051) but becomes statistically insignificant in the upper regime, suggesting that the benefits associated with bank size diminish as disaster-related media attention intensifies.

Credit growth (CG) exhibits a clearly non-linear trend in both models. In the lower regimes, CG has a negative effect on NPLs (-1.494 for the TRI and -1.268 for the PRI), indicating that credit expansion is associated with an improvement in credit quality under periods of relatively low climate-related media attention. Conversely, as soon as the TRI or

PRI exceeds its estimated threshold, the coefficient becomes positive (1.165 for the TRI and 0.893 for the PRI), suggesting that continued credit expansion in a context of heightened climate-policy and disaster-related media intensity may increase banks' exposure to riskier borrowers and, consequently, raise credit risk.

Bank diversification (DIVERS) generally helps to reduce credit risk. In the TRI model, the coefficient remains negative and significant between the two regimes, while in the PRI model diversification becomes particularly effective in the upper regime (-0.0774 , p -value 0.000). These results suggest that diversified income sources enhance banks' resilience against heightened climate-policy and disaster-related media attention intensity.

Some control variables show unexpected signs that warrant further discussion. In the TRI model, the capital adequacy ratio (CAR) is positively associated with non-performing loans in the lower regime (0.071, p -value 0.000), which may reflect a precautionary response that banks facing higher credit risk accumulate additional capital buffers. However, the CAR becomes negative and significant in the upper TRI regime (-0.065 , p -value 0.000), indicating that higher capitalization improves banks' ability to absorb heightened transition-related media shocks. On the other hand, in the PRI model, the CAR is insignificant in the lower regime but becomes positive and highly significant in the upper regime (0.0516, p -value 0.000). This unexpected outcome may reflect incentives for risk transfer or suggest that capital accumulation alone is insufficient to fully offset credit losses associated with periods of intense disaster-related media coverage.

Macroeconomic variables also have threshold-dependent effects. GDP per capita (GDPc) has a positive effect on non-performing loans in the lower TRI regime, but it negatively affects credit risk once the transition threshold is exceeded, indicating that richer economies are better able to absorb the costs associated with heightened climate-policy media attention. According to the PRI model, GDP per capita reduces non-performing loans in the lower regime, but becomes positively associated with credit risk in the upper regime. This suggests that periods of extreme media coverage regarding disaster events may reflect systemic economic distortions that compromise the benefits of economic development. Similarly, the credit-to-GDP ratio reduces non-performing loans in the lower TRI regime but increases them once the transition or physical climate risk indices exceed their respective thresholds. This underscores the potential vulnerability associated with excessive credit expansion during periods of high climate-related media attention.

Finally, banking inefficiency (INEFF) has mixed effects depending on the regime. It shows a weak negative association with NPLs in the TRI model, whereas in the PRI model its effect is insignificant in the lower regime but becomes positive and significant in the upper regime (0.00409, p -value 0.044). This result suggests that operational inefficiencies become more detrimental to credit quality when banks face heightened disaster-related media attention intensity.

5. Robustness Check

5.1. Alternative Empirical Model: Forward Orthogonal Deviations GMM

To assess the robustness of our results, we employ the generalized method of moments (GMM) with orthogonalized forward deviations, as proposed by Arellano and Bover (1995), as an alternative estimation method. The choice of this technique is strictly motivated by the fundamental structural characteristics inherent in banking data.

Firstly, the number of banks ($N = 230$) is greater than the number of periods in each cross-section ($T = 12$ years), satisfying the $N > T$ condition and justifying the use of GMM. Secondly, the dependent variable, non-performing loans (NPLs), is persistent, as shown by the significant and high coefficient of its lagged value (0.699, p -value = 0.000), indicating strong autocorrelation. Thirdly, the GMM technique controls for endogeneity,

unobserved heterogeneity, and dynamic relationships, while preserving cross-sectional variation between banks.

Table 6 presents the results of the GMM system estimations. The coefficients of most of the bank-specific and macroeconomic control variables remain highly consistent, in terms of significance, with our baseline panel threshold regression (PTR) estimates. In particular, the linear coefficients of the climate-policy media index (TRI) and the disaster-related media index (PRI) reflect the overall mean effects under GMM (0.029 and -0.059 , respectively, p -value = 0.000). The apparent sign differences between the GMM and threshold estimations are conceptually expected. While the GMM model captures a single linear relationship averaged across the entire sample, the dynamic panel threshold model reveals regime-dependent variations in the impact of media-conveyed climate risk, depending on the intensity of climate-related media attention. Furthermore, the post-estimation diagnostics validate our instrumentation strategy, showing an absence of second-order autocorrelation ((AR(2), p -value = 0.627) and confirming the validity of the instrument by non-significant Sargan (p -value = 0.603) and Hansen (p -value = 0.250) tests.

Table 6. Estimation results of system: GMM.

(GMM) with Orthogonal Forward Deviations		
Variables	Coefficient	Prob.
L.NPLs	0.699 ***	0.000
TRI	0.029 ***	0.000
PRI	-0.059 ***	0.000
ROA	0.001	0.333
SIZE	0.005 ***	0.000
CG	-0.189 ***	0.000
DIVERS	-0.0002 ***	0.000
CAR	0.010 ***	0.000
GDPc	-0.252 ***	0.000
CREDIT_GDP	0.030 ***	0.000
INEFF	0.003 ***	0.000
_cons	1.384 ***	0.000
AR (2)	0.49	0.627
Sargan test	197.11	0.603
Hansen test	216.22	0.250

Notes: This table reports the absence of second-order autocorrelation (AR(2)), and the validity of the instruments (Sargan and Hansen) confirms the reliability of the results obtained. *** denotes statistical significance at the 1% level.

5.2. Alternative Measures of Climate Risk

To ensure the reliability of our baseline results, we replaced our main independent variables with alternative indicators of transition climate risk and physical climate risk media attention. Specifically, we replicated our initial threshold specifications using the Climate Policy Uncertainty Index (CPU) developed by Gavriilidis (2021) and the Global Warming Index (GM) constructed by Faccini et al. (2023). Furthermore, to account for potential macroeconomic cyclical variations, we incorporated GDP per capita growth as an indicator of economic development.

The estimated results, presented in Table 7, corroborate our main findings. Structural threshold breaks remain clear and highly significant ($\gamma = 1.012$ for CPU and $\gamma = 0.305$ for GM, p -value = 0.000), demonstrating that extreme variations in policy uncertainty and climate attention consistently generate non-linear effects on credit risk within US banking institutions.

Table 7. Panel threshold model results using CPU (Climate Policy Uncertainty) and GM (Global Warming) indices.

	Lower Regime		Upper Regime	
	Transition Climate Risk (CPU)	Physical Climate Risk (GM)	Transition Climate Risk (CPU)	Physical Climate Risk (GM)
	$\gamma \leq 1.012$	$\gamma \leq 0.305$	$\gamma > 1.012$	$\gamma > 0.305$
NPLs _{t-1}	0.646 *** (0.000)	0.674 *** (0.000)	−0.092 *** (0.000)	−0.047 *** (0.000)
CPU	−1.618 *** (0.000)	-	1.659 *** (0.000)	-
GM	-	−11.980 *** (0.000)	-	11.932 *** (0.000)
ROA	−0.088 *** (0.003)	−0.158 *** (0.000)	0.097 *** (0.003)	0.175 *** (0.000)
SIZE	−0.032 (0.541)	−0.094 * (0.064)	0.040 (0.424)	−0.002 (0.937)
CG	0.598 *** (0.000)	0.625 *** (0.000)	−1.655 *** (0.000)	−1.575 *** (0.000)
DIVERS	−0.001 *** (0.000)	−0.0007 (0.195)	0.003 *** (0.006)	−0.051 *** (0.000)
CAR	0.059 *** (0.000)	0.075 *** (0.000)	−0.056 *** (0.000)	−0.064 *** (0.000)
GDP	−1.496 *** (0.000)	0.266 *** (0.000)	1.568 *** (0.000)	−0.266 *** (0.000)
CREDIT_GDP	0.614 *** (0.000)	0.183 *** (0.000)	−0.344 *** (0.001)	−0.120 *** (0.006)
INEFF	−0.003 ** (0.050)	−0.003 *** (0.000)	0.006 ** (0.023)	0.019 *** (0.000)
Threshold level (<i>p</i> -value)	1.012 *** (0.000)	0.305 *** (0.000)	1.012 *** (0.000)	0.305 *** (0.000)

Note: This table reports the impact of climate risk on banks' credit risk. Banks' credit risk, measured by the ratio of non-performing loans to total loans (NPLs), is the dependent variable in our model. CPU (Climate Policy Uncertainty) and GM (Global Warming) are used as alternative proxies for transition and physical climate risks, respectively. The results are estimated using the panel threshold model developed by [Seo and Shin \(2016\)](#). γ denotes the estimated threshold level. *p*-values are reported in parentheses. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

Although the robustness checks confirm the stability of our baseline results, certain limitations should be acknowledged. The alternative climate risk measures, namely the Climate Policy Uncertainty (CPU) index ([Gavrilidis, 2021](#)) and the Global Warming (GM) index ([Faccini et al., 2023](#)), are text-based indicators constructed from newspaper articles using keyword searches and Latent Dirichlet Allocation (LDA), respectively. As such, they may be subject to measurement error arising from variations in media coverage, editorial bias, or fluctuations in public attention, which do not necessarily reflect the actual evolution of climate risk or banks' direct exposure.

Furthermore, while the GM index is primarily designed to capture physical climate risk through news related to global warming and scientific evidence, it may also indirectly reflect transition climate risk, as increased attention to climate events can stimulate policy debates and regulatory actions ([Faccini et al., 2023](#)). Similarly, the CPU index measures uncertainty surrounding climate policy rather than the implementation of climate policies themselves.

Nevertheless, the consistency of the estimated threshold effects across alternative specifications increases confidence that the documented non-linear relationship between climate risk and bank credit risk is not driven by the construction of a single climate risk measure.

5.3. Alternative Measures of Climate Risk and Bank Credit Risk

To further test the robustness of our results, we conduct an additional sensitivity analysis by varying our main dependent variables and both independent variables simultaneously, while maintaining the same model specification and control variables as in baseline regression. We substitute non-performing loans with loan loss provisions represented by the ratio of loan loss provisions to total loans (PLL) to capture forward-looking credit risk management and provisioning strategies. Although loan loss provisions are primarily set aside to cover underlying credit risk, they can also be influenced by management discretion, particularly through earnings smoothing and capital management practices (Fonseca & Gonzalez, 2008; Bouvatier et al., 2014; Skala, 2020). Furthermore, loan loss provisions are closely linked to banks' capital adequacy and financial stability (Laeven & Majnoni, 2003; Agénor & Da Silva, 2017). Consequently, using loan loss provisions as an alternative dependent variable allows us to verify whether the identified threshold effects and the relationship between climate risk and bank credit risk remain robust when credit risk is measured from a forward-looking provisioning perspective rather than through actual defaults.

At the same time, the independent variables are replaced by the indices CPU developed by Gavrilidis (2021) and GM developed by Faccini et al. (2023).

As shown in Table 8, the structural results remain unchanged. The joint estimates of the thresholds ($\gamma = 1.707$ for CPU and $\gamma = 0.277$ for GM, p -value = 0.000) structurally validate the underlying non-linear model: large financial institutions retain sufficient operational resilience to withstand environmental shocks below the critical thresholds, but become clearly vulnerable to an increase in provisioning demands once the CPU and GM thresholds are exceeded.

Overall, the robustness analyses confirm the stability of the baseline findings across alternative specifications. Whether using an alternative econometric technique to address endogeneity (Table 6), alternative measures of climate risk (Table 7), or alternative measures of both climate risk and bank credit risk (Table 8), the main conclusions remain unchanged. The results consistently support hypotheses H1 and H2 and confirm the existence of significant threshold effects in the relationship between climate risk and bank credit risk. Although some coefficient estimates and threshold values differ across specifications, the direction and economic interpretation of the main results remain consistent, thus confirming the robustness of the baseline model.

Table 8. Panel threshold model results using loan loss provisions (PLL), CPU (Climate Policy Uncertainty), and GM (Global Warming) indices.

	Lower Regime		Upper Regime	
	Transition Climate Risk (CPU)	Physical Climate risk (GM)	Transition Climate Risk (CPU)	Physical Climate risk (GM)
	$\gamma \leq 1.707$	$\gamma \leq 0.277$	$\gamma > 1.707$	$\gamma > 0.277$
PLLt-1	0.549 *** (0.000)	0.398 *** (0.000)	−0.584 *** (0.000)	−0.402 *** (0.000)
CPU	−0.092 *** (0.000)	-	0.857 *** (0.000)	-
GM	-	−0.762 *** (0.000)	-	0.362 *** (0.000)
ROA	−0.231 *** (0.000)	−0.219 *** (0.000)	0.105 *** (0.000)	−0.178 *** (0.000)
SIZE	0.078 *** (0.000)	−0.282 *** (0.000)	−0.164 (0.000)	0.264 *** (0.000)

Table 8. Cont.

	Lower Regime		Upper Regime	
	Transition Climate Risk (CPU)	Physical Climate risk (GM)	Transition Climate Risk (CPU)	Physical Climate risk (GM)
CG	−0.505 *** (0.000)	0.078 *** (0.000)	−0.100 ** (0.027)	0.021 (0.698)
DIVERS	−0.0003 *** (0.000)	−0.005 *** (0.000)	0.040 *** (0.000)	0.005 *** (0.000)
CAR	0.006 *** (0.000)	−0.051 *** (0.000)	−0.174 *** (0.000)	0.070 *** (0.000)
GDPc	0.552 *** (0.000)	1.301 *** (0.000)	−2.020 *** (0.000)	−2.096 *** (0.000)
CREDIT_GDP	0.023 *** (0.000)	−0.050 *** (0.000)	0.072 *** (0.000)	0.147 *** (0.000)
INEFF	0.002 *** (0.000)	−0.005 *** (0.000)	0.034 (0.000)	0.020 *** (0.000)
Threshold level (<i>p</i> -value)	1.707 *** (0.000)	0.277 *** (0.000)	1.707 *** (0.000)	0.277 *** (0.000)

Note: This table reports the impact of climate risk on banks' credit risk. Banks' credit risk, measured by the ratio of loan loss provisions to total loans (PLL), is the dependent variable in our model. CPU (Climate Policy Uncertainty) and GM (Global Warming) are used as alternative proxies for transition and physical climate risks, respectively. The results are estimated using the panel threshold model developed by [Seo and Shin \(2016\)](#). γ denotes the estimated threshold level. *p*-values are reported in parentheses. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

6. Discussion

The main results of our study show that systemically important banks in the United States may be resilient to low levels of climate-related media attention up to a certain point but become vulnerable once that threshold is exceeded. Transition climate risk (TRI), proxied by US climate-policy media attention, decreases credit risk in the lower regime; above the threshold (upper regime), higher levels of transition climate risk increase credit risk. These results are consistent with the findings of [Y. Liu et al. \(2024\)](#). In line with the theory of creative destruction, Liu et al. argue that banks will be exposed to greater risk if they do not adopt innovative technologies or industries during the transition. Meanwhile, conflicting climate policies make it difficult for banks to increase their support for low-carbon industries. Therefore, they hypothesize that the initial negative relationship is mainly due to uncertainties in climate support policies, while policies that oppose the transition weaken this negative relationship. From both borrowers' and lenders' perspectives, market adjustments caused by climate policy and technological innovation will impact the demand and structure of traditional sectors, thereby increasing the risk of corporate default ([Capasso et al., 2020](#)). On the lenders' side, the transition to a low-carbon economy could result in asset and income losses for debtors, thereby increasing the risk of default. As a result, the share of non-performing loans (NPLs) in banks may increase ([Semieniuk et al., 2021](#)). This non-linear effect suggests that banks may be resilient to climate-policy media coverage up to a certain point but become vulnerable once this threshold is exceeded. Intense media focus on climate policy may reflect heightened loan default risk and depreciation of stranded assets for high-carbon firms, thereby increasing banks' exposure to external shocks.

Turning to the effect of the disaster-related media index (PRI), the coefficient is significantly negative in the lower regime, indicating that low levels of disaster media exposure are associated with lower credit risk (NPLs). This result is consistent with [Ginglinger and Moreau \(2023\)](#), who suggest that companies more exposed to climate risk reassess their operating and distress costs, making them adopt lower leverage strategies. Lower leverage decreases the likelihood of financial distress and loan defaults. On the other hand,

the effect becomes positive and significant, indicating that credit risk increases above the threshold (upper regime) during periods of high disaster-related media intensity. This shift suggests that as the intensity of media coverage regarding natural disasters spikes, it reflects that borrowers face greater financial stress, leading to higher loan defaults. Wu et al. (2023) highlight that slow environmental changes, such as sea level rise, lead to long-term depreciation of property values, while extreme events, such as floods, wildfires, or storms, cause immediate property damage (Shahid et al., 2017; Mueller et al., 2009; Kellenberg & Mobarak, 2011). When media coverage intensifies around these disruptions, it signals that borrowers hold assets at a higher risk of losing value, causing banks to become concerned that the value of the collateral may not be sufficient to cover the debt. This situation may cause the borrower to forfeit the collateral and default on their payment obligations, thereby increasing the bank's credit risk.

7. Conclusions, Implications, and Limitations

In recent years, the relationship between media-conveyed climate change awareness and financial stability has attracted significant attention in policy debates and academic literature, underscoring the need to understand how climate-related risks may affect the banking sector's resilience (Roncoroni et al., 2021). Given the growing literature on the socio-economic impacts of climate change, this study examines the significant and timely issue of media-conveyed climate risk and its impact on the credit risk of 230 major US banks. Recent evidence highlights how financial institutions are increasingly exposed to heightened credit risk due to climate-related factors (Faiella & Natoli, 2018). Our analysis aims to understand how transition climate risk (TRI) and physical climate risk (PRI) may influence banks' credit risk (NPLs) across different regimes. Our results reveal that low regimes of climate-related media attention are associated with a reduction in banks' credit risk; above the threshold (upper regime), the effect becomes positive and significant, indicating that higher transition climate risk (TRI) and physical climate risk (PRI) are associated with higher bank credit risk. These findings highlight the complexity of climate-related information flows in relation to bank credit risk. While moderate media attention regarding climate policy and disaster events can reflect periods of heightened borrower awareness and proactive risk mitigation that improve loan quality, higher climate policy-related media attention and extreme spikes in disaster coverage signal systemic financial stress that poses additional risks. Therefore, a nuanced approach to integrating media-based climate risk indicators into credit risk management is crucial to maintaining financial stability amid growing climate challenges.

Our study has significant implications for bank managers, regulators, governments, and investors, underscoring the need to integrate climate risk awareness into banks' operations and strategies. As key financial intermediaries, banks play a crucial role in ensuring financial stability; however, they face increasing challenges from climate-related media shocks that can signal vulnerabilities in credit quality and amplify credit risk. Our findings suggest that banks may benefit from prioritizing climate risk management by integrating forward-looking media-based indicators into their core strategic agendas. Such a commitment may enhance their reputation and may contribute to improved economic performance by supporting better credit risk management and financial stability (European Central Bank [ECB], 2020; Nieto, 2019). Additionally, the findings of this research can inform policymakers, regulators, and financial sector stakeholders seeking to better understand and mitigate the financial risks associated with media-conveyed climate change perceptions. Our findings also contribute to the ongoing policy debate on the banking sector's exposure to climate change risks (Faiella & Malvoliti, 2020; Galletta et al., 2021). Given global efforts to mitigate climate change, uncertainties related to physical and transition climate risk as reflected in public media pose significant challenges for the financial sector.

To mitigate these impacts, governments play a crucial role in strengthening climate change policies to minimize socio-economic losses during periods of intense media scrutiny, for example, by providing clear regulatory frameworks for reducing greenhouse gas emissions, promoting renewable energy, and enhancing infrastructure to withstand extreme weather events. In response, banks are also required to improve their environmental management systems and adopt rigorous environmental credit risk management practices (Mengze & Wei, 2015; Weber et al., 2008; Raut et al., 2017). These measures may help mitigate the adverse financial signaling associated with climate change risks, improve loan portfolio quality, and contribute to overall financial stability (European Banking Authority [EBA], 2020; Financial Stability Board, 2020). By promoting greater engagement on climate-related issues, banks can align with sustainable global development goals while safeguarding their financial health amid rising climate risks.

Despite the valuable implications and conclusions drawn from our study, it has certain limitations. Initially, we studied only major US banks; however, it would also be relevant to examine other financial intermediaries exposed to climate risks and to consider broader dimensions of risk, including country, political, financial, and economic risks. Such factors may interact with climate risk and indirectly influence banks' credit risk. In addition, panel threshold regression assumes abrupt regime shifts and does not account for gradual, smooth transitions between different levels of climate risk media intensity. Future research could seek to overcome these limitations by incorporating broader risk indicators and using panel smoothing techniques, such as panel smooth transition regression (PSTR), to investigate whether the effect of media-conveyed climate risk on bank credit risk evolves more gradually. Furthermore, we used indices measuring media coverage of policy decisions and climate-related natural disasters; however, other climate-related measures could also be considered. For example, physical climate risk could be assessed using regional climate data, and transition climate risk could be measured by developing a specific indicator for each bank. Finally, according to Birindelli et al. (2022), it would be interesting to understand the extent to which banks' commitment to climate change issues impacts their credit risk and whether this relationship is moderated by the environmental performance of the country where the bank is located. Lastly, while our robustness checks provide strong support for the stability of the results, they are based exclusively on quantitative evidence. Future research may complement these results with qualitative approaches, such as interviews with bank risk managers, regulators, or policymakers, to offer a deeper understanding of the management mechanisms through which media-driven climate risks may influence banks' credit risk and lending decisions.

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