The relationship between bank non – performing loans and climate policy uncertainty: A global perspective

Abstract:
This study investigates the relationship between bank non-performing loans (NPL) and climate policy uncertainty. Using a fixed effect based on panel data from 21 countries over the period 2010–2023, the study found empirical evidence of a statistically significant positive relation between climate policy uncertainty and bank - nonperforming loans. The findings suggest that uncertainty climate policies increase credit risk in the banking sector, adversely affecting business performance and investment decisions. Moreover, the impact of climate policy uncertainty on NPL is more pronounced in countries with weaker institutional frameworks and higher carbon intensity, as these conditions amplify financial instability by hindering effective risk assessment and increasing exposure to default risks, particularly in carbon-intensive industries. Therefore, also emphasize the importance of strengthening institutional quality and reducing carbon intensity in countries by focusing on enhancing regulatory clarity, establishing robust institutional frameworks, and facilitating the transition to low-carbon economies to safeguard financial sector resilience.
Keywords: *Nonperforming loans, Climate policy uncertainty, Institutional quality, sustainable development*

1. Introduction

Climate change has become an urgent global crisis, disrupting economies, straining resources, and reshaping financial landscapes. The increasing frequency and intensity of extreme weather events, coupled with rising carbon emissions, pose severe risks to societies and businesses alike. Climate change presents significant risks to the banking system, affecting asset quality, credit risk, and overall financial stability. Physical risks, including natural disasters and shifting weather patterns, can lead to increased loan defaults in sectors highly exposed to environmental changes. Transition risks, stemming from policy shifts and market adjustments, may reduce the value of carbon-intensive assets, thereby impacting the financial health of banks and other lending institutions. Existing literature underscores the importance of incorporating climate risks into financial regulation. Battiston et al. (2017) highlight the financial sector's vulnerability to climate-related risks and emphasize the necessity of integrating climate considerations into regulatory frameworks. Similarly, Dietz et al. (2016) examine the potential financial losses associated with climate change and stress the importance of strong policy interventions to mitigate these risks. These findings underscore the need for coordinated policy measures to enhance financial system stability in the face of climate-related uncertainties.

To address these challenges, governments worldwide have implemented various climate policies aimed at mitigating risks and promoting sustainability. Key measures such as carbon pricing, emission reduction targets, and renewable energy incentives play a crucial role in driving the transition toward a low-carbon economy. These regulations are designed to encourage sustainable investments, reduce dependence on fossil fuels, and enhance climate resilience.

However, policy instability remains a major obstacle. Frequent regulatory shifts, inconsistent commitments across nations, and delays in implementation create uncertainty for businesses and financial institutions. This unpredictability not only hampers investment in sustainable projects but also amplifies financial risks-physical risks from climate-related disasters and transition risks linked to the devaluation of carbon-intensive assets.

Climate Policy Uncertainty (CPU) significantly impacts economic growth, investment, financial markets, and consumer behavior. CPU refers to the unpredictability of government decisions, regulations, and policies related to climate change and the environment. Policy instability slows the transition to a low-carbon economy and creates risks for businesses and financial markets. Baker et al. (2016) demonstrated that policy uncertainty leads to reduced investment and economic stagnation, while Pástor & Veronesi (2013) highlighted its effect on stock market volatility, undermining investor confidence. IMF research finds that rising climate uncertainty can reduce GDP growth by 0.3% and increase economic volatility by 0.7%. Higher CPU discourages long-term capital allocation to green technologies and infrastructure, further weakening economic stability.

In the banking sector, CPU directly affects investment decisions, credit risk management, and overall financial stability. Unclear or frequently changing climate regulations make it difficult for banks to assess credit risk, particularly in industries such as energy, manufacturing, and real estate. The introduction of carbon taxes or stricter emission limits can financially strain businesses in fossil fuel-intensive sectors, increasing non-performing loan ratios and weakening credit portfolio quality. Conversely, inconsistent government support for renewable energy may hinder the profitability of green projects, making banks more hesitant to provide long-term financing. Additionally, CPU impacts asset valuations and investment portfolios, as shifting policies create uncertainty in the valuation of carbon-intensive and clean energy assets (Bolton & Kacperczyk, 2021). Rising CPU also increases financing costs for businesses in regulated industries, as lenders incorporate policy risks into credit pricing, leading to market distortions and heightened default risks. To mitigate these challenges, governments must establish clear, stable, and predictable climate policies that enable businesses and investors to make informed long-term decisions. A well-defined climate policy framework not only fosters sustainable growth but also reduces financial instability, supporting long-term economic resilience.

The selection of these 21 countries from 2010 to 2023 ensures a representative sample of both developed and developing economies, providing a comprehensive perspective on global economic and financial dynamics. Advanced economies such as the United States, United Kingdom, Germany, and Japan function as key financial centers with well-established regulatory frameworks, while emerging markets like Brazil, China, India, and Mexico play a critical role in global supply chains and are more susceptible to climate-related risks. Existing literature highlights the differential impact of climate policies on financial stability across economies. For instance, Dell et al. (2012) emphasize that climate change disproportionately affects developing economies, while Bolton and Kacperczyk (2021) argue that financial markets in developed economies are increasingly sensitive to climate-related risks. These 21 countries collectively account for a significant share of global GDP, trade, and investment, with major financial hubs such as New York, London, and Singapore influencing international markets. Furthermore, most are active participants in organizations such as the G7, G20, and WTO, shaping global economic, financial, and climate policies. Their inclusion enables a comprehensive analysis of the differential impacts of climate-related financial risks and policy uncertainty across economies at varying stages of development.

However, currently there is not much extensive empirical research on the relationship between climate policy uncertainty and non-performing loan ratio in these countries. Although there are many theories indicating that climate policy uncertainty can reduce investment, increase financial risk and affect firms' ability to repay debt, more quantitative studies are needed to determine the true extent of CPU's impact on NPL. This study aims to fill this gap by employing an econometric model that examines the effect of CPU on NPL ratios across a panel of developed and developing economies. The analysis leverages country-level data on climate policy uncertainty, financial stability indicators, and macroeconomic variables to provide empirical evidence on this relationship. The key findings suggest that heightened CPU is associated with rising NPL ratios, particularly in emerging markets where institution quality and carbon intensity are less robust. The findings have important implications for policymakers and financial institutions, helping banks refine risk assessments and guiding governments in designing climate policies that minimize financial disruptions.

The remainder of this study is organized as follows. Section 2 discusses the literature and presents hypotheses. Section 3 discusses the data collection, research framework and research methodology. Section 4 presents the study results and discusses their implications. Finally, the paper is concluded in section 5 with a summary of the main findings and their significance.

2. Literature review

2.1. Bank Non-Performing Loans (NPL) and its determinants

2.1.1. Definition and classification of Non-Performing Loans

Non-Performing Loan (NPL) refers to loans where borrowers fail to fulfill their repayment obligations as agreed in the initial contract. While definitions vary by country and institution, a loan is generally classified as non-performing if principal or interest payments are overdue by 90 days or more (Fofack, 2005). Some studies expand this definition to include problematic loans (Bernstein, 2004) or those that cease to generate profits for banks (Ernst & Young, 2004). In Vietnam, the State Bank defines NPL as loans overdue by 90 days or more beyond the contractual due date.

Due to the absence of a globally unified standard or guideline, the assessment and classification of NPL may vary depending on legal regulations, accounting standards, and risk management policies of different banking systems. For instance, a loan may be classified as NPL if interest payments within 90 days have been capitalized, refinanced, or deferred under a new agreement rather than paid on time. Additionally, if a loan is less than 90 days overdue but the lender no longer believes in the borrower's repayment capacity, it may still be classified as an NPL. Furthermore, loans that have reached maturity but remain unpaid are also considered NPL. The rise in NPL ratios not only affects the operational efficiency of banks but also erodes investor confidence and negatively impacts macroeconomic stability.

2.1.2. Negative impacts of Non-Performing Loans on the financial system and the economy system

A high non-performing loans (NPL) ratio in the banking system can lead to numerous negative consequences for both the financial system and the broader economy. First, when the NPL ratio rises, banks must allocate financial and human resources to handle non-performing debts, reducing their ability to extend new credit to the economy. This situation can suppress investment and consumption, thereby hindering economic growth. According to the study by Kostis (2020), non-performing loans are an inevitable consequence of abundant credit supply during periods of economic growth, and when the economic cycle reverses, rising NPL negatively impacts banks' lending capacity.

Beyond restricting credit supply, high NPL levels also increase funding costs. As credit risk escalates, banks are forced to offer higher interest rates to attract capital, and these increased costs are typically passed on to borrowers in the form of higher lending rates. As a result, financing costs for businesses and individuals rise, discouraging investment and business expansion. During the 2008-2009 global financial crisis, soaring NPL levels in many countries disrupted credit flows, plunging economies into deep recessions. For example, in the United States, the banking sector's NPL ratio surged from 1.5% in 2007 to 5.3% in 2010, triggering a wave of bank failures and significantly reducing businesses' access to credit (IMF, 2010).

Additionally, a high NPL ratio undermines investor and depositor confidence in the banking system, potentially leading to large-scale capital withdrawals and liquidity crises. When customers fear for a bank's stability, they tend to withdraw deposits or shift assets to alternative investment channels, exerting liquidity pressure on banks and weakening overall financial stability. According to the International Monetary Fund (IMF) report in 2010, during the financial crisis, Greek banks experienced a substantial decline in liquidity due to rising NPL levels and deteriorating customer confidence.

More importantly, the adverse effects of NPL extend beyond the banking sector and directly impact economic growth. When credit flows shrink and financial market confidence deteriorates, businesses face difficulties in expanding operations, while consumers become more cautious in their spending. This leads to a decline in aggregate demand, slowing economic recovery and growth. During the European debt crisis from 2010 to 2012, surging NPL ratios in countries such as Greece, Spain, and Italy significantly contributed to economic recessions. In particular, Greece's GDP contracted by up to 28% from its peak in 2007, marking one of the most severe peacetime economic downturns in a developed country (Lenoel, 2023).

Overall, NPL not only affects banking operations but also generates spillover effects across the entire economy. When NPL ratios exceed manageable levels, governments and financial regulators must implement stringent measures to mitigate risks and safeguard financial stability. This necessitates more prudent credit policies and stricter regulatory oversight to prevent the accumulation of non-performing loans, thereby ensuring sustainable economic development.

2.1.3. Factors affecting Non-Performing Loans

The non-performing loan (NPL) ratio in the banking system is shaped by macroeconomic and microeconomic factors, including economic growth, interest rates, monetary policy, and bank governance quality. Economic growth has an inverse relationship with NPL ratios, as higher GDP boosts income and loan repayment capacity, while downturns increase defaults (Salas et al., 2024; Vo et al., 2020). Interest rates also significantly impact NPL levels—higher rates raise borrowing costs, leading to more defaults, whereas lower rates ease repayment burdens (Espinoza & Prasad, 2010; European Central Bank, 2011).

Monetary policy plays a dual role: expansionary policies reduce NPL in the short term by improving credit accessibility, but excessive lending can later elevate default risks (Anwar et al., 2023). Bank governance quality is another critical determinant, as institutions with strong risk management and oversight tend to maintain lower NPL ratios. In contrast, weak governance, excessive credit expansion, or lack of transparency contribute to higher default risks (Khan et al., 2020).

Overall, NPL ratios reflect both the financial health of banks and broader economic conditions. Understanding these key drivers enables banks to enhance risk management strategies and helps policymakers implement measures to ensure financial system stability.

2.2. Climate Policy Uncertainty and economic impacts

2.2.1. Definition of Climate Policy

Climate policy consists of strategies designed to mitigate climate change and promote sustainability (Dupont et al., 2024). These policies focus on reducing greenhouse gas emissions, increasing renewable energy use, and strengthening resilience against climate impacts, aligning with Sustainable Development Goal 13 (Nature, 2023).

Climate policies can be classified into four main categories. Mitigation policies aim to reduce emissions through measures like the Emission Trading System (ETS), which helped the EU cut industrial emissions by 48% from 2005 to 2023. Carbon taxation, as seen in Sweden, has driven a 27% emissions reduction while supporting economic growth. Adaptation policies enhance climate resilience, exemplified by the Netherlands' "Room for the River" flood control program and Vietnam's climate-smart rice cultivation. Financial and technological support policies provide essential resources, such as the UN's Green Climate Fund, which aims to mobilize $100 billion annually for developing nations. Clean technology transfers, including solar energy projects in Africa, have expanded renewable energy access. Education and awareness policies promote behavioral change, with climate education integrated into national curricula and campaigns like "Earth Hour" encouraging public engagement.

These interconnected policies collectively support emission reductions, climate adaptation, and long-term sustainable development. A coordinated approach is crucial for fostering economic growth while ensuring climate resilience.

2.2.2. Explanation of Uncertainty in Climate Policy

Climate Policy Uncertainty (CPU) refers to the degree of uncertainty regarding government regulations, policy directions, and interventions related to climate change. CPU arises from changes in policy commitments, inconsistencies among regulatory agencies, or economic and political factors that influence the policymaking process. According to the study by Gavriilidis (2021), CPU is measured by the frequency of news articles related to climate policy uncertainty published in leading U.S. newspapers.

One of the primary causes of CPU is the frequent changes in legal frameworks and policy objectives. Governments may alter emission standards, adjust carbon taxes, or introduce new regulations without a clear roadmap, making it difficult for businesses and investors to predict the long-term impact of these decisions. The study by Fried et al. (2021) analyzed how uncertainty regarding when the U.S. federal government would implement climate policy created risks in investment decisions related to carbon-intensive capital. Additionally, differences in political perspectives between successive administrations also contribute significantly to CPU (Basseches et al., 2022). For example, in the United States, climate policy has fluctuated considerably across presidential terms, from withdrawing from the Paris Agreement under President Trump (2017) to rejoining under President Biden (2021). Subsequently, upon reassuming office, President Donald Trump once again withdrew the United States from the Paris Agreement, reversing U.S. climate policy (npr (2025)). This serves as a clear illustration of the uncertainty surrounding climate policy.

2.2.3. Climate Policy Uncertainty's impact on economic and financial dynamics

Climate Policy Uncertainty (CPU) can have extensive effects on investment decisions, capital flows, and economic stability. When climate policies are inconsistent, lack transparency, or risk sudden changes, businesses and investors tend to become more cautious, thereby weakening the momentum for sustainable economic development.

First, CPU reduces long-term investments as businesses require a stable policy environment to plan finances and implement development projects. In the renewable energy sector, many firms face risks when subsidies, tax incentives, or emission regulations frequently change. For instance, in Spain, the government initially committed to supporting solar energy development through a subsidy mechanism. However, in 2010, the government cut subsidies for wind and solar thermal energy, leading to a 35% reduction in subsidies for wind power producers by 2013 due to budgetary pressures, causing numerous clean energy companies to go bankrupt (Reuters, 2010). This abrupt policy shift significantly undermined investor confidence and hindered the growth of the renewable energy sector for years.

Additionally, CPU negatively impacts international capital flows, particularly Foreign Direct Investment (FDI). When a country's climate policy lacks clarity, foreign investors tend to withdraw capital or redirect investments to more stable markets. A study by Eweade and Gungor (2024) found that climate policy uncertainty correlates with reduced trade openness and FDI, whereas economic growth has a positive effect on both trade openness and FDI. Another study by Soussane et al. (2023), based on data from 200 countries spanning from 1970 to 2020, indicated that climate change acts as a financial risk for foreign investors. Multinational corporations often seek internationalization in regions with minimal financial risks, including those arising from climate change's impact on profits and productivity.

Beyond investment and capital flows, CPU also creates systemic risks in the economy due to heightened asset price volatility and financial market fluctuations. When governments introduce climate-related policies without adequate preparation or a clear roadmap, stock values in the energy, manufacturing, and transportation industries can be significantly affected. Lasisi et al. (2024) employed the GARCH-MIDAS model to examine the relationship between CPU and stock market volatility. The results indicated that stock market fluctuations respond significantly to CPU, and monitoring CPU provides both forecasting and economic benefits compared to disregarding it. The study underscores the importance of establishing clear and consistent climate policies to mitigate risks and volatility in financial markets, particularly for industries sensitive to climate policies.

Moreover, CPU strongly impacts high-carbon-emission industries such as oil and gas, mining, and steel production. When governments fail to provide a clear roadmap for emission regulations, companies in these sectors struggle with long-term planning. A notable example occurred between 2020 and 2023, when the U.S. and EU continuously altered their commitments to emission reduction policies, leading to substantial fluctuations in the market capitalization of major oil companies like Exxon Mobil, BP, and Shell. This volatility forced firms to delay or cut numerous investment projects, resulting in significant job losses in the industry and negatively affecting the global economy. Specifically, in October 2024, BP abandoned its goal of reducing oil and gas production by 2030, reflecting a strategic adjustment due to policy uncertainty (Reuters, 2024).

In conclusion, CPU not only weakens investment momentum and capital attraction but also generates systemic risks for financial markets and threatens economic stability. Without effective control measures and policy consistency, these uncertainties may continue to impede the transition toward a green and sustainable economy.

2.2.4. Policy risks impact the financial system

Climate Policy Uncertainty (CPU) has far-reaching effects on the global financial system, influencing key aspects such as banks' lending capacity, corporate capital costs, stock market volatility, systemic financial risks, exchange rate fluctuations, and crude oil prices. Recent empirical studies have provided substantial evidence of these impacts while emphasizing the importance of stable climate policies in ensuring the sustainability of financial markets.

One of the most pronounced impacts of Climate Policy Uncertainty (CPU) is its effect on macro-financial stability, particularly exchange rate volatility in developing economies. A study by Afshan et al. (2023) analyzed the interconnected effects of climate policy on economic policy uncertainty and geopolitical risk in relation to currency valuation in ASEAN countries from 2000 to 2022. The results indicate that rising climate policy uncertainty increases exchange rate volatility, amplifying the effects of economic policy uncertainty and geopolitical risk. This, in turn, may negatively affect macroeconomic stability and long-term economic growth in the region. Moreover, the study highlights a bidirectional relationship between climate policy uncertainty and exchange rate fluctuations, further reinforcing its implications for macroeconomic stability and sustainable economic expansion. Another study by Owjimehr et al. (2025) focuses on European countries from 2000 to 2022, analyzing how CPU, along with other climate shocks, influences financial stress. The findings indicate that while climate shocks may initially reduce financial stress—possibly due to their short-term effects on stock and currency markets—they lead to increased financial stress across all financial sectors over time. These studies underscore the importance of effective risk management strategies in the financial sector to mitigate climate-related risks.

In addition, CPU also increases financial risk, significantly affecting corporate performance. As policy risks rise, investors demand higher returns to compensate for uncertainty, leading to higher capital raising costs, especially for high-carbon-emitting companies. Zhao et al. (2025) analyzed the impact of climate policy uncertainty on the investment activities of listed companies in China from 2008 to 2022. The study shows that an increase in CPU reduces the investment levels of companies, particularly for those with high carbon emissions and state-owned enterprises. The authors also emphasize that when CPU increases, businesses face greater financial risks, resulting in higher capital costs and reduced investment capacity. Liu et al. (2023) found that CPU may drive innovation in certain industries but also increase financial risks and the likelihood of bankruptcy, especially for companies facing sudden policy changes. Therefore, climate policy uncertainty not only affects investment strategies but also poses significant challenges to corporate financial stability.

Climate Policy Uncertainty (CPU) has far-reaching impacts on corporate finance, altering investment strategies and capital allocation. The study by Ren et al. (2023) shows that as the level of climate policy uncertainty increases, businesses tend to reduce investment in financial assets, focusing instead on maintaining liquidity and core operations to mitigate the potential risks arising from policy changes. Gao et al. (2023) analyzed the impact of CPU on the U.S. tourism and hospitality industry. Based on data collected from 2001 to 2020, the study found that CPU reduces investment flows into sustainable tourism projects, while also increasing borrowing costs and decreasing investor confidence. These factors negatively affect the long-term growth of the industry and present challenges in balancing profit with environmental responsibility. These findings emphasize the importance of maintaining stable climate policies to help businesses devise effective financial strategies and minimize risks associated with uncertainty in the business environment.

In the energy sector, climate policy uncertainty significantly impacts crude oil prices and investment strategies within the industry. Research by He et al. (2024) demonstrated that fluctuations in CPU can serve as a predictor of crude oil price volatility through a dual-channel effect involving economic activity and financial markets. Specifically, as CPU levels rise, crude oil markets become more volatile, affecting investment decisions and business strategies within the energy sector. This study emphasizes the importance of continuous monitoring and assessment of CPU to forecast and manage crude oil price risks effectively.

The empirical evidence presented above not only reinforces the expectation that CPU has profound implications for the global financial system but also underscores the necessity of a clear, stable, and predictable climate policy roadmap. If climate policy uncertainty remains persistently high, financial systems will face escalating risks, thereby hindering capital mobilization efforts for sustainable development projects.

2.3. Hypothesis development

Financial markets are greatly impacted by climate uncertainty in a number of ways, including asset prices (Treepongkaruna et al., 2023, Tedeschi et al., 2024, Xu et al., 2024), investment strategies (Bai et al., 2023), and overall market stability (Liang et al., 2024, Curcio et al., 2023). On the asset side, banks are likely to curtail credit provision in environments of heightened CPU. This reticence stems from the potential adverse impacts of increased uncertainty on the viability of firms and projects that banks might otherwise finance (Berger and Sedunov, 2017; Wang et al., 2022). Companies and sectors heavily reliant on fossil fuels face the risk of asset devaluation as the world shifts towards renewable energy sources and sustainable practices (Treepongkaruna et al., 2023). This includes potential "stranded assets" in the oil, gas, and coal industries. Additionally, extreme weather events and climate-related disasters lead to increased market volatility. For instance, hurricanes, floods, and wildfires can cause sudden and significant drops in asset prices in affected regions and sectors (Di Tommaso et al., 2023; Jiang et al., 2024; Guo et al., 2024).

Creative destruction theory suggests that by providing funding to help replace high-carbon polluting technologies with low-carbon technologies, banks have an opportunity to reduce their own risk (Aghion et al., 2021). This risk reduction can be achieved by protecting the revenue of existing firms and fostering sustainable profits through financial support to adopt new low-carbon technology to reduce firms' financial risk. While the government imposes regulatory pressure on banks, it compels them to expedite their investments in emerging low-carbon technology sectors, such as the renewable energy industry. These investments can potentially boost banks' profitability (Azmi et al., 2021) and reduce their systemic risk (Cerqueti et al., 2021). This positive effect is labeled as the systemic risk reduction hypothesis.

On the other hand, the effects of climate policy uncertainty on bank systemic risk are ambiguous. Past studies on climate policy uncertainty have focused on its effect on the economy, CO_2 emissions, and risk-taking (Peters et al., 2020; Dai and Zhang, 2023). While these studies generate practical implications for bank operations, it is unclear how climate policy uncertainty may affect bank systemic risk. On the one hand, real options theory suggests that any uncertainty, including climate policy uncertainty, induces systemic risk by increasing the likelihood of banks making bad investment decisions due to incomplete information. CPU may also increase loan default risk and stranded asset depreciation for high-carbon firms, thereby increasing banks' exposure to external shocks. This negative effect is referred to as the systemic risk augmentation hypothesis.

H0: Countries with high CPU Index contribute to an increase in NPL ratio.

H1: Countries with high CPU Index contribute to a decrease in NPL ratio.

3. Research methodology

3.1. Data and sample

The sample consists of 132 observations from 21 countries over the period from 2010 to 2023. Regarding the climate uncertainty policy in each country, the author obtained information on climate policy uncertainty from the Economic Policy Uncertainty (EPU) database. The EPU database is a reliable source for measuring climate policy uncertainty, as it captures fluctuations in policy discussions, regulatory changes, and government actions. The data on bank non-performing loans is sourced from the World Development Indicators (WDI) database of the World Bank. Finally, in terms of control variables, the literature incorporates a variety of economic indicators taken from the WDI database, for example, lending interest rate, financial development, unemployment, capital to asset and trade.

3.2. Variable measurement

3.2.1. Non-performing loans

Following earlier empirical studies (e.g., Makri et al., 2014; Saliba et al., 2023), this study uses the ratio of the value of non-performing loans *(NPL)* to the total value of the loan portfolio (NPL/TL) as a measurement of non-performing loans. Non-performing loans *(NPL)* have been widely used as a measure of asset quality among lending institutions and are often associated with failures and financial crises in both the developed and developing world (Kevin Greenidge et al., 2011).

3.2.2. Climate policy uncertainty index

Regarding the independent variable, this study uses the annual global economic policy uncertainty (CPU) index scores collected from the Economic Policy Uncertainty Index website, to examine whether and to what extent climate policy uncertainty affects non-performing loans.

3.2.3. Control variables

To measure the impact of climate policy uncertainty on non-performing loans, this research uses several control variables that are introduced after referring to relevant literature (e.g., Saliba et al., 2023; Musyoka Mutinda & Of Nairobi, 2014; Koju et al., 2018; Kjosevski et al., 2019), including Lending interest rate (*LendRate*) is the bank rate that usually meets the short- and medium-term financing needs of the private sector. GDP per capita (*ln_GDPpc*) is measured as the total Gross Domestic Product (*GDP*) divided by the total population. We also include the domestic credit to the private sector by banks (% of GDP) as a proxy of financial market development (*FinancialDevelopment).* The unemployment rate (*Unemployment)* is measured as the total number of unemployed individuals as a percentage of the total labor force, based on national estimates. Bank capital to asset ratio (%) (*CaptialToAsset*) measured as the bank capital and reserves divided to total assets. *Trade* (% of GDP) is an economic indicator that measures the degree of a country's openness to international trade. It is calculated as the sum of exports and imports of goods and services divided by the total Gross Domestic Product (GDP), expressed as a percentage. The detailed description and source of all variables in my baseline regression model are set out in Table 1.

Table 1: Description of the Variables

Variables	Definitions	Signs	Sources
Dependent variable			
Non-performing loans (NPL)	Value of non-performing loans divided by the total value of the loan portfolio (NPL/TL)		WDI
Independent variables			
Climate policy uncertainty index (CPU)	The level of uncertainty in climate-related policies based on the frequency of relevant terms in major newspaper articles.	+	WDI
Control variables			
Lending interest rate (LendRate)	The lending rate is the bank rate that usually meets the short- and medium-term financing needs of the private sector	+	WDI

Variables	Definitions	Signs	Sources
The GDP per capita (ln GDPpc)	The natural logarithm (ln) of a country's GDP per capita, which is measured as the total Gross Domestic Product (GDP) divided by the total population, expressed in current US dollars.	-	WDI
FinancialDevelopment	Domestic credit provided by the banking sector to GDP (%) (DC/GDP)	-	WDI
Unemployment	Measurement of the total number of unemployed individuals as a percentage of the total labor force, based on national estimates.	+	WDI
Bank capital to asset ratio (%) (CapitalToAsset)	The bank capital and reserves are divided into total assets.	-	WDI
Trade (% of GDP)	The sum of exports and imports of goods and services divided by the total Gross Domestic Product (GDP)	±	WDI

Source. Authors' own compilation

3.3. Model specification

To investigate the impact of Climate policy uncertainty *(CPU)* on Non-performing loans *(NPL)*, this study specify the following model:

$$NPL_{it} = \beta_0 + \beta_1 CPU_{it} + \beta_2 LendRate_{i(t-1)} + \beta_3 ln\, GDPpc_{i(t-1)}$$
$$+ \beta_4 FinancialDevelopment_{i(t-1)} + \beta_5 Unemployment_{i(t-1)}$$
$$+ \beta_6 CapitalToAsset_{i(t-1)} + \beta_7 Trade_{i(t-1)}$$

The subscripts i and t denote a country and year respectively, whereas t-1 represents one year lagged. Further, β is the constant and ε is the error term.

By incorporating lagged variables into our model, we aim to establish the causal relationship between climate policy uncertainty and non-performing loans. Accounting for delayed effects smooths short-term fluctuations, providing more reliable insights into the long-term impact of climate policy uncertainty on financial stability. Given that regulatory uncertainty may influence economic activity, investment decisions, and credit risk, understanding this relationship is crucial for assessing the resilience of the banking sector under evolving climate policies.

4. Empirical results and discussion

4.1. Descriptive statistics and correlation analysis

Table 2: Descriptive Statistics

	N	Mean	SD	Min	p25	Median	p75	Max
NPL	132	3.922	4.071	.233	1.313	2.175	5.203	18.064
CPUIndex	132	4.902	0.540	3.296	4.582	4.927	5.202	6.377

ln GDPpc	132	9.813	1.072	7.111	9.223	10.089	10.668	11.175
LendRate	132	8.547	10.066	.5	3.548	5.316	8.726	52.1
FinancialDevelopment	132	83.368	45.754	13.805	50.79	72.669	124.385	184.367
Unemployment	132	6.018	2.693	1.827	3.875	5.292	7.601	13.697
CapitalToAsset	132	7.511	1.658	4.315	6.181	7.707	8.791	10.852
Trade	132	70.797	77.596	23.08	35.091	49.778	68.595	379.099

Source. Authors' own compilation

The details of variables are described in Table 2. The total number of observations required is 132. The mean *NPL* ratio accounts for 3.922% of total loans, with a standard deviation of 4.071%, indicating significant differences across countries. *NPL* ratio ranges from 0.233% to 18.064%, highlighting substantial disparities in *NPL* levels among the analyzed nations. The *CPU Index* has a mean of 4.902%, representing the share of articles discussing climate policy uncertainty. It ranges from 3.296% to 6.377%, with a standard deviation of 0.540%, indicating moderate cross-country differences. The mean values of *ln_GDPpc*, *LendRate, FinancialDevelopment, Unemployment, CapitalToAsset, Trade* are $9.813, 8.547%, 83.368%, 6.018%, 7.511%, and 70,797% respectively.

Table 3: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	VIF
(1) NPL	1.000								
(2) CPUIndex	-0.134	1.000							1.65
(3) ln_GDPpc	-0.349	0.241	1.000						1.81
(4) LendRate	0.015	0.171	-0.346	1.000					1.79
(5) FinancialDevelopment	-0.359	0.497	0.530	-0.260	1.000				2.90
(6) Unemployment	0.405	0.174	0.056	0.414	-0.092	1.000			1.52
(7) CapitalToAsset	-0.167	-0.070	-0.164	0.350	-0.508	-0.022	1.000		1.86
(8) Trade	-0.223	0.011	0.305	-0.176	0.248	-0.277	0.114	1.000	1.33

Source. Authors' own compilation

Table 3 presents the Pearson correlation matrix to examine multicollinearity among *NPL* (dependent variable), *CPU Index* (independent variable), and other key control variables used in the baseline regression analysis. Overall, all correlation coefficients are below 0.70, indicating no serious issues with correlation in this model.

Additionally, to test the potential effect of multicollinearity, we calculate the variance inflation factor (VIF), which is presented in the last column of Table 3. All variables have a VIF below 2.90, which is significantly lower than the standard threshold of 10 (O'Brien, 2007). The overall mean VIF value is 1.84, indicating that multicollinearity is not a concern in this empirical model.

4.2. Baseline regression results

Panel A of Table 4 presents the result of the baseline model to examine the impact of *CPU Index* on *NPL*. Column 1 shows the result of the model without fixed-effects (No FEs) to capture the overall relationship without accounting for unobserved heterogeneity across time or countries. Column 2 shows the result of the model using year fixed-effects (Year FEs) to eliminate general year-to-year time fluctuations that affect on NPL.

As can be seen in Panel A of Table 4, the estimated coefficients of *CPU Index* are positive and statistically significant at both estimations. When year fixed-effects (Year FEs) are included in the model, then the impact of *CPU Index* on *NPL* becomes even stronger (column 2). This result suggests that uncertainty climate policies (*CPU Index*) increases, which in turn negatively affects the financial system and raises the non-performing loan (*NPL*) ratio in the following year, this supports our hypothesis H0 (H0: Countries with high CPU Index contribute to an increase in NPL ratio). This effect may stem from the fact that policy uncertainty makes it difficult for businesses and investors to make long-term financial decisions, increasing the risk of default and reducing the financial institutions' ability to maintain liquidity. Our findings are consistent with prior research indicating that the *CPU Index* negatively influences bank value by worsening the effects of NPL (Fan et al., 2024). Our results support prior research, confirming that *CPU Index* not only reduces bank value but also directly increases the *NPL* ratio in the following year.

The results indicate that several control variables have a significant impact on *NPL*. *Unemployment* has a positive and statistically significant effect (both 2 columns), suggesting that higher unemployment rates lead to increased *NPL*, consistent with prior studies (Koju et al., 2018; Vo et al., 2020). Trade also shows a positive relationship with *NPL*, implying that countries with greater international trade exposure tend to have lower *NPL* due to improved liquidity and access to diverse capital sources, and vice versa.

The remaining control variables all have negative estimated coefficients and are statistically significant in both columns. Specifically, *ln GDPpc* has a significantly strong impact on *NPL*, this suggests that economic development enhances debt repayment capacity and reduces credit risk for banks (Koju et al., 2018; Mensah & Adjei, 2015). *CapitalToAsset* is also negative and statistically significant for NPL, meaning that banks with higher capital adequacy levels tend to have a better ability to absorb credit risk, which helps manage and reduce the risks associated with non-performing loans (*NPL*) (Anjom & Karim, 2015). Similarly, *FinancialDevelopment* and *LendRate* have impacts on NPL (Anjom & Karim, 2015) but influence on NPL is less pronounced compared to control variables as mentioned above.

Table 4: Baseline Regression Result and Robustness Tests

Panel A: Main result

VARIABLES	(1) No FEs	(2) Year FEs
L.CPUIndex	1.159*	2.031***
	(0.628)	(0.672)
L.ln_GDPpc	-1.254***	-1.659***
	(0.328)	(0.342)
L.LendRate	-0.114***	-0.160***
	(0.036)	(0.037)
L.FinancialDevelopment	-0.044***	-0.043***
	(0.010)	(0.010)
L.Unemployment	0.714***	0.824***
	(0.120)	(0.122)
L.CapitalToAsset	-0.916***	-0.752***
	(0.216)	(0.219)
L.Trade	0.007*	0.007*
	(0.004)	(0.004)
Constant	17.086***	15.249***
	(3.732)	(3.785)
Observations	127	127
R-squared	0.480	0.545

Panel B: Robusstness tests

VARIABLES	(3) Alternative clustering	(4) Exclude Covid
L.CPUIndex	2.031***	2.008**
	(0.446)	(0.852)
L.ln_GDPpc	-1.659***	-1.634***
	(0.330)	(0.362)
L.LendRate	-0.160***	-0.146***
	(0.034)	(0.047)
L.FinancialDevelopment	-0.043***	-0.055***
	(0.008)	(0.011)
L.Unemployment	0.824***	1.012***
	(0.155)	(0.188)
L.CapitalToAsset	-0.752***	-1.014***
	(0.153)	(0.253)
L.Trade	0.007**	0.010***
	(0.003)	(0.002)
Constant	15.249***	17.043***
	(2.086)	(4.177)
Observations	127	100
R-squared	0.545	0.586

Panel B: Robusstness tests

VARIABLES	(3) Alternative clustering	(4) Exclude Covid

Note. The table also contains the significance levels (p-values), where ***, **, and * measure the 1%, 5%, and 10% significance levels, respectively.

Source. Authors' own compilation

4.3. Robustness checks

In this section, we conduct several additional analyses to ensure the robustness of our baseline result. The results are presented in Panel B of Table 4. In column 1, we adopt an alternative model specification modifying by adjusting for cross year correlation within countries to test the robustness of this model. This approach allows us to account for persistent country-specific effects over time, ensuring that our results are not driven by unobserved heterogeneity across countries. Furthermore, the 2019 – 2023 period had many significant economic and social disruptions due to the global Covid-19 pandemic, which could strongly impact the variables in our model (He et al., 2020). To mitigate this concern, in column 2, we restrict our sample to the 2010 - 2019 period and re-estimate the baseline model accordingly. The result is largely consistent with our baseline result. As can be seen from the results present in column 2, the impact of *CPU* on *NPL* của các quốc gia remains positive and statistically significant.

The robustness test results are displayed in Table 4 and confirm the previous findings. Overall, our results suggest that both columns yield the same results as the Baseline regression result and the *CPU Index* variables, and control variables remain consistent across all models. Thus, it can be concluded that the model is robust. Furthermore, these results strengthen our research results.

4.4. Additional analysis

To measure the impact of *CPU* on *NPL* and determine whether the impact differs according to the level of Institutional quality, we use the Institutional quality as a moderating variable in the baseline regression model.

Kaufmann et al. (2010) define institutional quality as the manner in which authority is exercised within a country, encompassing three key aspects: government selection and oversight, policy formulation and implementation capacity, and adherence to institutional frameworks governing economic and social interactions. Prior studies have analyzed the relationship between institutional factors and non-performing loans (NPLs) using governance indicators such as the Worldwide Governance Indicators (WGI), which measure voice and accountability, political stability, government effectiveness, regulatory quality, rule of law, and control of corruption.

Table 5: Moderating Role of Institutional quality on the Impact of CPU on NPL

VARIABLES	(1) Low Institutional quality	(2) High Institutional quality
L.CPUIndex	3.442***	1.555**
	(1.015)	(0.648)

L.ln_GDPpc	-0.609	-0.890**
	(0.763)	(0.367)
L.LendRate	-0.215***	-0.020
	(0.049)	(0.091)
L.FinancialDevelopment	-0.070***	-0.027***
	(0.018)	(0.008)
L.Unemployment	0.760***	0.416***
	(0.210)	(0.098)
L.CapitalToAsset	-1.721***	-0.605***
	(0.389)	(0.176)
L.Trade	-0.005	0.007
	(0.006)	(0.005)
Constant	11.645*	7.689
	(6.356)	(5.768)
Observations	57	55
R-squared	0.808	0.694

Note. The table also contains the significance levels (p-values), where ***, **, and * measure the 1%, 5%, and 10% significance levels, respectively.

Source. Authors' own compilation

To examine the role of institutional quality in moderating the effect of Climate Policy Uncertainty (CPU) on NPL, this study classifies 21 countries into Low and High Institutional Quality groups using a median split of the Institutional Quality Index, derived from Principal Component Analysis (PCA) on six governance indicators. Countries below the median are categorized as Low Institutional Quality, while those at or above the median are classified as High Institutional Quality, ensuring a balanced dataset for robust analysis.

The results, presented in Table 5, indicate a significant heterogeneous effect of institutional quality on the relationship between CPU and NPLs. Specifically, countries with lower institutional quality experience a stronger impact of CPU on NPL, as weak governance and risk management make them more vulnerable to policy uncertainty. In contrast, countries with stronger institutional quality demonstrate better risk mitigation and hedging capacity, effectively reducing CPU's adverse effects on NPLs. Additional tests confirm that improved institutional environments significantly lower NPLs across both developed and developing economies (e.g., Goyal et al., 2023; Article & Bayar, 2019; Fajariyanto & Wasiaturrahma, 2024).

Table 6: Moderating Role of Carbon Intensity on the Impact of CPU on NPL

VARIABLES	(1) Lower CarbonIntensity	(2) Higher CarbonIntensity
CPUIndex	1.074	1.833*
	(1.058)	(0.865)
L.ln_GDPpc	-0.460	-1.367
	(0.422)	(0.955)

VARIABLES	(1) Lower CarbonIntensity	(2) Higher CarbonIntensity
L.LendRate	1.388***	-0.091*
	(0.360)	(0.047)
L.FinancialDevelopment	-0.030	-0.032
	(0.019)	(0.026)
L.Unemployment	1.094***	-0.008
	(0.129)	(0.160)
L.CapitalToAsset	-1.554***	-0.038
	(0.370)	(0.247)
L.Trade	-0.000	-0.005
	(0.005)	(0.005)
Constant	5.290	12.018**
	(3.764)	(4.662)
Observations	63	58
R-squared	0.828	0.656

Note. The table also contains the significance levels (p-values), where ***, **, and * measure the 1%, 5%, and 10% significance levels, respectively.

Source. Authors' own compilation

To ensure the heterogeneity of different countries, this study conducts an additional analysis examining the impact of climate policy uncertainty on bank non-performing loans across different levels of carbon intensity.

Specifically, the sample is divided into two subgroups: countries with lower carbon intensity and countries with higher carbon intensity. Countries with carbon intensity below the median are categorized as the lower carbon intensity group, indicating a lower reliance on fossil fuel-based energy sources and a greater adoption of cleaner energy alternatives. In contrast, countries with carbon intensity above the median are classified into the higher carbon intensity group, representing economies that depend more on carbon-intensive industries such as coal, oil, and gas production.

The regression results for both subgroups are presented in Table 6. The results indicate that *CPU* has a stronger effect on *NPL* in economies with higher carbon intensity. This suggests that financial institutions in these economies are more vulnerable to regulatory and transitional risks associated with climate policy changes. In contrast, for economies with lower carbon intensity, the effect of *CPU* on *NPL* is less pronounced, implying that these countries may have a more resilient financial system in the face of climate policy shifts. Notably, the results align with the findings of Bolton and Kacperczyk (2021), who document that financial institutions in high-carbon economies face greater exposure to climate transition risks, leading to deteriorating asset quality. In contrast, studies by Wang et al. (2024) suggest that in low-carbon economies, financial markets are more resilient to policy-induced shocks, as they are less reliant on fossil fuel-based industries.

5. Conclusions and recommendations

5.1. Conclusions

This study highlighted theoretical bases as well as empirical studies to examine the influence of climate policy uncertainty on bank non-performing loans across countries. The data was collected from the World Development Indicators database of the World Bank and the Economic Policy Uncertainty database. Agency database in 21 countries from the period 2010 - 2023. The results indicate that climate policy uncertainty has a significant impact on the level of non-performing loans in the banking sector. Specifically, heightened uncertainty regarding climate policies is positively correlated with an increase in NPLs, as businesses and borrowers face elevated financial risks stemming from regulatory unpredictability and the transition to sustainable practices. Empirical findings suggest that banks operating in countries with higher climate policy uncertainty are more susceptible to increased credit risk, primarily due to the ambiguous regulatory environment that influences investment decisions and business performance.

Furthermore, institutional quality and carbon intensity play a crucial role in mitigating the adverse effects of climate policy uncertainty on banking stability. Strong institutional quality and lower carbon intensity help mitigate these negative impacts. Specifically, well-developed institutions enhance policy credibility and regulatory enforcement, reducing uncertainty for financial markets, while economies with lower carbon intensity face fewer transition risks as they are less reliant on high-emission industries vulnerable to stringent climate policies.

5.2. Policy implications

This study provides critical insights into the relationship between climate policy uncertainty (CPU) and bank non-performing loans (NPLs), offering policy implications for financial regulators and banking institutions. The findings emphasize the necessity of long-term climate policy frameworks, including clearly defined carbon pricing mechanisms, emission reduction targets, and green investment policies, to enhance regulatory certainty and reduce financial risks. Implementing financial incentives for low-carbon industries and disincentives for high-carbon sectors can facilitate an orderly economic transition while mitigating financial instability.

Moreover, institutional quality plays a pivotal role in moderating the adverse effects of CPU on banking stability. Strengthening regulatory frameworks, governance mechanisms, and legal transparency can enhance policy credibility and reduce uncertainty in financial markets. Financial institutions should integrate climate-related risks into banking regulations, implement climate risk stress testing, and adopt environmental, social, and governance (ESG) principles to assess exposure to carbon-intensive industries. These measures can improve risk management practices, reduce NPL accumulation, and promote overall financial stability.

Despite these contributions, the study acknowledges several limitations, including a restricted dataset (21 countries), the challenges of accurately measuring CPU, and the insufficient integration of green financial instruments in credit risk assessment. Future research should focus on expanding the geographical scope of analysis, refining CPU measurement methodologies through big data and policy text analysis, and evaluating the long-term implications of CPU on financial stability. Such advancements will provide robust empirical evidence to support sustainable financial policymaking and enhance the resilience of the banking sector.

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