THE IMPACT OF CARBON MARKETS AND CLIMATE POLICY UNCERTAINTY ON FINANCIAL AND ECONOMIC SUSTAINABILITY: EVIDENCE FROM G7 COUNTRIES

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Abstract

Carbon markets are increasingly recognized as a pivotal mechanism for mitigating greenhouse gas emissions and fostering sustainable growth, yet their implications for financial and economic stability remain contested. Recent research demonstrates that carbon trading enhances long-term development and facilitates sustainable finance, while short-term volatility links carbon futures to fluctuations in green financial instruments such as bonds. In parallel, climate policy uncertainty (CPU) has been shown to amplify systemic risks and erode investor confidence in financial markets. This study provides empirical evidence on the joint effects of carbon markets and CPU on financial and economic stability in G7 countries over the period 2013–2023, marked by major global shocks including the COVID-19 pandemic and international conflicts. Employing panel econometric techniques (ordinary least squares (OLS), fixed effects model (FEM), random effects model (REM), generalized least squares (GLS)) with robustness tests (White, Fisher, Lagrangian multiplier (LM), and Hausman), the findings underscore that carbon markets contribute to long-term economic stability, whereas CPU induces short-term financial instability.

Keywords: Carbon Markets, Climate Policy Uncertainty, Financial and Economic Stability

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1. INTRODUCTION

Climate change has increasingly emerged as one of the most serious challenges to the global economy in the 21st century. Its growing manifestations, such as sea level rise, heatwaves, droughts, floods, and other extreme weather events with increasing frequency and intensity, not only cause direct damage to human lives and assets but also disrupt global supply chains, thereby threatening macroeconomic stability and the integrity of the international financial system. A large body of academic literature has emphasized that the impacts of climate change are multidimensional, with the potential to dampen economic growth, elevate financial risks, and exacerbate social inequality (Nordhaus, 1976; Tebaldi & Beaudin, 2016; Lin & Du, 2017; Rezai et al., 2018; Ferreira et al., 2023). Consequently, addressing climate change has become a top priority in the sustainable development strategies of many countries, particularly advanced economies such as those in the G7 group.

One of the most widely adopted policy instruments for combating climate change is the carbon market — a mechanism that prices greenhouse gas emissions to incentivize emitters to reduce their carbon output through the trading of emission allowances. A prominent example is the European Union Emissions Trading System (EU ETS), launched in 2005 as the world's first and largest multinational emissions trading system in terms of both transaction volume and sectoral coverage. In addition, other G7 countries such as the United States (U.S.), Canada, Japan, and the United Kingdom (UK) have also introduced a series of climate policies, including the Clean Power Plan, the Zero Emission Vehicle Act, the Green Industrial Strategy, and domestic carbon pricing mechanisms. These initiatives not only aim to fulfill commitments under the Paris Agreement but also promote carbon neutrality targets by encouraging a transition to renewable energy, improving energy efficiency, and shifting consumer behavior (Fan et al., 2016; Zhang & Managi, 2020; Lin & Huang, 2022; Ayhan et al., 2023; Geng et al., 2023).

However, despite these positive developments, the implementation of climate policies has often been inconsistent, subject to frequent changes, or lacking clarity in objectives and instruments — thereby increasing the degree of climate policy uncertainty (CPU). Such uncertainty may generate inconsistent market signals, elevate the cost of capital, hinder green investment, and pose risks to financial institutions, particularly in sectors vulnerable to environmental regulations such as energy, heavy industry, and transportation (Ramiah et al., 2013; Liang et al., 2024). Moreover, the volatility in carbon allowance prices driven by policy shifts, market expectations, and economic conditions represents a key factor affecting investment decisions, production efficiency, and the stability of financial markets.

Although these mechanisms have been discussed extensively in the literature, the overall relationship between carbon markets, CPU, and the stability of financial and economic systems remains underexplored from an empirical perspective, especially in today's global context, where climate and policy-related shocks increasingly propagate through financial, trade, and investment channels. The G7 group, comprising advanced economies with large-scale financial systems and a historical responsibility for greenhouse gas emissions, stands both as a major driver of and as a key respondent to climate shocks and policy volatility.

Research on the impacts of carbon markets and CPU on financial and economic stability has attracted increasing scholarly attention. However, to date, only Liang et al. (2024) have employed a network-based approach to conduct an in-depth analysis in the U.S. Building on and extending this line of inquiry, the present study provides a systematic examination of G7 countries during 2013–2023, a period marked by major global shocks, including the European debt crisis, the U.S.-China trade war, the COVID-19 pandemic, and the Russia-Ukraine war. By applying econometric models such as ordinary least squares (OLS), fixed effects model (FEM), and random effects model (REM), together with diagnostic tests, the study offers empirical evidence on the dual impacts of carbon markets and CPU on financial and economic stability.

The purpose of this study is to analyze the impacts of carbon markets and CPU on financial and economic stability in G7 countries. Specifically, it systematizes the theoretical framework, employs quantitative methods for empirical assessment, and examines the G7 experience. The key research question is:

RQ: How do carbon markets and CPU affect financial and economic stability in the G7?

This study is anchored in the literature on climate finance and transition risks, where carbon markets are conceptualized as instruments for internalizing environmental externalities, while policy uncertainty is treated as a source of financial and macroeconomic instability. By focusing on the G7 economies with systemic financial influence and historical responsibility for emissions, this study generates insights with global policy relevance.

This paper contributes to the existing literature by 1) providing new empirical evidence on the dual role of carbon markets and policy uncertainty in shaping stability outcomes in advanced economies; and 2) extending the debate on CPU by distinguishing its effects on financial versus economic stability.

The research team employs OLS, FEM, REM, along with relevant diagnostic tests such as White, Fisher, Breusch-Pagan Lagrangian Multiplier (LM), Hausman, and generalized least squares (GLS), implemented via STATA software, to evaluate the impact of carbon markets and CPU on financial and economic stability in G7 countries during the period from 2010 to 2023.

The remainder of the paper is structured as follows: Section 2 presents the literature review; Section 3 describes the data sources and research methodology; Section 4 presents the empirical results; Section 5 provides the discussion and recommendations; and Section 6 concludes the paper.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Literature review

Many scholars worldwide have examined the relationships between carbon markets, CPU, financial systems, and macroeconomic performance, focusing on their conceptual evolution, empirical measurement, and policy implications. The carbon market, particularly in the post-2015 period, has been widely recognized as a crucial economic mechanism to balance environmental commitments with growth objectives. As global carbon pricing systems expanded following the Paris Agreement, studies such as United Nations Development Programme (2022) underscored the carbon market's role in promoting cost-effective emission reductions, mobilizing green finance, and accelerating low-carbon transitions. Carbon trading systems, especially those in the EU, China, and other emerging economies, have become essential tools to internalize environmental externalities and integrate climate objectives into mainstream fiscal and monetary frameworks. By facilitating price discovery for carbon and stimulating cleaner production technologies, these markets contribute not only to environmental sustainability but also to macroeconomic stability through the reallocation of investment flows toward green sectors.

At the same time, research on CPU has expanded rapidly after 2015, highlighting how fluctuations in environmental regulations, taxation policies, and global governance frameworks influence both financial and economic dynamics. Baker et al. (2016) provided the first quantitative index to measure economic and policy uncertainty, which later served as a foundation for CPU analysis. Pindyck (2017) showed that uncertainty surrounding climate regulation discourages investment in clean technologies and delays corporate adaptation strategies, while Caldara and Iacoviello (2022) confirmed that CPU increases volatility and reduces banking sector resilience, leading to financial fragility. These findings imply that unpredictable policy environments amplify systemic risk and constrain the effectiveness of monetary and fiscal measures. Furthermore, as carbon pricing and climate finance become central to national development strategies, CPU emerges as a determinant of investor confidence and cross-border capital allocation.

From a macrofinancial perspective, both financial and economic stability have been increasingly analyzed through the lens of environmental policy dynamics. According to the International Monetary Fund (2017), maintaining financial stability in the era of climate transition requires not only sound regulatory frameworks but also adaptive risk management in response to policy uncertainty and environmental shocks. Blanchard et al. (2010) originally emphasized that economic stability relies on steady growth, moderate inflation, and low unemployment, and these dimensions have been deeply tested under the pressures of decarbonization policies and the rise of green finance. Since 2015, empirical studies have increasingly validated these linkages. Azzone et al. (2024) demonstrated that EU-issued greenhouse gas allowances exhibit a long-term cointegration relationship with risk-free interest rates and macroeconomic indicators, implying that carbon markets can enhance long-term economic stability while maintaining investment efficiency. However, they found that the effect on financial stability remains short-term and weak, suggesting that the transmission channel from carbon markets to banking resilience is not yet fully developed.

Similarly, Liang et al. (2024) examined the U.S. economy from 2008 to 2022 and confirmed that carbon markets have a positive and sustained effect on economic stability through improved investment confidence and capital efficiency, yet their short-run effects on financial stability are limited due to delayed policy responses. Liang et al. (2022) further provided evidence from China (2003–2020) that CPU negatively affects financial stability through expectations and capital flows, demonstrating that uncertainty-induced capital withdrawal and credit contraction can amplify financial stress. Caldara and Iacoviello (2022), using autoregressive distributed lag (ARDL) and error correction (ECM) models, validated these dynamics in the U.S., showing that long-term policy uncertainty can weaken both credit growth and risk-bearing capacity, with institutional quality shaping the degree of impact.

Despite the convergence of these findings, empirical evidence remains mixed and context-dependent. Liang et al. (2024) revealed that carbon markets and CPU jointly affect U.S. financial and economic stability through interconnectedness networks, with heterogeneous effects across quantiles indicating that the relationship is nonlinear and varies with different levels of volatility. D'Orazio (2025) emphasized the importance of climate-related financial regulations in safeguarding systemic stability during the green transition, arguing that central banks and prudential authorities play a vital role in reducing uncertainty spillovers. Similarly, Anwer et al. (2025) demonstrated that CPU significantly impacts the financing activities of major energy sector institutions, particularly in economies highly exposed to fossil fuel transitions. Morão (2025) provided further evidence from Portugal that CPU substantially affects output and inflation, while He et al. (2025) identified time frequency spillovers between CPU, energy, and stock markets, highlighting the temporal asymmetry of policy effects.

Together, these studies illustrate that the interaction between carbon markets and CPU is complex, nonlinear, and highly sensitive to institutional capacity and policy coherence. Carbon markets tend to promote long-term economic stability by fostering green investment, while CPU undermines short-term financial resilience through uncertainty-driven volatility. This duality creates both challenges and opportunities for policymakers, especially in developed economies where climate commitments are legally binding.

Therefore, this research focuses on the simultaneous impact of carbon markets and CPU on financial and economic stability in G7 countries during the period 2013–2023. By extending recent empirical frameworks and employing quantitative methods such as OLS, FEM, REM, and GLS, it aims to provide updated cross-country evidence, clarify the transmission mechanisms between environmental markets and macrofinancial indicators, and derive

policy implications for enhancing resilience and managing climate-related financial risks under conditions of uncertainty.

2.2. Hypotheses development

2.2.1. European Union Allowance (EUA) carbon price

Azzone et al. (2024) employed an ECM combined with the Johansen cointegration test to analyze the "C spread" phenomenon during Phase III of the EU ETS (2013–2020). Their study revealed a long-term cointegrated relationship between EUA and financial factors such as the Z-index and the risk-free interest rate, with the Z-index being the key explanatory variable. The findings suggest that EUA contributes positively to economic stability in the long run by enhancing liquidity and carbon market efficiency, especially if accepted as collateral by the European Central Bank (ECB). This mechanism promotes green investment and sustainable economic growth. In parallel, Liang et al. (2024) applied a frequency domain, quantile-based, and time-varying conditional network connectivity approach to examine the impacts of the carbon market and CPU on financial and economic stability in the U.S. from July 2008 to August 2022. The study found that the EUA has a positive and persistent effect on economic stability through structural shifts in energy consumption and carbon emission reduction, while its effect on financial stability is short-lived, weak, and extreme.

H1: The carbon market has an impact on financial and economic stability.

2.2.2. Climate policy uncertainty (CPU)

Liang et al. (2022) utilized an ARDL model to analyze the effects of the CPU index on financial stability in China from 2003 to 2020. Their results show a significantly negative long-term effect of CPU on financial stability, primarily through market expectation channels and reduced domestic investment flows. Similarly, Caldara and Iacoviello (2022) used an ARDL-ECM framework with U.S. data from 1997 to 2019 and found that CPU not only increases financial market volatility but also undermines the resilience of the banking system during periods of instability. However, the magnitude and direction of CPU impacts vary across institutional development levels and policy responses, particularly among G7 economies (Organisation for Economic Co-operation and Development [OECD], 2023).

H2: Climate policy uncertainty affects financial and economic stability.

2.2.3. Share of renewable energy consumption (SREC)

Abdibekov et al. (2023) applied a vector autoregression (VAR) model with impulse response and variance decomposition analyses in their comparative study using annual data from 1991 to 2019. The study indicated that share of renewable energy consumption (SREC) positively influences economic growth in Kazakhstan; however, no causal relationship was found based on the Granger causality test. In contrast, no significant relationship between SREC and economic growth was observed in Turkey. The impact of renewable energy shocks on economic growth in both countries is weak and short-term in nature.

H3: The share of renewable energy consumption in total energy use affects financial and economic stability.

2.2.4. National stock index (STOCK)

A study by Umoru et al. (2025) applied an ARDL model to assess the influence of stock market volatility and trading liquidity on yields in emerging Middle East and North Africa markets from 2000 to 2024. The findings show that high stock market volatility and liquidity fluctuations negatively affect yields, particularly under global economic policy uncertainty and exchange rate volatility. Similarly, Khayat and McMillan (2019), applying ARDL-ECM on data from developed economies, including the G7, demonstrated that sustainable stock market development can contribute to financial stability, especially when risk management and regulatory mechanisms are strengthened.

H4: The national stock index affects financial and economic stability.

2.2.5. Net domestic credit (LOAN)

Klein (2013) investigated the impact of net domestic credit on financial stability in emerging markets from 1998 to 2011 using a VAR model and long-term time series analysis. The results indicate that, while domestic credit can stimulate growth, inadequate credit management leads to rising non-performing loans (NPLs) and financial crises, thereby negatively affecting financial stability. Additionally, Foos et al. (2010) applied panel regression to data from developed economies (1997–2007) and found that net domestic credit positively affects economic development in the short term but, without prudent management, contributes to higher NPLs and weakens long-term financial stability. Sunday et al. (2024) also examined the effects of domestic credit on economic performance in Nigeria (1991–2022) using the ARDL bounds testing approach. Their findings suggest that domestic credit (public and private) positively affects gross domestic product (GDP) and interest rates and negatively impacts unemployment, although the short-term effects are statistically insignificant.

H5: Net domestic credit affects financial and economic stability.

2.2.6. Industrial production index (IPI)

Maritsa and Widarjono (2021) employed an ARDL model to examine Islamic banks and financial stability in Indonesia during the period from January 2015 to December 2019. They found that industrial production index (IPI) has a significant negative long-term impact on the stability of Islamic banks. In contrast, Kumar et al. (2024), using a combined ARDL and ECM model, found a positive relationship between IPI and financial stability based on multi-source data from November 2004 to July 2017.

H6: The industrial production index affects financial and economic stability.

2.2.7. Bond yields (BOND)

Petlele and Buthelezi (2025) analyzed the relationship between bond yields and economic growth in South Africa from 1986 to 2004 using a VAR model. Their study revealed a negative correlation between bond yields and GDP. In the short run, rising bond yields lead to temporary reductions in GDP growth. In the long run, persistently high yields correspond to prolonged economic slowdowns before recovery cycles set in.

H7: Bond yields affect financial and economic stability.

3. RESEARCH METHODOLOGY

3.1. Research model

This study employs an econometric model to evaluate the impact of the carbon market and CPU on financial and economic stability in G7 countries over the period from 2013 to 2023. The model is developed based on relevant theoretical frameworks and supported by previous empirical studies.

$$SFE_{i,t} = \beta_0 + \beta_1 EUA_{i,t} + \beta_2 CPU_{i,t} + \beta_3 SREC_{i,t} + \beta_4 STOCK_{i,t} + \beta_5 LOAN_{i,t} + \beta_6 IPI_{i,t} + \beta_7 BOND_{i,t} + \varepsilon_{i,t} \quad (1)$$

where, i denotes the country, t represents the year, and ε is the error term in the model.

• $SFE_{i,t}$ — stability of financial and economic systems: refers to the financial and economic stability of country i in year t, measured by two indicators, $GDPD_{i,t}$ and $FSI_{i,t}$.

Table 1. Variable descriptions in the research model

Characteristics	*Variable name*	*Symbol*	*Calculation method*	*Source*
Independent variables	European Union Allowance carbon price	*EUA*	Monthly data averaged annually by the Authors	Azzone et al. (2024)
	Climate policy uncertainty	*CPU*	Based on the frequency and impact of policy changes related to climate	Caldara and Iacoviello (2022), Liang et al. (2022), OECD (2023)
Dependent variables	Share of renewable energy consumption	*SREC*	$\frac{Renewable\ energy\ consumption}{Total\ energy\ consupmtion} \times 100$	Abdibekov et al. (2023)
	National stock index	*STOCK*	The value of the composite stock index representing the national financial market (e.g., S&P 500, Nikkei 225, DAX 30, CAC 40)	Khayat and McMillan (2019), Umoru et al. (2025)
	Net domestic credit	*LOAN*	$\frac{Total\ domestic\ credit\ to\ the\ private\ sector}{GDP} \times 100$	Klein (2013), Foos et al. (2010), Sunday et al. (2024)
	Industrial production index	*IPI*	The composite index measures the change in industrial output over time, standardized to the base year (here, the base year is 2015)	Maritsa and Widarjono (2021), Kumar et al. (2024)
	Bond yields	*BOND*	The average yield of medium and long-term government bonds, calculated based on market interest rates (%)	Petlele and Buthelezi (2025)

Source: Authors' elaboration.

3.2. Research data

The study uses a sample of G7 over the period from 2013 to 2023. These countries were chosen because the G7 includes large, developed economies that play a central role in the global financial system and have a profound impact on international supply chains as well as energy markets. They are also pioneering nations in designing and implementing carbon pricing mechanisms, such as ETSs and carbon taxes, which contribute to shaping global climate policies. Additionally, the G7 countries have comprehensive, transparent, and high-quality statistical data systems, facilitating the application of quantitative models, impact-oriented assessments, and hypothesis testing in the fields of economics, finance, and environment.

The dataset comprises multiple macroeconomic and climate-related indicators obtained from reliable international databases. Specifically, the carbon emissions allowance price (*EUA*) is sourced from Trading Economics and averaged annually by the Authors. The climate policy uncertainty (*CPU*) index is derived from the OECD Climate Policy Uncertainty Database[1] and the Climate Risk Database-Isetan Energy Finance Network[2], reflecting the frequency and impact of policy changes related to climate.

Macroeconomic variables include GDP deflator (*GDPD*), renewable energy consumption ratio to total energy consumption (*SREC*), and net domestic credit (*LOAN*), all retrieved from the World Bank Open Data platform[3]. The financial stability index (*FSI*) is obtained from the Asian Development Bank ARIC Database[4]. Industrial performance is measured by the industrial production index (*IPI*) from OECD (n.d.). Meanwhile, the national stock index (*STOCK*) and bond yield (*BOND*) are collected from an Investing website.

This study employs a quantitative research design, utilizing panel econometric models to examine the impact of carbon markets and CPU on financial and economic stability in G7 countries. The estimation strategies include pooled OLS, FEM,

[1] https://tinyurl.com/2pnn7w44
[2] https://www.cnefn.com/data/download/climate-risk-database/
[3] https://data.worldbank.org/
[4] https://aric.adb.org/database/fsi

REM, and GLS. To ensure model robustness and selection accuracy, diagnostic tests such as the White test, Fisher test, Breusch-Pagan LM test, and Hausman test are conducted. All empirical analyses are performed using STATA software.

In addition to these baseline approaches, alternative methodologies have been widely applied in literature and could provide further insights into the complex dynamics among the variables under consideration. For instance, Gajardo and Kristjanpoller (2017) adopted the detrended cross-correlation analysis to investigate cross-correlation features, asymmetric multifractality, and directional relationships in financial time series. This approach highlights the nonlinear, asymmetric, and time-varying characteristics inherent in economic and financial data.

Another promising technique is the time varying parameter vector autoregressive (TVP-VAR) model, which has proven to be a powerful tool for analyzing dynamic interdependencies. The TVP-VAR framework can capture evolving relationships, detecting nonlinearities, and exploring the transmission mechanisms across multiple variables over time.

In addition, the time domain connectedness framework developed by Diebold and Yilmaz (2009, 2012, 2014) has been extensively employed in recent empirical research (Maghyereh et al., 2019; Umar et al., 2019; Cui et al., 2021; Le et al., 2021; Su et al., 2022). This approach facilitates the analysis of interconnectedness by constructing network linkages among multiple variables, thereby revealing information flows and complex spillover effects within the system.

By combining the baseline econometric models with potential alternative methodologies, future research may achieve a more comprehensive understanding of how carbon markets and CPU affect financial and economic stability, while also enhancing the robustness and generalizability of empirical findings.

4. EMPIRICAL RESULTS

4.1. Descriptive statistics

To provide an overview of the variables employed in the empirical analysis, Table 2 summarizes the descriptive statistics for seven G7 countries over the period 2013–2023, based on 77 observations.

Table 2. Descriptive statistics

Variable	*Obs.*	*Mean*	*Std. dev.*	*Min*	*Max*
FSI	77	33.4129	7.2810	18.7	46.6
GDPD	77	105.7706	7.9376	96.31	128.48
EUA	77	422.5126	1073.129	-1.879	4337.025
CPU	77	1.6856	0.9072	0	3.64
SREC	63	13.7064	5.2667	5	23.9
STOCK	77	36.4903	14.4985	13.45	74.63
LOAN	65	459.4945	1755.59	2.77	13624.26
IPI	70	0.3486	3.8825	-11	11.7
BOND	77	1.4536	1.1675	-0.52	4.34

Source: Authors' elaboration.

Due to the lack of consistency in data collection, the table reports the number of observations, mean, standard deviation, minimum, and maximum values for each variable and the number of observations varies across variables: *SREC* has 63 observations, *LOAN* has 65, and *IPI* has 70. The average value of *GDPD* is 105.7706 with a standard deviation of 7.9376, ranging from 96.31 to 128.48, with the lowest recorded in Japan (2013) and the highest in the UK (2023). *FSI* has a mean of 33.4129 and a standard deviation of 7.2810, ranging from 18.7 to 46.6, with the lowest in Italy (2020) and the highest in the U.S. (2022). The average *EUA* is 422.5126, with the highest in the U.S. (2023) and the lowest in Japan (2017). *CPU* has an average value of 1.6856, ranging from 0 in Japan (2023) to 3.64 in Germany (2023). The average *SREC* is 13.7064, with the lowest in Japan (2013) and the highest in Canada (2020). The average *STOCK* is 36.4903, ranging from 13.45 in the U.S. (2013) to 74.63 in the UK (2021, 2022). The average *LOAN* is 459.4945, showing considerable variation, with the highest in Japan (2014) at 13,624.26 and the lowest in Italy (2013) at 2.77. The average *IPI* is 0.3486, ranging from -11 in Italy (2020) to 11.7 in Italy (2021). The average *BOND* is 1.4536, with a peak of 4.34 in Italy (2013) and a low of -0.52 in Germany (2020).

4.2. Model tests

4.2.1. Model misspecification tests

Test for correlation

To examine the potential relationships among the variables, a correlation matrix was constructed. Table 3 reports the correlation coefficients between all variables included in the study, allowing us to assess both the strength and direction of pairwise associations and to detect potential multicollinearity issues.

Table 3. Correlation matrix of variables

	FSI	*GDPD*	*EUA*	*CPU*	*SREC*	*STOCK*	*LOAN*	*IPI*	*BOND*
FSI	1.0000								
GDPD		1.0000							
EUA	0.2235	0.2378	1.0000						
CPU	-0.1086	0.7112	0.3066	1.0000					
SREC	0.0190	0.3326	-0.2615	0.0326	1.0000				
STOCK	0.0493	0.2032	-0.3084	0.2108	-0.4961	1.0000			
LOAN	0.0155	-0.2617	-0.1090	-0.3224	-0.3946	0.2316	1.0000		
IPI	0.1679	-0.0276	-0.0194	0.0221	-0.0863	0.0927	0.0197	1.0000	
BOND	0.5520	-0.2317	0.4373	-0.0299	-0.0834	-0.2980	-0.1847	0.2017	1.0000

Source: Authors' elaboration.

The results of the correlation matrix analysis in Table 3 indicate that all independent variables are correlated with the dependent variables, *FSI* and *GDPD*. These correlation results are consistent with most previous studies and align with the Authors' expectations during the research period from 2013 to 2023 in G7 countries. Furthermore, the relationships among the independent variables in the model all have correlation coefficients within the acceptable range, less than 0.8 and greater than -0.8. Therefore, it can be preliminarily concluded that multicollinearity is not present in the research model.

In addition, to ensure the model's validity, a multicollinearity test needs to be conducted. The detection of multicollinearity is based on the tolerance value and the variance inflation factor (VIF). According to Hair et al. (2009), when the VIF reaches 10 or more, strong multicollinearity is likely to occur. Hence, efforts should be made to keep the VIF as low as possible, ideally below 3. Multicollinearity refers to a situation where independent variables in the model are linearly correlated with each other. To test for multicollinearity, the research team employed the VIF model.

Table 4. Variance inflation factor coefficients

Variable	*VIF (FSI)*	*1 / VIF (FSI)*	*VIF (GDPD)*	*1 / VIF (GDPD)*
STOCK	2.62	0.3814	2.62	0.3814
SREC	2.45	0.4081	2.45	0.4081
EUA	2.39	0.4180	2.39	0.4180
CPU	1.75	0.5713	1.75	0.5713
BOND	1.47	0.6780	1.47	0.6780
LOAN	1.44	0.6942	1.44	0.6942
IPI	1.08	0.9217	1.08	0.9217
Mean VIF	1.89		1.89	

Source: Authors' elaboration.

The multicollinearity test results in Table 4 show that the VIF values of all independent variables are less than 10, so the multicollinearity phenomenon in the model is considered not serious.

Heteroscedasticity test

To assess the presence of heteroscedasticity in the estimated models, we employed the chi-square test along with skewness and kurtosis statistics. The results for Model 1 and Model 2 are reported in Table 5 and Table 6, respectively.

Assumptions:

- Assumption 1: No heteroscedasticity.
- Assumption 2: Heteroscedasticity is present.

Table 5. Heteroscedasticity test for Model 1

Source	*chi²*	*df*	*p*
Heteroskedasticity	38.36	35	0.3196
Skewness	4.87	7	0.6756
Kurtosis	3.99	1	0.0457
Total	47.22	43	0.3040

Source: Authors' elaboration.

Table 6. Heteroscedasticity test for Model 2

Source	*chi²*	*df*	*p*
Heteroskedasticity	41.82	35	0.1987
Skewness	16.06	7	0.0117
Kurtosis	0.08	1	0.7828
Total	59.96	43	0.0444

Source: Authors' elaboration.

Model 1

- $chi^2(35) = 38.36$;
- $Prob > chi^2 = 0.3196$.
- At the 5% significance level, we have: Prob = 0.3196 > 5%, so we accept assumption 1, indicating that the model does not exhibit heteroscedasticity.

Model 2

- $chi^2(35) = 41.82$;
- $Prob > chi^2 = 0.1987$.
- At the 5% significance level, we have: Prob = 0.1987 > 5%, so we accept assumption 2, indicating that the model does not exhibit heteroscedasticity.

First-order autocorrelation test

Assumptions:

- Assumption 1: No first-order autocorrelation.
- Assumption 2: First-order autocorrelation is present.

Model 1

- F (1, 5) = 4.682;
- Prob > F = 0.0828.
- At the 5% significance level, we have: Prob = 0.0828 > 5%, so we accept assumption 1, indicating that the model does not exhibit first-order autocorrelation.

Model 2

- F (1, 5) = 27.673;
- Prob > F = 0.0033.
- At the 5% significance level, we have: Prob = 0.0033 < 5%, so assumption 1 is rejected and the alternative assumption 2 is accepted, indicating that the model exhibits first-order autocorrelation.

Summary of diagnostic test results

Based on the diagnostic test results, multicollinearity is not considered a serious issue, and the model does not exhibit heteroscedasticity. However, the presence of first-order autocorrelation is detected in the model.

4.2.2. Model selection tests for Model 1

To evaluate the impact of the explanatory variables on financial stability (*FSI*), we first employed the OLS regression. Table 7 summarizes the regression results for Model 1, including coefficients, standard errors, and significance levels.

A comparison between the pooled OLS and the REM results is also conducted to identify the most appropriate model for explaining financial stability.

Table 7. Regression results for Model 1

Source	*Sum of squares*	*df*	*Mean square*
Model	804.3466	7	114.9067
Residual	669.8926	40	167.4732
Total	1474.2392	47	313.6679
Number of obs = 48 F (7,40) = 6.86 Prob > F = 0.0000 R-squared = 0.5456 Adj. R-squared = 0.4661 Root mean squared error= 4.0923			

Source: Authors' elaboration.

Table 8. Ordinary least squares regression analysis for Model 1

FSI	*Coefficient*	*Std. err.*	*t*	*P > |t|*	*Beta*
EUA	0.0025	0.0009	2.83	0.007	0.4669
CPU	-2.4871	0.9679	-2.57	0.014	-0.3623
SREC	0.8858	0.2358	3.76	0.001	0.6268
STOCK	0.2735	0.0647	4.23	0.000	0.7296
LOAN	0.0004	0.0003	1.11	0.272	0.1423
IPI	0.0571	0.1484	0.39	0.702	0.0427
BOND	3.7623	0.7800	4.82	0.000	0.6244
_cons	12.7217	4.9280	2.58	0.014	

Source: Authors' elaboration.

The REM was also estimated. Table 9 reports the REM results for Model 1, showing the coefficients and corresponding statistical significance.

Table 9. Random effects model regression for Model 1

FSI	*Coefficient*	*Std. err.*	*z*	*P > |z|*	*[95% conf. interval]*	
EUA	0.0025	0.0009	2.83	0.005	0.0008	0.0042
CPU	-2.4871	0.9679	2.57	0.010	-4.3842	-0.5901
SREC	0.8858	0.2358	3.76	0.000	0.4236	1.3479
STOCK	0.2735	0.0647	4.23	0.000	0.1467	0.4003
LOAN	0.0004	0.0004	1.11	0.266	-0.0003	0.0011
IPI	0.0571	0.1484	0.39	0.700	-0.2337	0.3479
BOND	3.7623	0.7800	4.82	0.000	2.2336	5.2911
_cons	12.7217	4.9280	2.58	0.010	3.0631	22.3804
sigma_u	0					
sigma_e	1.9219					
rho	0	(fraction of variance due to u_i)				

Source: Authors' elaboration.

Breusch-Pagan Lagrangian multiplier test

In order to determine the most appropriate specification between the OLS and REM models, the Breusch-Pagan LM test was conducted. The test results are presented in Table 10.

Assumptions:

- Assumption 1: No random effects.
- Assumption 2: Random effects are present.

$$FSI[ID,t] = Xb + u[ID] + e[ID,t] \quad (2)$$

Table 10. Breusch-Pagan Lagrangian multiplier test for Model 1

Components	*Var*	*SD = sqrt(Var)*
FSI	31.3668	5.6006
e	3.6938	1.9219
u	0	0

Source: Authors' elaboration.

Test results:

- Var(u) = 0;
- chibar^2(01) = 0.00;
- Prob > chibar^2 = 1.000.
- At the 5% significance level, we have: Prob > chibar^2 = 1.0000 > 5%, so we accept assumption 1, indicating that the OLS model is more appropriate than the REM model.

In conclusion, the FEM is identified as the most suitable model for the dataset.

First-order autocorrelation test for the fixed effects model

Assumptions:

- Assumption 1: No first-order autocorrelation.
- Assumption 2: First-order autocorrelation is present.

Test results:

- F (1, 5) = 4.682;
- Prob > F = 0.0828.
- At the 5% significance level, we have: Prob = 0.0828 > 5%, so we accept assumption 2, indicating that the model does not exhibit first-order autocorrelation.

Heteroscedasticity test for the fixed effects model

Assumptions:

- Assumption 1: No heteroscedasticity.
- Assumption 2: Heteroscedasticity is present.

Test results:

- chi^2 (6) = 570.67;
- Prob > chi^2 = 0.0000.
- At the 5% significance level, we have: Prob = 0.0000 < 5%, so we reject assumption 1, indicating that the model exhibits heteroscedasticity.

4.2.3. Model selection tests for Model 2

To determine the most appropriate model for Model 2, we first compare OLS and FEM using the Fisher test, and then compare FEM and REM using the Hausman test. The testing procedure is conducted step by step as follows.

The analysis is conducted step by step as follows, beginning with a comparison between the pooled regression (OLS) and the FEM.

Fisher test (F-test)

Assumptions:

- Assumption 1: Choose the OLS model.
- Assumption 2: Choose the FEM model.

Table 11. Regression results for Model 2

Source	*Sum of squares*	*df*	*Mean square*
Model	685.6516	7	97.9502
Residual	117.4500	40	2.9362
Total	803.1015	47	17.0873
Number of obs = 48 F (7,40) = 33.36 Prob > F = 0.0000 R-squared = 0.8538 Adj. R-squared = 0.8282 Root mean squared error= 1.7135			

Source: Authors' elaboration.

Table 12. Ordinary least squares regression analysis for Model 2

GDPD	*Coefficient*	*Std. err.*	*t*	*P > |t|*	*Beta*
EUA	0.0026	0.0004	7.00	0.000	0.6545
CPU	1.8028	0.4053	4.45	0.000	0.3558
SREC	0.8508	0.0987	8.62	0.000	0.6467
STOCK	0.1789	0.0271	6.61	0.000	0.6467
LOAN	0.0001	0.0001	0.70	0.490	0.0506
IPI	0.0356	0.0621	0.57	0.570	0.0361
BOND	-1.0874	0.3266	-3.33	0.002	-0.2445
_cons	83.1398	2.0634	40.29	0.000	

Source: Authors' elaboration.

Table 13. Fixed effect model regression for Model 2

GDPD	*Coefficient*	*Std. err.*	*t*	*P > |t|*	*[95% conf. interval]*	
EUA	0.0031	0.0008	3.70	0.001	0.0014	0.0048
CPU	0.7258	0.6202	1.17	0.250	-0.5331	1.9849
SREC	1.7468	0.2548	6.86	0.000	1.2297	2.2639
STOCK	0.0214	0.0475	0.49	0.629	-0.0733	0.1160
LOAN	0.0001	0.0001	0.65	0.518	-0.0002	0.0003
IPI	0.1174	0.0524	2.24	0.031	0.0111	0.2236
BOND	-1.2686	0.5408	-2.35	0.025	-2.3665	-0.1706
_cons	79.4114	2.8526	27.84	0.000	73.6203	85.2026
sigma_u	5.7623					
sigma_e	1.3478					
rho	0.9481	(fraction of variance due to u_i)				

Note: F test that all u_i = 0: F (5, 35) = 5.93. Prob > F = 0.0005.
Source: Authors' elaboration.

The overall significance of the regression model is evaluated using the F-test. The results show that:

- F (5, 35) = 5.93;
- Prob > F = 0.0005.

- At the 5% significance level, we have: p = 0.0005 < 5%, so we reject assumption 1, and choose the FEM model.

Table 14. Random effect model regression for Model 2

GDPD	*Coefficient*	*Std. err.*	*z*	*P > |z|*	*[95% conf. interval]*	
EUA	0.0026	0.0004	7.00	0.000	0.0018	0.0033
CPU	1.8028	0.4053	4.45	0.000	1.0084	2.5971
SREC	0.8508	0.0987	8.62	0.000	0.6573	1.0443
STOCK	0.1709	0.0271	6.61	0.000	0.1258	0.2320
LOAN	0.0001	0.0001	0.70	0.486	-0.0002	0.0004
IPI	0.0356	0.0621	0.57	0.567	-0.0862	0.1574
BOND	-1.0874	0.3266	-3.33	0.001	-1.7275	-0.4473
_cons	83.1398	2.0634	40.29	0.000	79.0956	87.1841
sigma_u	0					
sigma_e	1.3478					
rho	0	(fraction of variance due to u_i)				

Source: Authors' elaboration.

Hausman test

Assumptions:

- Assumption 1: REM is preferred.
- Assumption 2: FEM is preferred.

Table 15. Hausman test for Model 2

Variable	*FE*	*RE*	*Difference*	*Std.err.*
EUA	0.0031	0.0026	0.0006	0.0008
CPU	0.7258	1.8028	-1.0769	0.4695
SREC	1.7468	0.8508	0.8960	0.2348
STOCK	0.0232	0.1789	-0.1558	0.0391
LOAN	0.0001	0.0001	-0.0000	
IPI	0.1174	0.0356	0.0818	
BOND	-1.2686	-1.0874	-0.1812	0.4311

Source: Authors' elaboration.

The test results indicate that:

- chi2(7) = 31.39;
- Prob > chi2 = 0.0001.
- We observe that Prob = 0.0001 <5%; thus, assumption 1 is rejected, and the FEM is selected.

Based on the Hausman test results, the FEM is selected as the most suitable model, indicating that the unobserved individual effects are correlated with the regressors.

First-order autocorrelation test for the fixed effects model

Assumptions:

- Assumption 1: No first-order autocorrelation.
- Assumption 2: First-order autocorrelation is present.

Test results:

- F (1, 5) = 27.673;
- Prob > F = 0.0033.
- At the 5% significance level, we have: Prob = 0.0033 < 5%, so assumption 1 is rejected, indicating that the model exhibits first-order autocorrelation.

Heteroscedasticity test for the fixed effects model

Assumptions:

- Assumption 1: No heteroscedasticity.
- Assumption 2: Heteroscedasticity is present.

Test results:

- Chi^2 (6) = 31.32;
- Prob > chi2 = 0.0000.
- At the 5% significance level, we have: Prob = 0.0000 < 5%, so we reject assumption 1, indicating that the model exhibits heteroscedasticity.

4.3. Quantitative results assessing the impact of carbon markets and climate policy uncertainty on financial and economic stability

Table 16 below presents the regression results, highlighting both the magnitude and statistical significance of each variable's impact on financial and economic stability. The t-statistics and significance levels provide insight into the strength and direction of these relationships.

Table 16. Regression results

Variable	*FSI*	*GDPD*
EUA	0.025*** (3.98)	0.0025*** (8.45)
CPU	-2.1031*** (-2.72)	1.1697*** (2.73)
SREC	0.9388*** (4.77)	0.7746*** (7.44)
STOCK	0.2365*** (4.80)	0.1543*** (6.65)
LOAN	0.0004* (1.19)	-0.00001* (-0.23)
IPI	0.0744* (0.60)	0.0109* (0.51)
BOND	2.5849*** (3.70)	-1.1234*** (-3.76)

*Note: *** Correlation coefficient is significant at 0.01. ** Correlation coefficient is significant at 0.05. * Correlation coefficient is significant at 0.1.*
Source: Authors' elaboration.

5. DISCUSSION

Building upon the empirical findings in the previous section, this part discusses the validity of the proposed research hypotheses. By comparing the statistical results with theoretical expectations, each hypothesis is evaluated based on the strength and significance of the corresponding evidence. Table 17 summarizes the results of this evaluation.

Table 17. Discussion of research findings

No.	*Hypothesis*	*Result*
1	*H1*: The carbon market has an impact on financial and economic stability.	Accepted
2	*H2*: Climate policy uncertainty affects financial and economic stability.	Accepted
3	*H3*: The share of renewable energy consumption in total energy use affects financial and economic stability.	Partly accepted
4	*H4*: The national stock index affects financial and economic stability.	Partly accepted
5	*H5*: Net domestic credit affects financial and economic stability.	Partly accepted
6	*H6*: The industrial production index affects financial and economic stability.	Partly accepted
7	*H7*: Bond yields affect financial and economic stability.	Partly accepted

Source: Authors' elaboration.

Based on the research findings, the Authors offer several discussions regarding the impact of the carbon market and CPU on financial and economic stability, as follows.

Firstly, the *EUA* is statistically significant at the 1% level, indicating a positive correlation with both *FSI* and *GDPD*. Specifically, a 1 unit increase in *EUA* leads to a 0.0025 unit increase in both *FSI* and *GDPD*. This result aligns with the findings of Azzone et al. (2024), which assert that EUA not only promotes long-term economic stability but also facilitates green investment by enhancing

the liquidity and efficiency of the carbon market, especially when EUA is included in the ECB's collateral framework. However, the Authors' findings partially diverge from those of Liang et al. (2024), who demonstrate that EUA exerts a persistent and positive effect on economic stability through restructuring the energy production and consumption model and reducing carbon emissions. Meanwhile, the carbon market's influence on financial stability is assessed to be short-term, weak, and volatile. These findings underscore the need for deeper investigation into the carbon market's role in maintaining financial and economic stability amidst the transition to a green economy.

Secondly, the *CPU* is statistically significant at the 1% level and negatively impacts *FSI*; a 1 unit increase in *CPU* results in a 2.1031 unit decrease in *FSI*. Conversely, at the same level of significance, *CPU* positively affects *GDPD*, increasing it by 1.1697 units. Consistent with the transmission mechanism perspective, Liang et al. (2022) demonstrate that CPU undermines long-term financial stability through two interconnected channels. CPU deteriorates market expectations by amplifying investor pessimism and uncertainty about future policy directions, which suppresses risk appetite and increases market volatility. As expectations weaken, financial assets experience price instability and liquidity declines, eroding the system's resilience. Moreover, the CPU contributes to a decline in domestic investment flows, as firms delay or scale down long-term investment projects amid heightened regulatory and transition risks. The contraction of domestic capital formation reduces credit demand and limits financial intermediation, further constraining economic growth and weakening the structural foundation of financial stability. In a similar transmission framework, Caldara and Iacoviello (2022) emphasize that CPU heightens financial market volatility and weakens the resilience of the banking sector, particularly during periods of macroeconomic or policy instability. Specifically, elevated CPU amplifies uncertainty shocks that transmit through financial markets by increasing the sensitivity of asset prices and investor sentiment to new information. This heightened volatility erodes market confidence, reduces liquidity, and raises the cost of capital. Simultaneously, the CPU exerts pressure on the banking sector through the credit and balance sheet channels. Increased volatility and weaker loan performance elevate credit risk, constraining banks' lending capacity and impairing their ability to absorb shocks. Consequently, systemic vulnerability intensifies as both market instability and banking fragility reinforce each other, leading to a decline in the overall resilience of the financial system. Notably, the Authors' findings reveal that CPU exerts the strongest and most positive effect on economic stability, which contrasts with Liang et al. (2024), who found that CPU's impact on financial and economic stability is generally weak. This discrepancy highlights the necessity of a more comprehensive examination of the interrelationship among climate policy, financial markets, and economic growth, especially in a macroeconomic context increasingly influenced by environmental factors and carbon regulatory frameworks.

Thirdly, the *SREC* is statistically significant at the 1% level, indicating a positive relationship with both *FSI* and *GDPD*. Specifically, a 1 unit increase in *SREC* corresponds to increases of 0.9388 and 0.7746 units in *FSI* and *GDPD*, respectively. These findings align to some extent with the research by Abdibekov et al. (2023), which confirms that renewable energy consumption positively contributes to economic growth in Kazakhstan, highlighting the role of renewable energy in sustainable development. Although that study found no clear causal relationship and primarily short-term impacts, the empirical evidence still affirms the potential of renewable energy to enhance macroeconomic indicators. Expanding renewable energy not only reduces dependence on fossil fuels but also improves energy security, mitigates market risks, and boosts investor confidence, key elements in fostering financial stability. Moreover, from a green growth perspective, renewable energy investment can create jobs, improve the trade balance, and enhance economic resilience to external shocks. Therefore, renewable energy development is not only an environmental strategy but also a critical lever for long-term financial stability and economic growth.

Fourthly, the *STOCK* is statistically significant at the 1% level, showing a positive relationship with both *FSI* and *GDPD*. A 1 unit increase in *STOCK* corresponds to increases of 0.2365 units in *FSI* and 0.1543 units in *GDPD*. This result supports prior findings by Umoru et al. (2025), which emphasize the important role of stock market development in strengthening financial systems, particularly in emerging markets where liquidity and volatility directly influence yields and financial stability. Likewise, Khayat and McMillan (2019) argue that a well-developed and effectively regulated stock market contributes to macroeconomic stability by swiftly reflecting market signals and enhancing resource allocation efficiency. Additionally, rising stock indices often correlate with improved investor and business confidence, which fuels investment, consumption, and economic growth. Thus, stock indices not only measure market performance but also serve as barometers of a country's financial health and economic stability.

Fifthly, the *LOAN* does not show a statistically significant impact on *FSI* or *GDPD*. This finding is partially consistent with Sunday et al. (2024), who suggest that domestic credit positively affects *GDPD* in the long term but lacks short-term statistical significance. Similarly, Klein (2013) and Foos et al. (2010) emphasize that while net domestic credit can support early-stage economic growth, without proper risk supervision and regulatory measures, it may lead to increased NPLs, inflation, and adverse effects on financial stability. Although many previous studies have demonstrated the long-term benefits of *LOAN* for economic growth, this study finds no compelling evidence of a statistically significant short-term relationship between *LOAN* and *FSI* or *GDPD*. This suggests that the impact of domestic credit may depend on the stage of economic development and the quality of credit policy governance. Therefore, credit expansion should be cautiously managed and accompanied by robust risk control mechanisms to avoid

macroeconomic imbalances and ensure financial stability over the medium and long term.

Sixthly, the *IPI* also exhibits no significant impact on either *FSI* or *GDPD*. These findings diverge from those of Maritsa and Widarjono (2021) and Kumar et al. (2024). Specifically, Maritsa and Widarjono (2021) found that IPI has a significant negative impact on the long-term stability of Islamic banking. In contrast, Kumar et al. (2024) identified a positive relationship between IPI and financial stability using a combination of ARDL and ECM based on data collected from November 2004 to July 2017. The discrepancy in findings raises questions about the context-specific influence of industrial production on financial and economic stability, suggesting the need for further investigation into mediating factors and conditions that determine the extent of IPI's impact on financial systems and economic performance.

Seventhly, the *BOND*, at the 1% significance level, is positively associated with *FSI* but negatively associated with *GDPD*. Specifically, a 1 unit increase in *BOND* leads to a 2.5849 unit increase in *FSI* and a 1.1234 unit decrease in *GDPD*. These findings are consistent with those of Petlele and Buthelezi (2025), who observed a negative correlation between bond yields and economic growth. An increase in bond yields tends to dampen short-term economic growth and, if prolonged, may lead to recession before cyclical recovery. Hence, our findings reinforce the argument that bond yield fluctuations, particularly sharp upward trends, must be closely monitored as they can exert downward pressure on economic activity, especially in economies heavily reliant on credit and public investment. Consequently, interest rate policies and public debt management must strike a balance between controlling borrowing costs and maintaining macroeconomic stability.

Thus, it can be affirmed that to ensure financial stability in the context of climate change, it is necessary to build transparent, long-term climate policies and develop a synchronized carbon market and green financial instruments. This provides a crucial foundation for improving climate governance and enhancing financial resilience in the energy transition process.

6. CONCLUSION

This study provides new empirical insights into the complex relationship between climate-related variables, financial and economic stability. By examining the G7 countries, the analysis demonstrates that carbon markets, CPU, renewable energy, and financial market indicators all exert significant influences on financial stability, thereby offering both academic contributions and practical implications for policymaking.

The results highlight several key findings. Carbon markets, measured by the price of emission allowances in the EU, have a stabilizing effect on financial systems by channeling capital flows toward low-carbon industries and reducing systemic risks. Conversely, CPU negatively affects stability, as inconsistent or unpredictable policies undermine investor confidence and deter long-term green investments. Meanwhile, renewable energy, stock markets, and particularly bond markets support financial and economic stability, underscoring the growing role of green finance in fostering resilient economic systems.

From a policy perspective, the findings suggest the need to stabilize carbon markets, enhance the predictability of climate policies, strengthen risk management in renewable energy finance, and integrate climate considerations into banking and credit systems.

To operationalize these findings, the study proposes a set of short-term and long-term policy actions, prioritized according to their relative importance.

As for the short-term actions (market stabilisation measures), we have two proposals.

Firstly, stabilize the carbon market through price control mechanisms. Empirical results show that carbon price volatility significantly affects financial and economic stability. Sharp and unpredictable fluctuations in carbon prices can generate sudden cost shocks, increase default risks in high-emission industries, and spread throughout the financial system. Policymakers should, therefore, introduce effective price regulation instruments. Establishing a carbon price corridor with both a floor and a ceiling can ensure stable investment signals for green industries while preventing excessive cost escalation. Furthermore, creating a Carbon Market Stability Reserve Fund, similar to the EU ETS, would help manage the supply-demand balance of carbon credits and mitigate price volatility. Developing long-term carbon insurance contracts can also assist enterprises in planning carbon costs, reducing unexpected financial stress, and preventing risk contagion across banking, insurance, and capital markets. These coordinated measures are essential to safeguard macro-financial stability during the low-carbon transition.

Secondly, enhance the consistency and predictability of climate policies. The CPU index results indicate that inconsistent or short-lived climate regulations undermine market stability and investment confidence. To address this, governments should adopt a legally binding and long-term climate policy framework aligned with quantitative emission reduction targets. This framework must establish clear, enforceable pathways that stabilize market expectations and provide long-term investment signals. Moreover, a periodic review mechanism modelled after the Paris Agreement's global stocktake should be institutionalized to regularly adjust national targets based on scientific, technological, and macroeconomic developments. Such mechanisms combine flexibility with stability, maintaining coherence and predictability in climate policymaking. By doing so, they reinforce investor confidence, strengthen national emission reduction credibility, and promote sustainable structural transformation.

Concerning the long-term actions (structural and institutional reforms), we recommend the following measures.

Firstly, strengthen green financial risk management in renewable energy development.

The empirical model reveals a dual effect of renewable energy — it promotes economic growth but may increase financial risk if regulatory standards are weak. Therefore, alongside promoting

green investment, financial regulators should tighten green credit standards through the development of a comprehensive taxonomy of sustainable assets. This taxonomy will clarify which economic activities genuinely contribute to the green transition and enhance transparency. In parallel, standardizing green bond criteria is essential to ensure compliance with technical sustainability requirements, improve credibility, and prevent "greenwashing". Mandatory environmental, social, and governance disclosure for corporates and financial institutions will also improve risk assessment and capital allocation efficiency. Furthermore, to mitigate speculative behavior and prevent "green bubbles", financial leverage controls should be applied to green portfolios, and climate stress tests should be conducted to detect potential credit and market vulnerabilities. Together, these measures will strengthen the resilience of the financial system against climate transition risks.

Secondly, integrate climate risk into commercial banking systems. Empirical evidence from the *LOAN* variable shows that bank lending currently fails to fully account for climate-related risks, revealing a lack of integration in credit assessment and risk management frameworks. Financial institutions should embed climate risk evaluation criteria throughout the loan lifecycle, from approval and pricing to portfolio management. Implementing climate stress testing frameworks will assess the resilience of lending portfolios under extreme climate scenarios, while climate-related provisioning requirements will strengthen capital buffers for high-risk exposures. These tools will enhance banks' ability to accurately price climate risk, allocate credit prudently, and maintain financial stability amid the low-carbon transition.

Together, these short-term and long-term actions form a coherent roadmap to align financial stability with environmental sustainability, ensuring that the transition to a low-carbon economy proceeds smoothly and resiliently.

These implications are highly relevant not only for advanced economies but also for emerging markets, where designing transparent carbon markets, expanding green financial instruments, and incorporating climate risk into banking operations are vital to ensuring financial stability during the transition to a low-carbon economy.

Nevertheless, this research has certain limitations. First, it focuses solely on G7 countries with 999 observations, which may not fully capture the heterogeneity of global economies, particularly developing countries with institutional and structural differences. Second, data availability remains a constraint, as some national datasets lack regular updates, potentially affecting the robustness of results. Third, the study employs nine selected variables based on previous literature, which, while meaningful, may not comprehensively represent all factors influencing financial stability in the context of climate transition.

Future research should, therefore, broaden the geographical scope to include developing and transitional economies, improve data collection through multiple and more frequent sources, and incorporate additional variables that capture institutional quality, technological innovation, and behavioral aspects of financial markets. Such extensions will enrich both theoretical frameworks and practical applications, enabling a more complete understanding of how carbon markets and CPU interact with financial and economic stability.

In summary, this study provides evidence that carbon pricing mechanisms, consistent climate policies, and green finance are not only environmental instruments but also fundamental pillars of financial stability. By integrating these elements into financial governance, countries can build more resilient, adaptive, and sustainable financial systems capable of withstanding the challenges of climate change.

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