Does Climate Risk Always and Everywhere Affect Systemic Risk?

A Multi-Dimensional and Multi-Regional Analysis of the Relationship Between Climate and Systemic Risk.

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Abstract

This study uses a comprehensive United States and Europe dataset to examine the complex linkages between climate risk and systemic risk within the banking sector. While previous studies have often focused narrowly on specific systemic risk measures or limited geographical areas, our analysis integrates a broader range of climate and systemic risk indicators. The results indicate a nuanced and inconsistent relationship: physical climate risks, particularly from climate-driven disasters, are positively correlated with systemic risk measures such as ΔCoVaR and LRMES, though this pattern is less evident in SRISK and MES. Moreover, the association between climate risk and systemic risk varies regionally. The United States banks show a stronger impact than their European counterparts, likely due to differing regulatory environments and market structures. These findings suggest that central banks should adopt a multi-metric approach to evaluate climate-driven systemic risk and develop region-specific policy responses to address unique vulnerabilities. This study highlights the critical role of tailored regulatory interventions and the need for a proactive stance in managing climate-induced financial risks to safeguard global financial stability.

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Key Words: Climate Risk; Systemic Risk; Financial Stability; Banks

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1. Introduction

Climate change is one of the most pressing challenges of the 21st century, with experts forecasting even more severe consequences in the near future (IPCC, 2021; Giglio et al., 2021). As climate-related risks continue to rise, a critical question confronting financial sector regulators and researchers is whether climate risk influences systemic risk, and if so, through what mechanisms. The European Central Bank (ECB) has highlighted growing concerns about the potential impact of climate change on financial stability, warning that it could disrupt the ability of banks to provide essential services and impair the normal functioning of financial markets, which could ripple through the broader economy (ECB, 2021).

Climate change presents two primary risks to the financial system: physical and transition risks. Physical risks stem from large-scale natural disasters triggered by extreme weather events (such as hurricanes, tornadoes, droughts, and floods), as well as long-term shifts in climate patterns (such as rising sea levels). These risks directly threaten financial stability by increasing loan defaults, impairing asset values, and raising the probability of systemic crises. Transition risks arise from regulatory, technological, and market shifts aimed at reducing greenhouse gas emissions. Abrupt policy changes, such as the introduction of carbon taxes or emissions quotas, could destabilize financial systems by triggering the revaluation of assets, impairing corporate profitability, and increasing credit risks for banks exposed to carbon-intensive sectors (van der Ploeg and Rezai, 2020; Battiston et al., 2021).

However, there are also strong theoretical arguments that climate risk may only modestly or not affect financial stability in the medium to long term. Firstly, concerning physical risk, most of the collateral assets are insured, which should lower the impact on financial stability. Second, bank loans can be securitized hence banks will suffer little effect in the event of climate change shocks (Adrian and Shin, 2010). Third, banks are less likely to be affected by long-term climate risk since most of their loans have a shorter duration ranging from 3-5 years (Berg et al. 2017; Chodorow-Reich et al. 2022; Acharya et al., 2023), hence they can quickly adjust to rising climate risk. Banks respond to transition risk via the credit risk channel by adjusting loan pricing and quantities, shortening maturities, and restricting access to permanent financing for high-emission firms (Kacperczyk and Peydro, 2021; Chava, 2014). Fourth, climate change opens opportunities for banks to finance green projects allowing them to diversify their portfolios and offset their losses in investments in brown projects or firms hence facing low exposure to climate change (Delis et al., 2024). This theoretical uncertainty makes it essential to empirically test the link between climate risk and systemic risk.

Estimating the effect of climate risk on systemic risk is challenging. First, researchers must decide how to measure systemic risk. The academic debate on identifying the most effective systemic risk measures has intensified since the global financial crisis, bringing significant attention to four prominent metrics: Delta CoVaR (ΔCoVaR), SRISK, Marginal Expected Shortfall (MES), and LRMES. Benoit et al. (2013) provide a comprehensive analysis of these measures, offering both theoretical and empirical evaluations of ΔCoVaR, SRISK, and MES, and highlighting their respective strengths and limitations.

Second, researchers must decide how to measure climate risk. Climate risk has been measured through CO2 emissions, natural disasters, sea level rise exposure and banks environmental scores. As for systemic risk measures, these climate measures also have their strengths and weaknesses and measure different aspects of climate risk (Benoit et al., 2017). Hain (et al., 2023), for example, compared different metrics of physical climate risk and found that they are far from being perfectly correlated.

The few recent studies that estimate the relationship between systemic and climate risk have explored only some of the possible combinations of systemic and climate risk measures (Heo, 2024; Kanas et al., 2023; Curcio et al., 2023; Conlon et al., 2024). Heo (2024) measures systemic risk through the ΔCoVaR and MES and climate risk through sea level rise exposure, climate disasters count, environmental policy uncertainty, and bank-level environmental risk. Curcio et al. (2023) also use ΔCoVaR and MES to quantify systemic risk, but state-level extreme weather and climate disasters to measure climate risk. Kanas et al. (2023) use CATFIN (VaR) as a measure of systemic risk and CO2 emissions as a measure of climate risk. In addition, Conlon et al. (2024) examine the role of syndicated lending using United States syndicated loan data and state-level extreme weather events such as heat waves, storms, and floods, employing systemic risk measures such as CoVaR and MES. Finally, Birindelli et al. (2024) empirically examine the relationship between banks' climate change commitments and their exposure to systemic risk, as proxied by SRISK and LRMES.

While prior studies have investigated aspects of this relationship, most have focused narrowly on specific systemic risk measures or single geographical areas, such as the U.S. financial system. Our study departs from this approach by adopting a multi-dimensional framework, incorporating a broader range of climate and systemic risk measures, and comparing their interactions across two major regions: the United States and Europe. This allows us to determine to what extent the estimates of the relationship between systemic and climate risk depend on the measures used. That is, do we systematically find a positive and significant relationship between climate risk and systemic risk (as the above-mentioned studies suggest) or does the sign and significance of the relationship depend on the specific way climate and/or systemic risk is measured? Moreover, we analyse how the relationship between climate risk and systemic risk evolves, particularly before and after the Paris Agreement, providing new insights into the role of global policy milestones in shaping financial vulnerabilities.

Our analysis yields mixed findings on the impact of climate change on systemic risk. While some results show a positive association between climate risk and systemic risk, a larger portion indicates an insignificant relationship. Firstly, these results vary across measures of systemic risk. A positive relationship is primarily observed with ΔCoVaR and LRMES estimations but less so for SRISK and MES, consistent with the weak correlation we find among the four systemic risk measures. Secondly, the relationship between climate and systemic risk is different for the United States (U.S.) and the European data. The positive association between systemic and climate risk appears more pronounced for U.S. banks, whereas European banks exhibit a smaller and often insignificant effect.

By using this comprehensive and comparative approach, our study not only addresses gaps in the existing literature but also contributes actionable insights for regulators and policymakers. These insights emphasize the importance of tailored policy interventions and multi-metric approaches in managing climate-induced financial risks, particularly given the observed regional and temporal differences in systemic risk dynamics.

The remainder of the paper is organized as follows. Section 2 literature review and the possible channels. Section 3 describes the data, variables, and model used. Section 4 presents and discusses the main results. Section 5 conducts further cross-sectional analysis. Section 6 ends the study with concluding remarks.

2. Literature Review and Possible Channels

Over the last 10 years, researchers, such as Campiglio et al. (2018), Beard et al. (2021) and Kanas et al. (2023) primarily developed theoretical frameworks to describe potential pathways through which climate-related risks could become systemic. Climate change poses risks to financial stability through both physical and transition channels. Physical risks, like climate-driven disasters, can elevate systemic risk by increasing defaults and credit risk. For instance, climate events can weaken borrowers' ability to repay loans and depreciate collateral assets, affecting loan performance and profitability for banks (Wu et al., 2024; Delis et al., 2024; Chenet et al., 2021). Transition risks—arising from regulatory or market shifts—are especially significant in carbon-intensive industries, where policies like carbon taxes or emissions regulations impact asset values, elevate credit risk, and reduce firm profitability (Acharya et al., 2023). These risks affect highly leveraged sectors, potentially straining banks with exposures to these firms.

Physical risks also impact financial stability through collateral channels, as assets pledged as security (e.g., land or equipment) can lose value due to climate events (Islam and Singh, 2022). For example, hurricanes or rising sea levels can reduce property values and increase mortgage default rates (Bailey et al., 2019). Additionally, firms and households often lack adequate disaster insurance due to cost barriers, leaving them more vulnerable to climate shocks. Such unpreparedness can lead to higher loan defaults and non-performing loan ratios for banks (Wang et al., 2012; Nguyen and Phan, 2020).

In addition to credit risks, policy measures targeting carbon emissions create transition risks for banks exposed to high-emission sectors (Dietz et al., 2016; Battiston et al., 2017). For example, bans on fossil fuels or substantial carbon taxes could render assets in carbon-intensive industries "stranded," requiring early write-offs. It is estimated that approximately one-third of equity and fixed-income assets are tied to such industries, and a rapid shift toward carbon neutrality could result in substantial losses. A swift drop in carbon-intensive asset prices could trigger fire-sale conditions, creating economic shocks and elevating systemic risk.

Currently, there are only a handful of studies that have empirically examined the relationship between climate risk and systemic risk. Heo (2024) finds that climate change significantly increases systemic risk in U.S. banks. The study employs ΔCoVaR and MES as systemic risk measures, and utilizes climate risk data at the city, state, and country levels within the U.S. Curcio et al. (2023) empirical analysis focuses on the reaction of systemic risk in the United States financial sector to climate disasters costing over a billion dollars. Using Wilcoxon signed rank tests, and ΔCoVaR and MES to quantify systemic risk, the study demonstrates that significant increases in systemic risk typically occur after, rather than during, climate-induced events. This finding suggests that financial markets react to climate events with a certain delay, potentially underestimating their initial impact but recognizing the consequences as the disaster unfolds or concludes. Birindelli et al. (2024) empirically examine the relationship between banks' climate change commitments and their exposure to systemic risk, contributing to the ongoing debate about climate engagement and systemic risk. The study finds that banks with higher climate change commitments, measured by Carbon Disclosure Project (CDP) scores, contribute less to systemic risk.

Wu et al. (2024) examine the impact of a country's climate risk on the systemic risk of its banks from a global perspective. By utilizing the ND-GAIN Climate Index alongside systemic risk measures such as CoVaR and MES, they find that a country's higher exposure to climate risk significantly increases the systemic risk levels of its banks. This suggests that banks in countries facing greater climate vulnerabilities are more likely to contribute to overall financial instability. Conlon et al. (2024) examine the role of syndicated lending using U.S. syndicated loan data and state-level physical climate risk measures. Their findings demonstrate that climate risk exposure through cross-state lending increases systemic risks. Banks' exposure to climate change varies depending on the banks' locations and the type of customers they serve. Although not directly related to our study, Kanas et al. (2023) validate their theoretical model using network-based Vector Autoregression (VAR) and conditional Granger causality tests. These methodologies consistently reveal a positive correlation between CO2 emissions and systemic risk.

Most of the existing US-focused literature highlighted above suggests a positive correlation (Heo, 2024; Kanas et al., 2023; Curcio et al., 2023; Conlon et al., 2024). Adding to that, studies by Wu et al. (2023), and Song and Fang (2023), focusing on Chinese banks, found that temperature and precipitation shocks exacerbate systemic risks. However, Liu et al. (2024) present a contrasting perspective by exploring how climate policy uncertainty (CPU) affects systemic banking risk. Their findings, based on ΔCoVaR and MES as systemic risk measures, indicate that higher climate policy uncertainty is associated with lower systemic risk in banks. This highlights a key divergence from earlier research, suggesting that while environmental shocks may increase risk, uncertainty surrounding climate policies could have a stabilizing effect on the banking sector.

Our study conducts a comprehensive analysis using a broader range of systemic risk metrics, as well as country and bank-level climate risk measures. Unlike studies that focus primarily on physical risk, we examine both transition and physical climate risks. This approach acknowledges that some banks are more affected by climate-related policies and regulations, while others are more exposed to physical climate risks. By encompassing all dimensions of climate change exposure, we aim to gain a more thorough understanding of its impact on systemic risk.

Moreover, most existing studies focus solely on the United States samples (Heo, 2024; Kanas et al., 2023; Curcio et al., 2023; Conlon et al., 2024). Our study expands this scope by analyzing both the United States and Europe-listed banks, allowing for comparisons of country-specific characteristics that might influence the effect of climate risk. Focusing on the U.S. and European contexts provides opportunities to examine how differences in climate change exposure and policies can impact the relationship between climate and systemic risk.

3. Methodology

3.1 Data and sample

This study uses data from publicly listed banks in the United States and Europe between 2003 and 2023. The selected timeframe captures periods before and after major financial crises, as well as the introduction of key climate policies like the Paris Agreement. Financial data were sourced from the Capital IQ Pro database, and climate risk measures were compiled from multiple sources, including NOAA and Refinitiv Eikon. We limit the sample to banks with complete data to ensure consistency and comparability across different systemic risk measures resulting in 38,182 observations. To enhance the reliability of our results, all variables have been winsorised at the 1% and 99% levels to address data skewness and reduce the impact of outliers (Anginer et al., 2014).

3.2 Variable Description

3.2.1 Bank-level Systemic Risk Measures

Systemic risk measures are essential tools for understanding the vulnerabilities within the financial system and the potential impact of individual institutions on broader market stability. There has been an ongoing academic debate on the best systemic risk measure since the global financial crisis. Each systemic risk measure has its strengths and is suited to different aspects of systemic risk analysis (Benoit et al., 2013). The results from a single risk measure therefore often cannot be generalized. Instead, integrating multiple systemic risk measures into a broader framework is necessary to capture the various dimensions of systemic risk (Rodríguez-Moreno and Pena 2013; Ellis et al., 2022). [1] This section will explore four widely used systemic risk measures—ΔCoVaR, MES, SRISK, and LRMES. [2] These measures are recognised as the most central metrics in the systemic risk literature (Bisias et al., 2012; De Bandt et al., 2013; Benoit et al., 2017; Abendschein and Grundke, 2018; Grundke and Tuchscherer, 2019).

Delta Conditional Value-at-Risk (ΔCoVaR)

ΔCoVaR is a systemic risk measure that evaluates how a financial institution's distress impacts the broader financial system. Developed by Adrian and Brunnermeier (2016), it extends the Value-at-Risk (VaR) framework by calculating the difference in systemic risk when an institution is in distress versus a median state. This difference provides insights into how much the systemic risk increases when the bank experiences financial distress, making it a critical tool for regulators and policymakers aiming to monitor and mitigate systemic risks. ΔCoVaR is calculated using quantile regressions, focusing on the tail dependencies between a bank's returns and those of the overall system. The measure gained prominence for its ability to forecast systemic risk during the 2007 financial crisis.

ΔCoVaR is a valuable tool for assessing the marginal contribution of banks to systemic risk, offering timely warnings of potential financial crises. While it does not assume causality between individual bank distress and systemic risk, its reliance on systemic state variables can introduce reverse causality, complicating interpretation. Additionally, it treats banks with similar return correlations equally, potentially overlooking differences in size or volatility. Despite these limitations, ΔCoVaR's ability to highlight important tail dependencies makes it a crucial metric for systemic risk analysis (Adrian and Brunnermeier, 2016; Benoit et al., 2017).

To estimate ΔCoVaR we follow Adrian and Brunnermeier (2016). We begin by running quantile regressions to estimate the VaR (Value-at-Risk) and CoVaR (Conditional Value-at-Risk) for a bank as a function of state variables that describe the current market environment. State variables data was taken from Bloomberg. These state variables include changes in interest rates, the slope of the yield curve, liquidity spreads, credit spreads, market returns, stock market volatility (measured by the VIX index), and real estate sector returns. The quantile regression for each bank's return is run at the 5% quantile to capture tail risk, with the state

[1] Since different measures of systemic risk are not perfectly correlated, it is important to assess whether the effects of climate change on systemic risk are consistent across all four main measures. Billio et al. (2012) and Giglio et al. (2016) demonstrate that combining multiple systemic risk measures provides greater predictive accuracy during crises than relying on a single measure.

[2] Within each measure, there can further be variations (for example, SRISK can be scaled by assets). These will be explained in the the robustness check section.

variables lagging one period to account for their effect on risk over time. The results from this regression give the VaR for each bank, which is then used to calculate the CoVaR for the entire financial system, conditional on the bank being in distress.

The return rate of a single bank (r^i_t), and the state variables are introduced to establish a quantile regression model, and the quantile is selected as 5%. The 5% quantile of bank *i*'s returns can be calculated through quantile regression.

$$r_t^i = \alpha^i + \gamma_q^i M_{t-1} + \varepsilon_t^i \tag{1}$$

Above, M_{t-1} is the set of state variables, ε_t^i is the residual term in the regression of bank *i*. Bank *i*'s VaR*(5%)* is estimated through the above quantile regression with a 95 confidence level by using the estimated coefficients in Equation (1). The coefficients (predicted) α^i and γ^i obtained above are substituted into the following equation to obtain the value of a single bank $VaR^i_{t,0.05}$.

$$VaR_{t,0.05}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \tag{2}$$

We substitute the value of $VaR_{i,0.05,}$ and the estimated coefficients from equation (2) into equation (3) below to obtain the CoVaR of the banking industry conditional on bank *i*'s distress, that is, the systemic risk of the banking industry when a single bank suffers the greatest loss.

$$CoVaR_{t,0.05}^{system|i} = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} VaR_{t,0.05}^i + \hat{\gamma}_q^{system|i} M_{t-1} \tag{3}$$

Then apply the similar quantile regression with a confidence level of 50% to calculate bank *i*'s VaR (50%) and the CoVaR of the banking system conditional on bank *i*'s VaR (50%).

$$VaR_{t,0.5}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \tag{4}$$

$$CoVaR_{t,0.5}^{system|i} = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} VaR_{t,0.5}^i + \hat{\gamma}_q^{system|i} M_{t-1} \tag{5}$$

Next, we compute the ΔCoVaR by comparing the CoVaR of the financial system when the bank is at the 5% VaR level (high risk) with the CoVaR when the bank is at the 50% VaR level (median state). The difference between these two CoVaR values represents the bank's contribution to systemic risk.

$$\Delta \mathrm{CoVaR}_t^{\mathrm{i}}(0.05) = \mathrm{CoVaR}_t^{\mathrm{system|i}}(0.05) - \mathrm{CoVaR}_t^{\mathrm{system|i}}(0.5) \tag{6}$$

Higher ΔCoVaR values indicate higher systemic risk contributions. Typically, CoVaR is negative (the loss suffered by the entire banking system in the event of a risk event for a single bank), and the sign is often switched by multiplying the risk measure by -1. We estimate ΔCoVaR using data with weekly frequency and later average it to obtain quarterly values.

Marginal Expected Shortfall (MES)

MES introduced by Acharya et al. (2017), measures a bank's expected equity loss during extreme market downturns, specifically when the market experiences its worst 5% return days. It captures a bank's vulnerability to systemic risk and serves as a key indicator for identifying systemically important banks. MES is valued for its ease of implementation, frequent updates, and ability to act as an early warning indicator of systemic risk. It was a strong predictor of bank stress during the 2009 financial crisis. However, MES has limitations, including its inability to account for risk accumulation during low-volatility periods and its reliance on beta-based risk rankings.

To estimate MES we follow Acharya et al., (2017). MES for a bank *i* at time *t* is defined as the expected return of the bank's stock conditional on the market return falling below a certain quantile threshold (i.e., during market downturns):

$$MES_{i,t} = E[R_{i,t}|R_{m,t} \leq q_{\alpha} \quad (7)$$

Where: $R_{i,t}$ is the daily return of the stock of bank *i* at time *t*, $R_{m,t}$ is the daily return of the market at time *t*, q_{α} is the α-quantile of the market return distribution, typically set at a 5% threshold to capture tail risk, i.e., the worst 5% of market returns.

To calculate MES, we gather daily market return data from the Fama French website and the individual banks' return data from S&P Capital IQ. The data typically covers 252 trading days in a year. For a given year with 252 trading days, we calculate the 5% quantile (α=0.05) of the market returns. This corresponds to selecting the 12 worst daily market returns, as 5% of 252 days is approximately 12. Once the threshold q_{α} is determined, we identify the days when the market return $R_{i,t}$ is less than or equal to q_{α}. Then, for each bank, we calculate its average return on these specific days.

$$MES_{i,t} = \frac{1}{n} \sum_{t \in Tq} R_{i,t} \quad (8)$$

Where: T_q is the set of days when $R_{mt} \leq q_{\alpha}$ and *n* is the number of such days (in this case 12 days for α = 5%). This gave us the MES for the bank, representing the average return on days when the market is experiencing extremely negative returns. Since daily MES is calculated based on daily return data, we average the daily MES values to obtain a quarterly MES. We also invert the negative MES so that the larger values imply higher bank systemic risk.

Long Run Marginal Expected Shortfall (LRMES)

Introduced by Acharya et al. (2012) and further developed by Brownlees and Engle (2017). LRMES offers a longer-term perspective on systemic risk compared to MES by estimating the expected equity loss of a bank in the event of a 40% drop in the market over six months. LRMES is designed to capture a bank's vulnerability to systemic risk over a longer horizon, typically in response to sustained market shocks. LRMES is especially useful for understanding the resilience of banks over extended periods of stress, rather than just during short-term market shocks. By focusing on longer time horizons, LRMES helps identify institutions that may face significant solvency challenges if adverse market conditions persist, offering a valuable tool for both regulators and market participants concerned with the long-term stability of the financial system. Following Archaya et al. (2012), we construct LRMES using the following formula:

$$LRMES = 1 - \exp\left(\log\left(1 - d\right) \times Beta\right) \tag{9}$$

Where *d* is the six-month crisis threshold for the market index decline. By default, the crisis threshold for market decline is set to be 40%, *beta* is the bank's beta coefficient.

Systemic Risk Index (SRISK)

SRISK was first introduced by Acharya et al. (2012) and further developed by Brownlees and Engle (2017). SRISK extends MES by incorporating both market-based and balance sheet information to estimate the capital shortfall of a financial institution during a financial crisis. It measures the amount of additional capital an institution would need to remain solvent if a systemic crisis occurred. SRISK is often considered the most comprehensive systemic risk measure because it accounts for an institution's leverage, size, and expected losses. It provides a long-term view of systemic risk, making it particularly relevant for regulators tasked with monitoring the health of the financial sector. Higher SRISK scores indicate greater vulnerability to crises[3]. One advantage of SRISK is its ability to serve as an ex-ante indicator, helping regulators quantify the build-up of systemic risk. During the 2007-2009 financial crisis, SRISK successfully identified several systemically important banks that later experienced

[3] To facilitate cross-country comparison, SRISK can be expressed as a percentage of Nominal GDP or stock market capitalization.

severe capital shortfalls, highlighting its predictive power (Acharya et al., 2014; Boucher et al., 2014). However, a disadvantage is that the inclusion of market capitalization and liabilities in the calculation can inflate the systemic risk score for large firms, potentially skewing comparisons.

To estimate SRISK, we first calculate the Long Run Marginal Expected Shortfall (LRMES), which represents the expected equity losses during a crisis. These expected losses are then combined with the firm's current equity market value and its outstanding debt to determine the capital shortfall that would arise in a crisis. Following Archaya et al. (2012), we, construct SRISK using the following formula:

$$SRISK_t^i = kDebt_t^i - (1-k)Equity_t^i(1 - LRMES) \tag{10}$$

where k is the prudential capital requirement set at 8% for banks in the Americas and 5.5% for banks in Europe, reflecting differences in accounting standards. $Equity^i_t$ represents the bank's current market capitalization, and $Debt^i_t$ is the bank i's book value of debt.

3.2.2 Climate Risk Measures

Two types of climate risks are considered in this analysis: physical and transition risks. Physical risks arise from climate-driven disasters (e.g., hurricanes, floods) and long-term environmental changes, such as rising sea levels. Transition risks, on the other hand, stem from regulatory, technological, and market shifts associated with the transition to a low-carbon economy. Key indicators include physical risk measures such as the count of climate disasters, exposure to sea level rise, and the Global Climate Physical Risk Index (GCPRI), as well as transition risk measures like emissions intensity, Scope 3 estimates, and indices of environmental policy uncertainty. Some of these indicators have been used in prior studies (e.g., Wu et al., 2023; Song and Fang, 2023; Heo, 2024; Liu et al., 2024).

However, several bank-level climate transition risk measures, such as Climate Transition Risk Exposure (CTRE) and individual bank climate policies, remain underexplored in the literature examining the relationship between systemic risk and climate change. While these measures have been utilized in broader climate finance studies (e.g., Ramzan and Ali, 2024; Martini et al., 2024), their potential to provide deeper insights into systemic risk dynamics remains largely untapped.

We organize this section by first focusing on macro-level measures and then focusing on bank-level climate risk measures.

3.2.2.1 Country, State, and City-Level Climate Risk Measures

Sea Level Rise Exposure

Building on Heo (2024), we use sea level rise exposure as a proxy for physical climate risk, sourcing data from the National Oceanic and Atmospheric Administration (NOAA). This measure indicates the vulnerability of geographic areas to rising sea levels, impacting coastal communities, infrastructure, and property values. By highlighting potential flood zones, NOAA's sea level rise data offers valuable insights into the long-term exposure faced by communities, businesses, and financial institutions. To maintain consistency, we align city-level sea level exposure data with bank locations. This city-specific data is obtained from the Urban Adaptation Assessment (UAA), an interactive database developed by the Notre Dame Global Adaptation Initiative (ND-GAIN). The UAA covers over 270 U.S. cities across all 50 states, each with a population exceeding 100,000.

Climate Disasters Count

We follow Heo (2024) and use climate disasters data from the Federal Emergency Management Agency (FEMA). We use the number of climate disasters by state and year as a proxy for physical climate risk. FEMA tracks, assesses, and records data on climate-related disasters across the United States. This data provides insights into the frequency, scale, and financial impact of various climate-related events, such as hurricanes, floods, wildfires, and severe storms, and is widely used in climate risk analysis and disaster preparedness efforts.

Climate Risk-NDGAIN

We utilize the Notre Dame Global Adaptation Initiative (ND-GAIN) Index from the University of Notre Dame to assess climate risk at the country level. The NDGAIN index provides an annual assessment of each country's vulnerability to climate disruptions and readiness to leverage resources for adaptive actions. Climate Risk-NDGAIN is measured as the opposite of its NDGAIN. The index ranges from 0-100. The higher the value of Climate Risk NDGAIN the higher the country’s climate risk. It is calculated as follows:

NDGAIN= (Readiness – Vulnerability+1) *50

Global Climate Physical Risk Index (GCPRI)

Using daily data from meteorological stations, the Global Climate Physical Risk Index (GCPRI) dataset has been developed for 170 countries, with a focus on four extreme climate events: extreme low temperatures (LTD), extreme high temperatures (HTD), extreme rainfall (ERD), and extreme drought (EDD).[4] Covering the years 1993 to 2023, this index compiles a country-level measure of climate physical risk by integrating these events into a comprehensive index. The process involves defining the thresholds for each event type to determine what constitutes "extreme" conditions before aggregating them into a unified metric for each country. The raw meteorological data are sourced from the National Oceanic and Atmospheric Administration (NOAA).

Environmental Policy Uncertainty (EPU)

The measure of environmental policy uncertainty is based on indices developed by Noailly et al. (2022), who analyse 15 million news articles from the archives of ten prominent U.S. newspapers over the past four decades. Using machine learning techniques, the authors identify articles related to environmental policy and create a monthly index that reflects U.S. environmental policy uncertainty. This news-based index captures the proportion of articles focused on environmental policy by scaling the monthly count of environmental and climate policy articles against the total monthly volume of news. An increase in the index indicates a higher volume of environmental policy news, which can raise awareness among economic agents about current regulations and potential new restrictions.

Gavriilidis Climate Policy Uncertainty

Following Liu et al. (2024) we use the Climate Policy Uncertainty (CPU) Index constructed by Gavriilidis (2021). The measure is developed by examining articles from eight major U.S. newspapers. Gavriilidis identifies content specifically addressing climate change and policy uncertainty, calculating the index as a ratio of these relevant articles to the total number of articles, with values standardized for consistency. This measure captures the intensity of climate policy uncertainty, where elevated index values indicate higher levels of uncertainty.[5]

Berestycki Climate Policy Uncertainty

The country level climate policy uncertainty index we use was constructed by Berestycki et al. (2022). They calculate Climate Policy Uncertainty (CPU) by counting articles from major newspapers that contain all three terms—climate, policy, and uncertainty—at least once per article, carefully reviewing each to exclude any misreporting. The index displays a time-series

[4] Direct URL to data: https://doi.org/10.6084/m9.figshare.25562229.v1
[5] Data is available from 2005-2021.

pattern and trend aligned with real-world events. Notably, peaks in the CPU indexes correspond with significant shifts in climate policies, such as policy rollbacks or the introduction of new regulations. For example, in the United States, the CPU index rose sharply during the 2010 Waxman-Markey discussions and again in 2017 when President Trump announced the U.S withdrawal from the Paris Agreement. Importantly, the CPU measure reflects uncertainty about climate policies rather than public concern about climate risks.

3.2.2.2 Bank Level Climate Risk Measures

Environmental Risk

Heo (2024) also uses bank level environmental risk, a textual measure constructed by Hassan et al., (2019).[6] They use a machine learning-based keyword algorithm to generate a set of environmental policy bigrams that capture firm-specific exposure to environmental risks. We use their firm-level environmental policy exposure measure as a proxy for bank-level environmental risk.

Environmental Score

The environmental score measures a company's impact on living and non-living natural systems, including the air, land and water, as well as complete ecosystems. It reflects how well a company uses best management practices to avoid environmental risks and capitalize on environmental opportunities to generate long term shareholder value. It includes three sub-components: resource utilization, emissions reduction and green innovation. The scores are graded on a scale of 0 to 100 with zero means the worst and 100 means the best environmental performance. We collect the data from Refinitiv Eikon database.

Bank Climate Policy

Following Ramzan and Ali, 2024, we compute an index that outlines a bank's climate policy. A bank voluntarily sets a policy or commitment to address climate change issues. We collect the data from Refinitiv Eikon database for items such as policy emission, Equator Principles, and fossil fuel divestment policy. The information is directly from the bank's response to the Refinitiv climate change information request. For example, there are questions like, is the bank a signatory of the Equator Principles? Does the bank have a public commitment to divest from

[6] The data can be downloaded in the following link: https://www.firmlevelrisk.com/links

fossil fuel? If a bank has a policy, it takes the value of one; otherwise, it is assigned zero. Therefore, the climate policy index represents the aggregate sum of these values.

$$\text{Climate Policy}=\sum_{i=1}^{n} C_i$$

where C_i is defined as one if the policy exists for item *i* and zero otherwise.

Refinitiv Emissions Intensity

Emissions Intensity refers to the ratio of a company's greenhouse gas (GHG) emissions, specifically Scope 1 and Scope 2 emissions relative to its revenue. This metric is calculated by dividing the total carbon dioxide equivalent (CO_2) emissions by the company's revenue, expressed in metric tons of CO_2 per million dollars of revenue. It provides insight into how efficiently a company generates revenue concerning its environmental impact. A lower emissions intensity indicates that a company produces fewer emissions per unit of revenue, suggesting more efficient operations. Data is downloaded from Refinitiv Eikon database.

Refinitiv Scope 3 Estimate

Total estimated scope 3 emissions in tonnes divided by revenues. Scope 3 are indirect emissions from the bank's supply chain and other external activities. Data is downloaded from Refinitiv Eikon database.

Bloomberg Scope 2 Intensity

It is calculated as metric tonnes of greenhouse gases in carbon dioxide equivalent emitted from indirect operations per million of sales revenue in the company's reporting currency. Data is downloaded from Bloomberg.

Bloomberg Emission Intensity

It is calculated as total metric tonnes of CO2 emitted per million of sales revenue in the company's reporting currency. Sum of annual Scope 1 and Scope 2 carbon emissions at the end of the year. Scope 1emissions are caused by the combustion of fossil fuels. Scope 2emissions originate from the purchase of electricity, heating, or cooling. The ratio is calculated based on data items disclosed in company filings. Data is downloaded from Bloomberg.

Bank Climate Transition Risk Exposure (BCTRE) Scope 1

Following Martini et al. (2024), we construct time-varying Bank Climate Transition Risk Exposure (BCTRE) scores to measure banks' exposure to climate transition risk based on the carbon footprint of their borrowers, addressing Acharya et al. (2023)'s call for research on banks' climate risk exposure. This measure evaluates carbon emissions concentration across bank borrowers over time, using syndicated loan data and Scope 1 emissions both from Refinitiv Eikon. BCTRE is calculated as the weighted average of Scope 1 emissions in each bank’s syndicated loan book, normalized by the bank's total loan book value at quarter-end to adjust for bank size. By including emissions from global lending portfolios, this measure captures carbon risks from loans financed abroad and accounts for regulations, like carbon taxes, that may impact banks’ foreign borrowers (Laeven and Popov, 2023).

Bank Climate Transition Risk Exposure (BCTRE) Regulatory

We construct the Bank Climate Transition Risk Regulatory Exposure measure to assess banks' exposure to climate-related regulatory risks through their borrowers. This measure combines each borrower’s weighted loan share in a bank’s portfolio with the borrower’s climate regulatory exposure score, a textual metric based on Sautner et al. (2023). This score reflects the frequency of bigrams related to regulatory shocks about climate change, as they appear in earnings call transcripts.

Bank Climate Transition Risk Exposure (BCTRE) Opportunity

Measures how a bank is exposed through its borrowers using the weighted outstanding loan share times the borrower’s climate opportunity exposure score. The climate opportunity exposure is a textual measure constructed by Sautner et al. (2023). It is measured as the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of earnings conference calls.

3.2.3 Control Variables

Following closely related literature (Heo, 2024; Liu et al., 2024, Wu et al., 2024; Conlon et al., 2024), our empirical model incorporates key bank characteristics relevant to systemic risk, alongside macro-level control variables. To account for economies of scale, we include *Bank Size* (log of total assets). *Size Squared* (the squared log of total assets) is also included to capture potential nonlinear effects. Additional controls include *Bank Profitability* (return on assets) and *Bank Liquidity* (cash and equivalents scaled by assets).

We control for funding structure with *Bank Deposits* (total deposits to assets) and for business model diversity with *Non-interest Income to Assets*, which reflects engagement in non-traditional banking activities. *Bank Capital* is represented as the ratio of bank equity to assets. We measure loan exposure through *Loan Asset* (net loans scaled by assets), and *Loan Loss Reserve* (loan loss provisions to assets) accounts for loan risk. *Loan Growth*, calculated as the growth rate of the loan-to-assets ratio, is also included.

We add macroeconomic variables: the national *Inflation Rate* and *GDP per Capita*. When using BCTRE scores at the bank-borrower level, we further control for borrower characteristics, including Firm Size, Firm Return on Assets, and Firm Interest Coverage. Detailed definitions of all control variables are provided in the appendix.

3.3 Model Construction

We estimate the following model:

$$Sytemic\ Risk_{i,t+1} = \alpha + \beta Climate\ risk_{i,t} + \theta Controls_{i,t} + \delta_t + \lambda_i + \varepsilon_{i,t} \quad (11)$$

where $Sytemic\ Risk_{i,t+1}$ is *ΔCoVaR, MES, SRISK, or LRMES* of bank i in quarter *t+1*. The coefficient β explains the nexus between climate change risk and systemic risk. *Climate Risk* includes the relevant physical or transition risk measure for bank i. $Controls_{i,t}$ include bank-level variables (e.g., size, profitability) and macroeconomic factors (e.g., inflation, GDP per capita) in quarter t. δ_t are time fixed effects that are controlled for in all the regressions to account for economy-wide shocks on bank risk and λ_i are bank fixed effects.[7] We forward lag the dependent variables by one quarter to address potential endogeneity. Standard errors are clustered at the bank level to address potential cross-sectional and serial correlation in the error terms (Petersen, 2008).

3.4 Descriptive Statistics

We conduct a correlation analysis of the systemic risk measures and report the results in Table 1.[8] A noteworthy observation from the results is the weak correlations of the four systemic risk measures. The correlations are all positive and significant at the 1% level, but generally low, suggesting these metrics capture distinct aspects of systemic risk. For instance, ΔCoVaR moderately correlates with MES (0.288), indicating some overlap, while weaker correlations

[7] We include bank fixed effects for all regressions except when we use sea level rise since sea lever rise measure does not change over time.
[8] Refer to the appendix for the correlation analysis of the climate risk measures.

with SRISK (0.136) and LRMES (0.139) suggest it assesses a different risk aspect. SRISK has low correlations with MES and LRMES, highlighting its distinct focus on capital shortfall risk. Overall, these low correlations imply each metric provides unique insights into systemic risk. The weak correlations align with previous literature, such as Billio et al. (2012) and Giglio et al. (2016), that emphasize the importance of considering multiple dimensions of systemic risk. The Climate Risk pairwise correlation matrix is in Appendix Table A3.

Table 1: Systemic Risk Pairwise Correlation Matrix

Variables	ΔCoVaR	SRISK	MES	LRMES
ΔCoVaR	1.000			
SRISK	0.136***	1.000		
MES	0.288***	0.185***	1.000	
LRMES	0.139***	0.100***	0.217***	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2 presents summary statistics for the key variables used in our empirical tests, showing unstandardized systemic risk measures. Summary statistics of the climate variables are shown in Table A4. For regression analysis, we use standardized measures of systemic and climate risk to enhance comparability.

The descriptive statistics for systemic risk measures highlight variability in banks' risk exposure. ΔCoVaR, with an average of 0.013 and low variability (standard deviation of 0.012), reflects generally modest risk contributions across banks, though values reach up to 0.158. SRISK, averaging 0.012 with a standard deviation of 0.019, shows low variability in capital shortfalls, though a few banks face elevated risk levels. MES has a low mean of 0.014 and a standard deviation of 0.038, suggesting limited exposure to expected losses, though some banks face heightened risk, as seen in the range from -2.05 to 0.662. LRMES shows the widest range, with a mean of 0.093, a high standard deviation of 1.642, and values spanning from -81.651 to 1, indicating that some banks are significantly vulnerable to market downturns. These metrics collectively underscore differences in systemic risk exposure, with LRMES displaying the greatest dispersion.

The statistics show that our sample comprises small and big banks as indicated by minimum values for *Bank Size* (log total assets) of 10.81 and a maximum value of 21.16. *Bank Profitability*, represented by Return on Assets (ROA), shows an average of 0.908, suggesting that, on average, banks generate a modest return relative to their assets. The standard deviation of 0.874 indicates considerable variation in profitability across banks, implying a range of performance levels. The minimum ROA is -3.688, reflecting instances of significant losses among some banks, while the maximum of 6.992 highlights a few banks achieving notably high profitability. The median ROA of 0.937, close to the mean, suggests a relatively symmetric distribution, with most banks clustered around a slightly positive return. *Bank Capital*, calculated as the ratio of bank equity to assets, has a standard deviation of 0.043 which suggests moderate variability in capital levels across banks. With a minimum of 0.033, some banks operate with very low capital ratios, potentially increasing their financial vulnerability, while a maximum of 0.555 points to a few banks with relatively high capital buffers. The mean *Inflation* is 2.674, with a standard deviation of 2.509, reflecting divergence in inflation levels in different countries.

Table 2: Summary Statistics

Variable	N	Mean	SD	Min	Median	Max
ΔCoVaR	38182	.013	.012	-.03	.01	.158
SRISK	38182	.012	.019	0	0	.181
MES	38182	.014	.038	-2.05	.012	.662
LRMES	38182	.093	1.642	-81.651	.244	1
Bank Deposits	35160	.75	.125	.205	.784	.929
Bank Size	38182	14.956	1.992	10.81	14.603	21.16
Size squared	38182	227.641	62.926	116.864	213.25	447.75
Bank Liquidity	34981	.053	.053	.002	.035	.361
Non-Interest Income	35794	.003	.003	-.002	.002	.027
Bank Capital	38164	.105	.043	.033	.1	.555
Bank Profitability	34618	.908	.874	-3.688	.937	6.992

Net Loans to Assets	34871	.668	.124	.207	.685	.881
Loan Loss Reserves	34418	1.697	1.721	.265	1.248	13.719
Loan Growth	34454	.002	.047	-.715	.002	2.446
Inflation	38109	2.674	2.509	-4.448	2.13	72.309
GDP per capita	38109	53774.59	13801.57	2185.317	54844.24	97316.87

ΔCoVaR, MES, SRISK, or LRMES are the bank systemic risk measures. Bank Deposits are bank deposits scaled by total assets. Size is the natural logarithm of total assets. Liquidity is cash and cash equivalence scaled by total assets. Non-interest income is non-interest income scaled by total assets. Bank Capital is book equity scaled by assets. ROA is the return on assets. Loan Loss Reserves is total loan loss provision to assets. Loan Growth is the growth rate of loan to assets ratio.

4. Empirical Results

Table 3 serves as a foundation for this study, providing an overview of findings from prior research on the relationship between climate risk and systemic risk. Panel A, which focuses on U.S. based studies, reveals a consistently strong relationship across most climate risk measures and systemic risk indicators. Studies such as Heo (2024) demonstrate that higher physical and transition climate risks are associated with increased systemic risk, as reflected in measures like ΔCoVaR and MES. These results align with those of Conlon et al. (2024) and Wu et al. (2023, 2024), reinforcing the argument that physical climate risks, such as sea level rise and climate disasters, exacerbate systemic vulnerabilities in the banking sector.

However, the relationship between transition risks, such as environmental and climate policy uncertainty (EPU), and systemic risk is less straightforward. While Heo (2024) finds a positive and significant association between EPU and systemic risk, Liu et al. (2024) report contrasting results using a different climate policy uncertainty measure by Gavriilidis, where the relationship is negative and statistically significant. Liu et al. argue that while transition risks destabilize high-carbon industries, they simultaneously foster growth in low-carbon sectors, potentially offsetting systemic risk. This inconsistency highlights the sensitivity of systemic risk measures to the choice of climate risk indicators and suggests that transition risks might have a dual impact, depending on the industries or regions under consideration.

Table 3, Panel B, presents findings from studies that could not be replicated in this analysis due to differences in data availability or sample composition. For example, Conlon et al. (2024) employ cross-state lending data to measure unexpected climate risk, while Liu et al. (2024) and

Wu et al. (2024) rely on global datasets that differ significantly from the U.S.-focused samples used here. These results highlight the variability of systemic risk dynamics across different data sources and geographical contexts.

Table 3: Existing Studies - Original Results

Climate Measures↓	Authors	ΔCoVaR	SRISK	MES	LRMES	Sample
Panel A - USA Only Studies - Original Results						
Sea Level Rise	Heo (2024)	0.0005***	x	0.0035*	x	36820
CDC	Heo (2024)	0.2225**	x	0.4627**	x	27688
EPU	Heo (2024)	0.0016***	x	0.0210***	x	36820
Gavriilidis CPU	Liu et al. (2024)	-1.645**	x	-2.173**	x	4102
Environ risk	Heo (2024)	0.1086***	x	1.0508***	x	6949
Panel B - Other close studies not replicated						
Berestycki CPU	Liu et al. (2024)	-1.750***	x	-1.857***	x	6197
CRI_Bank_Cross	Conlon at al. (2024)	0.027***	x	0.147***	0.013***	12142
Climate Risk-ND-GAIN	Wu et al. (2024)	0.179***	x	x	x	10247

*ΔCoVaR, MES, SRISK, or LRMES are the bank systemic risk measures. The higher the values of these measures, the higher the systemic risk. Sea Level Rise- is at US City level. CDC is Climate Disasters Count which is at US state level. EPU is U.S Environmental Policy Uncertainty index by Noailly at the country level. Gavriilidis CPU is the U.S Climate Policy Uncertainty index constructed by Gavriilidis at country level. Environ risk is a textual environmental risk which is at bank level constructed by Sautner et al., 2023. Berestycki CPU is the G20 Climate Policy Uncertainty constructed by Berestycki. CRI_Bank_Cross is U.S bank level unexpected climate risk acquired through cross-state lending. Climate risk-ND-GAIN is a country's climate risk measured as the opposite of its NDGain..For panel A, the control variables used include bank size, size squared, deposit to assets, liquidity to assets, non-interest income, bank capital, ROA, net loans to assets, loan loss reserve, loan growth. Variable definitions in appendix A1. *** p<0.01, ** p<0.05, * p<0.1.*

Table 4 replicates prior studies on the relationship between climate risk measures and systemic risk in the U.S. sample, with mixed findings. Consistent with Heo (2024), we observe a significant positive relationship between sea level rise and systemic risk (ΔCoVaR and MES), reinforcing the view that physical climate risks exacerbate systemic vulnerabilities. However, our results for climate disasters and bank-level environmental risk are statistically insignificant, diverging from Heo's findings, possibly due to differences in sample size, time, or banks' post-Paris Agreement adaptations.

For environmental policy uncertainty (EPU), we find a significant positive relationship with ΔCoVaR, consistent with Heo, but no significant effect for MES. Incorporating Gavriilidis' climate policy uncertainty (CPU), as in Liu et al. (2024), reveals a significant negative relationship with systemic risk, supporting the idea that regulatory uncertainty can both destabilize high-carbon industries and foster opportunities in low-carbon sectors.

The differences between our results and prior studies highlight the evolving nature of systemic risk responses to climate risks, particularly post-Paris Agreement. They also underscore the importance of data sources and the construction of climate risk measures. Policymakers should adopt a nuanced approach that considers these dynamics while harmonizing datasets to enable robust analyses.

Table 4: U.S. Sample - Replication and Expanded Results

Systemic Risk / Climate	ΔCoVaR	SRISK	MES	LRMES	Sample Size
Sea Level Rise	0.0642**	0.0254	0.0133*	0.00818***	24063
CDC	0.00765	-0.00958	-0.00886	0.00283	23557
EPU	0.0195***	0.0856***	-0.0274	0.0226***	24063
Gavriilidis CPU	-0.0208***	-0.119***	-0.0684*	0.00693	17259
Environ risk	-0.00133	0.00903	0.00476	0.00109	6252

*ΔCoVaR, MES, SRISK, or LRMES are the bank systemic risk measures. The higher the values of these measures, the higher the systemic risk. Sea Level Rise- is at the US City level. CDC is Climate Disasters Count which is at the US state level. EPU is Environmental Policy Uncertainty. Gavriilidis CPU is the climate policy uncertainty constructed by Gavriilidis. Environ risk is Bank level environmental risk which is at the bank level. The control variables used include bank size, size squared, deposit to assets, liquidity to assets, non-interest income, bank capital, ROA, net loans to assets, loan loss reserve, and loan growth. Both dependent and independent variables are standardized. Standard errors are clustered at the bank level. Variable definitions in Appendix A1. *** p<0.01, ** p<0.05, * p<0.1.*

Table 5 presents results from our analysis using three climate risk measures—Climate Risk ND-GAIN, the Global Climate Physical Risk Index (GCPRI), and Berestycki's Climate Policy

Uncertainty (CPU)—which, to our knowledge, have not been previously applied to investigate the climate risk-systemic risk relationship using a U.S.-only sample.

Climate Risk ND-GAIN consistently shows a positive and statistically significant relationship with systemic risk across all four metrics (ΔCoVaR, SRISK, MES, and LRMES), indicating that higher climate risk correlates with greater systemic vulnerability. Conversely, Berestycki's CPU measure demonstrates a negative and significant impact across all systemic risk measures, supporting arguments that climate policy uncertainty fosters low-carbon investment opportunities, offsetting risks from high-carbon sectors. The GCPRI results are mixed, with a positive and significant effect on ΔCoVaR and LRMES, but insignificant or negative effects for SRISK and MES. This suggests that physical climate risks may influence different aspects of systemic risk unevenly.

Overall, these findings highlight how various climate risk measures differentially impact systemic risk. The consistency of the Climate Risk ND-GAIN and Berestycki CPU results across all measures underscores their robustness in assessing systemic risk, while the mixed results for GCPRI suggest further investigation is needed to understand its real effects.

Table 5: U.S. Sample - New Climate Risk Measures

Systemic Risk / Climate	ΔCoVaR	SRISK	MES	LRMES	Sample
Climate Risk-ND-Gain	0.552***	0.882***	1.172***	0.0296*	22862
GCPRI	0.123***	-0.0334	-0.0211	0.0484**	24063
Berestycki CPU	-0.0687***	-0.0628***	-0.0566***	-0.00367*	24063

*ΔCoVaR, MES, SRISK, or LRMES are the bank systemic risk measures. The higher the values of these measures, the higher the systemic risk. Climate risk-ND-GAIN is a country's climate risk measured as the opposite of its NDGain. GCPRI is the Global Climate Physical Risk Index. Berestycki CPU is the climate policy uncertainty constructed by Berestycki. The control variables used include bank size, size squared, deposit to assets, liquidity to assets, non-interest income, bank capital, ROA, net loans to assets, loan loss reserve, and loan growth. Both dependent and independent variables are standardized. Standard errors are clustered at the bank level. Variable definitions in Appendix A1. *** p<0.01, ** p<0.05, * p<0.1.*

Next, we turn to bank-level climate risk measures that have attracted less attention in climate risk and systemic risk literature. Table 6 shows mixed results ranging from a strongly significant positive relationship to an insignificant effect. The results vary across climate and systemic risk indicators.

Higher environmental scores show a significant negative relationship with MES, suggesting that improved environmental performance may reduce systemic risk, although this effect is not robust across all systemic risk measures. Conversely, emissions intensity measures (from both Refinitiv and Bloomberg) consistently exhibit positive and significant effects on systemic risk, indicating that higher emissions contribute to greater systemic vulnerabilities. Scope 3 emissions estimates, however, show no significant impact, highlighting limitations in capturing indirect emissions.

Banks' voluntary climate commitments and internal carbon policies reveal no significant relationship with systemic risk across all measures. This suggests that such policies, while potentially beneficial for environmental reputation, do not materially reduce systemic vulnerabilities. When analysing banks' climate exposures through their borrowers, the results indicate that Scope 1 emissions and regulatory climate risk exposures (BCTRE Scope 1 and BCTRE Reg) positively and significantly affect systemic risk for some measures. This underscores the importance of tracing climate risks from borrowers to banks via loan portfolios. However, climate opportunity exposures show no significant effect, suggesting that growth in low-carbon investments may not yet offset systemic vulnerabilities tied to high-carbon borrowers. Both the regulatory and opportunity exposures are derived through textual analysis of borrower-level climate data, highlighting the potential of such innovative methodologies to capture nuanced relationships between borrower climate risks and bank systemic vulnerabilities.

As with the physical climate risk measures discussed above, the transition risk measures also show that the effect is mostly positive though the statistical significance differs across the different systemic risk measures.

Table 6: U.S. Sample - Bank-Level Climate Measures

Systemic / Climate ↓	ΔCoVaR	SRISK	MES	LRMES	Sample
Environ Score	-0.0100	-0.0608	-0.0366**	0.000598	8303
Ref Emission Intensity	0.0378***	0.0194	0.0262***	0.00246***	8303
BB Scope 2 Intensity	0.125***	0.0482*	-0.00206	0.00275**	966
BB Emission Intensity	0.0340***	0.0656***	0.0183*	0.00411**	748
Scope 3 Estimate	0.0747	-0.0241	0.00406	-0.0119	6500
Bank Climate Policy	-0.0105	0.00673	-0.00376	0.00135	8214
BCTRE Scope 1	-0.00130	0.0283**	0.0169***	-0.00155	7019

BCTRE Reg	0.00745	0.0257*	-0.00124	0.000887**	12420
BCTRE Opp	0.00691	0.000290	-0.00640	0.000154	12420

*ΔCoVaR, MES, SRISK, or LRMES are the bank systemic risk measures. The higher the values of these measures, the higher the systemic risk. Environ Score is environmental pillar score. Ref Emission Intensity is emissions intensity from Refinitiv. BBScope2 is GHG Scope 2 Intensity Per Sales from Bloomberg. BB Emission Intensity is Total Carbon (CO2) Emissions Intensity Per Sales from Bloomberg. BCTRE Scope 1 is Bank Climate Transition Risk Exposure (BCTRE) Scope 1. BCTRE Reg is Bank Climate Transition Risk Exposure (BCTRE) Regulatory. BCTRE Opp is Bank Climate Transition Risk Exposure (BCTRE) Opportunity. The control variables used include bank size, size squared, deposit to assets, liquidity to assets, non-interest income, bank capital, ROA, net loans to assets, loan loss reserve, and loan growth. Both dependent and independent variables are standardized. Standard errors are clustered at the bank level. Variable definitions in Appendix A1. *** p<0.01, ** p<0.05, * p<0.1.*

Table 7 focuses on the European sample, examining the relationship between systemic risk and both country-level and bank-level climate measures. The results highlight notable differences compared to the U.S. sample, emphasizing the region-specific nature of the climate risk-systemic risk nexus. For country-level measures, the Global Climate Physical Risk Index (GCPRI) shows a positive and statistically significant relationship with systemic risk for ΔCoVaR and MES. ClimateRisk-ND-GAIN produces mixed results, with positive and statistical significance for SRISK and MES.

Bank-level climate measures generally have weaker effects in Europe compared to the U.S. sample. Environmental scores, emissions intensity, and Scope 3 emissions estimates show mostly insignificant relationships across all systemic risk measures. The most notable exception is loan portfolio exposures, where climate transition risk exposures (BCTRE Scope 1) demonstrate significant effects on systemic risk through SRISK and LRMES. This underscores the importance of tracing borrower-level climate risks to understand their systemic implications.

Overall, these findings indicate that the relationship between climate risk and systemic risk is less pronounced in Europe compared to the U.S., particularly for bank-level measures. The results also highlight the importance of regional context in shaping systemic vulnerabilities, cautioning against generalizing findings from one region to another.

Table 7: Europe Sample - Country and Bank-Level Climate Measures

Systemic / Climate ↓	ΔCoVaR	SRISK	MES	LRMES	Sample
ClimateRisk-ND-Gain	-0.143	0.870***	0.244*	-0.0528	3946
GCPRI	0.215***	0.110	0.193***	0.00642	3933
Environ risk	0.00186	0.0112	0.00198	0.000774	1337

Environ Score	0.00680	-0.0195	-0.0257	0.000498	2010
Ref Emissions Intensity	0.0154	-0.0226	-0.00584	0.000963	2010
BB Emissions Intensity	-0.00346	-0.0522	-0.0123	0.00225	1235
Scope 3 Estimate	0.0104	0.00325	0.0583	-0.00260	1108
Bank Climate Policy	0.0270	-0.0105	-0.0147	-0.00122	1980
BCTRE Scope 1	-0.0102	0.0283**	-0.0272	0.0047***	2081
BCTRE Reg	0.000449	-0.00553	0.00659	0.0000890	1704
BCTRE Opp	0.00804	-0.000561	-0.00065	-0.00214**	1704

*ΔCoVaR, MES, SRISK, or LRMES are the bank systemic risk measures. The higher the values of these measures, the higher the systemic risk. Climate risk-ND-GAIN is a country's climate risk measured as the opposite of its NDGain. GCPRI is the Global Climate Physical Risk Index. Environ risk is environmental risk at the bank level. Environ Score is the environmental pillar score. Ref Emissions Intensity is emissions intensity from Refinitiv. BB Emissions Intensity is Total Carbon (CO2) Emissions Intensity Per Sales from Bloomberg. BCTRE Scope 1 is Bank Climate Transition Risk Exposure (BCTRE) Scope 1. BCTRE Reg is Bank Climate Transition Risk Exposure (BCTRE) Regulatory. BCTRE Opp is Bank Climate Transition Risk Exposure (BCTRE) Opportunity. The control variables used include bank size, size squared, deposit to assets, liquidity to assets, non-interest income, bank capital, ROA, net loans to assets, loan loss reserve, and loan growth. Both dependent and independent variables are standardized. Standard errors are clustered at the bank level. Variable definitions in Appendix A1. *** p<0.01, ** p<0.05, * p<0.1.*

Table 8 presents the results of the combined analysis of the U.S. and European samples, allowing for a comparison to earlier results where the U.S. and Europe were analysed separately. While the earlier tables highlighted pronounced regional differences with U.S. banks generally showing stronger relationships between climate risk and systemic risk than European banks, the combined sample coefficients in Table 8 reveal more muted effects. Most coefficients are small and statistically insignificant, suggesting a less consistent or negligible overall impact when the two regions are pooled together.

This inconsistency likely reflects the underlying differences in regulatory frameworks, market structures, and climate vulnerabilities between the U.S. and Europe. The earlier separation allowed these regional nuances to be observed, whereas combining the samples may obscure these distinctions. The mixed results across systemic risk measures and climate risk indicators underscore the complexity of the relationship and suggest that analysing U.S. and European samples separately provides more actionable insights into region-specific dynamics.

Table 8: Combined Sample – Country and Bank-Level Climate Measures

Systemic / Climate ↓	ΔCoVaR	SRISK	MES	LRMES	Sample
ClimateRisk-ND-Gain	-0.379***	0.307*	-0.0110	-0.0362	26808
GCPRI	0.208***	-0.0644	0.139***	0.00610	27996
Environ risk	-0.00128	0.0121	0.0105	0.000973	7589
Environ Score	-0.0319	-0.0247	-0.0330**	-0.00200	10313
Ref Emissions Intensity	0.0296***	0.0113	0.0199	0.00373***	10313
BB Emissions Intensity	0.0177	0.0231	0.0123	0.00409	1983
BB Scope 2 Intensity	0.0660*	0.00568	-0.0213	-0.00275	2441
Scope 3 Estimate	0.0114	0.0294	0.0263	0.0112*	7608
Bank Climate Policy	-0.0173	0.0187	-0.00414	-0.000991	10194
BCTRE Scope 1	-0.0180**	-0.00154	0.0140	0.00120	9481
BCTRE Reg	-0.00291	0.0224***	0.0104	0.000662	14460
BCTRE Opp	0.00534	0.00480	0.0000381	0.000891	14460

*ΔCoVaR, MES, SRISK, or LRMES are the bank systemic risk measures. The higher the values of these measures, the higher the systemic risk. Climate risk-ND-GAIN is a country's climate risk measured as the opposite of its NDGain. GCPRI is the Global Climate Physical Risk Index. Environ risk is the environmental risk at the bank level. Environ Score is the environmental pillar score. BB Scope 2 Intensity is GHG Scope 2 Intensity Per Sales. BB Emissions Intensity is the Total Carbon (CO2) Emissions Intensity Per Sales from Bloomberg. BCTRE Scope 1 is Bank Climate Transition Risk Exposure (BCTRE) Scope 1. BCTRE Reg is Bank Climate Transition Risk Exposure (BCTRE) Regulatory. BCTRE Opp is Bank Climate Transition Risk Exposure (BCTRE) Opportunity. The control variables used include bank size, size squared, deposit to assets, liquidity to assets, non-interest income, bank capital, ROA, net loans to assets, loan loss reserve, and loan growth. Both dependent and independent variables are standardized. Standard errors are clustered at the bank level. Variable definitions in Appendix A1. *** p<0.01, ** p<0.05, * p<0.1.*

Overall, the results from our comprehensive analysis reported above, provide evidence that the relationship between climate risk and systemic risk is not stable. It depends on the combination of the measures and sample used. European banks, operating within stricter regulatory frameworks and more proactive climate policies, may exhibit reduced sensitivity to certain climate risks. This underscores the importance of region-specific interventions and regulatory harmonization in addressing systemic vulnerabilities.

The mechanisms behind these results are multifaceted and require further investigation. Cultural factors, such as differing risk appetites across regions, may explain some of the variability. Regulatory and market conditions also likely play a role, with jurisdictions that enforce stricter climate policies possibly mitigating risks more effectively. For example, higher environmental policy uncertainty in less regulated regions may exacerbate the systemic risk contribution of transition risks. Future studies could investigate these mechanisms in greater depth, exploring how policy design and market behavior interact to influence systemic risk.

In practice, central banks and regulators must adopt a tailored approach to climate-driven systemic risk. This includes recognizing the diversity in climate vulnerabilities across regions and financial institutions, as well as using a multi-metric framework to capture the complexities of systemic risk. The results emphasize the need for proactive, region-specific policy measures to manage climate-related risks effectively and promote financial stability.

5. Further Analysis

5.1 Policy Shocks

Next, we examine how climate transition risk influences systemic risk through borrowers' exposure to environmental policies. If climate risk is transmitted to the banking sector via borrowers' loan portfolios, we expect an increase in systemic risk following environmental policy shocks. To test this hypothesis, we use emissions trading systems (ETS) as the policy shock and borrowers' Scope 1 emissions as the primary measure of exposure. Our estimations are conducted using a combined sample of US and European banks. We introduce a difference-in-differences (DiD) variable, which takes the value of one after a country where a borrower operates implements an ETS and zero otherwise. To assess the impact of climate risk, we interact this ETS DiD variable with bank-level climate risk exposure.

The key results from these interaction coefficients are reported in Table A4. The results show positive and statistically significant coefficients for ETS × BCTRE Scope 1 at the 5% level for two systemic risk measures: ΔCoVaR (0.109) and SRISK (0.100). However, the coefficients for MES and LRMES are not statistically significant. Next, we focus on the exposure of US banks specifically to climate transition risks. Here, the results are mixed—one systemic risk measure indicates a negative and statistically significant relationship, while the other two exhibit positive and significant associations. In another set of estimations, we exclude US-based borrowers and examine the exposure of US banks to non-US borrowers. The findings reveal three positive coefficients, with MES being the exception, showing a negative coefficient. Turning to the European banks, we find that the results remain insignificant regardless of whether we include or exclude European borrowers in the analysis.

While some differences emerge across the four systemic risk measures, the overall evidence suggests that borrowers' climate risks can indeed be transmitted through their loan portfolios to the financial sector. However, the relationship appears weak and statistically insignificant in the European banking sector.

5.2 Principal Component Analysis

The results in Table A5 present the outcomes of the PCA of the systemic risk measures (ΔCoVaR, MES, SRISK, and LRMES) against climate measures. The conclusion remains consistent, as the results remain mixed even after aggregating the four systemic risk measures. The analysis is divided into two panels. Panel A, which focuses on country-level climate measures, generally shows a negative relationship between systemic risk and climate factors, though some variability exists across different contexts. Panel B, examining bank-level climate measures, reveals a more nuanced relationship, with some measures showing positive associations with systemic risk while others exhibit mixed or inconsistent patterns. Overall, these findings highlight the complexity of the relationship between climate risks and systemic risk, with differing dynamics depending on the level of analysis and the specific measures considered.

5.3 Cross-Sectional Analysis - Big Banks

Table A6 presents the results of the impact of climate risks on systemic risk for large banks, defined as those with assets exceeding $1 billion, focusing on the interaction effect between climate risk and the "Big bank" variable. The findings suggest that large banks tend to amplify systemic risk under certain climate-related conditions, particularly for country-level climate measures, indicating that their scale may heighten sensitivity to these risks. However, the results for bank-level climate measures are mixed, with some evidence that high-emission-intensity banks among large institutions contribute more significantly to systemic risk, while other measures show inconsistencies in their interaction effects. These mixed results underscore the complexity of the relationship and the need to carefully consider the unique characteristics and dynamics of large banks in the context of climate risks and systemic vulnerabilities.

5.4 Cross-Sectional Analysis - Before and After the Paris Agreement

Table A7 examines how the relationship between climate risk and systemic risk changes before and after the Paris Agreement, with pre-Paris defined as years prior to 2016 and post-Paris as years from 2016 onward. Based on the results in Panel A, the impact of climate risk on systemic risk is more pronounced post-Paris Agreement. The findings suggest that systemic risk becomes more sensitive to climate-related policy and regulatory changes after the Paris Agreement, particularly in the case of country-level climate measures. However, bank-level measures in Panel B show mixed insignificant results. The overall trend highlights that the estimated relationship between climate risk and systemic risk is inconsistent across different measures and samples.

6. Conclusion

Theoretically, climate risk can impact systemic risk, which means central banks would need to monitor the climate risk of banks. However, whether this impact is substantial or not is an empirical question. Testing the relationship between climate risk and systemic risk is challenging as both climate and systemic risks can be measured in various ways. Moreover, the correlation between these different measures of systemic risk is relatively limited, as is the correlation between different climate risk measures. In this paper, we analyse whether the estimated relationship between climate risk and systemic risk is consistent across different measures of climate risk and different measures of systemic risk, or instead depends on which specific measure of climate risk and which specific measure of systemic risk is used.

Our comprehensive analysis of U.S. and European banks underscores the complex and often region-dependent nature of climate-related systemic risks. Overall, while physical climate risks have a more direct association with systemic risk, the effects of transition risks appear to be more limited, possibly reflecting adaptation measures within the financial sector. We also find that U.S. banks demonstrate a stronger correlation between climate and systemic risks than European banks. Further analysis highlights that large banks tend to amplify systemic risk under certain climate conditions, although inconsistencies remain. Additionally, the post-Paris Agreement period shows a more pronounced relationship between climate risk and systemic risk, suggesting that policy frameworks play a significant role in shaping these dynamics. These findings underscore the importance of contextual factors in understanding the climate risk-systemic risk relationship.

Despite its contributions, this study has limitations that warrant further exploration. First, data constraints may introduce biases, particularly due to the reliance on available climate and systemic risk measures, which may not fully capture the multidimensional nature of these risks. Additionally, the mixed results observed in this study underscore the challenges of interpreting inconsistencies across metrics, highlighting the need for more refined and harmonized measures.

Future research could explore additional regions beyond the U.S. and Europe to assess whether the findings hold in other contexts, particularly in emerging markets where climate vulnerabilities and financial systems differ significantly. Additionally, refining systemic risk measures to better align with climate factors such as integrating dynamic measures that account for evolving policy landscapes and climate adaptation could enhance our understanding. Further exploration of sector-specific vulnerabilities and the role of interbank linkages in amplifying or mitigating climate risks would also provide valuable insights.

Our findings suggest that central banks should adopt a multi-metric approach to evaluate climate-driven systemic risk, avoiding reliance on a single risk measure. Furthermore, region-specific policy frameworks may be required to address the unique climate vulnerabilities inherent within different financial systems. These insights emphasize the role of central banks in shaping climate resilience, urging a proactive, tailored approach to policymaking in the face of escalating climate risks.

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Appendix

Table A1: Summary Statistics of Climate Measures

	N	Mean	SD	Min	Median	Max
Sea Level Rise	27856	.121	.343	0	0	2
Climate Disasters Count	27290	2.736	2.223	0	2	12
EPU	27856	-.091	.968	-1.485	-.422	2.726
Gavriilidis CPU	20960	-.065	.969	-1.727	-.073	2.977
Environmental risk	8493	.555	.943	0	.306	33.813
Berestycki CPU	29079	1.657	.917	.129	1.469	5.289
Climate Risk-ND-Gain	36169	68.466	4.053	47.025	68.891	76.482
GCPRI	36145	18.736	14.457	0	13.889	72.245
Environmental Score	10801	28.355	29.865	0	21.153	97.024
Bank Climate Policy	10680	.025	.156	0	0	1
Refinitiv Emissions Intensity	10801	0	0	0	0	.012
Refinitiv Scope3 Estimate	7543	.001	.017	0	.001	1.469
Bloomberg Scope 2 Intensity	3196	6.455	8.809	0	4.087	95.963
Bloomberg Emissions Intensity	2676	10.608	12.442	.004	8.169	179.225
BCTRE Scope 1	13000	11.342	137.445	0	.138	7980.265
BCTRE Reg	18556	.004	.054	0	0	4.928
BCTRE Opp	18556	.261	2.66	0	0	131.935

Table A2: Variable Definition:

Variable[9]	Definition	Source
Dependent Variables - Systemic Risk Measures		
ΔCoVaR	The change between the bank's CoVaR when it is under financial distress and in its median state. The estimation is based on quantile regressions.	Authors' Computation
MES	Measures a bank's vulnerability to systemic risk by assessing its average loss of market equity during the worst 5% of return days for the banking industry.	Authors' Computation
SRISK	The expected capital shortfall of a given bank, conditional on a severe market crisis affecting the whole financial system. The value of capital a bank would need to raise to continue functioning during a financial crisis.	Authors' Computation
LRMES	Quantifies a bank's vulnerability to market downturns by measuring its stock's co-movement with the industry index, capturing potential equity losses in a systemic crisis.	Authors' Computation
Independent Variables- Climate Risk Measures		
Sea Level Rise Exposure	NOAA's "intermediate" sea level rise projection for the year 2040. The sea level rise exposure is matched at the city level to be consistent with bank locations using data from the National Atmospheric Administration (NAA).	National Oceanic and Atmospheric Administration (NOAA)

[9] All Variables at quarterly frequency. Detailed variables description is in section 3.2.

Climate Disaster Count (CDC)	The number of climate disaster declarations (flood, severe storms, hurricanes, fire, snow, drought, tornado, etc) by state and year.	Billion Dollar Weather and Climate Disasters
Environmental Policy Uncertainty (EPU)	The textual measure by Noailly et al. (2022). The indices examine 15 million news articles sourced from the archives of ten U.S. newspapers, utilizing machine learning techniques for analysis.	Noailly, Nowzohour, and van den Hauvel (2022)
Climate Risk-ND-Gain	It measures the country's exposure, sensitivity and capacity to adapt to the adverse impacts of climate change.	Notre Dame Global Adaptation Initiative
Berestycki Climate Policy Uncertainty	A textual measure constructed from leading national newspapers using words related to uncertainty, climate change and climate policies.	Berestycki et al. (2022)[10],
Gavriilidis CPU	Climate Policy Uncertainty textual measure constructed from eight leading US newspapers using words related to uncertainty, climate change and climate policies.	Gavriilidis (2021)
Global Climate Physical Risk Index (GCPRI)	The weighted average across four measures extreme low and high temperature, rain and drought days.	Guo, Ji, & Zhang (2024)
Environmental Risk	A textual environmental risk proxy at the bank level developed by Hassan et al. (2019). It captures risk from environmental policies as reported by listed firms.	Hassan, Hollander, van Lent, Tahoun (2019)
Refinitiv Scope3 Estimate	Total estimated scope 3 emissions in tonnes divided by total assets	Refinitiv Eikon
Refinitiv Emissions Intensity	Percentage change year on year of Greenhouse gas emissions indirect, scope 3 to million revenues USD.	Refinitiv Eikon

[10] The data contains a dozen but not all G20 countries.

Bloomberg Scope 2 Intensity	It is calculated as metric tonnes of greenhouse gases in carbon dioxide equivalent emitted from indirect operations per million of sales revenue in the company's reporting currency.	Bloomberg
Bloomberg Emissions Intensity	It is calculated as total metric tonnes of CO_2 emitted per million of sales revenue in the company's reporting currency. The ratio is calculated based on data items disclosed in company filings.	Bloomberg
Environmental Score	Measures how well a company uses best management practices to avoid environmental risks and capitalize on environmental opportunities to generate long term shareholder value.	Refinitiv Eikon
Bank Climate Policy	Does the financial company have a public commitment to divest from fossil fuel?	Refinitiv Eikon
Bank-firm Exposure Scope 1	Measures how a bank is exposed through its borrowers using the weighted outstanding loan share times the borrower's scope 1 emissions.	Author's computation
Bank-firm Exposure Regulatory	Measures how a bank is exposed through its borrowers using the weighted outstanding loan share times the borrower's climate regulatory exposure score	Author's computation
Bank-firm Exposure Opportunity	Measures how a bank is exposed through its borrowers using the weighted outstanding loan share times the borrower's climate opportunity exposure score	Author's computation
Bank Controls Variables		
Size	Bank size is the natural logarithm of a bank's total assets	S&P Capital IQ (Capital IQ)
Size Squared	Bank size squared	Capital IQ

Deposits to Assets	Total deposits scaled by total assets	Capital IQ
Bank Capital	Total bank equity scaled by total assets	Capital IQ
Profitability	Bank's return on assets	Capital IQ
Liquidity to Assets	The sum of cash and cash equivalence scaled by assets	Capital IQ
Non-Interest Income	Non-interest income scaled by assets	Capital IQ
Loan to Assets	Net loans scaled by total assets	Capital IQ
Loan Loss Provision	Total loan loss reserves scaled by total assets	Capital IQ
Loan Growth	The growth rate of loans to assets ratio	Capital IQ
Macro-economic Control Variables		
Inflation	Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly.	World Development Indicators of the World Bank (WDI)
GDP per Capita	GDP per capita is gross domestic product divided by midyear population.	WDI

Table A3: Climate Risk Pairwise Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Sea Level Rise	1.00													
(2) Climate Disasters Count	-0.11	1.00												
(3) EPU	0.00	0.16	1.00											
(4) Gavriilidis CPU	0.00	0.16	1.00	1.00										
(5) Environmental risk	-0.01	0.00	0.00	0.00	1.00									
(6) Berestycki CPU	0.00	0.27	0.11	0.11	-0.02	1.00								
(7) Climate Risk-ND-Gain	0.00	-0.15	-0.36	-0.36	-0.14	-0.31	1.00							
(8) GCPRI	-0.01	-0.25	0.08	0.08	-0.10	-0.24	0.06	1.00						
(9) Environmental Score	0.09	-0.13	-0.05	-0.05	0.19	-0.20	-0.32	-0.14	1.00					
(10) Bank Climate Policy	0.06	-0.03	0.03	0.03	0.07	0.05	-0.04	-0.04	0.28	1.00				
(11) Ref Emissions Intensity	-0.05	-0.14	-0.13	-0.13	0.00	-0.17	-0.11	-0.06	0.13	-0.04	1.00			
(12) Ref Scope3 Estimate	-0.11	-0.12	0.00	0.00	-0.14	-0.05	-0.01	-0.01	-0.04	-0.01	-0.01	1.00		
(13) BB Scope 2 Intensity	-0.26	-0.13	-0.22	-0.22	-0.13	-0.21	0.07	-0.10	-0.10	-0.15	0.43	-0.14	1.00	
(14) BB Emissions Intensity	-0.23	-0.15	-0.21	-0.21	-0.08	-0.18	-0.04	-0.07	-0.11	-0.14	0.93	0.16	0.68	1.00

Table A4: USA and Europe -Combined Sample – Policy Shocks

Systemic Risk / Climate	ΔCoVaR	SRISK	MES	LRMES	Sample Size
ETS× BCTRE Scope 1	0.109**	0.100**	0.068	0.029	
ETS× BCTRE Scope 1-EU firms	0.153	0.237***	-0.033	0.063**	1884
ETS× BCTRE Scope 1- US	-0.002	0.310*	-0.122***	0.071***	7019
ETS× BCTRE Scope 1– US banks – non-US firms	0.130***	0.313	-0.121***	0.084***	1,341
ETS× BCTRE Scope 1– EU banks	0.035	0.044	-0.002	-0.001	2081
ETS× BCTRE Scope 1– EU banks – non-EU firms	0.024	-0.002	0.086	0.002	1018

*ΔCoVaR, MES, SRISK, or LRMES are the bank systemic risk measures. The higher the values of these measures, the higher the systemic risk. ETS is Emissions Trading System. BCTRE Scope 1 is Bank Climate Transition Risk Exposure (BCTRE) Scope 1. The control variables used include bank size, size squared, deposit to assets, liquidity to assets, non-interest income, bank capital, ROA, net loans to assets, loan loss reserve, and loan growth. Both dependent and independent variables are standardized. Standard errors are clustered at the bank level. Variable definitions in Appendix A1. *** p<0.01, ** p<0.05, * p<0.1.*

Table A5: Principal Component Analysis (PCA) of ΔCoVaR, MES, SRISK and LRMES

Panel A – Country-Level Climate Measures						
PCA -Systemic Risk						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CDC	EPU	Gavriilidis CPU	Berestycki CPU	ND Gain	GCPRI
Climate Risk-USA	-0.002	-0.003	-0.094***	-0.009	-0.190**	-0.143***
	(0.009)	(0.015)	(0.013)	(0.007)	(0.081)	(0.048)
Climate Risk-Europe	-	-	-	0.062	0.544**	0.259***
	-	-	-	(0.111)	(0.232)	(0.066)
Climate Risk-Combined	-0.002	-0.003	-0.094***	0.009	-0.165*	0.099*
	(0.009)	(0.015)	(0.013)	(0.047)	(0.091)	(0.058)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

*The table presents regression results exploring the relationship between bank-level climate measures and systemic risk using the principal component analysis (PCA) of systemic risk metrics. Results are reported for three different samples: USA, Europe, and Combined, across six country-level climate measures. CDC is Climate Disasters Count which is at the US state level. EPU is Environmental Policy Uncertainty. Gavriilidis CPU is the climate policy uncertainty constructed by Gavriilidis. Climate risk-ND-GAIN is a country's climate risk measured as the opposite of its NDGain. GCPRI is the Global Climate Physical Risk Index. Berestycki CPU is the climate policy uncertainty constructed by Berestycki. Controls include bank size, profitability, liquidity, and other financial characteristics, along with year and firm fixed effects to account for temporal and bank-specific factors. Robust standard errors are reported in parentheses, and significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.*

Panel B – Bank-Level Climate Measures							
PCA -Systemic Risk							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Environ risk	Envir Score	ClimatePol	Ref Emiss Intens	Scope3Est	BBScope2Intensity	BB Emiss Intens
Climate Risk-USA	0.009	-0.053	-0.015	0.044***	0.060	0.069***	0.064***
	(0.010)	(0.035)	(0.026)	(0.013)	(0.052)	(0.016)	(0.012)
Climate Risk-Europe	0.016	0.075*	0.020	0.055*	-0.007	-0.328***	0.009
	(0.014)	(0.043)	(0.031)	(0.031)	(0.012)	(0.093)	(0.029)
Climate Risk-Combined	0.014*	-0.033	-0.008	0.048***	0.004	-0.013	0.049**
	(0.008)	(0.027)	(0.021)	(0.014)	(0.005)	(0.052)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*The table presents regression results exploring the relationship between bank-level climate measures and systemic risk using the principal component analysis (PCA) of systemic risk metrics. Results are reported for three different samples: USA, Europe, and Combined, across seven bank-level climate measures. Environ risk is environmental risk at the bank level. Environ Score is the environmental pillar score. ClimatePol is Bank Climate Policy. Ref Emissions Intensity is emissions intensity from Refinitiv. Scope 3 Est is estimated scope 3 emissions. BBScope2 is GHG Scope 2 Intensity Per Sales from Bloomberg. BB Emissions Intensity is Total Carbon (CO2) Emissions Intensity Per Sales from Bloomberg. Controls include bank size, profitability, liquidity, and other financial characteristics, along with year and firm fixed effects to account for temporal and bank-specific factors. Robust standard errors are reported in parentheses, and significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.*

Table A6: USA Sample- Cross-Section Test- Big Banks

	Panel A – Country-Level Climate Measures					
	PCA -Systemic Risk					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CDC	EPU	Gavriilidis CPU	Berestycki CPU	ND Gain	GCPRI
Climate Risk	-0.029*	-0.040*	-0.084***	0.056***	-0.469***	-0.074
	(0.016)	(0.021)	(0.016)	(0.014)	(0.094)	(0.050)
Big bank	0.122***	0.125***	0.130***	0.120***	-0.057	0.126***
	(0.028)	(0.028)	(0.034)	(0.027)	(0.038)	(0.028)
Big bank*Climate Risk	0.035**	0.049***	-0.018	-0.083***	0.490***	-0.137***
	(0.016)	(0.018)	(0.012)	(0.015)	(0.065)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,724	26,301	18,646	26,301	24,611	26,301
R-squared	0.330	0.320	0.272	0.321	0.320	0.324
Number of banks	517	537	464	537	532	537
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

*The table presents results from regressions examining the relationship between country-level climate risk measures and systemic risk, represented by the principal component analysis (PCA) of systemic risk metrics. Climate Risk captures the primary independent variable, with additional interaction terms for large banks (Big bank) and the interaction between large banks and climate risk (Big bank*Climate Risk) to explore differential impacts. CDC is Climate Disasters Count which is at the US state level. EPU is Environmental Policy Uncertainty. Gavriilidis CPU is the climate policy uncertainty constructed by Gavriilidis. Climate risk-ND-GAIN is a country's climate risk measured as the opposite of its NDGain. GCPRI is the Global Climate Physical Risk Index. Berestycki CPU is the climate policy uncertainty constructed by Berestycki. Controls include bank size, profitability, liquidity, and other financial characteristics, along with year and firm fixed effects to account for temporal and bank-specific factors. Robust standard errors are reported in parentheses, and significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.*

Panel B – Bank-Level Climate Measures							
PCA -Systemic Risk							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Environ risk	Environ Score	Climate Pol	Ref Emiss Inte	Scope3Est	BBScope2Intensity	BB Emiss Inten
Climate Risk	0.153***	0.046	0.000	-0.014	0.498	0.069***	0.064***
	(0.048)	(0.074)	(0.000)	(0.268)	(0.630)	(0.016)	(0.012)
Big bank	0.266***	-0.157**	-0.129**	-0.114**	0.148	-0.136**	0.207***
	(0.091)	(0.068)	(0.059)	(0.055)	(0.129)	(0.059)	(0.067)
Big bank*Climate Risk	-0.146***	-0.100	-0.015	0.057	-1.289**	0.000	0.418*
	(0.050)	(0.073)	(0.026)	(0.268)	(0.603)	(0.000)	(0.224)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,253	8,589	8,500	8,589	6,693	6,693	993
R-squared	0.785	0.765	0.765	0.766	0.738	0.738	0.915
Number of banks	143	280	280	280	276	276	27
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*The table presents results from regressions examining the relationship between bank-level climate risk measures and systemic risk, represented by the principal component analysis (PCA) of systemic risk metrics. Climate Risk captures the primary independent variable, with additional interaction terms for large banks (Big bank) and the interaction between large banks and climate risk (Big bank*Climate Risk) to explore differential impacts. Environ risk is environmental risk at the bank level. Environ Score is the environmental pillar score. ClimatePol is Bank Climate Policy. Ref Emissions Intensity is emissions intensity from Refinitiv. Scope 3 Est is estimated scope 3 emissions. BBScope2 is GHG Scope 2 Intensity Per Sales from Bloomberg. BB Emissions Intensity is Total Carbon (CO2) Emissions Intensity Per Sales from Bloomberg. Controls include bank size, profitability, liquidity, and other financial characteristics, along with year and firm fixed effects to account for temporal and bank-specific factors. Robust standard errors are reported in parentheses, and significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.*

Table A7: USA Sample- Cross-Section Test- After Paris Agreement

Panel A – Country-Level Climate Measures						
PCA -Systemic Risk						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CDC	EPU	Gavriilidis CPU	Berestycki CPU	ND Gain	GCPRI
Climate Risk	0.028	0.397***	-0.159***	-0.143***	-0.093	-0.338***
	(0.017)	(0.072)	(0.022)	(0.028)	(0.083)	(0.040)
Paris	0.241***	-0.297***	0.017	0.244***	0.239***	0.222***
	(0.041)	(0.073)	(0.038)	(0.038)	(0.041)	(0.039)
Paris*Climate Risk	-0.042**	-0.429***	0.197***	0.120***	0.000	0.000
	(0.018)	(0.071)	(0.028)	(0.030)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,724	26,301	18,646	26,301	24,611	26,301
R-squared	0.330	0.319	0.271	0.319	0.315	0.319
Number of banks	517	537	464	537	532	537
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

*The table presents results from regressions examining the relationship between country-level climate risk measures and systemic risk, represented by the principal component analysis (PCA) of systemic risk metrics. Climate Risk captures the primary independent variable, with additional interaction terms for Paris and the interaction between Paris and climate risk (Paris*Climate Risk) to explore differential impacts. CDC is Climate Disasters Count which is at the US state level. EPU is Environmental Policy Uncertainty. Gavriilidis CPU is the climate policy uncertainty constructed by Gavriilidis. Climate risk-ND-GAIN is a country's climate risk measured as the opposite of its NDGain. GCPRI is the Global Climate Physical Risk Index. Berestycki CPU is the climate policy uncertainty constructed by Berestycki. Controls include bank size, profitability, liquidity, and other financial characteristics, along with year and firm fixed effects to account for temporal and bank-specific factors. Robust standard errors are reported in parentheses, and significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.*

Panel B – Bank-Level Climate Measures							
PCA -Systemic Risk							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Environ risk	Environ Score	Climate Pol	Ref Emissions Intensity	Scope3 Est	BB Scope2 Intensity	BB Emissions Intensity
Climate Risk	0.014	-0.013	0.025	0.044***	0.060	0.068***	0.062***
	(0.016)	(0.058)	(0.044)	(0.012)	(0.052)	(0.015)	(0.012)
Paris	0.681***	0.214***	-0.070	0.207***	0.000	-0.626***	-0.571***
	(0.046)	(0.062)	(0.072)	(0.059)	(0.000)	(0.072)	(0.099)
Paris*Climate Risk	-0.011	-0.048	-0.052	-0.031	0.000	0.088	0.086
	(0.016)	(0.043)	(0.036)	(0.041)	(0.000)	(0.078)	(0.110)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,253	8,589	8,500	8,589	6,693	993	774
R-squared	0.784	0.765	0.765	0.766	0.738	0.915	0.920
Number of banks	143	280	280	280	276	27	27
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*The table presents results from regressions examining the relationship between bank-level climate risk measures and systemic risk, represented by the principal component analysis (PCA) of systemic risk metrics. Climate Risk captures the primary independent variable, with additional interaction terms for Paris and the interaction between Paris and climate risk (Paris*Climate Risk) to explore differential impacts. Environ risk is environmental risk at the bank level. Environ Score is the environmental pillar score. ClimatePol is the Bank Climate Policy. Ref Emissions Intensity is emissions intensity from Refinitiv. Scope 3 Est is estimated scope 3 emissions. BBScope2 is GHG Scope 2 Intensity Per Sales from Bloomberg. BB Emissions Intensity is Total Carbon (CO2) Emissions Intensity Per Sales from Bloomberg. Controls include bank size, profitability, liquidity, and other financial characteristics, along with year and firm fixed effects to account for temporal and bank-specific factors. Robust standard errors are reported in parentheses, and significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.*