University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2025-07
February 2025

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Climate Risks and Predictability of Financial Risks in the US Banking Sector

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Abstract

In this paper, we relate physical and transition climate risks of the United States (US) to systemic risk of its banking sector. We start by estimating the systemic risk of 128 bank stock prices of the US over the period 26th May 2008 to 30th June 2023, taking the time-varying financial risk meter (FRM) approach, which relies on the Lasso quantile regression model. The FRM for the overall system of banks, as well as for large, medium, and small banks separately, exhibits notable peaks during COVID-19 in particular, and the global financial and European sovereign debt crises. Subsequently, using a nonparametric causality-in-quantiles test, which is robust to misspecification due to nonlinearity and structural breaks, we show that news-based metrics of physical and transition risks can significantly predict the entire conditional distribution of the FRMs over the full-sample and in a time-varying manner, with strongest causal impacts derived from news on international summits, compared to those on natural disasters, global warming, and US climate policies. Further analysis shows that all four climate risk factors consistently exert a positive impact on the conditional quantiles of the FRMs, supporting the premise that climate risks can damage assets and augment operating costs in the banking sector. Our findings have important policy implications which concern the stability of the banking sector.

Keywords: US bank stocks; financial risk meter (FRM); climate risks; nonparametric causality-in-quantiles test; predictability

JEL Codes: C21; C22; G21; Q54

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1. Introduction

In line with the burgeoning area of research focusing on the nexus between climate change risks and asset markets (see, Giglio et al. (2021), Del Fava et al. (2024) and Gupta et al. (forthcoming) for detailed reviews), a few papers analyse the impact of such risks on the banking sector (Battiston et al., 2017; Cortés and Strahan, 2017; Roncoroni et al., 2021; Le at el., 2023),[1] including bank stocks (Boungou and Urom, 2023). The growing focus on this sector should not come as a surprise, since banks, which play a financial intermediary role, are exposed to both physical climate risks (caused by physical phenomena) and transition climate risks (resulting from a shift towards "green" energy) through changes in credit risks, market risks, and lending standards (Battiston et al., 2021; Acharya et al., 2023; de Bandt et al., 2024), which can lead to a change in the value of bank assets, including bank portfolios, and an increase in bank operating costs (Cahen-Fourot et al., 2021).

As far as the literature on climate risks and banking sector performance is concerned, Battiston et al. (2017) conduct a climate stress test on the 50 largest European Union banks, revealing that second-round effects can be of comparable magnitude to first-round effects. The first-round effects originate from climate-policy-relevant sectors, such as investment and pension funds. Cortés and Strahan (2017) trace out how multi-market banks in the United States (US) adjust their credit supply decisions in response to local, exogenous shocks to credit demand triggered by natural disasters. Using property damage as an instrument for lending growth, these authors find that credit in unaffected but connected markets declines, but by a little less than 50 cents per dollar of additional lending in shocked areas.[2] Roncoroni et al. (2021) explore the effects on financial stability, both analytically and empirically, in the context of Mexico's banking sector, considering its interplay with market conditions. They show that, in the wake of mild climate policy shocks, a disorderly transition from business as usual to a 2°C temperature rise (i.e., the international climate change target to limit global warming) produces important losses for the financial system, especially if market conditions are weak. Le at el. (2023), using an international sample of 6433 commercial banks in 109 countries between 2005 and 2019, illustrate that increased physical climate risks lead to decreased bank stability in terms of profitability, asset quality and liquidity risks. Erhemjamts et al. (2024) consider US commercial banks and show that negative sentiment arisen from the exposure to climate risk is associated with deteriorated financial performance, whereas a stronger ESG engagement can lessens such a harmful

[1] The reader is referred to de Bandt et al. (2024) for a comprehensive review of studies related to this area, which also includes a discussion of unpublished working papers.

[2] This finding is in line with that of Blickle et al. (2022), who show that natural disasters over the last twenty-five years have had small effects on the performance of US banks.

impact. Interestingly, Boungou and Urom (2023) find that physical and transition risks related to climate change in the US have a negative impact on the stock performance, i.e., returns, of global and G20 banks[3].

We aim to add to this embryonic literature on the impact of climate risks on bank stock performance, particularly in the US, by, firstly, developing a time-varying systemic risk measure (i.e., the financial risk meter (FRM)) for 128 US banks over the period 26th May 2008 to 30th June 2023, then analysing the causal effect of various physical and transition climate risks on the FRMs of aggregate, small, medium, and large banks. For the first, we construct the FRM, following Mihoci et al. (2020), based on the least absolute shrinkage and selection operator (Lasso) quantile regression designed to capture tail event co-movements, thus allowing us to understand characteristics of the stock returns of 128 US banks in the context of interdependencies in a network topology. We not only develop a FRM for all 128 banks, but do the same for small, medium, and large banks to detect possible heterogeneity in the behaviour of systemic risk contingent on the size of market capitalization. For the second, we use the nonparametric causality-in-quantiles test of Jeong et al. (2012) to analyse the predictive impact of measures of physical and transition climate risks of the US on the FRMs of the aggregate, small, medium, and large banks. The advantage of this purely data-driven, (i.e., nonparametric) quantiles-based test is its ability to provide robust inferences of predictability over the entire conditional distribution (beyond the conditional mean) of the FRMs. Hence, this test is able to capture the causal effect of climate risks on low, normal and high levels of systemic risks in the banking sector, by accommodating any misspecification that standard linear quantile regression models, as used by Boungou and Urom (2023), might suffer due well-established evidence of nonlinearity and structural breaks in high-frequency (daily) data.

To the best of our knowledge, this is the first paper to analyse the predictive role of climate risk factors associated with natural disasters, global warming, international summits, and US climate policy, as developed by Faccini et al. (2023), on measures of tail risks of disaggregated stock prices of a large number of US banks using a robust non-parametric test of causality at quantiles. In this context, our paper is closest to the work of Curcio et al. (2023), who show that physical risks in the form of billion-dollar climate disasters in the US can increase the systemic risk (measured by delta conditional value at risk and the marginal expected shortfall) of the S&P 500 Banks Industry Group GICS Level 2.[4] Understandably, our work can be considered an extension of Curico et al. (2023), considering both physical and transition

[3] On a related front, Cao (2025) examines the influence of climate change on the interconnectedness across the tail-risk of stock markets, showing that physical risk intensifies the total and directional connectedness, unlike transition risk.
[4] See Wu et al. (2024) for a corresponding study at the global-level dealing with the positive relationship between vulnerability and weak adaptability (readiness) to physical climate risks on systemic risk, captured by delta conditional value at risk of 1,570 listed banks from 120 countries.

climate risks over various levels (quantiles) of systemic risk associated with the overall banking sector, as well as for these banks characterized by size market capitalization.

The performance of the banking industry is a useful indicator for financial markets of credit quality, consistency in flow of liquidity, and degree of fear surrounding banking insolvencies that exist in the wider financial system (Ampudia and Van den Heuvel, 2022; O'Donnell et al., 2024). Understandably, appropriate modelling and prediction of systemic risk involved in the banking sector, with the latter capturing financial stability in the industry, is indeed of paramount concern for investors, bankers, and policymakers in the wake of ever increasing climate risks and the transition towards a greener economy.

The remainder of the paper is organized as follows: Section 2 outlines the basics of the methodologies involving the FRM and the nonparametric causality-in-quantiles test. Section 3 presents the data, while Section 4 discusses our empirical findings and Section 5 concludes the paper.

2. Methodology

In this section, we present the basics of the FRM and the nonparametric causality-in-quantiles test.

2.1. The Financial Risk Meter (FRM)

The FRM is constructed as the mean value over the series of penalization terms computed based on the log-returns of the stock prices of the 128 US banks in our sample, following Mihoci et al. (2020). We firstly introduce the linear quantile Lasso regression approach as discussed in Härdle et al. (2016).

Considering a large number (128) of banks denoted by *k*, and indexed by $j \in \{1, \ldots, k\}$, the total number of covariates is $k + m - 1$, where *m* is the number of macroeconomic and financial control variables, discussed in the next section (Section 3). There are *T* total observations, with time indexed by *t*. We use a sliding window *s* given by $s \in \{1, \ldots, (T - (n - 1))$ having a size of n = 500 observations to compute the time-varying FRM. Having introduced this notation, the quantile Lasso regression can be written as:

$$X_{j,t}^{s} = \alpha_j^s + A_{j,t}^{s,T} \beta_j^s + \epsilon_{j,t}^s \tag{1}$$

where $A_{j,t}^{s,T} = [\begin{smallmatrix} M_{t-1}^s \\ X_{-j,t}^s \end{smallmatrix}]$, while M_{t-1}^s is the vector of our macro-finance variables of dimension *m* and $X_{-j,t}^s$the vector of log-returns of the stock prices for the other banks except bank *j* at time *t* and for the windows s (with this latter vector having a dimension of *p-m*).

The estimation for this regression uses a L_1-norm quantile regression (Li and Zhu, 2008), which is formally written as:

$$\min_{\alpha_j^s,\beta_j^s}\{n^{-1}\sum_{t=s}^{s+(n-1)}\rho_t(X_{j,t}^s-\alpha_j^s-A_{j,t}^{s,T}\beta_j^s)+\lambda_j^s\left\|\beta_j^s\right\|_1\} \quad (2)$$

where, λ_j^s is a penalization parameter, while we define the function $\rho_\tau(u)$ as:

$$\rho_\tau(u)=|u|^c|I(u\leq 0)-\tau| \quad (3)$$

where, for c having a value of 1, we get the quantile regression.

For equation (2), the crucial choice is of the penalization parameter λ_j^s. One can use the Bayesian information criterion (BIC) or, following Yuan (2006), the generalized approximate cross-validation criterion (GACV), which is shown by Yuan and Lin (2006) to have a better performance from a statistical point of view. Hence, we determine λ_j^s using the GACV criterion, such that $\lambda_j^s$is the solution to this minimization problem:

$$\min GACV(\lambda_j^s)=\min\frac{\sum_{t=s}^{s+n}\rho_t(X_{j,t}^s-\alpha_j^s-A_{j,t}^{s,T}\beta_j^s)}{n-df} \quad (4)$$

where *df* measures the actual dimensionality of the fitted model.

Following this approach, we get a λ_j^s for each bank. The final λ_j^s, i.e., the FRM, is computed as a mean of the set of k banks:

$$\text{FRM}=\frac{1}{k}\sum_{j=1}^{k}\lambda_j^* \quad (5)$$

We construct the FRM not only for all banks in our sample, irrespective of market capitalization, but also for three categories of bank (small, medium, and large) classified based on the market capitalization of each bank, with details presented in the next section.

2.2. Nonparametric Causality-in-Quantiles Test

In this sub-section, we briefly present the methodology for testing nonparametric causality based on the framework of Jeong et al. (2012).

Let y_t denote the FRM for the overall banking system, or for small, medium, and large banks, and x_t a particular climate risk, i.e., natural disaster, global warming, international summit, and US climate policy. Further, let $Y_{t-1}\equiv(y_{t-1},\ldots,y_{t-p})$, $X_{t-1}\equiv(x_{t-1},\ldots,x_{t-p})$, $Z_t=(X_t,Y_t)$, and $F_{y_t|\cdot}(y_t|\,\bullet)$ denote the conditional distribution of y_t given $\bullet$. Defining the θ-th conditional quantile function of the lagged values of the variables ($Z_t = (X_t, Y_t)$) in the bivariate system as $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. The rejection of the null hypothesis indicates quantiles-based Granger causality, with the following testable hypotheses in the θ-th quantile:

$$H_0:\ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{6}$$

$$H_1:\ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{7}$$

Jeong et al. (2012) show that the feasible kernel-based (standard normal) test statistic has the format:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{8}$$

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile, and $\mathbf{1}\{\bullet\}$ is the indicator function. The *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by:

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \tag{9}$$

with $L(\bullet)$ denoting the kernel function.

The empirical implementation of this nonparametric causality-in-quantiles testing involves specifying: the bandwidth (h), lag order (p), and kernel types for $K(\cdot)$ and $L(\cdot)$. We use $p = 1$ based on the BIC, h is determined by the leave-one-out least-squares cross validation, and we employ Gaussian kernels for $K(\cdot)$ and $L(\cdot)$.

3. Data

From an initial sample of 149 banks from the US,[5] we keep a final sample of 128[6], selected for having available and common daily price data observations from 23rd June 2006 to 30th June 2023. Interestingly, our period of study is comprehensive, encompassing crises of varying nature and scale, namely the 2007-2009 global financial crisis, the European sovereign debt crisis, the 2020 COVID-19 pandemic, and the 2023 turmoil in the US banking industry. The 128 banks included in the final sample

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[5] The initial sample is banks with a minimum market value of 250 million USD to overcome potential market structure issues that are very common with small bank stocks and to ensure that bank stocks have a certain level of liquidity.
[6] Bearing in mind that the starting dates of bank stock price data are not the same across all banks, a common starting date is selected to give the maximum number of banks according to data availability, while ensuring that the 2007-2009 global financial crisis is included in the final sample period.

have a combined market capitalization exceeding $1.40 trillion. Details of the selected banks, collected from DataStream, are presented in Appendix Table A1, including bank stock symbol, bank name, and bank market value, collected at the end of the sample period. We classify banks into three groups: small-, medium- and large-sized, having market capitalizations below $2 billion, between $2 billion and $10 billion, and above $10 billion, respectively. This leads to groupings of 13, 51, and 64, large, medium, and small banks, respectively.

In line with Mihoci et al. (2020), we use seven macro-finance indicators as controls: the Dow Jones Real Estate Investment Trusts (REITs) index, which reflects the market performance of US direct real estate investment, including publicly traded REITs and REITs-like securities; S&P 500 composite index, which is the most popular barometer of the stock market performance of large US publicly-traded companies from various sectors and industries; CBOE VIX, which measures the US stock market's expectation of volatility over the next 30 days as implied from S&P 500 index options; Moody's BAA corporate rate, which reflects the yield on corporate bonds that have relatively low risk; 10-year Treasury bill rate; 3-month Treasury constant maturity rate; Aruoba-Diebold-Scotti (ADS) Business Conditions index (Aruoba et al., 2009), which is a coincident business cycle indicator that reflects US business activity and thus the overall health of the US economy; and the shadow short rate (SSR) following Krippner (2013), which is an appropriate proxy of conventional and unconventional monetary policies. Data on these control variables are collected from Refinitiv Datastream, except SSR data, which is downloaded from: https://www.ljkmfa.com/visitors/, and the sample periods match that of the final sample of the daily log-returns for the 28 US bank stocks, i.e., 23rd June 2006 to 30th June 2023.

For the measures of climate risk used to predict the FRMs, we rely on Faccini et al. (2023), who employ the latent Dirichlet allocation (LDA) technique, an unsupervised textual analysis method, to dissect climate-change risks and construct climate-risk factors. Faccini et al. (2023) apply LDA to articles that contain the words "climate change" and "global warming", published daily from 3rd January 2000 to 30th June 2023 in Thomson Reuters News Archive. LDA deconstructs the news corpus into so-called "topics" that can be characterized in terms of the frequency distribution of words. Hence, once the LDA technique identifies the topics, Faccini et al. (2023) give every topic an economic interpretation and, in addition, are able to compute time series of the topic shares (that is, the proportion of an article's text associated with a given topic) that represent how news coverage has evolved over time for any given topic. Finally, Faccini et al. (2023) identify four major climate-related topics of interest: the occurrence of natural disasters (ND), the role of emissions in relation to global warming (GW), US climate policy (USCP), and climate change-related international summits (IS), with the data available for download from: https://sites.google.com/site/econrenatofaccini/home/research?authuser=0. We consider news on the first two topics to be directly informative about the physical risks of climate change, and news about the latter two topics to be mostly informative about transition risks. ND, GW, USCP and IS are plotted in Appendix Figure A1.

4. Empirical Results

We first investigate the constructed FRMs involving all 128 banks (FRM-All), and for small (FRM-Small), medium (FRM-Medium), and large (FRM-Large) banks, derived based on a rolling-window of 500 observations, covering the period 26th May 2008 to 30th June 2023. As can be seen in Figure 1, FRM-All shows sharp increases during the COVID-19 pandemic, to the extent that it is even higher than the peak of the global financial crisis. The FRM-Small, FRM-Medium, and FRM-Large results, firstly, have a heterogeneous pattern, and hence, warrant a disaggregated analysis of the systemic risk in the banking sector contingent on levels of bank market capitalization. While FRM-Medium seems to mimic the pattern of FRM-All, FRM-Large has evidence of peaks during the global financial crisis and in the wake of the European sovereign debt crisis, though it continues to be smaller in magnitude than during the outbreak of the coronavirus pandemic. Compared to FRM-All, FRM-Medium, and FRM-Large, the behaviour of FRM-Small is quite distinct with similar-sized values during the global financial crisis and the COVID-19 outbreak, and a relatively smaller peak corresponding to the European sovereign debt crisis, besides constantly higher values than the other FRMs for the rest of the sample period. Of the three size categories, FRM-Large records the highest value during COVID-19, followed by FRM-Small and FRM-Medium.

[INSERT FIGURE 1 HERE]

Next, we turn our attention to the predictability of the conditional distributions of FRM-All, FRM-Large, FRM-Medium, and FRM-Small, based on the four climate risk factors (ND, GW, USCP, and IS) using the nonparametric causality-in-quantiles test, with the results reported in Table 1. We can draw the following general conclusions: (a) as observed, the four climate risk factors tend to predict, in a statistically significant manner (primarily at the 1% level), the entirety of the respective conditional distributions (over the quantile range 0.10 to 0.90) of the FRMs; (b) across the FRMs, the strongest evidence of predictability, in terms of the size of the standard normal test statistic, tends to be associated with international summits (IS), followed by US climate policy (USCP) for FRM-Large and FRM-Medium, and global warming (GW) for FRM-All and FRM-Small; and (c) for each FRM, the causal impact of all four climate risk factors is weakest at the extreme ends of the conditional distributions, with the predictive effect being relatively stronger at moderate levels of low and high quantiles of FRMs. This latter finding seems to suggest that, as systemic risk in the US banking sector tends to increase, the prediction role of climate risk for the FRMs becomes important, then declines when the conditional median, i.e., the normal state, is reached, picking up again until systemic risk becomes moderately high, only to fall at the extreme upper quantiles.

The pattern of causal influence of climate risk on the FRMs seems to be intuitive in the sense that, when systemic risk is initially quite low, investors in the banking sector rely relatively less on the information content of climate risk for understanding future values of FRMs, with ND, GW, USCP and IS playing more of a role for moderately low values and beyond the normal situation, i.e., the median. Again, as seen from Figure 1, with extreme values of FRMs associated with crises, especially the COVID-19 pandemic, the role of climate risk factors in Granger causing systemic risk of the US banking industry tends to become comparatively less important, possibly due to (non-fundamental) herding (Kirimhan et al., 2024).

In summary, our findings highlight the predictive role of not only physical risk, as in the related paper of Curcio et al. (2023), but also of transition risk, notably international summits on climate change, which is much stronger than that of physical risk in explaining, especially moderately low and high levels of systemic risk, possibly due to the international nature of the US banking system.

[INSERT TABLE 1 HERE]

Although robust predictive inference is derived from the nonparametric causality-in-quantiles test, it is interesting to estimate the sign of the effects of ND, GW, USCP and IS on FRM-All, FRM-Large, FRM-Medium, and FRM-Small over the quantile range 0.10 to 0.90, especially to verify whether climate risk factors tend to positively impact systemic risk in the US banking sector. However, in a nonparametric framework, this is not straightforward, as we need to employ the first-order partial derivatives, while the estimation of the partial derivatives for nonparametric models can give rise to complications, because nonparametric methods exhibit slow convergence rates, due to the dimensionality and smoothness of the underlying conditional expectation function. Alternatively, one can look at a statistic that summarizes the overall effect or global curvature (i.e., the global sign and magnitude), but not the entire derivative curve. A natural measure of global curvature is the average derivative (AD) using the conditional pivotal quantile, based on approximation or the coupling approach of Belloni et al. (2019), which allows us to estimate the partial ADs. Based on the ADs reported in Table 2, the results show that the four climate risk factors consistently tend to positively impact the FRMs over their respective conditional quantiles. One must realize that, while higher values of ND and GW signal increased physical risks, frequent meetings involving changes in climate policies at the domestic and global level, i.e., higher values of USCP and IS, respectively, can be indicative of higher transition risks due to climate policy uncertainty. This finding of a positive effect of climate risks on the systemic risk of the banking system, generally aligns with the idea that climate risks can lead to asset damage and devaluation[7] (Dietz et al., 2016), potentially harming the assets, including the portfolios, of banks (Chenet et al., 2015; Cahen-Fourot et al., 2019), bearing in mind that climate risks can also increase the operating costs of banks (Cahen-Fourot et al., 2019).

[INSERT TABLE 2 HERE]

Finally, even though the full-sample (static) quantiles-based predictive model allows us to study the effect of climate risks on the various levels of FRM, it would be interesting to see whether the evidence of predictability holds at each point in time. Given this, in Figure 2 we present the results of the rolling nonparametric causality-in-quantiles test for the climate risks factors on the FRMs, based on a window size of 500 observations covering the period 23rd April 2010 to 30th June 2023. As can be seen from the figures, the general pattern of the strength of causality reported in Table 1 for the full-sample, i.e., weaker impacts at the tails and stronger effects at moderately low and high quantiles, continues to hold at each point in time from ND, GW, USCP and IS (in particular) to FRM-All, FRM-Large, FRM-Medium and FRM-Small. However, it must be mentioned that, in terms of statistical significance, predictability is often insignificant at the extreme quantiles, especially the upper quantile of 0.90, until COVID-19, after which such risks become more frequent, particularly ND, GW, and USCP (see Figure A1).

[INSERT FIGURE 2 HERE]

5. Conclusion

In this paper, we examine the causal impact of various US physical and transition climate risk factors on the time-varying systemic risk of the US banking sector, differentiating large, medium, and small banks. To achieve this, we firstly estimate tail event co-movements across a large number of US banks over the period 26th May 2008 to 30th June 2023, using the financial risk meter (FRM) approach, which relies on the Lasso quantile regression model. The FRM for the overall system of 128 bank stock prices, as well as disaggregated versions of the same for large-, medium-, and small-sized banks, exhibit peaks during COVID-19 in particular, and the global financial and European sovereign debt crises. We apply a nonparametric causality-in-quantiles test, which is robust to misspecification due to possible nonlinearity and structural breaks in the relationship between FRM and climate risks. The main results show that both physical and transition risks can predict, in a statistically significant manner, the entire conditional distribution of the FRMs. Interestingly, the strongest causal impacts are derived from news on international summits on climate change, compared to natural disasters, global warming and US climate policies, especially for moderately low and high levels of FRM, with these effects holding over time. Furthermore,

[7] Nguyen et al. (2025) underline the negative impact of climate change risks on credit ratings of firms, which hinder firms' access to debt financing.

climate risks consistently have a positive impact on the various conditional quantiles, capturing states of systemic risk to the banking system.

Overall, our results confirm that climate change and the US banking system are highly connected, and that physical and transition risks can jeopardize the stability of the US banking sector, and potentially the entire economy, given that banks represent a critical component of the financial system, acting as lenders, custodians of deposits for customers, and managers of financial infrastructure, thus being at the heart of financial crises. Naturally, the adverse effect of climate risks on the macroeconomy can deepen through the indirect effect emanating from rises in the systemic risk of the banking sector. Hence, from a policy perspective, in tandem with green fiscal policy, our results call for prudential regulations involving simultaneous implementation of low and high capital requirements on banks contingent on loans provided by them for clean and high-carbon activities, respectively (Dafermos and Nikolaidi, 2021; Dunz et al., 2021; Lamperti et al., 2021), which should assist in reducing the pace of global warming.

Given that physical and transition climate risks are shown to have a predictive ability for tail risks of the banking sector, it would be interesting for future studies to analyse the in-sample and out-of-sample predictability of these risks on the conditional distribution (quantiles) of volatility of bank returns, as in Xiao and Koenker (2009), an important input for optimal portfolio decisions of investors, which is highly likely to be impacted by the well-established leverage effect (Black, 1976) in financial markets.[8]

[8] As part of a preliminary analysis, we fit the two-component beta-skew-*t*-exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model developed by Harvey and Sucarrat (2014) to each of the log-returns of the 128 bank stock prices to obtain our measure of volatility. It must be pointed out that the beta-skew-*t*-EGARCH model is superior to other GARCH-class models, as it is robust to jumps or outliers, which exists over our sample period covering various crises and the COVID-19 pandemic. The model incorporates the characteristics of leverage, conditional fat-tails, and conditional skewness, while simultaneously dividing volatility into a short term and a long term component, with these being the most common characteristics associated with time-varying volatility. Note that we also estimate the one-component case of the beta-skew-*t*-EGARCH model, but choose the two-component version, because the log-likelihood is higher in the latter case, indicating a better fit of the log-returns of the 128 bank stock data, with complete details of this result available upon request from the authors. Having derived estimates of volatility from the two-component beta-skew-*t*-EGARCH framework, we run the nonparametric causality-in-quantiles test on the first principal component (PC) of the 128 volatility series, due to the four climate risks factors. Based on the results reported in Table A2 of the Appendix, there is strong evidence of predictability, at the 1% level of significance, over the entire conditional distribution of the PC of volatility emanating from ND, GW, USCP and IS. This finding motivates us in the future to delve into the issue of volatility forecasting for each of the bank's stock prices due to physical and transition climate risks.

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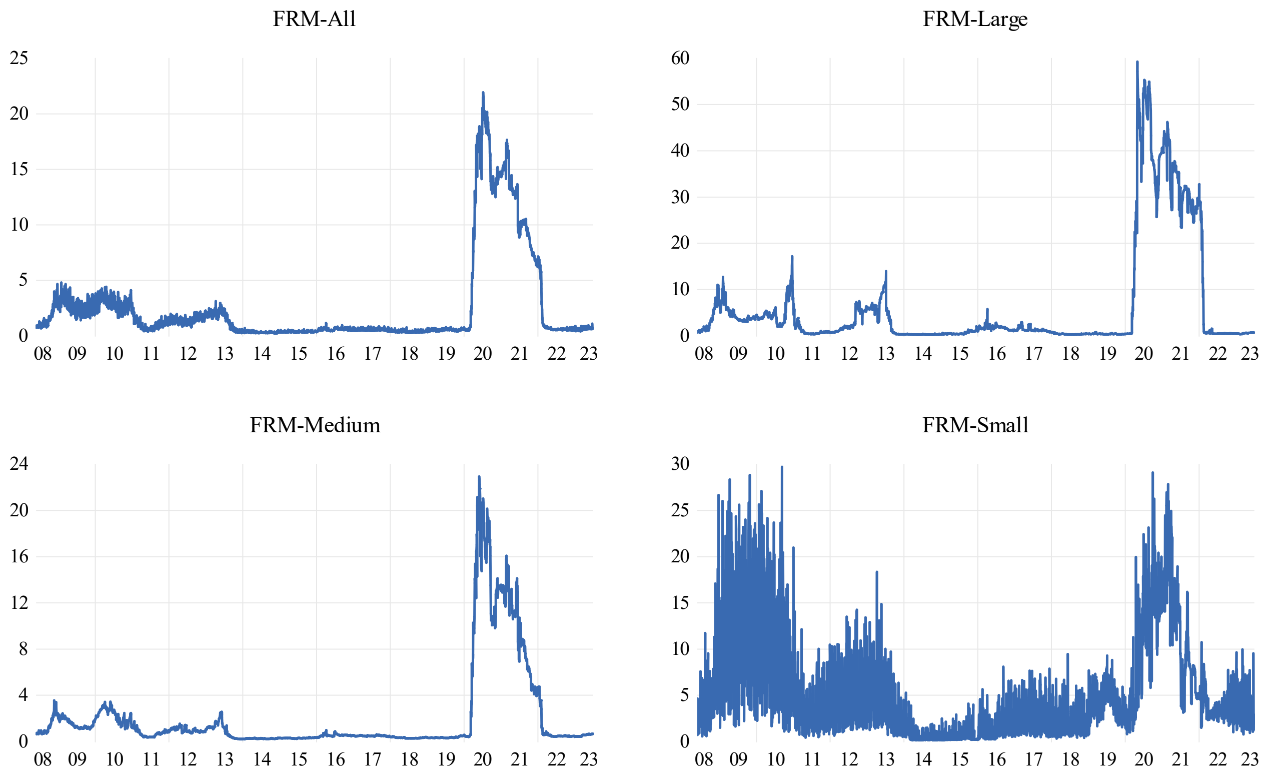
Figures and Tables:

Figure 1: Financial risk meters (FRMs)



Note: Own computations based on Equations (1) to (5) outlined in detail in subsection 2.1.

Table 1. Nonparametric quantile causality test results of climate risks on systemic risk of US banks

θ: FRM-All	ND	GW	USCP	IS
0.1	9.9719***	9.6950***	9.2523***	14.4379***
0.2	13.8409***	15.6238***	13.7943***	21.5651***
0.3	14.1217***	17.1618***	14.8546***	22.0918***
0.4	11.1820***	14.9722***	11.3856***	16.8881***
0.5	9.6035***	9.8267***	9.6608***	11.6050***
0.6	7.2864***	7.4310***	9.4580***	9.9013***
0.7	7.6584***	7.0452***	9.1268***	10.5009***
0.8	9.6276***	9.3902***	9.6944***	11.5320***
0.9	8.6222***	8.6026***	8.2784***	10.4321***
θ: FRM-Large	ND	GW	USCP	IS
0.1	7.1741***	6.6046***	6.7892***	8.2807***
0.2	10.4271***	9.2308***	8.6877***	11.7798***
0.3	10.0178***	9.0462***	10.7516***	8.2464***
0.4	7.9630***	6.9822***	9.8032***	4.9070***
0.5	9.8156***	8.8068***	10.7691***	7.5620***
0.6	11.6937***	11.9922***	12.5529***	14.0821***
0.7	12.9238***	13.6560***	13.1435***	19.9755***
0.8	12.8843***	11.6162***	12.5592***	19.5211***
0.9	6.5826***	6.4066***	7.5061***	8.4562***
θ: FRM-Medium	ND	GW	USCP	IS
0.1	5.0470***	4.5372***	5.9250***	3.7867***
0.2	7.3200***	6.5969***	8.6383***	6.3264***
0.3	7.4758***	6.9574***	7.9805***	6.5779***
0.4	6.9921***	6.4085***	8.2021***	3.4357***
0.5	8.1661***	7.4579***	9.7948***	5.8231***
0.6	10.6696***	9.1794***	11.2558***	13.0072***
0.7	12.0422***	9.3195***	12.9464***	13.6138***
0.8	8.6646***	7.7100***	10.5287***	9.4888***
0.9	4.4333***	4.1359***	5.9616***	3.5097***
θ: FRM-Small	ND	GW	USCP	IS
0.1	3.2152***	3.0713***	3.5255***	1.8812*
0.2	7.3617***	8.4242***	7.7586***	6.8876***
0.3	9.6517***	11.5163***	11.3076***	12.3410***
0.4	11.1108***	13.8436***	12.1241***	14.2908***
0.5	9.5481***	11.5342***	10.0385***	11.2415***
0.6	9.2986***	11.0520***	10.1592***	11.8500***
0.7	8.4766***	10.3510***	10.6899***	10.7914***
0.8	6.8019***	7.0668***	8.5317***	7.1503***
0.9	4.4575***	4.6188***	5.1160***	4.0375***

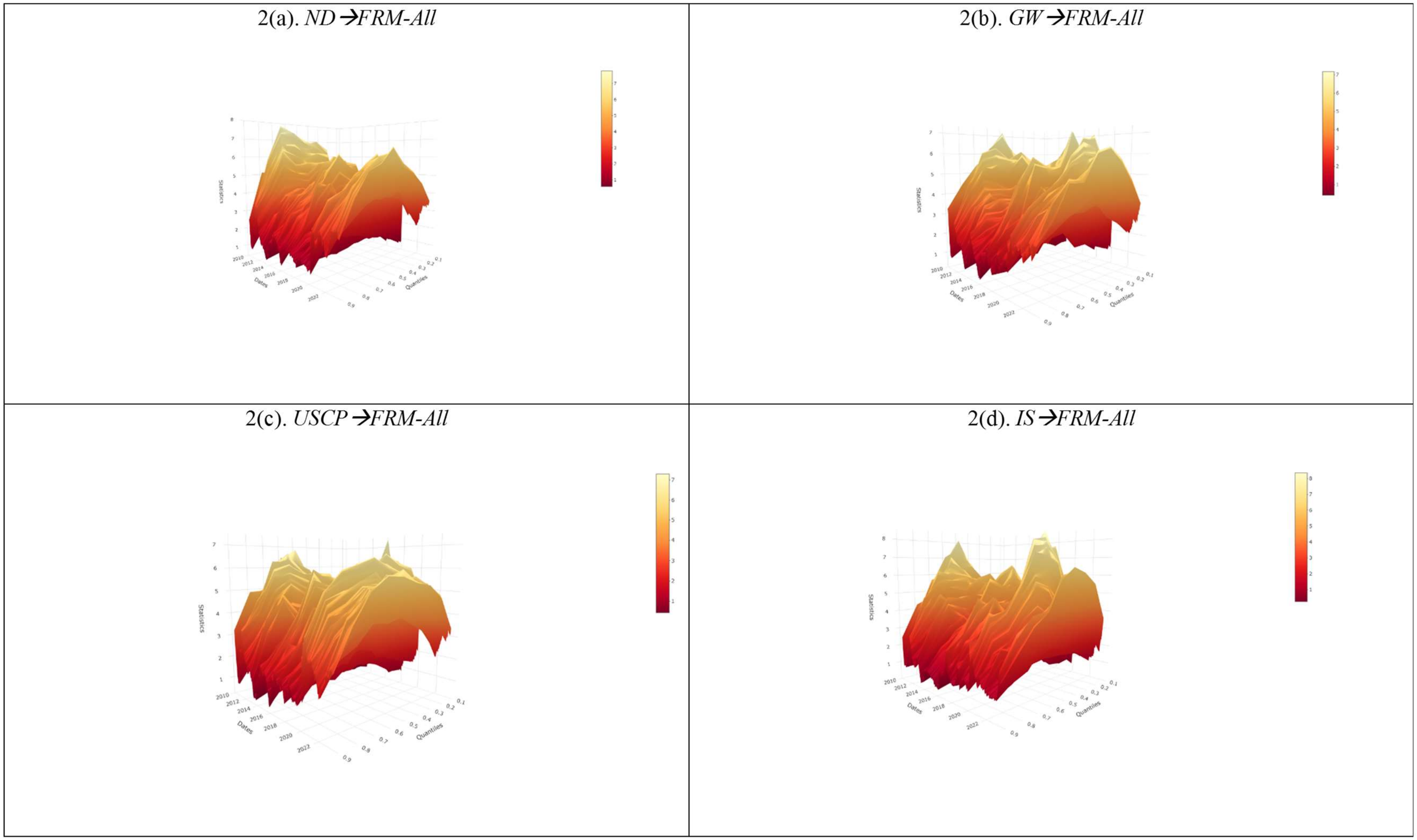
Note: *** and * indicate rejection of no Granger causality from a particular climate risks factor (natural disasters (ND), global warming (GW), US climate policy (USCP), international summits (IS)) to a bank-group-specific financial risk meter (FRM) at 1% (critical value: 2.575) and 10% (critical value: 1.645) levels of significance, respectively, for a particular quantile (θ).

Table 2. Average derivative estimates for the effect of climate risks on systemic risk of US banks

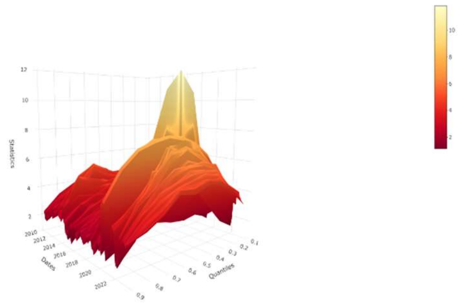
θ: FRM-All	ND	GW	USCP	IS
0.1	0.1480	0.2684	0.1753	0.1476
0.2	0.2118	0.4510	0.2676	0.2121
0.3	0.3149	0.6573	0.3891	0.3411
0.4	0.4499	0.9433	0.5717	0.4924
0.5	0.6620	1.3809	0.8333	0.6351
0.6	0.9836	1.9042	1.1629	0.8402
0.7	1.5451	2.9204	1.7500	1.2048
0.8	2.4928	4.7870	2.6267	1.8300
0.9	5.1519	8.3904	4.8607	3.8017
θ: FRM-Large	ND	GW	USCP	IS
0.1	0.1218	0.2548	0.1636	0.1878
0.2	0.1923	0.4401	0.2897	0.3491
0.3	0.3101	0.7137	0.4856	0.4802
0.4	0.4954	1.3479	0.8149	0.6868
0.5	0.9123	2.3827	1.3220	1.0041
0.6	1.6789	3.5578	2.0340	1.3984
0.7	2.9159	6.1221	3.9314	2.0219
0.8	6.0765	12.0158	6.5359	3.1324
0.9	13.6432	21.8775	12.4656	7.1972
θ: FRM-Medium	ND	GW	USCP	IS
0.1	0.1177	0.2128	0.1388	0.1052
0.2	0.1710	0.3487	0.2054	0.1597
0.3	0.2442	0.4770	0.2861	0.2205
0.4	0.3512	0.6501	0.4065	0.3099
0.5	0.4873	0.9653	0.5888	0.4046
0.6	0.6869	1.3292	0.8314	0.5504
0.7	1.0304	2.0655	1.2382	0.8049
0.8	1.8359	3.7738	1.9607	1.3226
0.9	4.1572	7.0025	4.0029	2.7164
θ: FRM-Small	ND	GW	USCP	IS
0.1	0.4498	0.7196	0.4920	0.2547
0.2	0.7924	1.3206	0.9301	0.6104
0.3	1.1274	2.0566	1.3000	1.0253
0.4	1.6263	2.9368	1.6844	1.5266
0.5	2.1637	3.9260	2.3548	2.2122
0.6	2.8981	5.3191	3.1056	2.9190
0.7	3.9742	7.1436	4.3057	4.2924
0.8	6.0491	9.9702	5.7719	7.0026
0.9	10.1781	16.2119	8.8683	13.5509

Note: Entries correspond to average derivative (AD) estimates of the sign of the effect of each particular climate risk factor (natural disasters (ND), global warming (GW), US climate policy (USCP), international summits (IS)) on a bank-group-specific financial risk meter (FRM) at a particular quantile (θ).

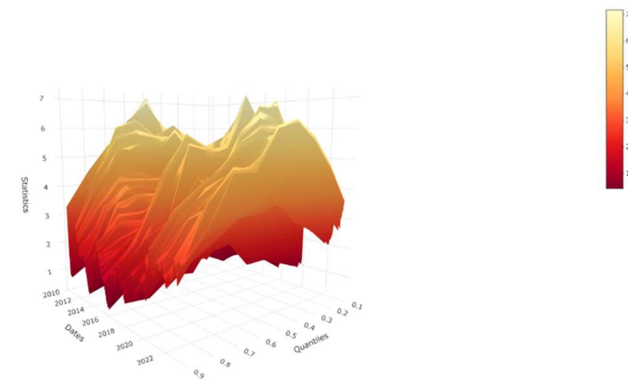
Figure 2. Time-varying nonparametric quantile causality test results of climate risks on systemic risk of US banks



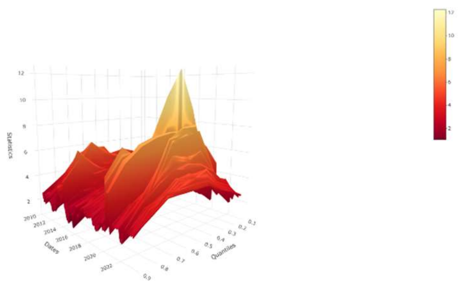
2(e). *ND*→*FRM-Large*



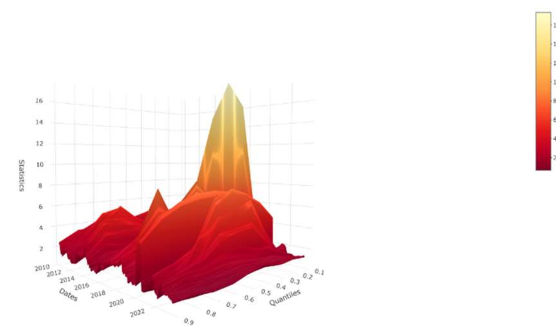
2(f). *GW*→*FRM-Large*



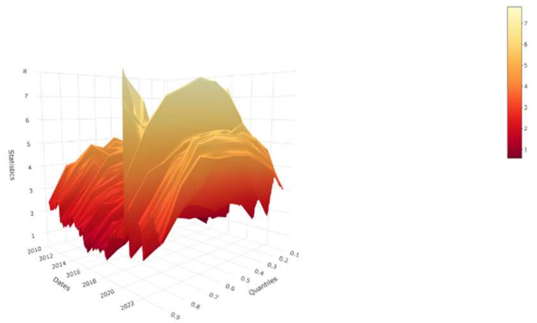
2(g). *USCP*→*FRM-Large*



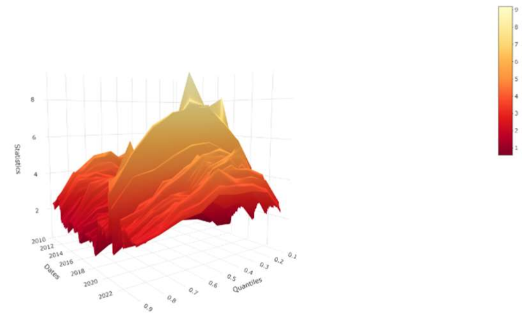
2(h). *IS*→*FRM-Large*



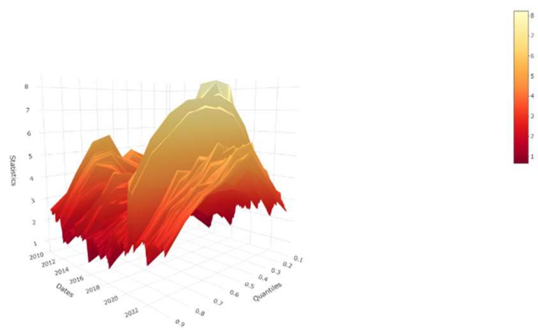
2(i). *ND→FRM-Medium*



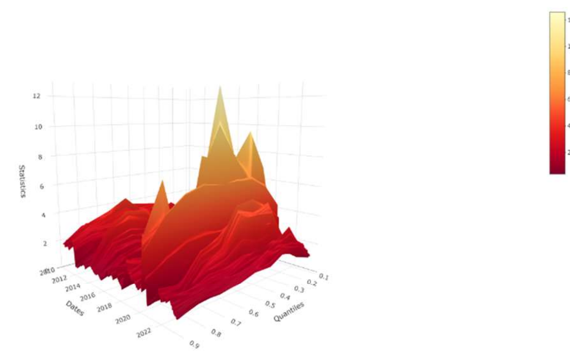
2(j). *GW→FRM-Medium*



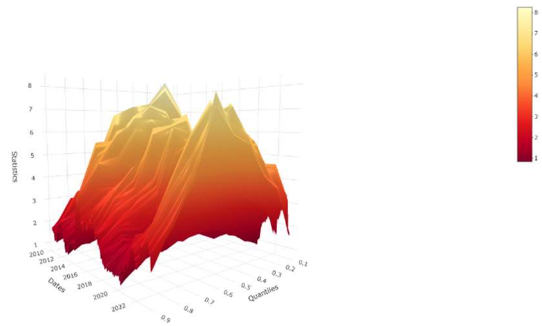
2(k). *USCP→FRM-Medium*



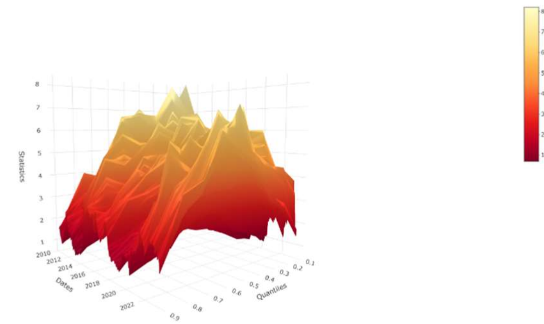
2(l). *IS→FRM-Medium*



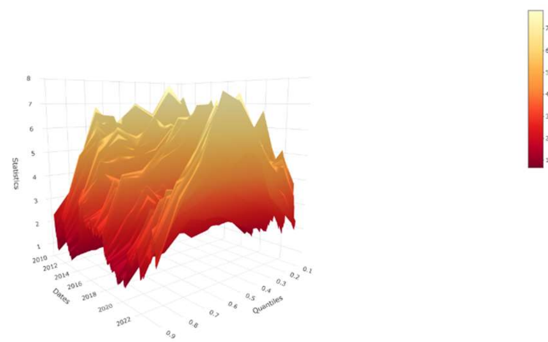
2(m). *ND→FRM-Small*



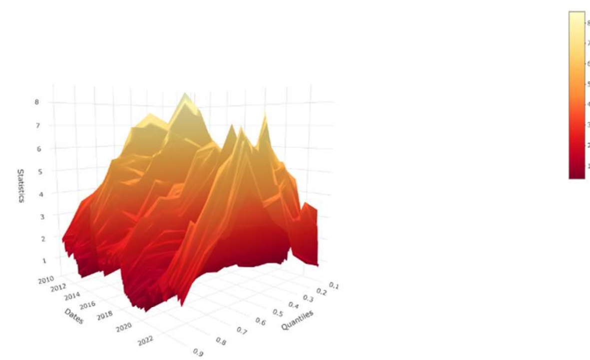
2(n). *GW→FRM-Small*



2(o). *USCP→FRM-Small*



2(p). *IS→FRM-Small*



Note: *x*→*y* implies that *x* Granger causes *y* at a specific quantile of *y* at a particular point in time using 500 rolling-window observations, with *x* = ND, GW, USCP and IS, and *y* = FRM-All, FRM-Large, FRM-Medium and FRM-Small, with Statistics in the *z*-axis corresponding to the standard normal test statistic that *x* does not Granger cause *y*.

Appendix:

Table A1. Bank ticker, name, market capitalization, and headquarter location details

Symbol	Bank Name	Bank Market Value
	Large-sized banks	
JPM.N	JPMorgan Chase & Co	$426,671,439,782
BAC.N	Bank of America Corp	$230,285,853,547
WFC.N	Wells Fargo & Co	$152,388,325,986
C.N	Citigroup Inc	$80,089,966,310
USB.N	US Bancorp	$57,716,709,676
PNC.N	PNC Financial Services Group Inc	$48,674,676,479
TFC.N	Truist Financial Corp	$41,158,058,987
FCNCA.OQ	First Citizens BancShares Inc (Delaware)	$21,121,441,839
MTB.N	M&T Bank Corp	$20,869,700,463
FITB.OQ	Fifth Third Bancorp	$18,418,040,877
RF.N	Regions Financial Corp	$17,416,285,602
HBAN.OQ	Huntington Bancshares Inc	$16,245,240,909
KEY.N	KeyCorp	$10,819,222,738
	Medium-sized banks	
NYCB.N	New York Community Bancorp Inc	$8,900,895,597
EWBC.OQ	East West Bancorp Inc	$7,924,500,245
WBS.N	Webster Financial Corp	$7,546,984,751
FHN.N	First Horizon Corp	$7,123,449,008
CMA.N	Comerica Inc	$6,417,516,670
CBSH.OQ	Commerce Bancshares Inc	$6,228,765,400
CFR.N	Cullen/Frost Bankers Inc	$6,139,146,647
SSB.OQ	SouthState Corp	$5,686,805,582
BOKF.OQ	BOK Financial Corp	$5,668,594,055
WAL.N	Western Alliance Bancorp	$5,597,816,722
PB.N	Prosperity Bancshares Inc	$5,474,328,538
ZION.OQ	Zions Bancorporation NA	$5,398,408,647
PNFP.OQ	Pinnacle Financial Partners Inc	$5,290,206,434
OZK.OQ	Bank Ozk	$5,287,486,125
BPOP.OQ	Popular Inc	$5,043,171,091
WTFC.OQ	Wintrust Financial Corp	$4,870,028,073
VLY.OQ	Valley National Bancorp	$4,792,071,861
SNV.N	Synovus Financial Corp	$4,689,040,215
HOMB.N	Home BancShares Inc	$4,620,881,848
ONB.OQ	Old National Bancorp	$4,619,980,310
COLB.OQ	Columbia Banking System Inc	$4,411,273,012
CADE.N	Cadence Bank	$4,346,379,681
FNB.N	FNB Corp	$4,223,318,085
FFIN.OQ	First Financial Bankshares Inc	$4,192,308,927
UBSI.OQ	United Bankshares Inc	$4,147,903,406

HWC.OQ	Hancock Whitney Corp	$3,656,888,730
GBCI.N	Glacier Bancorp Inc	$3,473,722,240
FINN.PK	First National of Nebraska Inc	$3,364,397,680
UCBI.OQ	United Community Banks Inc	$3,279,164,230
BANF.OQ	BancFirst Corp	$3,226,974,418
UMBF.OQ	UMB Financial Corp	$3,134,356,987
TCBI.OQ	Texas Capital Bancshares Inc	$3,052,851,389
ABCB.OQ	Ameris Bancorp	$2,887,948,060
IBOC.OQ	International Bancshares Corp	$2,874,726,186
ASB.N	Associated Banc-Corp	$2,666,775,660
CATY.OQ	Cathay General Bancorp	$2,661,617,699
AX.N	Axos Financial Inc	$2,647,134,034
FBP.N	First Bancorp	$2,569,280,564
CBU.N	Community Bank System Inc	$2,540,917,766
CVBF.OQ	CVB Financial Corp	$2,531,883,078
WSFS.OQ	WSFS Financial Corp	$2,495,993,808
INDB.OQ	Independent Bank Corp (Massachusetts)	$2,473,348,993
SFNC.OQ	Simmons First National Corp	$2,318,162,737
AUB.N	Atlantic Union Bankshares Corp	$2,283,143,251
PPBI.OQ	Pacific Premier Bancorp Inc	$2,278,614,033
FULT.OQ	Fulton Financial Corp	$2,250,480,734
BOH.N	Bank of Hawaii Corp	$2,190,582,731
SBCF.OQ	Seacoast Banking Corporation of Florida	$2,063,342,023
FFBC.OQ	First Financial Bancorp	$2,054,690,215
TBBK.OQ	Bancorp Inc	$2,040,462,523
HTH.N	Hilltop Holdings Inc	$2,003,525,850
	Small-sized banks	
FRME.OQ	First Merchants Corp	$1,832,415,892
TOWN.OQ	TowneBank	$1,815,822,395
WAFD.OQ	Washington Federal Inc	$1,811,779,489
UNPA.PK	UNB Corp	$1,751,888,730
PRK.A	Park National Corp	$1,673,333,296
NBTB.OQ	NBT Bancorp Inc	$1,637,695,320
RNST.OQ	Renasant Corp	$1,593,164,172
WSBC.OQ	WesBanco Inc	$1,566,973,637
BANR.OQ	Banner Corp	$1,533,857,079
EFSC.OQ	Enterprise Financial Services Corp	$1,490,131,183
OFG.N	OFG Bancorp	$1,480,391,180
TRMK.OQ	Trustmark Corp	$1,447,361,252
NWBI.OQ	Northwest Bancshares Inc	$1,431,096,535
CHCO.OQ	City Holding Co	$1,391,266,985
HTLF.OQ	Heartland Financial USA Inc	$1,365,663,983
SYBT.OQ	Stock Yards Bancorp Inc	$1,364,969,870
FCF.N	First Commonwealth Financial Corp	$1,362,002,660

LKFN.OQ	Lakeland Financial Corp	$1,341,602,091
CASH.OQ	Pathward Financial Inc	$1,315,998,751
PFS.N	Provident Financial Services Inc	$1,278,641,381
FBNC.OQ	First Bancorp (North Carolina)	$1,255,501,920
WABC.OQ	Westamerica Bancorp	$1,203,982,212
HOPE.OQ	Hope Bancorp Inc	$1,185,780,033
TCBK.OQ	Trico Bancshares	$1,162,221,274
BUSE.OQ	First Busey Corp	$1,149,854,846
SRCE.OQ	1st Source Corp	$1,132,679,980
STBA.OQ	S&T Bancorp Inc	$1,107,868,364
OCFC.OQ	OceanFirst Financial Corp	$1,029,180,345
SASR.OQ	Sandy Spring Bancorp Inc	$1,015,684,034
PACW.OQ	PacWest Bancorp	$976,792,482
BHLB.N	Berkshire Hills Bancorp Inc	$958,517,065
FBMS.OQ	First Bancshares Inc (Mississippi)	$939,310,416
SBSI.OQ	Southside Bancshares Inc	$934,578,551
PEBO.OQ	Peoples Bancorp Inc	$926,349,807
PFBC.OQ	Preferred Bank	$916,006,783
LBAI.OQ	Lakeland Bancorp Inc	$896,756,557
QCRH.OQ	QCR Holdings Inc	$895,784,449
RBCAA.OQ	Republic Bancorp Inc	$877,281,634
BRKL.OQ	Brookline Bancorp Inc	$873,351,580
GABC.OQ	German American Bancorp Inc	$868,566,147
DCOM.OQ	Dime Community Bancshares Inc	$864,675,531
BFC.OQ	Bank First Corp	$827,552,269
CFFN.OQ	Capitol Federal Financial Inc	$788,522,551
CNOB.OQ	ConnectOne Bancorp Inc	$764,744,539
TMP.A	Tompkins Financial Corp	$745,882,742
EGBN.OQ	Eagle Bancorp Inc	$745,554,960
FMCB.PK	Farmers & Merchants Bancorp	$717,143,700
FMBH.OQ	First Mid Bancshares Inc	$690,081,469
WTBFB.PK	WTB Financial Corp	$689,858,505
PFC.OQ	Premier Financial Corp (OHIO)	$689,592,609
OSBC.OQ	Old Second Bancorp Inc	$671,912,857
CTBI.OQ	Community Trust Bancorp Inc	$653,628,252
HFWA.OQ	Heritage Financial Corp	$618,944,148
GSBC.OQ	Great Southern Bancorp Inc	$615,353,979
FBAK.PK	First National Bank Alaska	$607,250,199
HBIA.PK	Hills Bancorp	$600,766,328
FMBL.PK	Farmers And Merchants Bank of Long Beach	$597,655,800
FCBC.QQ	First Community Bankshares	$573,602,670
TRST.OQ	TrustCo Bank Corp NY	$551,518,313
UVSP.OQ	Univest Financial Corp	$541,683,634
HTBK.OQ	Heritage Commerce Corp	$541,267,633

CCBG.OQ	Capital City Bank Group Inc	$524,701,658
GCBC.QQ	Greene County Bancorp	$489,350,585
BHRB.OQ	Burke & Herbert Bank & Trust Co	$376,780,800

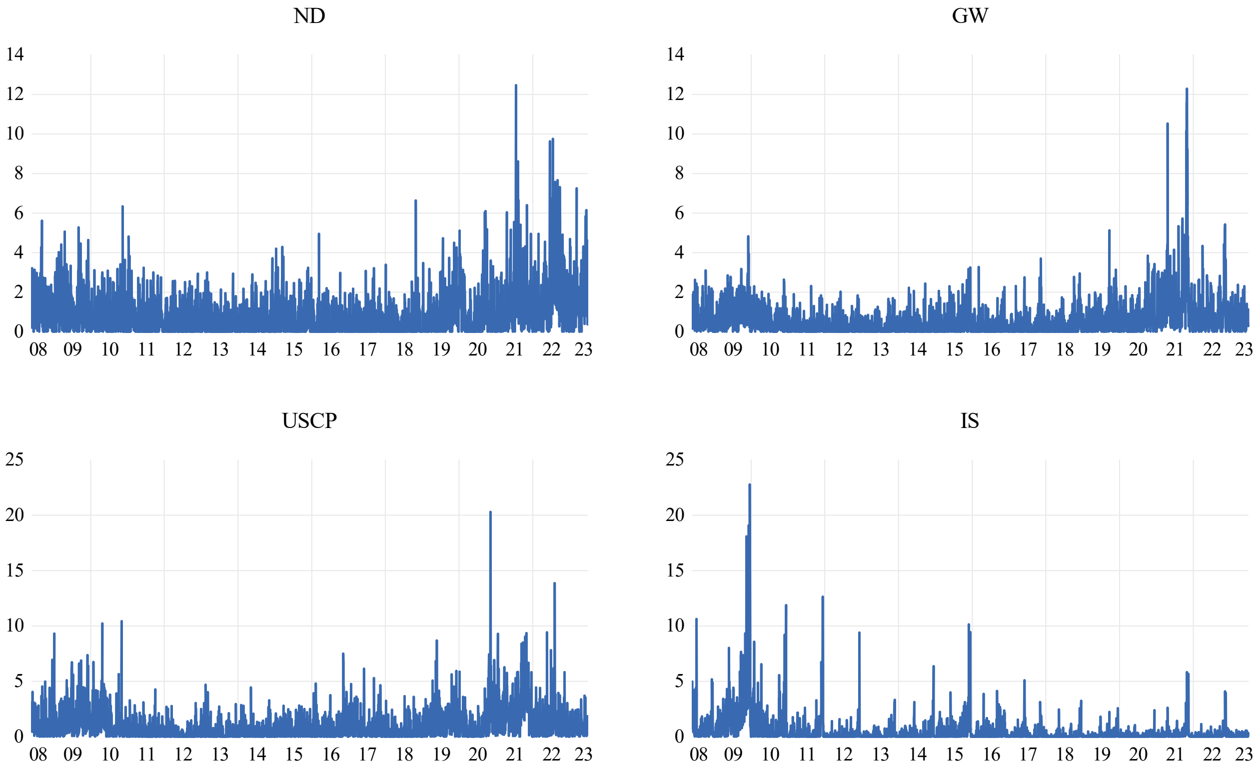
Note: Bank data collected from Refinitiv Datastream.

Table A2. Nonparametric quantile causality test results of climate risks on volatility of US bank stock returns

θ: PC-Volatility	ND	GW	USCP	IS
0.1	7.1396***	8.2772***	7.1744***	9.9002***
0.2	10.6024***	12.1156***	12.4413***	15.1513***
0.3	10.3830***	10.4441***	13.1260***	12.5601***
0.4	8.0598***	7.6124***	8.9036***	8.9373***
0.5	7.2805***	6.7835***	6.7128***	7.3555***
0.6	6.9792***	4.7858***	4.1853***	5.3577***
0.7	5.1789***	4.5615***	3.1467***	5.1947***
0.8	4.6291***	5.5846***	3.6496***	5.0784***
0.9	3.7328***	4.3438***	4.8520***	5.7609***

Note: *** indicates rejection of no Granger causality from a particular climate risks factor (natural disasters (ND), global warming (GW), US climate policy (USCP), international summits (IS)) to the principal component of volatility (PC-Volatility), derived from the two-component beta-skew-*t*-EGARCH model, estimated for all 128 bank returns, at the 1% (critical value: 2.575) level of significance for a particular quantile (θ).

Figure A1. Plot of climate risks



Note: Natural disasters: ND; global warming: GW; US climate policy: USCP, and; international summits: IS.