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# Reaction of European bank and non-bank financial equities to physical climate risk: Evidence from quantile dependence and time-varying predictability

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**Abstract:** This study analyses the pricing of physical climate risk in European financial equity markets by looking at the differentiated responses of banks and non-bank financial institutions. Daily data from December 2012 to December 2023 are used to study the predictive, causal, and distributional effects of physical climate risk on sectoral equity returns. The measurement of physical climate hazard is through a new text-based Physical Climate Risk Index, created from coverage in European financial media, which captures real-time investor attention to climate-related hazards. In terms of methodology, it employs an extensive econometric framework that integrates the wild-bootstrap likelihood ratio test for assessing return predictability, time-varying causal changes, and cross-quantilograms for studying asymmetric quantile-dependent dependencies at short, medium, and long-run horizons. The results provide strong evidence that physical climate risk has a statistically significant adverse predictive effect on both banking and non-bank financial equity returns, with more pronounced impacts for non-bank institutions. Time-varying causality intensifies in periods of heightened climate stress, particularly around major heat waves, droughts, and wildfire episodes within Europe. Further cross-quantilogram results reveal substantial asymmetries, stronger downside effects in the short run, and evidence of gradual market adaptation over longer horizons. Overall, the findings indicate that physical climate risk is a financially material, dynamically priced risk factor, underscoring the need for climate-aware sector-specific asset-pricing regulation and dynamic stress-testing frameworks.

***Keywords:*** *Physical climate risk, Bank and non-bank financial institutions, Equity returns, Time-varying causality, Cross-quantilogram, Predictability, European financial markets, Climate finance.*

## 1. Introduction

In recent years, the global financial landscape has witnessed a growing awareness of the material risks posed by climate change. Among the most pressing are *physical climate risks*, hazards stemming from extreme weather events, long-term environmental shifts, and natural disasters that increasingly disrupt economic activity, asset valuation, and financial stability. Europe, in particular, has faced record-breaking heatwaves, wildfires, floods, and droughts over the past decade, all of which have intensified concerns about the vulnerability of financial markets to climate-induced disruptions [1, 2].

While climate change is often examined through the lens of macroeconomic performance, less attention has been paid to its direct and dynamic influence on financial market behavior, especially in high-frequency contexts. In particular, physical climate risk remains an underexplored determinant of financial equity returns, despite growing evidence that climate shocks can trigger asset repricing, capital


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withdrawals, or shifts in investor sentiment. Moreover, the economic system is not a monolith; banking institutions and non-bank financial firms such as insurers, investment funds, and asset managers face different exposures and transmission mechanisms when climate stress materializes [3, 4]. Yet, the literature has largely failed to draw this distinction empirically.

This study addresses this critical gap by assessing whether physical climate risk significantly predicts the returns of European bank and non-bank financial equities. To do so, we employ a rich, daily dataset covering the period from December 14, 2012, to December 29, 2023. Our measure of physical climate risk is based on the Physical Climate Risk Index recently developed by Bua et al. [5], which uses advanced textual analysis of financial media to generate a real-time proxy for climate hazard intensity and investor awareness.

Methodologically, we combine three complementary econometric techniques. First, we apply the Wild-Bootstrap Likelihood-Ratio (WBLR) test developed by Kim and Shamsuddin [6] to examine whether climate risk carries statistically significant predictive power over sectoral equity returns. Second, we adopt the Time-Varying Causal Change (TVCC) framework proposed by Shi et al. [7] to capture how the relationship between climate risk and financial returns evolves, particularly during periods of heightened climate stress. Third, we employ the Cross-Quantilogram (CQ) approach to explore how the dependence structure varies across different quantiles of the return distribution, offering insights into whether climate shocks disproportionately affect markets during bullish or bearish phases. By integrating these tools, our analysis provides a nuanced and high-frequency perspective on the interaction between physical climate risk and financial market performance. Our findings contribute to the growing literature on climate-finance dynamics by highlighting asymmetric, directional, and time-varying effects and by differentiating between institutional segments within the financial system.

This study makes three key contributions. First, it extends the empirical literature by providing high-frequency evidence of how physical climate risk is internalized in financial equity markets. Second, it offers a distributional perspective by analyzing reactions across different market conditions, capturing both extreme downside and upside responses. Third, it reveals sector-specific sensitivity, showing that non-bank financial institutions may be more immediately exposed to climate hazards due to their direct ties to market sentiment and asset pricing mechanisms.

The implications are far-reaching. Regulators and central banks are increasingly tasked with integrating climate risk into supervisory frameworks, and this study underscores the need for dynamic stress testing and sector-specific disclosure standards. For investors, understanding how and when climate risk affects financial returns is vital for portfolio diversification, risk management, and long-term asset allocation [8, 9].

The remainder of the paper is organized as follows: Section 2 reviews related literature. Section 3 describes the data and methodologies used in the analysis. Section 4 presents empirical results and discusses their policy relevance. Section 5 concludes with a summary of findings and policy insights.

## 2. Theoretical Framework and Literature Review

### *2.1. Theoretical Framework*

The theoretical foundation for examining the relationship between physical climate risk and financial equity returns lies at the intersection of climate finance, asset pricing theory, and risk transmission channels. From a neoclassical perspective, asset prices reflect the discounted value of future cash flows, which are sensitive to changes in risk perception, macroeconomic expectations, and external shocks. Climate-related physical risks such as floods, droughts, and wildfires represent increasingly material externalities that disrupt economic activity, impair corporate earnings, and trigger asset re-pricing. As such, they are now recognized as financially relevant phenomena rather than merely environmental issues [10].

The theoretical linkage between climate risk and financial returns can be framed within Merton's [11] Intertemporal Capital Asset Pricing Model (ICAPM), which allows for time-varying investment opportunities and recognizes that investors respond to shocks that affect long-term consumption and


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wealth. Physical climate risks, by inducing extreme shocks or systemic disruptions, alter investors' expectations of future economic states and risk premiums. These risks may increase volatility and cause investors to demand higher compensation, particularly in sectors vulnerable to environmental hazards [12].

In the context of financial markets, two channels are particularly relevant: the valuation channel and the risk perception channel. The valuation channel posits that asset prices adjust downward as climate risks threaten cash flows, damage physical assets, or reduce firm productivity [13]. The risk perception channel, on the other hand, suggests that investors may overreact to climate-related events or media coverage, causing short-term market dislocations [14]. These dynamics are especially salient for non-bank financial institutions such as insurers, asset managers, and funds, which are more market-facing and less protected by regulatory capital buffers than banks.

Given the complex, nonlinear, and potentially asymmetric nature of these interactions, traditional linear models are insufficient to capture the full depth of the relationship. Instead, this study adopts advanced methodologies, WBLR, TVCC, and CQ, that allow for time variation, directional dependence, and quantile-specific responses. These frameworks align well with the theoretical premise that financial reactions to physical climate risk are dynamic, context-specific, and subject to varying investor sentiment.

*2.2. Literature Review*

The financial implications of climate change have become an increasingly urgent area of empirical inquiry, particularly as climate-related disasters disrupt economic stability and amplify financial market risks. A growing body of literature has sought to quantify the extent to which climate-related risks, both transitional and physical, affect financial systems. However, the bulk of these studies focus on transition risks, such as carbon pricing or regulatory shocks [15], leaving the direct market consequences of physical climate hazards relatively underexplored.

Recent empirical contributions highlight the growing importance of physical climate risk in asset pricing and investor behavior. For instance, Klusak et al. [16] demonstrate that climate risk exposure significantly influences sovereign credit ratings and bond yields. Similarly, Pagliari [8] finds that climate disasters exert downward pressure on equity valuations, especially for firms in climate-sensitive sectors like utilities, insurance, and real estate. However, few studies systematically differentiate between the financial sector's subcomponents, banks versus non-banks, or account for the temporal dynamics of these impacts.

A small but emerging stream of research has begun to assess how financial firms internalize climate-related shocks. Boungou and Urom [4] show that extreme weather events influence the volatility of European financial indices, suggesting a risk re-pricing mechanism in response to climate stress. Chalabi-Jabado and Ziane [1] further distinguish between direct exposure (e.g., asset impairment) and indirect exposure (e.g., borrower default), identifying banks and insurers as channels of climate-related financial contagion. However, these studies tend to rely on static or linear models, which may obscure significant tail risks and time-varying effects.

Methodologically, there is a shift toward more nuanced approaches that reflect the nonlinear and asymmetric characteristics of climate-financial interactions. For example, Soni [17] and Ali et al. [18] employ wavelet and quantile regression frameworks to show that the climate–finance nexus is both scale-dependent and distribution-sensitive. These methods reveal that financial reactions are strongest during extreme market conditions, whether bullish or bearish, and may differ across return quantiles. This supports the need for tools such as cross-quantilograms, which identify directional spillovers across the distribution, and TVCC methods, which capture causal relationships over time.

Despite these advances, a significant empirical gap remains. First, few studies examine high-frequency (daily) data, even though climate shocks often cause immediate market responses. Second, most literature fails to distinguish between bank and non-bank financial institutions, despite their differing risk exposures and transmission pathways. Third, the application of robust statistical techniques such as WBLR and

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TVCC in this context is rare, even though these tools offer improved inference on causality and predictability under non-standard conditions.

This study addresses these gaps by investigating the predictive power and time-varying relationship between physical climate risk and the returns of European bank and non-bank financial equities, using a suite of advanced econometric techniques on daily data from 2012 to 2023. It provides new insights into how different segments of the financial system absorb and reflect climate stress and informs more tailored policy and investment responses.

### *2.3. Research Gap*

Despite the growing relevance of clean technologies and digital transformation in shaping future economic systems, the literature remains underdeveloped in exploring how global shocks, particularly those stemming from oil market volatility, impact the connectedness structure among emerging technology sectors. Existing studies predominantly examine the effects of oil price shocks on traditional financial markets or macroeconomic aggregates, with limited attention given to innovation-driven industries such as artificial intelligence (AI), robotics, fintech, and future mobility systems. Moreover, these studies often utilize low-frequency data and static methodologies, which are insufficient to capture the high-frequency, rapidly evolving interdependence among innovative investments.

Furthermore, the integration between energy volatility and sectoral technological networks is fragmented, with few efforts dedicated to understanding how systemic oil shocks alter spillover patterns within frontier technology assets. While Rolling-Window Vector Autoregression (RW-VAR) frameworks have been applied in financial contagion studies, they remain underutilized in the context of disruptive technology ecosystems, particularly during turbulent economic regimes characterized by uncertainty, geopolitical tension, and commodity price shocks.

To address these gaps, this study offers a novel contribution by employing the dynamic connectedness approach of Antonakakis et al. [19] through RW-VAR to quantify and visualize the time-varying connectedness among nine forward-looking technology sectors: communication, exploration, transportation, fintech, cryptocurrency, future materials, future security, AI, and robotics. Using high-frequency daily data spanning from May 2018 to December 2024, the study captures structural shifts and shock transmission mechanisms induced by oil-related and market-wide volatility events. In doing so, it provides policymakers, investors, and innovation strategists with fresh empirical evidence on resilience, vulnerability, and contagion channels within the global tech-investment landscape under energy-driven stress.

## 3. Methodology and Data

### *3.1. Bootstrap Test for Predictability of Asset Returns*

To assess whether physical climate risk significantly predicts the returns of European bank and non-bank financial equities, first, we apply the wild-bootstrap likelihood-ratio (WBLR) test for asset returns introduced by Kim and Shamsuddin [6]. Predictive regressions are a standard tool in empirical finance for assessing the extent to which asset returns can be explained by a given variable [20-22]. In their canonical form, these models express future stock returns as linear functions of past values of a state variable. However, as Stambaugh [23] highlights, least-squares estimation of the predictive slope coefficient is prone to bias in finite samples when the predictor exhibits high persistence. This bias arises from the endogeneity introduced by contemporaneous correlation between the innovations in the return series and those in the predictor [24, 25]. As the persistence of the predictor increases, the distortion in the distribution of the estimator becomes more pronounced, undermining the validity of conventional statistical inference in predictive settings. To address this shortcoming, Kim and Shamsuddin [6] propose a bootstrap inference based on the likelihood ratio test in a restricted VAR form of predictive regression. This method is not reliant on the assumption of normality, nor does it require bias correction, as endogeneity is accounted for via the generalized least squares estimator [26].
The bivariate system is specified as a first-order restricted VAR:

$$BR_t = \alpha_0 + \beta_1 PCR_{t-1} + \varepsilon_t \quad (1)$$
$$NBR_t = \alpha_0 + \beta_2 PCR_{t-1} + \varepsilon_t \quad (2)$$
$$PCR_t = \alpha_1 + \theta PCR_{t-1} + \gamma_t \quad (3)$$

Where BR, NBR, and PR refer to bank-sector returns, non-bank-sector returns, and physical climate risk, respectively. $\varepsilon_t$ and $\gamma_t$ are white noise error terms.

The predictive ability of PCR is tested under the null hypothesis that $\beta_j = 0$ (no predictability) and the alternative is $\beta_j \neq 0$, In which case, PCR fails to predict either BR or NBR. Eqs. (1) and (3), as well as eqs. (2) and (3) represent the first-order restricted VAR models, which are estimated via the generalised least squares (EGLS) method.

The likelihood ratio test is employed to test the null hypothesis of no predictability ($H_0\!: \beta_j = 0$) is specified as follows:

$$LR = T[\log(\det(\Sigma(H_0)) - \log(\det(\Sigma(H_1))] \quad (4)$$

Where T represents the sample size, $\det()$ represents the matrix determinant, and $\Sigma(H_i)$ represents the generalised least squares residual covariance matrix under $H_i (i = 0 \text{ or } 1)$. The WBLR test for a given sample is performed in 3 steps as described below.

Stage 1: Parameters are estimated using the EGLS estimator under $H_0\!: \beta_j = 0$ in Eqs. (1) & (3), and (2) & (3).

Stage 2: Artificial data is generated via residual sampling under the null hypothesis as follows.

$$BR_t^* = \hat{\alpha}_0 + \hat{\beta}_1 PCR_{t-1}^* + \hat{\varepsilon}_t^* \quad (5)$$
$$NBR_t^* = \hat{\alpha}_0 + \hat{\beta}_2 PCR_{t-1}^* + \hat{\varepsilon}_t^* \quad (6)$$
$$PCR_t^* = \hat{\alpha}_1 + \hat{\theta} PCR_{t-1}^* + \hat{\gamma}_t^* \quad (7)$$

Where $(\hat{\varepsilon}_t^*, \hat{\gamma}_t^*)$ denotes a random resample from $\{(\hat{\varepsilon}_t, \hat{\gamma}_t)\}_{t=1}^{T}$.

Stage 3: The WBLR test statistic is determined thus:

$$LR^* = T[\log(\det(\Sigma^*(H_0)) - \log(\det(\Sigma^*(H_1))] \quad (8)$$

Where, $\Sigma^*(H_i)$ refers to the EGLS residual covariance matrix obtained under $H_i (i = 0 \text{ or } 1)$.

### *3.2. Time-Varying Causal Change Detection*

As a robustness check of the results from the WBLR test, we also conduct the time-varying causal change detection (TVCC) test proposed by Shi et al. [7]. The reliability of statistical inference regarding relationships between economic and financial variables often hinges on the specific sample period under investigation [27]. Empirical linkages identified in one time span may dissipate or even reverse when examined in alternative periods, highlighting the sensitivity of conventional causality tests to temporal instability. This limitation underscores the importance of employing econometric techniques that explicitly account for structural changes over time. In response, recent advancements have introduced right-tailed unit root testing procedures in conjunction with date-stamping methodologies to detect and precisely locate episodes of structural breaks [28-30]. Building on these innovations, Shi et al. [7] proposed a time-varying Granger causality framework that captures evolving causal dynamics within data, which is adopted in this study to uncover further temporal variations in the causal interplay between physical climate risks and the returns of both bank and non-bank financial equities in Europe.

For a VAR(m) model with $y_{1t}$ and $y_{2t}$ series, the formal Granger causality testing approach as described by Baum et al. [31] is given thus:

$$y_{1t} = \alpha_0^1 + \sum_{k=1}^{m} \alpha_{1k}^1 y_{1t-k} + \alpha_{2k}^1 y_{2t-k} + \varepsilon_{1t} \quad (9)$$
$$y_{2t} = \alpha_0^2 + \sum_{k=1}^{m} \alpha_{1k}^2 y_{1t-k} + \alpha_{2k}^2 y_{2t-k} + \varepsilon_{2t} \quad (10)$$

Granger causality is assessed through Wald-type joint significance tests on the lagged terms of the counterpart variable. To accommodate evolving causal structures and pinpoint the timing of structural changes, recursive estimation techniques are applied. These methods generate sequences of test statistics across rolling time windows, allowing inference on the temporal stability of causal relationships.

Specifically, three alternative algorithms are considered: (i) the forward expanding window, a classical recursive estimation scheme described in Thoma [32]; (ii) the rolling window method, based on the works of Swanson [33] and Arora and Shi [34]; and (iii) the recursive evolving window, as developed by Phillips et al. [30]. The use of these complementary algorithms enables a robust assessment of how causal dynamics between the variables evolve across different periods and structural regimes.

### *3.3. Quantile-Dependence and Directional Predictability via Cross-Quantilogram*

Finally, we employ the cross-quantilogram (CQ) methodology to investigate the directional and quantile-dependent relationship between physical climate risk and movements in non-bank and bank sector returns in Europe. Initially introduced by Han et al. [35], the CQ framework enables the analysis of dependence structures between two time series across all quantile combinations, thereby facilitating a deeper exploration of how specific segments of one distribution relate to one another. Such a feature is particularly valuable in financial analyses characterized by asymmetric transmission mechanisms and tail-dependent dynamics [36]. In contrast to conventional correlation measures that capture average linear co-movements around the mean, the CQ approach is tailored to detect dependencies concentrated in the distributional tails, such as during episodes of market stress or crisis-induced transitions [37]. The general form of the CQ statistic is given by:

$$p_\alpha(k) = \frac{E[\psi_{\alpha 1}(y_{1t}-q_{1t}(\alpha 1))\psi_{\alpha 2}(y_{2t-k}-q_{2t-k}(\alpha 2))]}{\sqrt{E[\psi^2_{\alpha 1}(y_{1t}-q_{1t}(\alpha 1))]}\sqrt{E[\psi^2_{\alpha 2}(y_{2t-k}-q_{2t-k}(\alpha 2))]}} \tag{11}$$

where $\psi_\alpha(\mu) \equiv 1(\mu < 0) - \alpha$ denotes the quantile-hit function. The QC is computed for two distinct quantile levels, $\alpha = (\alpha 1, \alpha 2)$, where $\alpha 1$ corresponds to the physical climate risk, and $\alpha 2$ to the returns series. In practical estimation, the sample cross-quantilogram is calculated as:

$$\hat{p}_\alpha(k) = \frac{\sum_{t=k+1}^{T} \psi_{\alpha 1}[(y_{1t}-\hat{q}_{1t}(\alpha 1))\psi_{\alpha 2}(y_{2t-k}-\hat{q}_{2t-k}(\alpha 2))]}{\sqrt{\sum_{t=k+1}^{T} \psi^2_{\alpha 1}(y_{1t}-\hat{q}_{1t}(\alpha 1))}\sqrt{\sum_{t=k+1}^{T} \psi^2_{\alpha 2}(y_{2t-k}-\hat{q}_{2t-k}(\alpha 2))}} \tag{12}$$

To assess the joint statistical significance of these directional dependencies, a Ljung–Box-type test is employed, defined as:

$$\hat{Q}^{(p)}_\alpha = \frac{T(T+2)\sum_{k=1}^{p}(k)}{T-k} \tag{13}$$

The null hypothesis $H_0\colon p_\alpha(k) = 0$ for every lag $k \in \{1 \cdots, p\}$ implies an absence of serial directional dependence between the specified quantiles of the two series.

In this paper, CQ analysis is implemented across multiple temporal resolutions, daily (1-day), weekly (5-day), and monthly (22-day) frequencies, to uncover potential lead–lag structures between transition risk shocks and clean energy equity returns. This allows for a detailed assessment of whether movements in physical climate risks tend to precede, coincide with, or follow adjustments in the returns of financial equities, and whether these dynamics differ across the distribution of returns. The results are visualized through heatmaps generated from the CQ matrices, where colour gradients reflect the magnitude and direction of the estimated quantile-level associations. This visualization provides an intuitive representation of asymmetric dependencies and nonlinear spillovers across market states.

### *3.4. Data*

This study utilizes daily time-series data spanning the period from 12-14-2012 to 12-29-2023 to investigate the reaction of returns on European bank and non-bank financial equities to physical climate risk. The availability of high-frequency data on the variables of interest determines the sample window. As a measure of climate-related physical risk, the analysis employs the physical climate risk Index developed by Bua et al. [5]. This index represents a novel approach to quantifying physical climate risks by leveraging textual analysis of financial media. Specifically, it is constructed by systematically scanning a large corpus of articles from prominent European financial newspapers for keywords and phrases associated with physical climate risks. To maintain temporal comparability and adjust for fluctuations in media volume, the frequency of identified terms is normalized by the total number of articles published

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during each time interval. The resulting index captures the relative importance of physical climate risk in the news, offering a high-frequency proxy for attention to climate-related structural change. By transforming qualitative textual signals into a continuous quantitative measure, the index facilitates the empirical analysis of how perceived physical climate risk influences asset prices, volatility, and risk premia. This approach provides a dynamic lens for understanding investor responsiveness to evolving climate policy landscapes. The Transition Risk Index is publicly available for download at: https://www.policyuncertainty.com/Climate_Risk_Indexes.html.

The banking sector's financial equity is proxied by the STOXX 600 Banks Index (SX7P). The index is a sectoral sub-index of the broader STOXX Europe 600 Index, specifically designed to track the performance of central banking institutions across European markets. It comprises the largest and most liquid publicly listed banks in the region, including both commercial and investment banks operating across diverse national jurisdictions. The index provides a benchmark for the European banking sector, capturing its valuation dynamics, sector-specific risks, and macro-financial sensitivities. The returns of the SX7P index are computed using the formula: $\log \text{return} = \frac{\text{Price}_t}{\text{Price}_{t-1}}$. The data is downloadable at https://www.investing.com/indices/stoxx-600-banks-pr.

The non-banking sector, on the other hand, is proxied by the STOXX 600 Financials Index (SXFP). This index is likewise a sector-specific sub-index for the broader STOXX Europe 600 Index, capturing the performance of Europe's leading non-bank financial institutions. SXFP comprises asset managers, investment firms, stock exchanges, consumer finance companies, and other capital market intermediaries. This index provides a comprehensive benchmark for the financial services sector, which plays a pivotal role in capital allocation and risk pricing within the European economy. Unlike traditional banks, the institutions within SXFP primarily engage in investment, advisory, and market facilitation activities rather than deposit-taking and lending. As such, the index reflects the dynamics of financial markets and investment flows more directly than banking indices. The returns of this sectoral Index are also obtained through the formula: $\log \text{return} = \frac{\text{Price}_t}{\text{Price}_{t-1}}$. In this case, the data was downloaded fromhttps://www.investing.com/indices/stoxx-600-financial-services-pr.

Table 1 presents the summary statistics for the returns of bank and non-bank financial equities, as well as the physical climate risk index. As shown in Table 2, the mean daily returns, like volatility, are approximately zero for all indices. The results also show that while the physical climate risk index is positively skewed, the returns of financial equities are negatively skewed. Excess kurtosis is detected in all three indices. The Jarque and Bera [38] normality test indicates non-normality for all three indices, and the stationarity test of Elliott et al. [39] indicates that all variables are stationary. The Ljung-Box serial autocorrelation test results (Q (10) and Q2(10)) confirm the absence of autocorrelation in the data series. Figure 1. Presents the trends of the indices used for empirical analysis.

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**Table 1.**
Statistical Properties of Variables.

| | PCR | NBR | BR |
|---|---|---|---|
| Mean | -0.003 | 0 | 0 |
| Variance | 0 | 0 | 0 |
| Skewness | 0.835a | -0.871a | -0.850a |
| Ex. Kurtosis | 1.743a | 11.779a | 11.012a |
| JB | 687.380a | 16712.789a | 14634.184a |
| ERS | -6.839a | -14.371a | -23.487a |
| Q(10) | 122.732a | 17.653a | 10.718b |
| Q2(10) | 46.006a | 582.964a | 347.431a |

**Note:** (1) Ex. Kurtosis, JB, and ERS denote the statistics for excess kurtosis, the Jarque-Bera test for normality, and the stationarity test of Elliott et al. [39], respectively. (2) Q(10) and Q2(10) are the Ljung and Box [40] serial correlation test statistics. (3) a & b denote statistical significance at 1% and 5%, respectively.

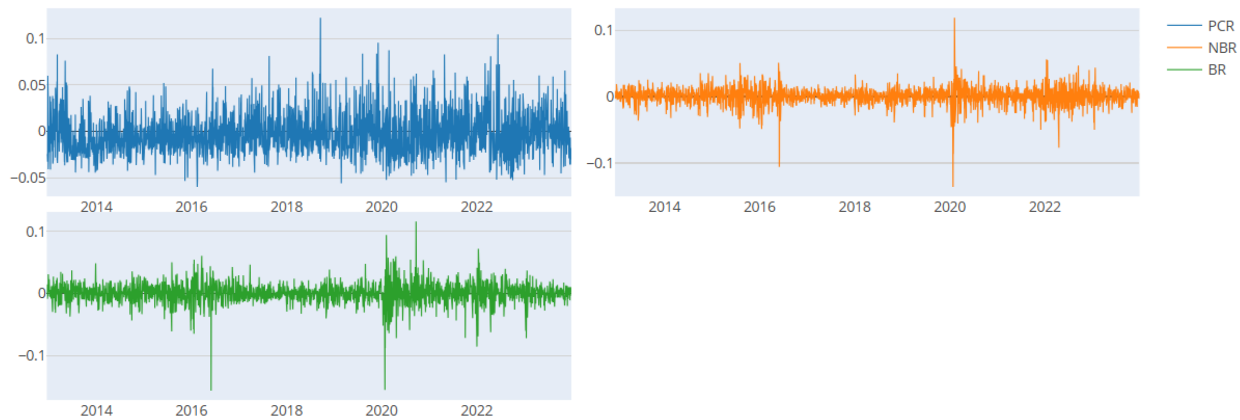


**Figure 1.**
Trends of PCR, NBR, and BR.

## 4. Empirical Results

### *4.1. Preliminary Analysis*

#### *4.1.1. Test for Nonlinear Dependence*

Before implementing sophisticated econometric techniques such as TVCC and CQ, it is crucial to examine the statistical characteristics of the time series data to ensure appropriate methodological choices [41, 42]. One key diagnostic employed for this purpose is the BDS [43] test, which is designed to identify departures from the assumption of independent and identically distributed (i.i.d.) data and to uncover potential nonlinear dependencies. Given that both the TVCC and the CQ methods are tailored to detect nonlinear and quantile-dependent linkages, confirming the presence of such complex structures lends strong support to their application over conventional linear tools. Table 2 presents the outcomes of the BDS test. For every variable, the test rejects the null hypothesis of i.i.d. behavior at the 5% significance level or better across multiple embedding dimensions (2-6). This uniform rejection underscores the presence of hidden structural patterns and nonlinear features in the data that standard mean-based econometric techniques are likely to overlook. These findings are methodologically significant, as they validate the need to adopt more advanced econometric techniques capable of uncovering directional, asymmetric, and distribution-specific relationships.

**Table 2.**
BDS test results.

| | Dimensions | | | | |
|---|---|---|---|---|---|
| **Variables** | **2nd** | **3rd** | **4th** | **5th** | **6th** |
| PCR | 0.016[b] | 0.047[a] | 0.069[a] | 0.075[a] | 0.080[a] |
| NBR | 0.173[a] | 0.292[a] | 0.371[a] | 0.430[a] | 0.469[a] |
| BR | 0.158[a] | 0.265[a] | 0.334[a] | 0.372[a] | 0.389[a] |

**Note:** a & b denote statistical significance at 1%.

### *4.1.2. Nonlinear and Quantile-Based Unit Root Tests*

Due to the nonlinear nature of the data series, as revealed by both the J-B and BDS tests, rather than following the conventional approach to unit root testing, we perform two different types of unit root tests. We perform both the nonlinear unit root test (ESTAR) of Kapetanios et al. [44] and the quantile-based Augmented Dickey-Fuller (QADF) unit root test. This choice is because these tests capture distinct and complementary features of nonstationarity that conventional linear tests may overlook. The ESTAR test is designed to detect nonlinear mean-reverting behavior in the presence of potential structural changes or smooth transitions, making it particularly suitable for time series that exhibit regime-dependent dynamics. However, while ESTAR accounts for nonlinearity in the adjustment process, it still focuses on the behavior of the conditional mean, potentially missing heterogeneity across the distribution.

In contrast, the QADF test extends the analysis by evaluating stationarity at different quantiles of the distribution, allowing researchers to assess whether the persistence of shocks differs across the tails and the center of the series. This is crucial for variables affected by asymmetric shocks, fat tails, or heterogeneous responses to extreme events, standard features in climate and financial risk data. Employing both tests provides a more robust diagnostic framework, ensuring that stationarity is not mistakenly assumed or rejected based solely on evidence from the conditional mean.

The results of the ESTAR unit root tests are reported in Table 3. The method permits the lag length to be either fixed (FIXED) or determined endogenously using information criteria such as Akaike (AIC) and Schwarz (SIC), or via a data-dependent approach, the general-to-specific at 5% (GTS05) and 10% (GTS10) significance levels, respectively. As shown in Table 3, regardless of the lag selection criterion, the presence of unit roots in the level is rejected for all variables. The test results, therefore, suggest that PCR, NBR, and BR are optimally described in their level forms. Table 4 presents the results of the QADF across various quantiles (0.1, 0.25, 0.5, 0.75, and 0.9). For each variable and across all specified quantiles, the test statistics are statistically significant at the 1% level. This indicates the rejection of the null hypothesis of a unit root and suggests that these series not only exhibit stationarity around the mean (as confirmed by the earlier ERS and ESTAR results reported in Tables 2 and 3, respectively), but also across the broader distribution, including its extremes. Overall, the ERS, ESTAR, and QADF tests jointly affirm that the physical climate risk index, as well as the returns of bank and non-bank financial equities, satisfy the stationarity condition. The application of nonlinear econometric techniques employed in this study is thus justified.

**Table 3.**
ESTAR unit root test results.

| **NBR** | | | | | |
|---|---|---|---|---|---|
| **Criteria** | **Test. Stat** | **P-value** | **1% CV** | **5% CV** | **10% CV** |
| Fixed | -6.631[a] | 0.000 | -3.478 | -2.932 | -2.655 |
| AIC | -6.631[a] | 0.000 | -3.482 | -2.934 | -2.655 |
| SIC | -6.631[a] | 0.000 | -3.478 | -2.930 | -2.652 |
| GTSO5 | -6.631[a] | 0.000 | -3.482 | -2.933 | -2.654 |
| GTS10 | -6.631[a] | 0.000 | -3.483 | -2.935 | -2.655 |
| BR | | | | | |
| Criteria | Test. Stat | P-value | 1% CV | 5% CV | 10% CV |
| Fixed | -5.563[a] | 0.000 | -3.478 | -2.932 | -2.655 |
| AIC | -5.563[a] | 0.000 | -3.482 | -2.934 | -2.655 |
| SIC | -5.563[a] | 0.000 | -3.478 | -2.930 | -2.652 |
| GTSO5 | -5.563[a] | 0.000 | -3.482 | -2.933 | -2.654 |
| GTS10 | -5.563[a] | 0.000 | -3.483 | -2.935 | -2.656 |
| PCR | | | | | |
| Criteria | Test. Stat | P-value | 1% CV | 5% CV | 10% CV |
| Fixed | -7.606[a] | 0.000 | -3.478 | -2.932 | -2.655 |
| AIC | -7.606[a] | 0.000 | -3.482 | -2.934 | -2.655 |
| SIC | -7.606[a] | 0.000 | -3.478 | -2.930 | -2.652 |
| GTSO5 | -7.606[a] | 0.000 | -3.482 | -2.933 | -2.654 |
| GTS10 | -7.606[a] | 0.000 | -3.483 | -2.935 | -2.656 |

**Note:** a denoted statistical significance at 1%.

**Table 4.**
QADF Unit Root Test results.

| | **Quantiles** | | | | |
|---|---|---|---|---|---|
| **Variables** | **0.1** | **0.25** | **0.5** | **0.75** | **0.9** |
| PCR | -6.602[a] | -8.504[a] | -8.569[a] | -9.223[a] | -10.12[a] |
| NBR | -4.652[a] | -6.010[a] | -8.052[a] | -8.715[a] | -10.116[a] |
| BR | -4.894[a] | -6.200[a] | -7.427[a] | -9.219[a] | -9.362[a] |

**Note:** a [&] b denote statistical significance at 1% and 5%, respectively.

### *4.2. WBLR Test Results*

Table 5 reports the outcomes of the WBLR test evaluating whether physical climate risk has predictive power over the returns of European banks (BR) and non-bank financial institutions (NBR). The negative and statistically significant predictive coefficients for both sectors ($\beta = -21.692$ for banks and $\beta = -25.239$ for non-banks) indicate that higher levels of physical climate risk are associated with lower subsequent returns in both segments of the financial system. This relationship holds under both asymptotic and bootstrap inference frameworks, thereby confirming that the effect is both statistically robust and economically meaningful. The larger absolute magnitude and higher statistical significance of the coefficient for non-bank financial institutions suggest that this segment is more sensitive to the pricing of physical climate risk than traditional banks. This may reflect the greater market-based exposure of asset managers, investment firms, and financial service providers to climate-induced valuation shocks and reallocation pressures. In contrast, while banks are affected primarily through the credit and collateral channels, the non-bank sector is more directly tied to equity market sentiment and regulatory expectations regarding climate resilience.

The fact that both sectors exhibit negative coefficients supports the interpretation that physical climate risk dampens expected returns as investors reprice risk, demand higher premiums, or withdraw capital in anticipation of climate-related disruptions. This implies that European financial markets, particularly institutions with asset exposure and operational dependencies on climate-sensitive sectors, are responsive to information about physical climate hazards, which directly affect borrower solvency, asset valuations, and investor sentiment. These findings align with existing empirical evidence showing that financial firms are materially exposed to climate risks through their portfolios and operational dependencies [1, 4, 45, 46]. The results from the WBLR test confirm that physical climate risk is not merely an exogenous environmental factor but a financially significant variable that is increasingly internalized in market pricing dynamics across the European financial sector. The empirical evidence from the WBLR test reinforces and extends existing research by demonstrating that the negative financial impact of physical climate risk is not confined to high-emissions sectors but is also evident across financial intermediaries, including both traditional banks and non-bank financial institutions.

**Table 5.**
WBLR test results.

| | Predictive coefficient (β) | Asymptotic p-value | Bootstrap p-value |
|---|---|---|---|
| BR | -21.692[b] | 0.001 | 0.019 |
| NBR | -25.239[a] | 0.000 | 0.008 |

**Note:** 1. This table presents predictive coefficients and their wild-bootstrap p-values. (2) 1000 bootstrap iterations are used. (3) [a and b] indicate rejection of the null hypothesis of no predictability at 1% and 5% levels, respectively.

### *4.3. Time-Varying Causal Change Results*

To establish how the causal dependence between the returns of financial equities and physical climate risk evolves, we further perform and report the time-varying causal change detection test. Table 6 presents robust Wald statistics measuring the direction and intensity of causal flows between the variables. Across two of the three estimation algorithms (forward-expanding, rolling window, and recursive evolving), the evidence supports a statistically significant causal effect from physical climate risk to the returns of the non-bank financial sector. Furthermore, across all three estimation algorithms, the evidence supports a statistically significant causal effect from physical climate risk on the returns of the banking sector. These findings corroborate results from the WBLR method, further reinforcing the conclusion that financial firms are materially exposed to climate risks through their portfolios and operational dependencies. This conclusion further reinforces the claims made by previous authors [1, 4, 8, 45, 46].

**Table 6.**
Time-varying causal change results.

| Wald | $PCR \overset{gc}{\rightarrow} NBR$ |
|---|---|
| Forward | 8.512 |
| Rolling | 35.487[a] |
| Recursive | 35.487[a] |
| Wald | $PCR \overset{gc}{\rightarrow} BR$ |
| Forward | 9.634[c] |
| Rolling | 56.412[a] |
| Recursive | 56.412[a] |

**Note:** (1) [a] represents statistical significance at 1%. (2) Robust Wald test statistics based on 199 bootstrap replications are reported.

In addition to full-sample inference, the time-varying framework enables a more detailed analysis of temporal variations in causal relations by visualizing test statistics over time and benchmarking them against bootstrap-derived critical thresholds, following the methodology of Shi et al. [47] and Shi et al. [7]. Periods of statistically significant causality are identified when the Wald statistic curve exceeds the critical values at the 90% or 95% confidence levels. Figures 2 through 7 illustrate the temporal profile of causal dependence between the variables under each of the three algorithms. The first three figures (Figures 2–4) depict the evolving causal effect of physical climate risk on the returns of the non-bank financial sector. The last three figures (Figures 5–7) depict the evolving causal effect of physical climate risk on the returns of the bank sector.

Focusing on the relationship between physical climate risk and the returns of non-bank financial equities, Fig. 2 shows the time-varying result generated by the forward-expanding algorithm, indicating the absence of any relationship between the variables. This corroborates the forward-expanding algorithm reported in Table 6. However, the time-varying results generated by the other two algorithms, which are relatively similar, indicate the presence of time-varying links between the variables. Specifically, we find that physical climate risk was a significant predictor of non-bank financial sector returns, primarily in periods of substantial climate-related events. For instance, considerable predictability was detected.

Significance is detected around 2017–2018; this period coincides with the outbreak of heatwaves and wildfires in Southern Europe. During this period, southern Europe experienced record-breaking heatwaves, with temperatures exceeding 40 °C in Spain, Italy, and the Balkans. These conditions triggered widespread wildfires in Portugal and Greece, resulting in economic losses and increased insurer liabilities. The financial sector likely reacted to the escalating physical climate risks by repricing tangible asset-backed securities and by rising volatility in insurance-linked securities. Also, the statistical significance recorded in 2019–2020 coincides with the unseasonal heat and early drought onset in Europe. 2019 saw exceptional spring and summer heatwaves, with France recording over 46 °C, impacting agriculture and hydropower output. In early 2020, unusually warm and dry winters diminished snowpack and altered river flows, early signals of intensified climate variability. 2022 was Europe's most extreme climate year; the statistical significance recorded during this period is probably a reflection of that. A 500-year drought covered more than 30% of the continent. Major rivers like the Rhine and Po dried significantly, disrupting freight, energy production, and agriculture. Heatwaves intensified crop failures and drove spikes in energy demand, straining utilities and insurers. Financial institutions are likely to have reassessed risk models in light of persistent losses and climate attribution studies, making this the most climate-reactive period on record for European markets. Overall, each significant causal interval on the graph corresponds with escalating physical climate stress events, each disrupting economic systems and prompting reactive repricing or volatility within financial sectors. The evidence supports a robust link between extreme weather events and sector-specific market responses, particularly for banks and insurers exposed to climate-sensitive portfolios.

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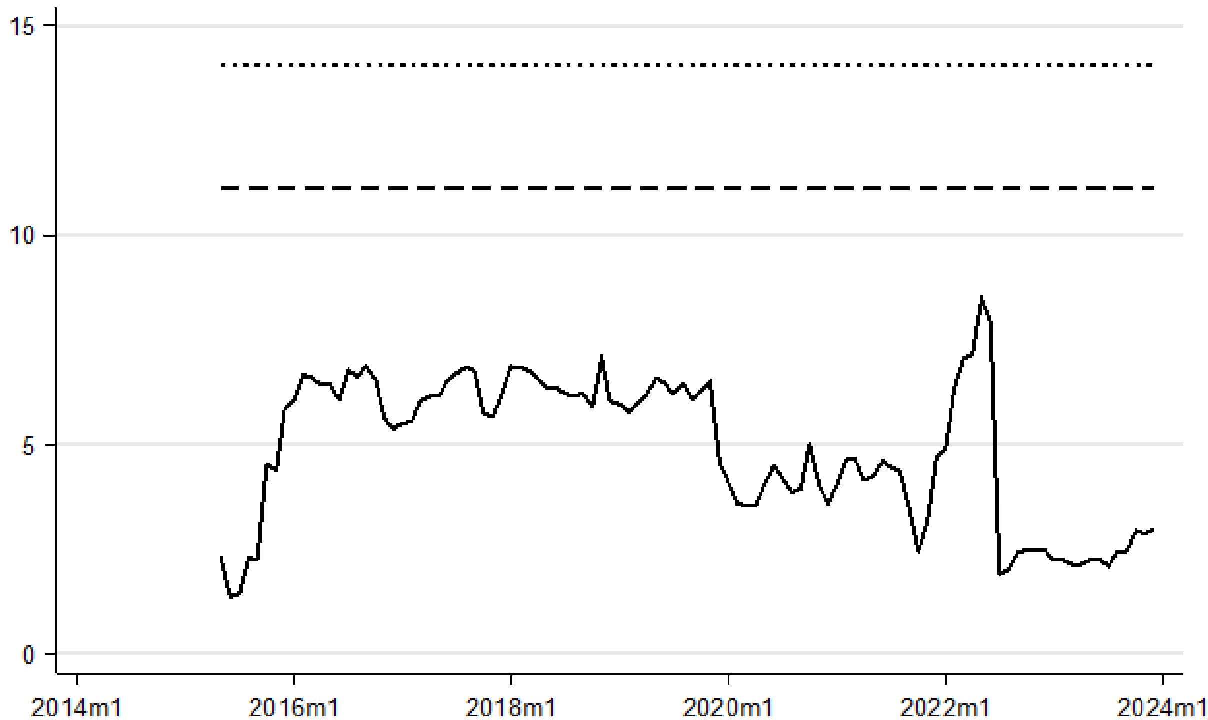


**Figure 2.**
Forward expanding Wald test for NBR Granger-caused by PCR with 90th and 95th percentiles of bootstrapped test statistics

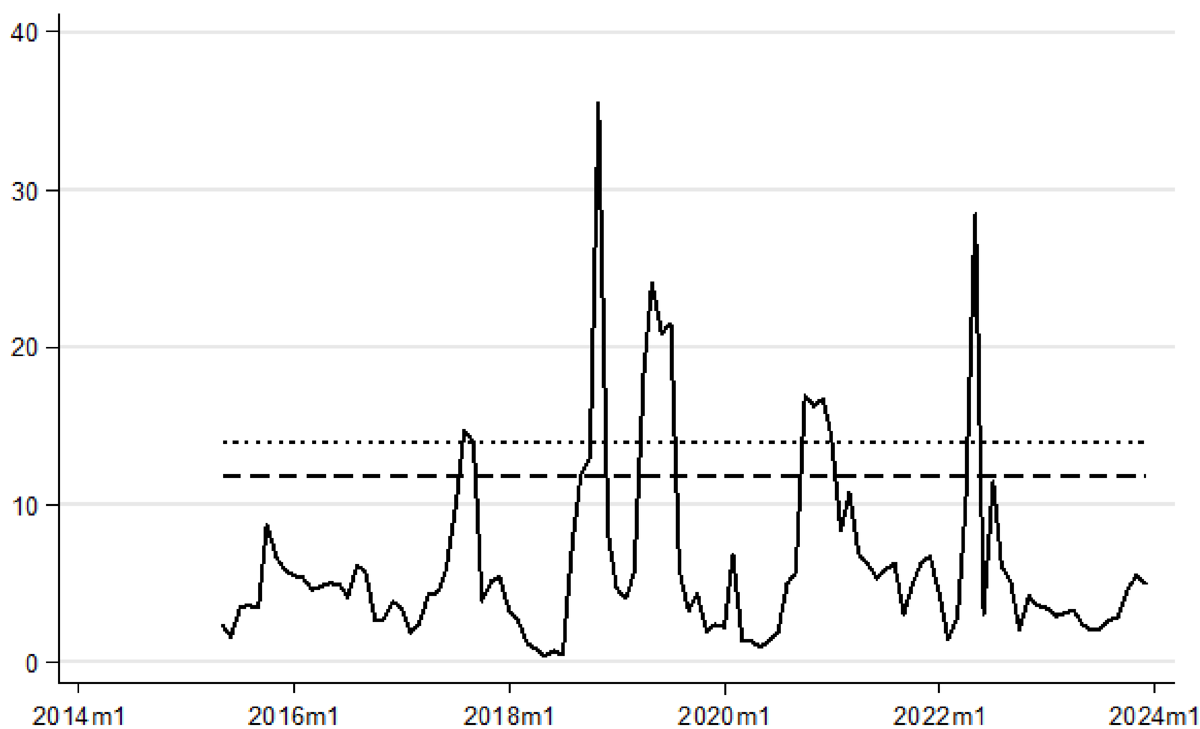


**Figure 3.**
Rolling Wald test for NBR Granger-caused by PCR with 90th and 95th percentiles of bootstrapped test statistics.

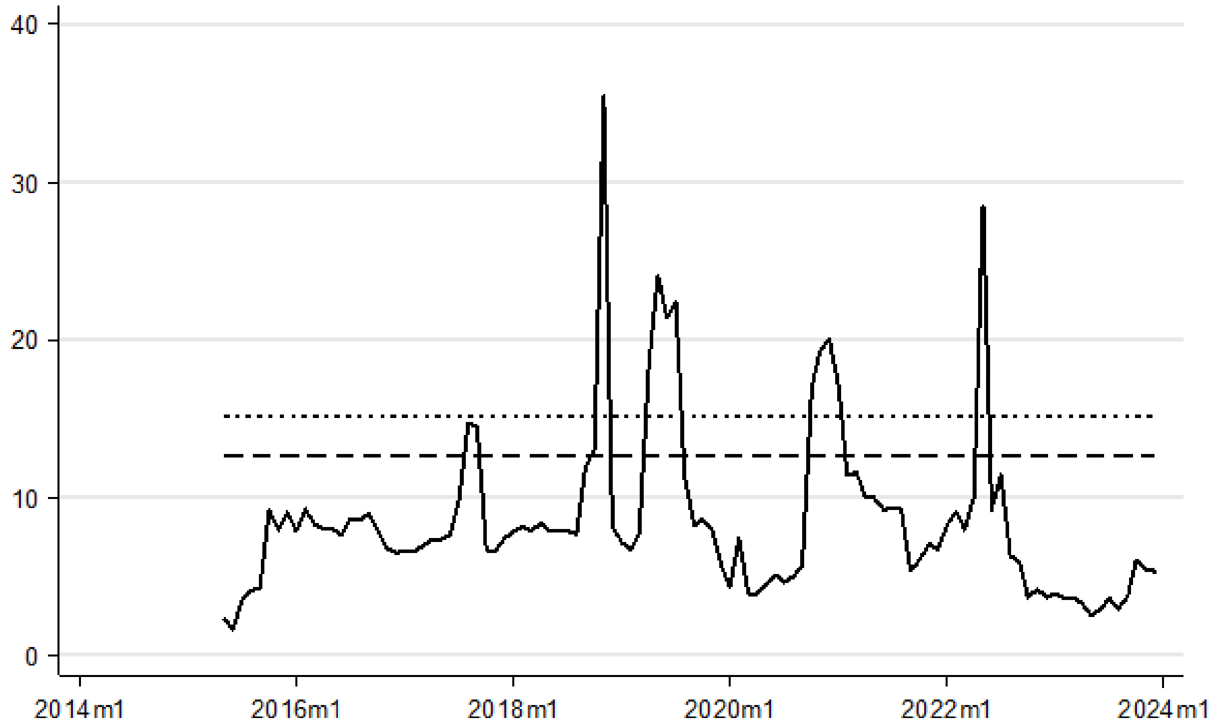


**Figure 4.**
Recursive expanding Wald test for NBR Granger-caused by PCR with 90th and 95th percentiles of bootstrapped test statistics.

Concerning the time-varying relationship between physical climate risk and the returns of the European bank sector, figures 4-7 confirm the existence of various degrees of causal effects. Across the three figures, statistical significance is observed in 2015–2016, a period reflecting early climate awareness and the momentum of the Paris Agreement. However, primarily a transition-policy milestone, the lead-up to the agreement was marked by increased public attention to climate vulnerability, including severe flooding in the UK and Central Europe in late 2015. This spike may reflect early financial market responses to the anticipated impacts of climate extremes and policy signals, particularly in sectors sensitive to physical risks such as insurance and real estate. Statistical significance also exists around 2019-2020. This coincides with the COVID-19 pandemic. While initially a health crisis, it became entangled with environmental discourse through the EU's emphasis on a "green recovery".

Additionally, 2020 witnessed prolonged droughts and wildfires across Eastern and Southern Europe, reinforcing the salience of physical climate risk. Market participants may have reassessed climate-related exposures in portfolios during this period in response to both physical climate events. From a market perspective, the pandemic acted as a stress test for how financial systems internalize risks. It amplified concerns about the materiality of physical climate risks, showing how global shocks, whether viral or environmental, can lead to asset re-pricing, capital flight from vulnerable sectors, and sudden liquidity shortages.

The most pronounced and sustained peak in the causality test occurs in early to mid-2022, which aligns with what has been widely described as Europe's most extreme climate year. A record-breaking drought affected vast regions, drying rivers such as the Rhine and the Danube, critical for industrial transportation and hydropower. Wildfires surged across France, Spain, and Portugal, and crop yields plunged, straining the economies of agriculture, energy, and transportation. These acute and widespread disruptions likely triggered a repricing of climate risk across financial markets, leading to a sharp, statistically significant increase in the test statistic. Overall, these results demonstrate the macro-financial

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relevance of physical climate shocks, supporting their inclusion in scenario-based stress testing and policy frameworks.

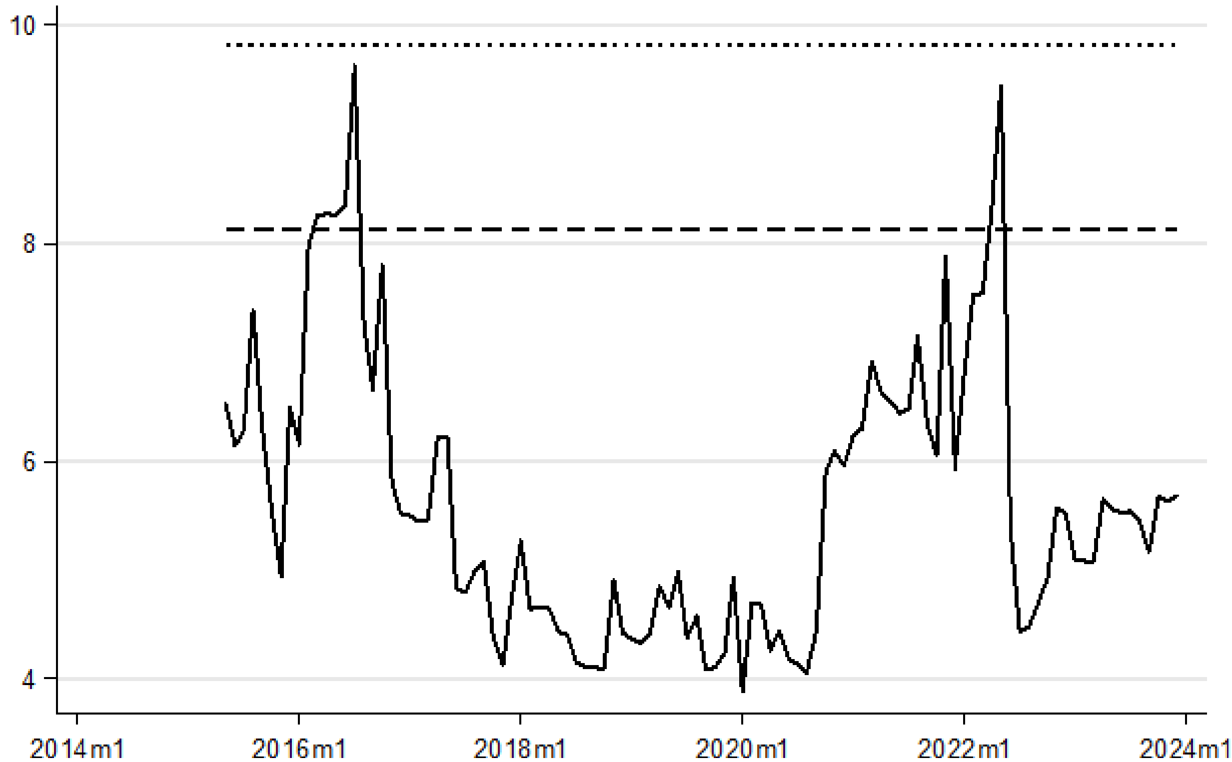


**Figure 5.**
Forward expanding Wald test for BR Granger-caused by PCR with 90th and 95th percentiles of bootstrapped test statistics.

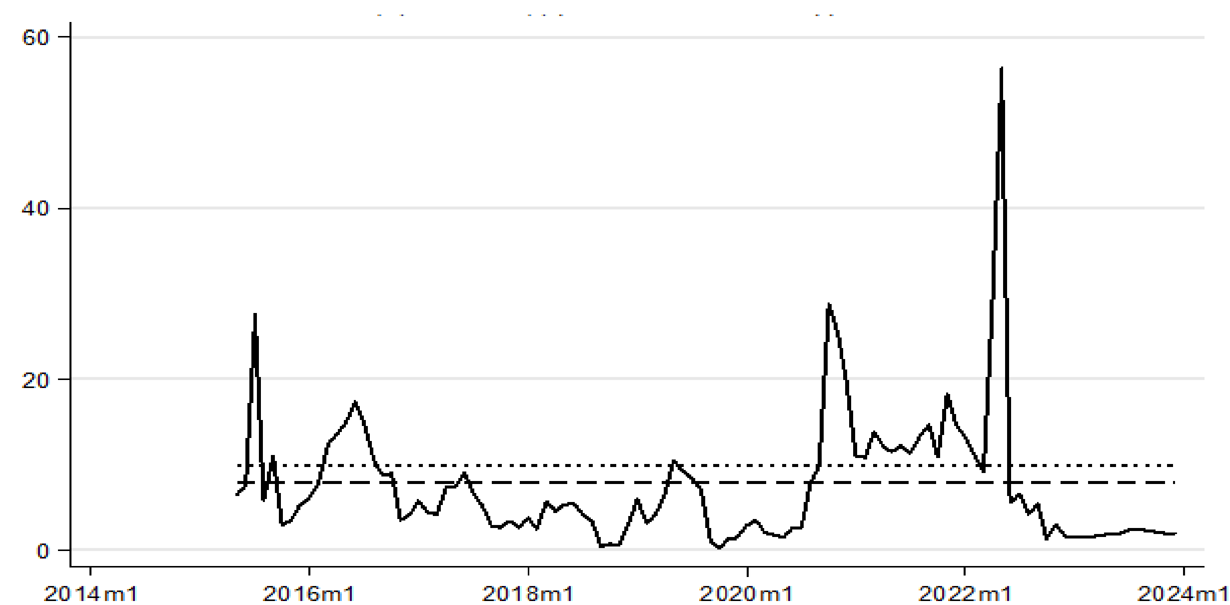


**Figure 6.**
Rolling Wald test for BR Granger-caused by PCR with 90th and 95th percentiles of bootstrapped test statistics.

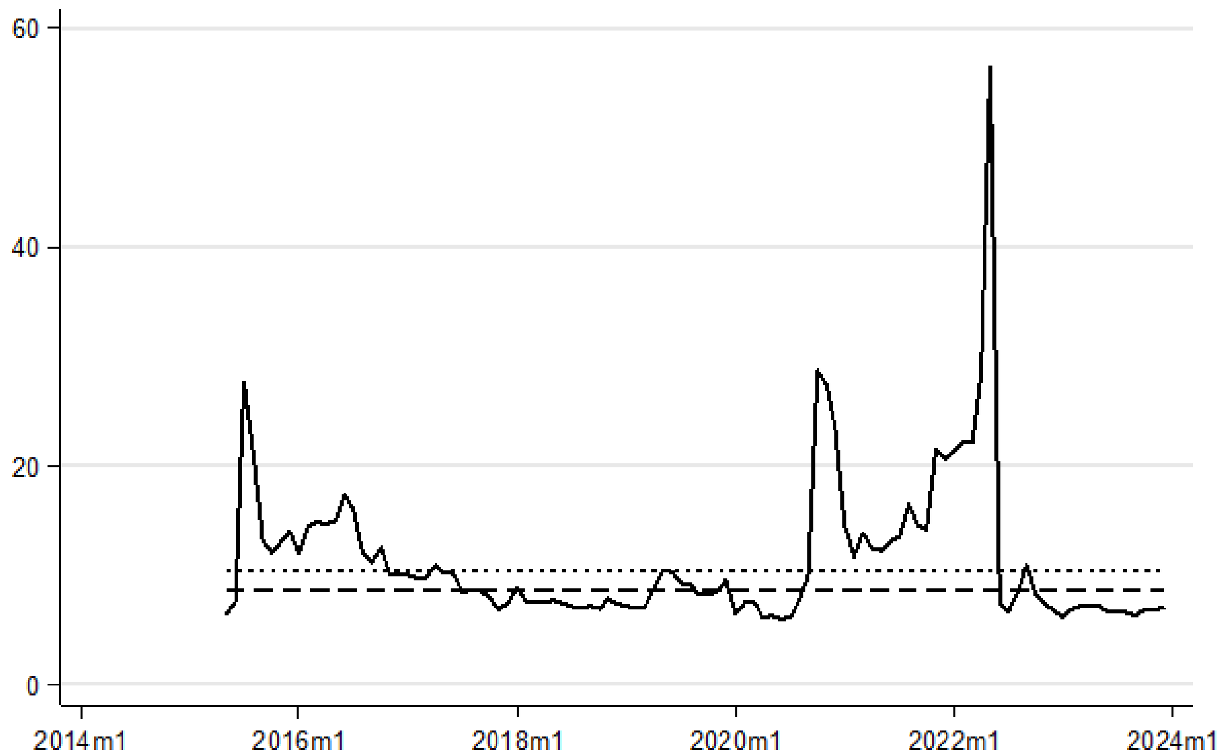


**Figure 7.**
Recursive expanding Wald test for BR Granger-caused by PCR with 90th and 95th percentiles of bootstrapped test statistics.

*4.4. Cross-Quantilogram Test Results.*

The heatmaps in Figure 8 display the directional dependence between physical climate risk and the returns of non-bank financial equities in Europe across three lag structures: lag 1 (short-run), lag 5 (medium-run), and lag 22 (long-run). At the daily lag, the dependence pattern is mixed but leans slightly toward negative associations, especially in the middle to higher quantiles of the returns series. This suggests that firms with high returns in the period of returns are much more sensitive to physical climate risks in Europe. The predominantly negative short-term impact likely reflects market disruptions, insurance liabilities, and operational risks associated with climate disasters (e.g., flash floods and storms). For instance, the 2015–2018 Central European floods and heatwaves had immediate adverse impacts on insurers, asset managers, and investor sentiment. At the 5-day horizon, the relationship appears more heterogeneous. Red patches, however, slightly dominate. This suggests that after the initial shock, some financial firms may experience a rebound or resilience effect. Markets might be reacting to early policy or recovery signals, or firms might start reallocating portfolios to hedge or capitalize on climate-related exposures. At the 22-day lag, red becomes dominant, indicating a stronger, more persistent positive relationship between physical climate risk and non-bank financial sector performance. This implies that over longer horizons, the financial sector may benefit from increased awareness and repositioning, especially in ESG-aligned investments, catastrophe bonds, and insurance product innovations. Climate-related capital reallocations and regulatory adaptation (such as EU-wide climate risk disclosures) may also be priced in positively. The results suggest a time-varying and quantile-dependent response of non-bank financial services to physical climate risk.

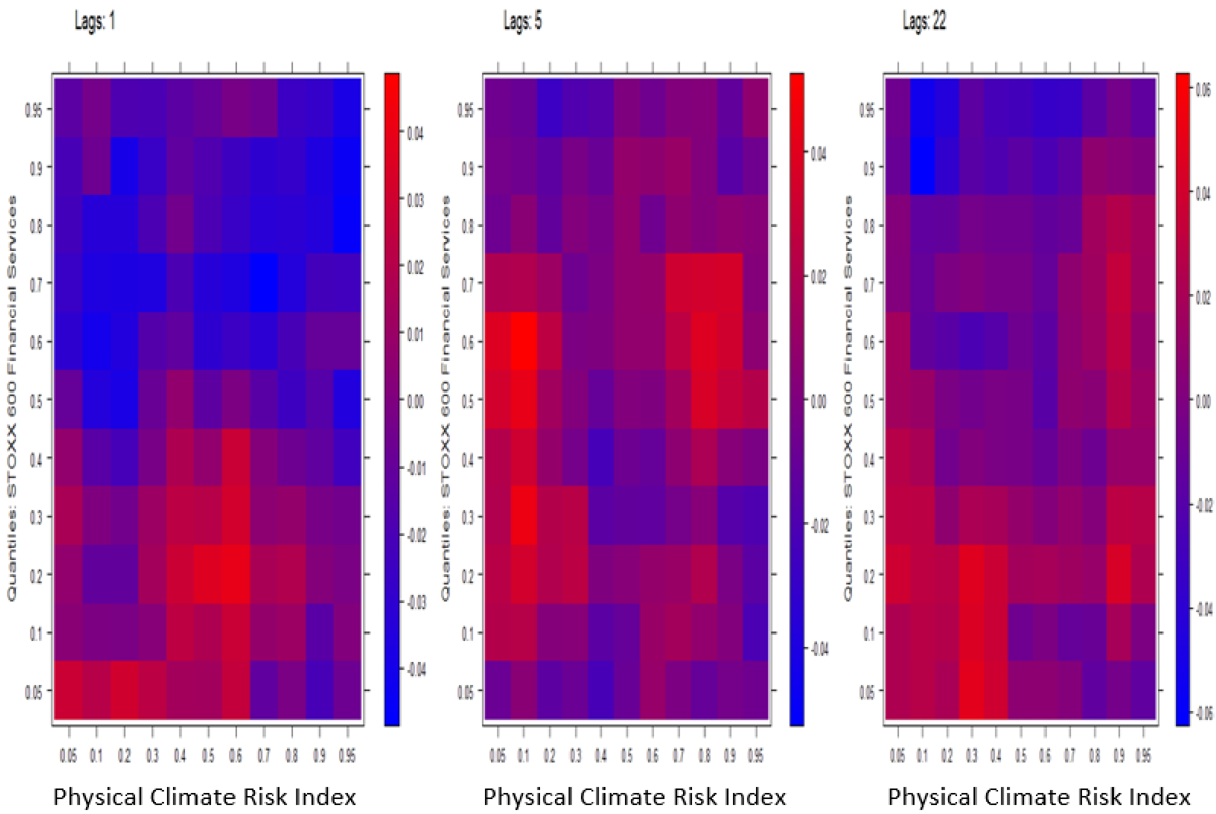


**Figure 8.**
Cross-quantilogram (PCR→NBR).

The heatmaps in Figure 9 illustrate the results of a cross-quantilogram analysis between physical climate risk and the returns of the European banking sector at three different lags: 1 day, 5 days, and 22 days, representing short-, medium-, and long-term horizons, respectively. The first panel (Lag 1) reveals a strong predominance of blue hues across nearly all quantile combinations, indicating a broad-based negative dependence between physical climate risk and bank returns in the immediate aftermath of climate shocks. This is consistent with market behavior during acute climate events such as the 2017 Central Europe floods, the 2018 droughts, and the 2021 Germany–Belgium floods, which caused severe economic damage, disrupted infrastructure, and triggered concerns about asset quality and credit risk in the banking sector. During such periods, investor sentiment tends to be risk-averse, leading to rapid sell-offs in climate-exposed financial stocks. In the second panel (Lag 5), a visible shift toward red hues suggests that the negative impact diminishes over time and that adaptive mechanisms or market corrections are emerging. The medium-term response implies that while physical climate events may initially depress bank returns, the market eventually distinguishes between institutions based on their climate resilience, portfolio exposure, and disclosure practices. For example, banks that are better capitalized, diversified, or engaged in climate risk assessments may be viewed more favorably as the dust settles. This transition phase may also coincide with policy responses or forward guidance from central banks and financial regulators.

By the 22-day horizon (third panel), the matrix becomes more heterogeneous but remains predominantly red, reflecting a mainly positive long-term association between physical climate risk and bank returns. This suggests that, following climate-related disruptions, some banks are strategically repositioning by reallocating assets, supporting green finance initiatives, or integrating physical risk analytics into their operations. Such actions could foster investor optimism and a premium for climate-adaptive banking practices. The long-term market behavior may also be influenced by the increasing alignment between financial actors and climate policy instruments, which indicate strong regulatory support for climate-resilient investments and banking innovation in risk mitigation. Overall, the dominant relationship shifts from negative to positive as we move from short-term to long-term lags, reinforcing concepts of market learning, resilience signaling, and dynamic adaptation in financial behavior. This temporal evolution highlights that, while physical climate risk is initially viewed as a shock, it eventually becomes internalized within asset pricing models, investor expectations, and institutional strategies. The results emphasize the importance of time-varying approaches to analyzing climate risk exposure, and support calls to incorporate physical climate risk into financial risk assessments and stress-testing protocols across banking systems.

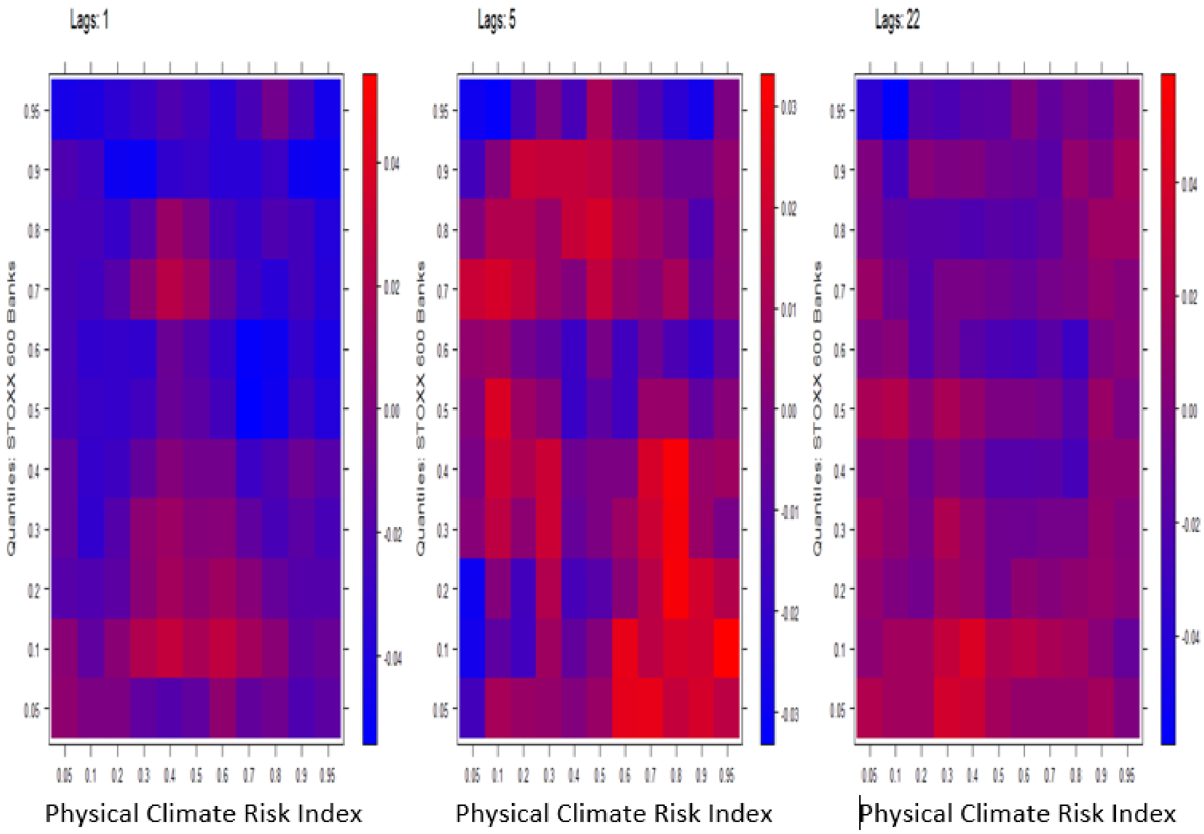


**Figure 9.**
Cross-quantilogram (PCR→ BR).

### *4.5. Discussion of Findings*

This study investigates the predictive and time-varying effects of physical climate risk on the returns of European financial equities, specifically banks (BR) and non-bank financial institutions (NBR). Utilizing nonlinear and distribution-aware econometric tools, including WBLR, TVCC, and CQ methods, the analysis provides compelling evidence on how financial markets internalize and respond to climate-related shocks. The findings are discussed below in light of policy and regulatory frameworks.

Initial diagnostic results from the BDS and QADF tests confirm that the data series exhibit strong nonlinear structures and distribution-specific stationarity. This supports the methodological decision to apply quantile- and time-varying econometric approaches. These findings reinforce prior arguments [41] that traditional linear time-series models may obscure the complex interdependencies between climate and financial risks. From a policy perspective, this underlines the need for financial regulators to incorporate nonlinear dynamics and tail behavior into supervisory stress tests and early-warning systems, such as those designed by the European Central Bank (ECB) and the European Systemic Risk Board (ESRB).

The WBLR results reveal statistically significant and economically meaningful adverse predictive effects of physical climate risk on both BR and NBR. However, the impact is more pronounced in the non-bank financial sector, suggesting that market-based entities such as insurers, asset managers, and financial service providers are more sensitive to physical climate shocks. This divergence likely reflects the greater market exposure and valuation dependency of non-bank institutions. Given this finding, financial supervisors should consider calibrating climate-related prudential tools and capital requirements differently across financial subsectors. These findings align with emerging literature that recommends a granular, sector-sensitive approach to climate-related financial regulation [1, 4, 8].

Time-varying Granger causality tests (based on forward-expanding, rolling, and recursive algorithms) further demonstrate that the causal influence of physical climate risk on financial equity returns intensifies during periods of major climate events. Notable windows of statistical significance correspond to events such as the 2017–2018 Southern Europe heatwaves and wildfires, the 2020 droughts, and the extreme 2022 climate conditions that disrupted river transport, energy supply, and agriculture across Europe. These results suggest that the pricing of climate risk in financial markets is episodic and stress-induced. Regulators should thus adopt a dynamic, scenario-based approach to stress testing that includes high-resolution climate data and lagged response functions. The EU's efforts to integrate climate considerations into the Capital Requirements Directive (CRD) and Solvency II frameworks would benefit from these insights.

The cross-quantilogram analysis provides further granularity, revealing that the dependence structure between climate risk and financial returns is both quantile- and time-horizon-dependent. For non-bank institutions, the short-run (lag 1) effects are mainly adverse, reflecting market disruption and insurer liability concerns during climate shocks. Medium-run effects (lag 5) show signs of a rebound, while long-run effects (lag 22) are increasingly positive, potentially reflecting adaptive strategies, policy signals, or portfolio reallocation toward climate-resilient assets.

Finally, banking equities follow a similar pattern but with greater initial vulnerability and a more delayed recovery. The long-term positive association at lag 22 supports the view that institutions engaging in green finance, climate disclosure, or risk mitigation strategies may be rewarded by the market over time. These dynamic responses validate the growing policy emphasis on climate-related disclosure (e.g., CSRD, SFDR), green taxonomies, and the strategic integration of ESG principles into investment strategies.

## 5. Conclusion and Policy Insights

### *5.1. Conclusion*

This study explores the dynamic relationship between physical climate risk and the performance of financial equities in Europe, focusing on both bank and non-bank financial institutions. Drawing on a comprehensive dataset of daily observations from December 14, 2012, to December 29, 2023, we assess whether physical climate risk significantly predicts asset returns in these sectors. For this purpose, we use the Physical Climate Risk Index, which offers a novel, text-based measure of climate-related physical hazards derived from financial media narratives. To robustly evaluate this relationship, we implement a multi-method empirical strategy. First, we employ the WBLR test to determine whether physical climate risk holds predictive power over financial returns. To validate the robustness of these findings, we apply the TVCC test, which uncovers the evolving nature of causality over time. Lastly, we adopt the CQ methodology to investigate how the dependence between climate risk and financial returns varies across different quantiles and time horizons.

The results provide compelling evidence that physical climate risk exerts a statistically and economically significant influence on financial equity returns in Europe, particularly for non-bank institutions. These effects are not only dynamic but also quantile-dependent and stronger during extreme market conditions and periods of heightened climate stress. Time-varying results further show that the financial impact of physical climate risk intensifies during major climate events, such as heatwaves, wildfires, and prolonged droughts, with both the bank and non-bank sectors demonstrating distinct sensitivity profiles. These findings contribute to the growing body of literature on climate-financial interlinkages by highlighting the predictive and asymmetric role of physical climate risk across the financial system. They also emphasize the importance of integrating climate risk into financial modeling, supervision, and risk assessment practices. In doing so, the study supports the call for more adaptive, forward-looking regulatory frameworks that account for the episodic and intensifying nature of climate-induced financial disruptions.

*5.2. Policy Insights*

The findings of this study carry significant implications for financial policymakers, regulators, and institutional investors. They reveal that physical climate risk is not just an environmental issue but a factor with measurable and varying effects on financial markets, particularly within the European banking and non-bank financial sectors. These implications suggest several policy directions to strengthen market resilience and align the economic system with the realities of climate risk.

The consistent and statistically significant effect of physical climate risk on equity returns, especially in the non-bank financial sector, underscores its growing relevance to financial market behavior. This suggests the need to integrate climate risk into financial supervision frameworks formally. Regulators such as the European Central Bank (ECB) and the European Systemic Risk Board (ESRB) could enhance their climate risk monitoring tools by incorporating real-time climate exposure indicators, such as drought severity, flood risk, or temperature anomalies, into regular financial stability assessments.

The study shows that non-bank financial firms, such as insurers and asset managers, are more sensitive to physical climate events than traditional banks. This distinction may reflect their greater exposure to market valuation dynamics and their lesser reliance on credit-based capital buffers. Therefore, prudential regulation should not adopt a one-size-fits-all approach. Instead, climate-related capital buffers or disclosure standards could be tailored across sectors to ensure institutions with higher exposure are adequately protected and transparent in their risk communication.

The time-varying nature of causality observed in the study, especially during major climate shocks such as the 2022 European drought, suggests that static stress testing may be insufficient. Financial authorities are encouraged to develop more flexible, event-responsive stress-testing methods that can account for both short-term shocks and longer-term climate disruptions. These tools could draw on historical patterns of market response to climate events, as well as scenario analyses that anticipate future risk amplification under worsening climate conditions.

The transition from short-term negative to long-term positive effects in the quantile-based analysis suggests that markets may reward firms that adapt effectively to climate risk. This reinforces the value of robust disclosure regimes. Regulatory efforts like the EU's Sustainable Finance Disclosure Regulation (SFDR) and Corporate Sustainability Reporting Directive (CSRD) are critical to ensuring that investors have the information needed to assess climate vulnerability and resilience. Forward-looking communication from regulators can also help anchor investor expectations and reduce reactionary market behavior during periods of stress.

The long-term positive association between climate risk and financial performance, especially for institutions engaged in green finance or adaptation strategies, points to the need for expanded use of climate-aligned instruments. Products such as catastrophe bonds, green securitizations, and parametric insurance can help absorb climate shocks and channel capital into resilient sectors. Policies that lower barriers to these innovations through tax incentives, clearer regulatory frameworks, or alignment with the EU taxonomy could accelerate the financial system's transition to climate readiness.

*5.3. Future Studies*

This study provides robust empirical evidence that physical climate risk is materially internalized in the pricing of financial assets in Europe. The dynamic and asymmetric effects observed across banking and non-banking sectors support the growing momentum to integrate climate risk into financial stability assessments, disclosure frameworks, and prudential regulation. Future research should expand the geographic scope and explore interaction effects between transition risks and geopolitical shocks.

## Institutional Review Board Statement:

The authors mentioned in the manuscript have agreed to authorship, read, and approved the manuscript, and provided consent for submission and subsequent publication of the manuscript.

## Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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