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Do Climate Risks Affect Stock Markets? Quantile Connectedness Analysis for Major European Economies

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Abstract

This study examines the interconnectedness between climate-related risks and five major stock markets in Europe, which aims to become the first continent with a net-zero emission balance, using daily data from 16 April 2013 to 29 December 2023. We employ two methodologies: quantile connectedness to investigate the impact of climate risks on stock market volatility in different market circumstances and quantile time-frequency connectedness to examine the short-term and long-term spillover effects. Our results indicate that transition and physical risks have asymmetric effects on market indices, which are particularly pronounced during crisis periods. The study emphasizes that European markets are heterogeneous with respect to climate risks and that these differences create systemic risk diversification. Therefore, strategies to address climate risks need to be tailored to country specificities.

Keywords: Climate change, climate risks, financial markets, quantile connectedness analysis

JEL Classification: Q54, G32, G15, C58

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1. Introduction

Climate change is one of human history's most prominent global problems, arguably the most critical. So much so that climate change is expected to affect many areas, from biodiversity to human health, agricultural productivity to migration and security, and energy and infrastructure to macroeconomy. Nordhaus (2019) argued that climate change is a "global public good" because the costs and benefits spill outside the market and are not reflected in market prices. In other words, the danger is more significant than thought, and the future of humanity is at risk in many ways. This study focuses on macroeconomics, particularly financial markets, as one of the areas at risk.

Carney (2015) mentioned three risk channels through which climate change can affect macroeconomic stability. These are physical, transition and liability risks. Physical risks refer to acute or chronic weather events resulting from the gradual global climate change. Transition risks involve the potential consequences during the adaptation to mitigation policies for the effects of climate change. Liability risks are the effects that may arise in future if parties damaged by the impacts of climate change demand compensation from those responsible. Today, many studies (Albanese *et al*., 2024; Bats *et al*., 2024; Bouri *et al*., 2023b; Chabot and Bertrand, 2023; Ma *et al*., 2024) examine how physical and transition risks, which are today's potential problems, are transmitted to financial markets. For example, Bua *et al*. (2024) developed physical and transition risk indices with newspaper content, based on the text-based approaches of Engle *et al*. (2020). Bua *et al*. (2024) also reported that the indices precisely capture the adaptation effects of the 2015 Paris Agreement and its aftermath and some extreme weather events[1]. Thus, these indices are reliable for detecting relationships on financial markets (Arfaoui *et al*., 2024; Del Fava *et al*., 2024; Li *et al*., 2024).

Climate change is becoming an increasingly important risk factor on global financial markets. Investors and policymakers want to understand how climate risks affect stock markets. After the 2015 Paris Agreement, many countries committed to reducing carbon emissions. Additionally, in recent years, the rising frequency of extreme weather events worldwide has led to significant losses, particularly in the insurance, agriculture, real estate and energy sectors. These recent events have heightened financial market risks through the abovementioned channels. The increasing impact of climate change on financial markets, as in all other areas, is the major motivation for this study. This study aims to analyse the impact of physical and transition climate risks on five major European stock markets using different methods. The answer to why European financial markets are being analysed

1 Please see Bua *et al.* (2024) for important dates of physical and transition risks.

is clear: The Europe is expected to be the first continent with a net-zero emission balance. Europe is the most proactive region in the world in combating climate change and has one of the markets with high sensitivity to climate risks. We focus on the period after 2013 due to major regulatory advancements, particularly after the 2015 Paris Agreement, which spurred strategic initiatives and robust frameworks for sustainable finance.

The existing literature predominantly examines the impact of climate risks on financial markets under average market conditions using traditional connectedness models. However, studies investigating the transmission mechanisms of these risks during periods of heightened market volatility, such as financial crises, remain limited. Furthermore, research into European financial markets primarily focuses on broad market trends without adequately capturing cross-country differences. Given Europe's leading role in climate policies and the green transition, a more comprehensive examination of how climate risks affect financial markets in this region is warranted. This study contributes to the literature by analysing the impact of climate risks on five major European stock markets from a dynamic perspective. Integrating the quantile connectedness and quantile time-frequency connectedness approaches provides a nuanced understanding of how these risks propagate across financial markets under varying market conditions and time horizons. This methodological advancement enhances our comprehension of how climate risks influence financial stability during crisis periods and highlights cross-country heterogeneities. Therefore, this study fills a critical gap in the literature, offering theoretical and empirical insights into the transmission of climate risks on financial markets.

The rest of the paper is organized as follows: Section 2 summarizes empirical literature. Section 3 presents the data. Then, Section 4 describes the methodology. Section 5 clarifies the empirical results. Section 6 concludes.

2. Theoretical Background and Empirical Literature Review

2.1 Theoretical background

The vital question that needs to be answered is: What theoretical link exists between climate risks and financial markets? For many years, financial markets have been affected by economic indicators such as growth, inflation and employment (Fama, 1970), macroeconomic policies (Bernanke and Kuttner, 2005), companies' performance (Ball and Brown, 1968), geopolitical circumstances (Bekaert *et al.*, 2005) and investor behaviour (Shiller, 2000). In addition, there is a new but rapidly growing body of literature, especially studies theoretically discussing whether climate risks have an impact on financial markets (Batten, 2018; Battiston *et al*., 2021; Campiglio *et al*., 2019; ECB, 2021; Feyen *et al*., 2020; Fried *et al*., 2021; IMF, 2020; Krogstrup and Oman, 2019).

Moreover, literature reviews compiling theoretical and empirical studies addressing the links of climate risks to financial markets are also increasing (Campiglio *et al*., 2023; Capriotti *et al*., 2024; Eren *et al*., 2022; Geraci *et al*., 2023; Venturini, 2022). One of the common features of these studies, which focus on the impact of climate risks on financial markets and the macroeconomy in general, is that they seek the answer to the above question. Feyen *et al*. (2020) stated that climate change is an important source of risk for the financial sector, with its negative direct and indirect effects of physical and transition risks on the financial markets manifesting both suddenly and gradually. Physical and transition risks affect financial assets and, therefore, balance sheets of financial institutions; they are transmitted to financial markets through four financial risk channels: operational risk, market and liquidity risk, credit risk and underwriting risk. Table 1 summarizes financial risk channels paired with climate risks (Feyen *et al*., 2020).

Table 1: Financial risk channels for climate risks

Risk	Physical risks	Transition risks
Operational risk	– *Damage to financial infrastructure, branches and office buildings*	– *Reputational impacts of not adjusting to "green" investment policies and potential greenwashing*
Market and liquidity risk	– *Impact on asset valuations* – *Pro-cyclical materialization of losses and tighter funding and liquidity conditions* – *Drive up commodity and energy prices*	– *Impact on asset valuations* – *Pro-cyclical materialization of losses and tighter funding and liquidity conditions* – *Drive up commodity and energy prices*
Credit risk	– *Negative impact on borrower repayment capacity*	– *Quality of credit exposures to carbon-intensive sectors could deteriorate if low collateral prices increase credit risk, especially when uninsured*
Underwriting risk	– *Damage to insurance companies, increase in premiums and rendering some activities uninsurable*	– *New insurance products that include green technologies or exclude brown ones*

Source: Feyen *et al*. (2020)

Climate risks on global financial markets are dynamic and interconnected in nature. The transmission of climate risks is not uniform; instead, it follows specific propagation paths and specific financial markets act as key nodes in the propagation of these risks (Yin and Cao, 2024). Given the long-term and systemic nature of climate risks, their impact on financial stability and market behaviour has become a crucial area of inquiry (Wu *et al*., 2024). Ma *et al*. (2024) highlighted that climate-related news is critical in shaping financial market dynamics and risk transmission mechanisms.

Moreover, studies in this area show that climate risk spillovers increase during financial instability and highlight the need for robust regulatory frameworks. These risks do not operate in isolation but interact with broader macroeconomic dynamics, influencing key financial indicators such as volatility, risk premiums and asset valuations. Climate risks manifest through direct economic disruptions and financial contagion channels, shaping investor sentiment and market expectations. Physical risks can cause damage to production facilities, disruptions in the supply chain and increased insurance costs. Such negatives can lead to an increase in production costs, a decrease in profitability, a negative impact on expectations, a decrease in consumer confidence and a decrease in total demand. Stock returns are expected to be negatively affected by all of these.

On the other hand, transition risks involving regulations on carbon emissions affect fossil fuel-intensive (brown) sectors and sustainable (green) sectors differently. For example, carbon taxes could reduce the profitability of brown industries. Conversely, increased interest in sustainable sectors may increase the stock prices of green industries. In the transition to low-carbon technologies, some companies may lose their competitive advantage, while companies that quickly adapt to new technology can gain one. These effects can increase risk and volatility on stock markets (Battiston *et al*., 2021; Bolton *et al.,* 2020; Campiglio *et al*., 2019; Carney, 2015; Feyen *et al*., 2020). Giglio *et al*. (2021) reported two main approaches to modelling climate risks. The first addresses uncertainty about how climate change will progress, while the second involves how economic growth affects climate change. Climate disasters trigger negative effects of climate risks on the real estate and financial sectors by increasing the likelihood of future negative events and positive economic growth, creating more carbon emissions. Other potential approaches are asset pricing (higher risk premium), preferences (Epstein-Zin preferences that consider long-term consumption growth) and model (policy) uncertainty. Firstly, assets positively exposed to climate risk command a higher risk premium, while assets that hedge climate risk carry a negative risk premium. Secondly, the Epstein–Zin preferences, which consider long-term consumption growth rather than a short-term consumption-oriented function, magnify the effects of long-term climate risks and highlight the long-term consequences of climate shocks, affecting the structure of discount rates. Finally, as the perception of uncertainty regarding the modelling of climate change increases, the risks brought by climate change are seen as higher, and accordingly, risk premiums increase (Giglio *et al.*, 2021).

Campiglio *et al*. (2023), in line with the ideas of many other studies, argued that climate risks are transmitted to financial markets through the following channels: (i) *asset channel*, where climate events render companies' capital assets unusable or decrease their value, leading to financial losses; (ii) *investment channel*, where firms must increase capital expenditures to adapt to a low-carbon economy by investing in necessary infrastructure and technological transformation; (iii) *production network channel*, where demand shifts and supply chain disruptions affect firms' revenues and operational costs; (iv) *credit channel*, where firms face higher borrowing costs and increased insurance premiums due to rising climate risks.

Through these channels, the impact of climate risks on financial markets continues to grow, influencing asset valuations, investment decisions and overall market stability. However, the extent to which investors accurately price these risks remains uncertain, raising concerns about potential market distortions, misallocations of capital and systemic financial vulnerabilities that could exacerbate economic instability in the long run.

2.2 Empirical literature

Although stock market risk studies have increased significantly following the 2008 crisis, they have perhaps reached their peak recently with studies investigating the impact of climate risks on these markets. The empirical literature, which previously covered mostly physical risks, has begun to consider both physical and transition risks separately in recent years. Faccini *et al*. (2021), one of the first studies to emphasize this distinction, used physical risks such as natural disasters and global warming together with transition risks such as US climate policy and international summits. According to them, only the effects of climate policy are priced into the US stock market, especially the more pronounced and short-term effects in the period 2012-2018. Studies such as An *et al*. (2022), Antoniuk and Leirvik (2024), Hengge *et al*. (2023), Wu and Wan (2023) and Yang *et al*. (2023) have also focused on this significant relationship, that is, transition risks. Hengge *et al*. (2023) argued that mitigation policies are a cost-increasing factor in carbon-intensive sectors, whereas Yang *et al*. (2023) asserted that only positive climate news is priced in the stock market, not negative news. On the other hand, Antoniuk and Leirvik (2024) associated events that weaken mitigation policies with positive abnormal returns in brown sectors. An *et al*. (2022) reported that the impact of transition risks on the Chinese stock market is strong in the short and medium term, but uncertain in the long term. Wu and Wan (2023), on the other hand, attributed the spread of transition risks to factors such as similar economic conditions and increased import dependency among countries in their study of 42 countries.

Studies that empirically divide climate risks into two and analyse physical risks and transition risks separately have occupied a wide place in the literature in recent years (Albanese *et al.*, 2024; Ardia *et al.*, 2023; Bats *et al.*, 2024; Bouri *et al.*, 2023a; Bouri *et al.*, 2023b; Bua *et al.*, 2024; Chabot and Bertrand, 2023; Ma *et al.*, 2024; Rebonato, 2024; Tran *et al.*, 2023). Rebonato (2024) argued that physical and transition risks are important in asset valuation and that considering them separately would be more beneficial for the investor. Chabot and Bertrand (2023) also stated that physical and transition risks negatively affect financial stability in the European financial system. Similarly, Albanese *et al.* (2024), who investigated the dynamics of 28 European countries, presented findings that stock markets are positively (negatively) affected by transition (physical) risks in the short term. However, according to the findings, transition risks are also effective in the long term.

While Tran *et al.* (2023) and Bats *et al.* (2024) emphasized that physical risks have more significant and clear effects on financial markets than transition risks, Bouri *et al.* (2023b) provided contrary evidence. While Ardia *et al.* (2023) argued that climate risks increase (decrease) the prices of green (brown) stocks, Ma *et al.* (2024) similarly found that both physical and transition risks affect the returns on green bonds and that negative news triggers excessive risks to green bonds. In more detail, Bua *et al.* (2024) reported that increases in transition risks increase the returns on green stocks, but increases in physical risks reduce the returns on brown stocks. Adediran *et al.* (2024) added to these and argued that 100% of green stocks protect investors against climate risks. Bouri *et al.* (2023a) reported that physical and transition risks are positively linked to a long-term correlation with clean energy and technology stock indices (especially higher transition risks). Studies such as Muhajir (2024) and Pata *et al.* (2024) have analysed ESG-compliant bonds that consider environmental, social and governance (ESG) criteria rather than green bonds focusing only on environmental projects. Pata *et al.* (2024) argued that physical and transition risk indices increase ESG market development at high levels, while Muhajir (2024) puts forward that climate risks negatively affect ESG-compliant bond yields.

Some studies concentrate more on the direct physical risks of climate change. Physical risks are good predictors of stock market volatility and largely capture key moments in stock market returns (Bouri *et al.*, 2024; Wu *et al.*, 2024). However, drought and precipitation risks significantly affect both spread speed and magnitude more than temperature risks

(Yin and Cao, 2024). Balcilar *et al*. (2023) proved that these risks have a short-term out-of-sample predictive value for stock markets. Climate risks generally appear to be a strong determinant in predicting stock market returns and volatilities (Adediran *et al*., 2024; Ma *et al*., 2023; Rebonato, 2024). Especially after the Paris Agreement adopted in 2015, investors' awareness of climate risks and the sensitivity of financial markets to climate risks have increased (Antoniuk and Leirvik, 2024; Bats *et al*., 2024; Bua *et al*., 2024; Tran *et al*., 2023).

3. Data

To represent and compare the performance of European stock markets, we use the daily closing prices of the stock market indices of five major European countries. These countries are France (CAC 40), Germany (DAX), Italy (FTSE MIB), Switzerland (SMI) and the UK (FTSE 100). These five countries collectively account for approximately 70% of the European Union's GDP and are among Europe's largest economies. Furthermore, these countries play leading roles in climate policies and exhibit high sensitivity to climate risks on their financial markets. For instance, Germany and France are prominent in renewable energy investments and setting ambitious carbon neutrality goals, while the UK stands out as a leader in sustainable finance regulation. Therefore, these indices provide strong representative power for analysing the relationship between climate risks and European financial market dynamics.

Bua *et al*. (2024) developed climate risk indices, namely the physical risk index (PRI) and the transition risk index (TRI), to monitor daily changes in physical and transition climate risks. These indices, constructed using text-based methods derived from European climate change news, offer a ranked list of phrases associated with both physical and transition risks (Bua *et al*., 2024). The PRI and TRI effectively detect unexpected spikes in discussions about these risks, ensuring that new developments or changes in perceived climate risk are reported. News and scientific texts about climate risks include acute and chronic physical hazards (physical risks), approaches to adaptation and mitigation and goals for achieving net-zero emissions (transition risks). Unlike traditional climate risk indicators (*e.g.*, CO_2 emissions or temperatures), which offer static measurements, the PRI and TRI provide a dynamic approach, enabling the analysis of short-term market responses to change climate risk perceptions. Due to these characteristics, these indices are particularly suited for our quantile connectedness methodology, allowing us to better understand risk spillovers under extreme market conditions.

Table 2: Summary statistics

	TRI	PRI	CAC 40	DAX	FTSE MIB	SMI	FTSE 100
Mean	−0.002	−0.001	0.028	0.029	0.022	0.024	0.012
Variance	0.021	0.022	1.641	1.520	2.436	0.939	1.036
Skewness	0.902*** (0.000)	0.856*** (0.000)	−0.649*** (0.000)	−0.617*** (0.000)	−1.192*** (0.000)	−0.892*** (0.000)	−0.745*** (0.000)
Kurtosis	3.988*** (0.000)	1.580*** (0.000)	8.516*** (0.000)	10.099*** (0.000)	12.736*** (0.000)	9.796*** (0.000)	10.528*** (0.000)
J–B	2418.277*** (0.000)	685.256*** (0.000)	9366.741*** (0.000)	11611.002*** (0.000)	21189.636*** (0.000)	12512.700*** (0.000)	14267.734*** (0.000)
ERS	−8.528*** (0.000)	−3.292*** (0.001)	−15.318*** (0.000)	−6.280*** (0.000)	−11.463*** (0.000)	−10.760*** (0.000)	−16.072*** (0.000)
Q(20)	233.615*** (0.000)	291.348*** (0.000)	13.241 (0.216)	21.103** (0.011)	28.887*** (0.000)	17.763** (0.043)	16.536* (0.070)
Q2(20)	59.961*** (0.000)	54.558*** (0.000)	1083.046*** (0.000)	872.231*** (0.000)	603.318*** (0.000)	839.684*** (0.000)	1266.723*** (0.000)

Notes: *p*-values are given in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Source: Authors' own calculations

Our dataset[2] covers a period from 16 April 2013 to 29 December 2023, relevant for examining how European financial markets responded to climate risks after the European debt crisis. This timeframe includes both data availability and more frequent extreme weather events, important physical and transitional climate events such as the Paris Agreement in 2015 and the EU's implementation of national policies for its own climate regulation and transition to a low-carbon economy, as well as political and social traumas such as Brexit, the Russo-Ukrainian war and COVID-19 (Hossain *et al*., 2024).

Table 2 presents descriptive statistics for the PRI, the TRI and market indices. The FTSE MIB has the highest variance, followed by the CAC 40, DAX, FTSE 100 and SMI. This implies that the FTSE MIB shows the largest volatility, while the SMI has the lowest variance. The model parameters show positive skewness for climate risk indices, meaning that

2 Climate risk indices and European stock market indices are retrieved from from the Economic Policy Uncertainty database (Economic Policy Uncertainty, n.d.) and Investing.com (n.d.).

the right tail of the distribution is longer. This suggests that the variables are asymmetric and have a low central tendency. Long tails in the data indicate the possibility of tail dependence between variables under extreme conditions. The skewness and kurtosis results suggest that these variables can exhibit tail dependence under extreme conditions, which may be appropriate for a quantile-level analysis. The Jarque–Bera test is significant, indicating that the model parameters are not normally distributed. Moreover, the ERS test confirms that the model parameters are stationary at the 1% significance level.

This analysis highlights the asymmetric nature of market variables, their high variance and potential dependence under extreme conditions, suggesting that quantile-based analysis may be appropriate for understanding the impact of climate risks on financial markets.

4. Methodology

We conduct the analysis using two methods that provide different perspectives on connectedness: the dynamic quantile connectedness approach (Chatziantoniou *et al*., 2021) focuses on connectedness across quantiles, offering insights into how climate risks influence European market volatility. On the other hand, quantile time-frequency connectedness (Chatziantoniou *et al*., 2022) offers a time-frequency domain analysis, which helps understand how connectedness evolves over different time horizons.

4.1 Dynamic quantile connectedness approach

We employ the quantile vector autoregression (QVAR) method, as outlined by Ando *et al*. (2022), to investigate the connection between climate risks and the major European stock indices. Our methodology is based on the quantile connectedness approach developed by Chatziantoniou *et al*. (2021), giving us the ability to estimate connectedness at the lower, middle and higher quantiles, therefore proving the variations in connectedness with different market conditions under bearish, bullish and standard market phases. QVAR is an extension of the VAR connectedness approach (also known as the volatility spillover), which was initially developed by Diebold and Yilmaz (2009, 2012), and enhances it by enabling analysis across different quantiles.

The QVAR model can be mathematically expressed as follows:

$$\boldsymbol{y}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \boldsymbol{\Phi}_j(\tau)\, \boldsymbol{y}_{t-j} + \boldsymbol{u}_t(\tau) \quad (1)$$

In Equation (1), $\boldsymbol{y}_t(\tau)$ is the vector of endogenous variables at the time t and the quantile τ, $\boldsymbol{\mu}(\tau)$ is the vector of quantile-specific intercepts. $\boldsymbol{\Phi}_j(\tau)$ denotes the matrix of quantile-specific autoregressive coefficient for the lag j of the endogenous variables and $\boldsymbol{u}_t(\tau)$ is the vector of quantile-specific error terms; p is the model lag length and is selected based on the Bayesian information criterion (BIC).

To analyse the dynamic connectedness, the QVAR model (p) transformed into its quantile vector moving average (QVMA – (∞)):

$$\boldsymbol{y}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \boldsymbol{\psi}_i(\tau)\boldsymbol{u}_{t-i}(\tau) \tag{2}$$

where $\boldsymbol{\psi}_i(\tau)$ represents the impulse-response function at the quantile τ. This transformation allows us to assess how shocks spillover through the model across different quantiles, capturing the dynamic connectedness between climate risks and stock indices.

Following that, we employ the generalized forecast error variance decomposition (GFEVD) method, proposed by Koop *et al.* (1996):

$$\phi_{ij}^{g}(H,\tau) = \frac{\Sigma(\tau)_{jj}^{-1} \sum_{h=0}^{H}\left((\boldsymbol{\psi}_h(\tau)\boldsymbol{\Sigma}(\tau))_{ij}\right)^2}{\sum_{h=0}^{H}(\boldsymbol{\psi}_h(\tau)\boldsymbol{\Sigma}(\tau)\boldsymbol{\psi}_h'(\tau))_{ii}} \tag{3}$$

Here, $\phi_{ij}^{g}(H,\tau)$ is the GFEVD at the horizon H and the quantile τ, providing a measure of the forecast error variance of the variable i due to shocks in the variable j. The vector $\boldsymbol{e_i}$ has a value of one at the i-th position and zero elsewhere, while $\boldsymbol{\Sigma}(\tau)$ represents the covariance matrix of the residuals at the quantile τ. This decomposition provides insight into the impact of climate risk shocks on the volatility of the stock indices across different market conditions.

Finally, we calculate the total connectedness index (TCI), based on the methodology of Diebold and Yilmaz (2009, 2012), to measure the total degree of connectedness across variables in the model:

$$TCI(H,\tau) = \frac{1}{k-1}\sum_{i=1}^{k}\sum_{j=1,i\neq j}^{k}\phi_{ij}^{g}(H,\tau) \tag{4}$$

Here, k signifies the total number of variables in the model. A higher degree of interconnectedness among the variables is indicated by a higher TCI value, which indicates the degree to which climate risks are integrated into the financial markets.

The dynamic connectedness "TO" others and the dynamic connectedness "FROM" others are the two components of the total directional connectedness. The dynamic connectedness "TO" ($C_{i\to j}(H)$) is computed as follows:

$$C_{i\to j}(H) = \sum_{j=1,i\neq j}^{k}\phi_{ij}^{g}(H,\tau) \tag{5}$$

The value of this measure represents the impact that shocks in the variable i have on all other variables j in the model. Conversely, the dynamic connectedness "FROM" ($C_{i\leftarrow j}(H)$) is calculated by summing the impact of shocks in all other variables j on the variable i:

$$C_{i\leftarrow j}(H)=\sum_{j=1,i\neq j}^{k}\phi_{ij}^{g}(H,\tau) \tag{6}$$

The difference between the connectedness "TO" and "FROM" gives the "NET" total directional connectedness, which indicates whether a particular variable is primarily a transmitter or a receiver of shocks within the network.

4.2 Quantile time-frequency connectedness

Our methodology incorporates the quantile time-frequency connectedness (QTF) approach, as proposed by Chatziantoniou *et al*. (2022), in addition to the previous approach. The QTF approach extends the quantile connectedness approach (Chatziantoniou *et al*., 2021), combining it with frequency-domain analysis to capture how connectedness varies over both time and frequency. This approach enables a more detailed connectedness analysis by considering different investment timeframes.

The QTF approach facilitates the examination of connectedness in terms of short-term and long-term components, offering insights into the impact of climate risks on European financial markets across different time spans. Utilizing frequency-domain analysis distinguishes between high-frequency connectedness, reflecting short-term shocks and low-frequency connectedness, capturing more enduring structural changes within the market.

The QTF approach involves transforming the QVAR model into its moving average form, as outlined in Equations (1) and (2) in the initial model. Subsequently, the GFEVD is calculated based on Equation (3). After this, the QVAR model is transformed into the frequency domain using spectral analysis. This process involves calculating the frequency response function, which decomposes the connectedness into different frequency components:

$$\theta_{ij}(\omega)=\frac{\sum_{h=0}^{\infty}(\boldsymbol{\Phi}_h(\tau)\boldsymbol{\Sigma}(\tau)\boldsymbol{\Phi}_h'((\tau))_{ij}e^{-i\omega h}}{\sum_{h=0}^{\infty}(\boldsymbol{\Phi}_h(\tau)\boldsymbol{\Sigma}(\tau)\boldsymbol{\Phi}_h'((\tau))_{ii}} \tag{7}$$

Here, ω refers to the frequency and $\theta_{ij}(\omega)$ indicates the contribution of shocks from the variable j on the forecast error variance of the variable i at the frequency ω. This decomposition allows us to assess connectedness across different time scales, distinguishing between short-term market dynamics and long-term structural changes.

Next, we compute several directional connectedness metrics (Diebold and Yilmaz, 2009, 2012). The net pairwise directional connectedness (NPDC) indicates the net directional impact between two specific variables at different frequencies. It is calculated as follows:

$$NPDC_{ij}(\omega)=\theta_{ij}(\omega)-\theta_{ji}(\omega) \tag{8}$$

This metric indicates whether one variable predominantly affects another or vice versa at the frequency ω. Additionally, the connectedness "TO" is captured by the expression:

$$TO_i(\omega) = \sum_{j \neq i} \theta_{ji}(\omega) \tag{9}$$

Conversely, the connectedness "FROM" is calculated as:

$$FROM_i(\omega) = \sum_{j \neq i} \theta_{ij}(\omega) \tag{10}$$

This sum represents the degree to which the variable *i* affected by shocks from all other variables *j* at the frequency ω (as a receiver).

Finally, to summarize the overall level of interconnectedness in the model, we compute the total connectedness index (TCI):

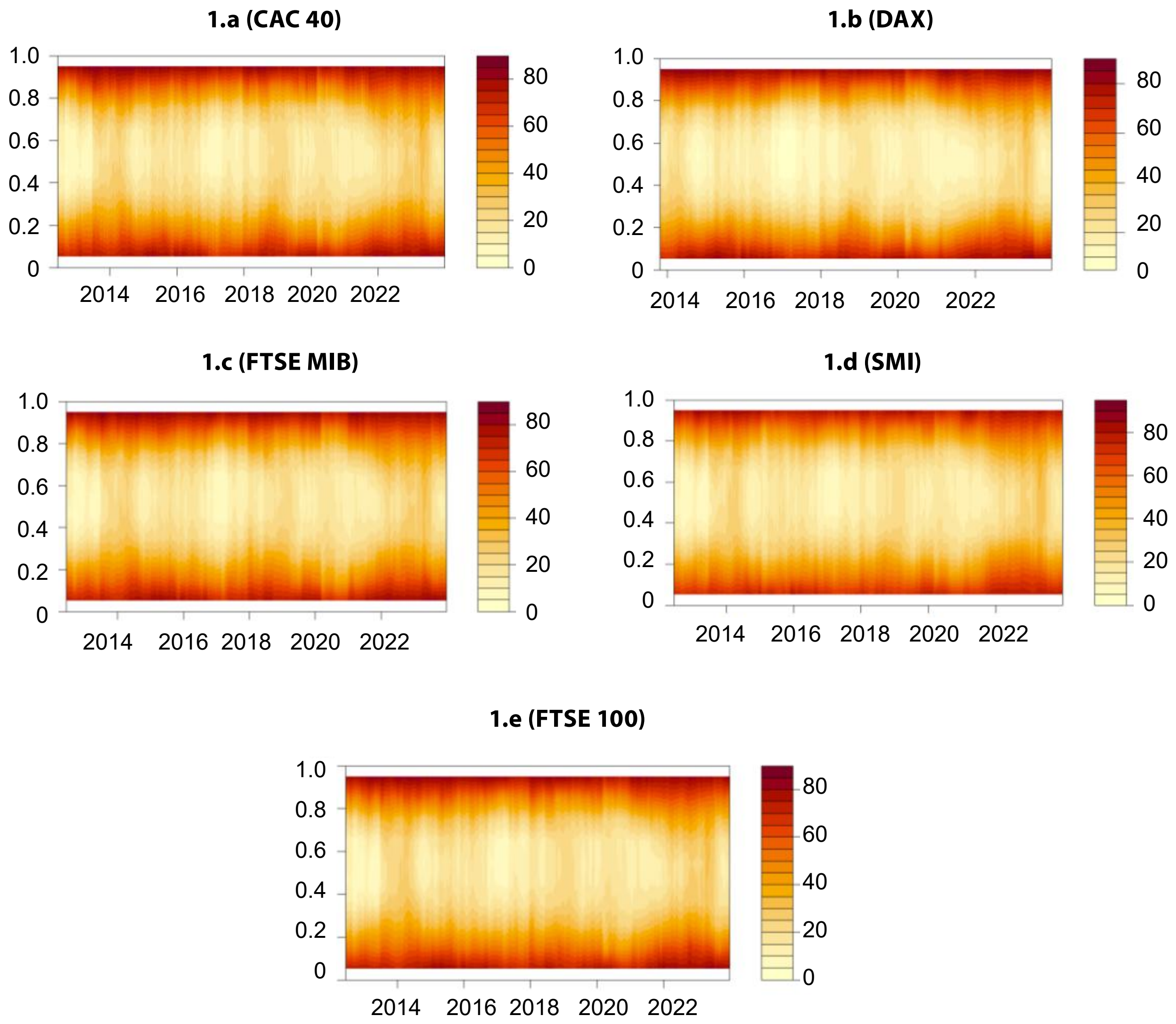
$$TCI(\omega) = \frac{1}{k-1} \sum_{i=1}^{k} \sum_{j=1, i \neq j}^{k} \theta_{ij}(\omega) \tag{11}$$

A higher TCI value indicates a stronger degree of interconnectedness, reflecting the extent to which climate risks are integrated into financial market dynamics across different time horizons.

5. Empirical Results and Discussion

5.1 Dynamic quantile connectedness between climate risks and major European markets

Figure 1: Total dynamic connectedness across quantiles



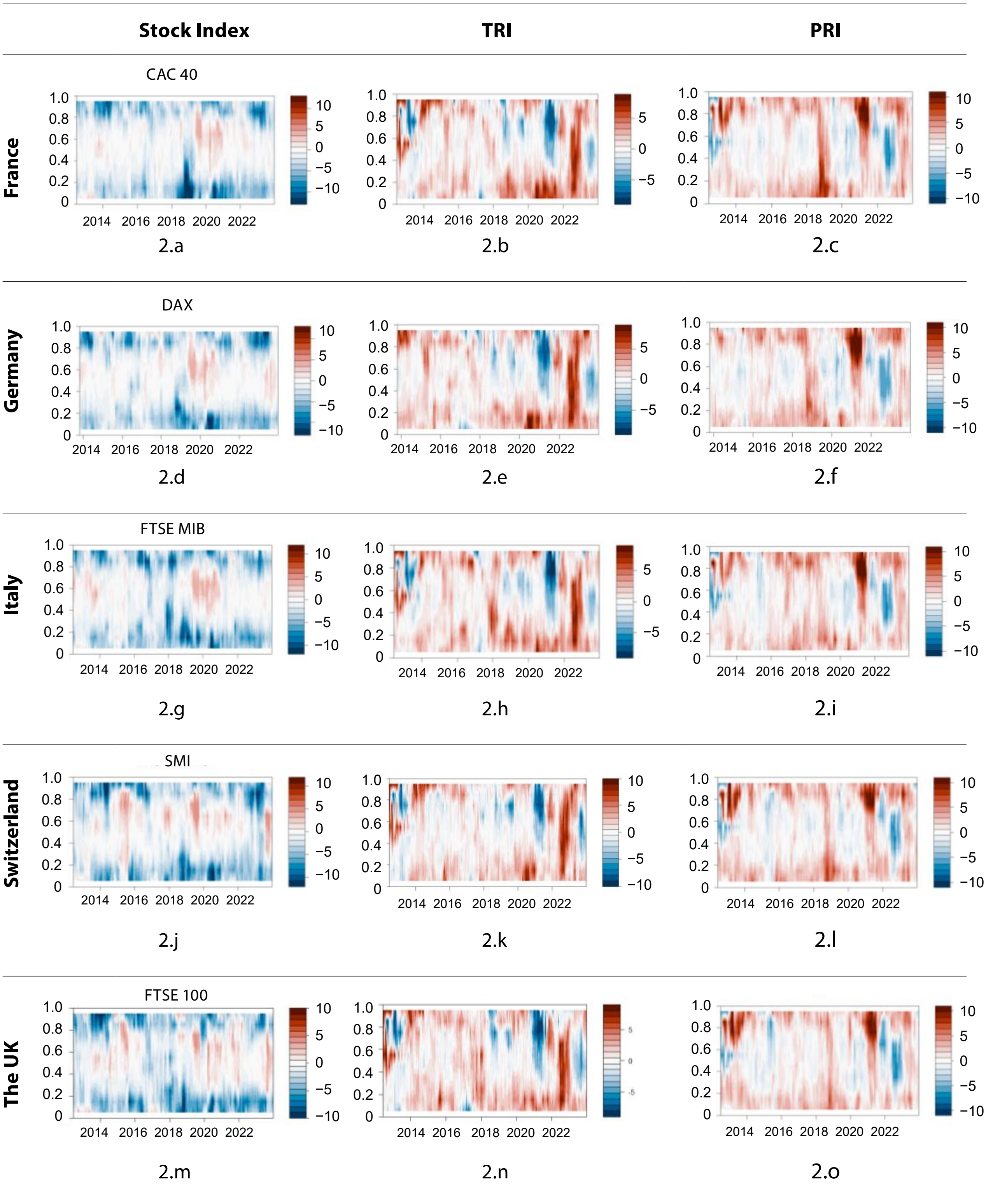
Source: Authors' own elaboration

Figure 1 analyses the connectivity between each market index, the PRI and the TRI by quantiles over time. This analysis presents the impact of the PRI and TRI on European stock market indices under different market conditions (from low to high volatility). The vertical axis represents quantiles, where the lower quantiles (0–0.2) represent stable market conditions and higher quantiles (0.8–1) represent periods of high volatility or crises. Darker colours indicate stronger connectivity, reflecting a higher influence of climate risks on market volatility. The observation of more intensely coloured areas, especially at higher quantiles, suggests that the connectedness of the TRI and PRI on market indices increases when market conditions involve high risk or volatility. This suggests that the PRI and TRI may have an asymmetric impact on market risks. Specifically, increased connectivity in high volatility periods aligns with findings of Feyen *et al*. (2020), suggesting that climate risks intensify asset valuation and funding conditions during crises. For instance, connectivity in France's CAC 40 spiked significantly during the yellow vest protests of 2018, indicating heightened market uncertainty consistent with Campiglio *et al*. (2023), reflecting asset channel impacts through decreased valuation of corporate assets.

In the CAC 40 and DAX indices, the impact of the PRI and TRI increases amid crises and uncertainty (Figures 1.a and 1.b). In Figure 1.a (CAC 40), connectivity at the 0.9 quantile spikes in 2018, likely due to the yellow vest protests in France, increasing market uncertainty and sensitivity to climate risks. This shows that German and French markets are more sensitive to climate risks. The FTSE MIB, SMI and FTSE 100 showed less connectivity changes than the others (Figures 1.c, 1.d and 1.e). In certain times, the PRI and TRI effects are noteworthy. At lower quantile levels (*e.g.*, between 0.2 and 0.5), the FTSE MIB index shows increased connectedness with climate risk indices. This may suggest that the Italian market is more sensitive to climate risks even under stable market conditions. This finding indicates that the climate risks have asymmetric impacts across markets, intensifying significantly during turbulent economic periods.

In each heatmap in Figure 2, the darker blue colours represent the net intake index, *i.e.*, periods when the index receives more shocks in each period, while the darker red colours represent the net transmission index, *i.e.*, periods when the index transmits more shocks to other markets. These colours visualize the role of each index *vis-à-vis* climate risks – whether it is a receiver or a transmitter – over specific time periods.

Figure 2: Net total directional connectedness across quantiles



Source: Authors' own elaboration

Figure 2 shows that the French and German indices have similar patterns at high quantiles (*e.g.*, 0.8 and above). Both countries are net receivers during high volatility, indicated by blue shades, suggesting that they are more vulnerable to climate risks during crises. However, Germany assumed the net transmitter role between 2016 and 2020, aligning with Germany's energy transition policies, especially its 2016 emission reduction targets and the 2019 Climate Action Law targeting carbon neutrality by 2050. This role transition aligns with the operational risk channel identified by Feyen *et al*. (2020), highlighting Germany's impact on transmitting climate risk to other markets. Italian and Swiss connectedness is more balanced. Italy is more vulnerable to climate risks, especially at low quantiles, indicating a less volatile energy transition economy. On the other hand, Switzerland's stable financial market is more resilient to the TRI and PRI. After 2020, the UK became a major net transmitter. Especially at higher quantiles, the UK was observed to be an important actor in the integration of climate risks into financial markets. The UK's shift aligns with post-Brexit policy adjustments and increased focus on sustainable finance regulations. Additionally, the prolonged impact seen after 2020 highlights how sustained policy shifts can maintain higher levels of market connectivity over extended periods. This is consistent with the investment channel of Campiglio *et al*. (2023), emphasizing increased capital expenditures in transitioning to a low-carbon economy.

On a period basis, the period 2014–2016 can be evaluated as a time in which the impact of climate risks was felt less. In the period 2016–2020, it was observed that especially Germany and the UK assumed a net transmitter role. Germany's energy transition policies and the UK's Brexit process increased the impact of the TRI on these markets and strengthened their roles as net transmitters. After 2020, *i.e.*, after the pandemic, the UK reinforced its net transmitter position with red tones due to the changes in its energy policy after Brexit. In summary, we conclude that the UK has assumed a high net transmitter role under the TRI effect, Germany has been observed to be a periodic net transmitter due to its energy policies, while France, Switzerland and Italy have been positioned more as net receivers during crisis periods. This emphasizes that the systemic effects of climate risks on European financial markets vary across countries and market conditions.

5.2 Quantile time-frequency connectedness between climate risks for major European markets

Tables 3, 4, 5, 6 and 7 examine the quantile time-frequency connectedness between major European markets and climate risks. This analysis allows us to examine the interaction of each index with climate risks over different time frequencies. Looking at the total connectedness in this context, as seen in Tables 3 and 4, the CAC 40 and DAX indices have a high total self-connectivity and show a low net value. On the other hand, the FTSE 100 index has a higher ratio of transmission to total connectedness (Table 7).

The short-term and long-term connectivity components allow us to assess whether market indices are more sensitive to short-term or long-term climate risks. All the indices exhibit higher short-term connectedness components. This suggests that climate risks have short-term effects on market dynamics. Table 5 and 7 show that the FTSE MIB and FTSE 100 indices are more susceptible to climate risks in the short term than other markets. This short-term emphasis supports the findings of An *et al*. (2022) of significant short-term and medium-term impacts of transition risks, as well as the Epstein–Zin preference theory of Giglio *et al*. (2021), which underscores how immediate market responses amplify the perceived impact of climate risks. In the long run, however, connectivity has declined significantly, suggesting that the long-term impact of climate risks on markets is more limited and the connectedness weakens over time. For example, the SMI has relatively lower long-term connectedness, suggesting that Switzerland is resilient to climate risks (Table 6).

Table 3: Dynamic quantile time-frequency connectedness table for CAC 40

		CAC 40	TRI	PRI	FROM
CAC 40	Total	89.85	4.96	5.19	10.15
	Short-term	75.40	4.14	4.41	8.55
	Long-term	14.45	0.82	0.79	1.61
TRI	Total	5.09	78.77	16.15	21.23
	Short-term	4.49	68.69	12.99	17.48
	Long-term	0.59	10.08	3.16	3.75
PRI	Total	4.53	16.76	78.70	21.30
	Short-term	3.86	13.27	66.78	17.13
	Long-term	0.68	3.49	11.93	4.17
TO	Total	9.62	21.72	21.34	52.68
	Short-term	8.35	17.41	17.4	43.15
	Long-term	1.27	4.31	3.95	9.53
NET	Total	−0.53	0.49	0.05	26.34/17.56
	Short-term	−0.20	−0.07	0.27	21.58/14.38
	Long-term	−0.33	0.56	−0.22	4.76/3.18

Notes: Results are based on a 200-day rolling-window QVAR model with a lag length of order 1 (BIC) and a 100-step-ahead generalized forecast error variance decomposition.

Source: Authors' own calculations

Table 4: Dynamic quantile time-frequency connectedness table for DAX

		DAX	TRI	PRI	FROM
DAX	Total	90.35	4.87	4.78	9.65
	Short-term	75.42	3.99	4.11	8.11
	Long-term	14.93	0.87	0.67	1.54
TRI	Total	5.40	78.41	16.18	21.59
	Short-term	4.86	68.49	12.94	17.80
	Long-term	0.54	9.93	3.25	3.79
PRI	Total	4.28	17.36	78.36	21.64
	Short-term	3.56	13.74	66.16	17.3
	Long-term	0.73	3.62	12.21	4.34
TO	Total	9.68	22.23	20.96	52.87
	Short-term	8.41	17.74	17.05	43.2
	Long-term	1.27	4.49	3.91	9.67
NET	Total	0.04	0.64	−0.68	26.44/17.62
	Short-term	0.31	−0.06	−0.25	21.60/14.40
	Long-term	−0.27	0.7	−0.43	4.84/3.22

Notes: Results are based on a 200-day rolling-window QVAR model with a lag length of order 1 (BIC) and a 100-step-ahead generalized forecast error variance decomposition.

Source: Authors' own calculations

Table 5: Dynamic quantile time-frequency connectedness table for FTSE MIB

		FTSE MIB	TRI	PRI	FROM
FTSE MIB	Total	90.13	4.79	5.07	9.87
	Short-term	75.75	3.96	4.31	8.28
	Long-term	14.39	0.83	0.76	1.59
TRI	Total	4.74	79.44	15.82	20.56
	Short-term	4.19	69.16	12.77	16.97
	Long-term	0.55	10.27	3.05	3.60
PRI	Total	4.26	16.7	79.04	20.96
	Short-term	3.68	13.23	67.09	16.91
	Long-term	0.57	3.48	11.95	4.05
TO	Total	9.00	21.50	20.90	51.39
	Short-term	7.88	17.19	17.09	42.16
	Long-term	1.12	4.31	3.81	9.24
NET	Total	−0.87	0.93	−0.07	25.70/17.13
	Short-term	−0.40	0.22	0.18	21.08/14.05
	Long-term	−0.46	0.71	−0.24	4.62/3.08

Notes: Results are based on a 200-day rolling-window QVAR model with a lag length of order 1 (BIC) and a 100-step-ahead generalized forecast error variance decomposition.

Source: Authors' own calculations

Table 6: Dynamic quantile time-frequency connectedness table for SMI

		SMI	TRI	PRI	FROM
SMI	Total	89.84	5.06	5.10	10.16
	Short-term	73.92	4.36	4.39	8.74
	Long-term	15.92	0.71	0.71	1.42
TRI	Total	5.59	78.03	16.39	21.97
	Short-term	4.83	67.99	13.16	17.98
	Long-term	0.76	10.04	3.23	3.99
PRI	Total	4.69	16.68	78.63	21.37
	Short-term	3.91	13.24	66.80	17.15
	Long-term	0.78	3.45	11.83	4.22
TO	Total	10.28	21.75	21.49	53.51
	Short-term	8.74	17.59	17.55	43.88
	Long-term	1.54	4.15	3.94	9.63
NET	Total	0.11	−0.23	0.11	26.75/17.84
	Short-term	−0.40	0.22	0.18	21.08/14.05
	Long-term	0.12	0.16	−0.28	4.82/3.21

Notes: Results are based on a 200-day rolling-window QVAR model with a lag length of order 1 (BIC) and a 100-step-ahead generalized forecast error variance decomposition.

Source: Authors' own calculations

Table 7: Dynamic quantile time-frequency connectedness table for FTSE 100

		FTSE 100	TRI	PRI	FROM
FTSE 100	Total	89.11	5.45	5.44	10.89
	Short-term	74.33	4.46	4.50	8.96
	Long-term	14.79	0.99	0.94	1.93
TRI	Total	5.14	78.49	16.37	21.51
	Short-term	4.42	68.59	13.17	17.59
	Long-term	0.72	9.90	3.20	3.92
PRI	Total	4.42	16.67	78.91	21.09
	Short-term	3.61	13.35	66.86	16.96
	Long-term	0.81	3.32	12.05	4.13
TO	Total	9.55	22.12	21.81	53.48
	Short-term	8.03	17.81	17.67	43.5
	Long-term	1.53	4.31	4.14	9.98
NET	Total	–1.33	0.61	0.72	26.74/17.83
	Short-term	–0.93	0.22	0.71	21.75/14.50
	Long-term	–0.4	0.39	0.01	4.99/3.33

Notes: Results are based on a 200-day rolling-window QVAR model with a lag length of order 1 (BIC) and a 100-step-ahead generalized forecast error variance decomposition.

Source: Authors' own calculations

Analysis with the TRI and PRI assesses how each index responds to these two types of risk. The TRI values are exceptionally high for the DAX and the FTSE 100 indices (Table 4 and 7), suggesting that Germany and the UK are more susceptible to the TRI effect. Conversely, the PRI presents a more balanced structure and has a lower impact than the TRI (Table 3 and 5). This shows that physical climate risks affect market dynamics less, notably in France and Italy.

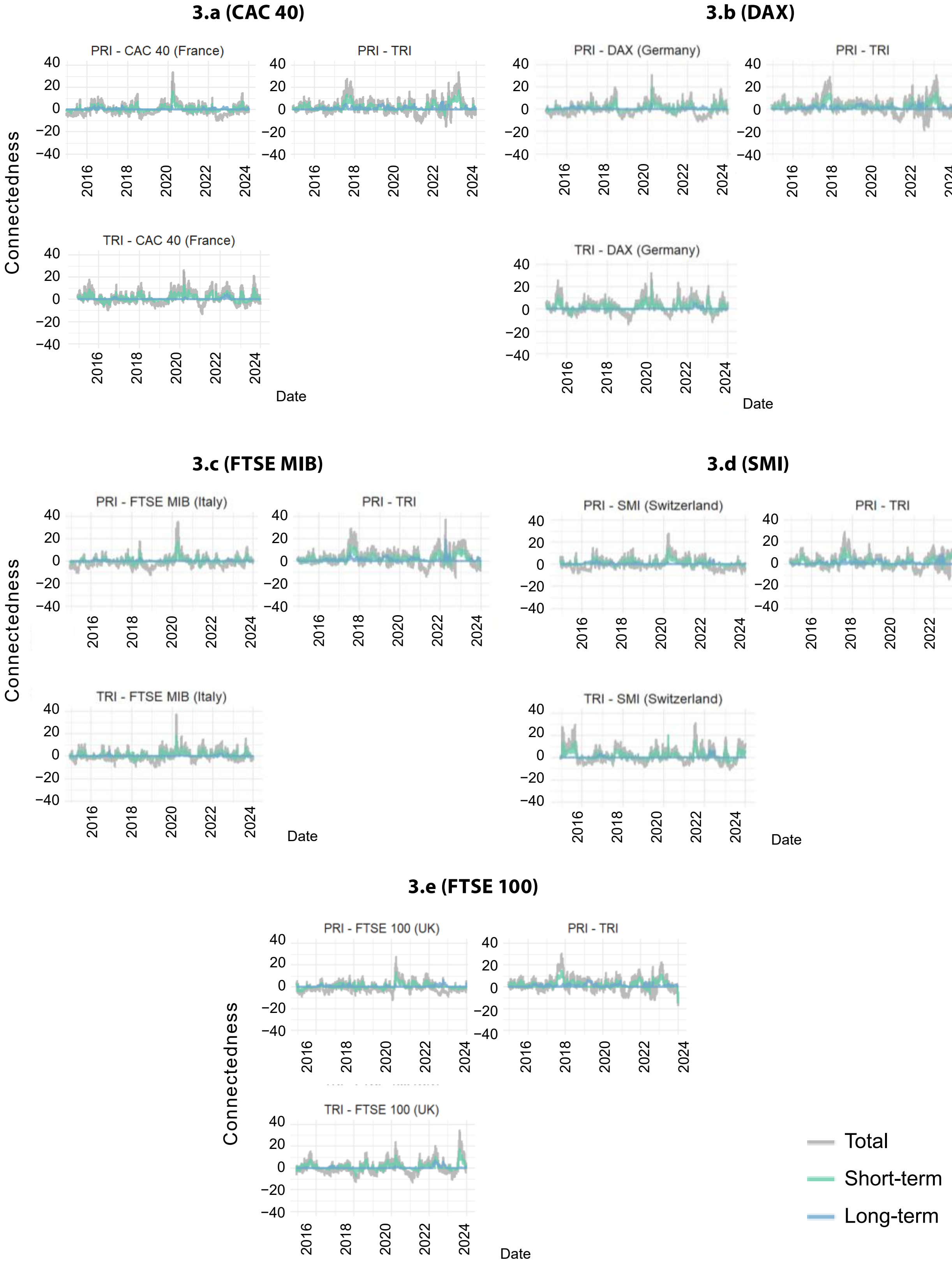
This connectedness analysis details the responses of major European market indices to climate risks and how these responses vary in the short and long term. Countries such as the UK and Germany are exposed to a high TRI in the short term due to the uncertainties created by energy transition policies, while France, Switzerland and Italy appear to be more resilient to climate risks in the long term. The fact that European markets do not exhibit a homogeneous structure *vis-à-vis* climate risks reveals that energy transition policies lead to cross-country differences and these differences create a diversity in systemic risks.

Figure 3 plots the net pairwise directional connectedness of European markets to climate risks on a short-term and long-term basis. We observe that the effects of the TRI and PRI increase significantly across all the markets, especially around 2020. The volatilities in this period were associated with the uncertainties created by the COVID-19 pandemic as well as the acceleration of energy transition processes. Sharp increases in connectedness values around 2020 clearly correspond with rapid policy shifts towards energy transition and heightened market uncertainties. Consistent with the short-term TRI effects reported in the tables, the graphs show that the TRI generates high volatility in the short term. The strong short-term impact of the TRI suggests that these countries are more sensitive to energy transition policies and that transition risks lead to immediate market reactions. Figure 3 also illustrates periods of divergence between short-term and long-term connectedness, highlighting episodes when markets initially react strongly but stabilize over the longer term. For instance, the PRI exhibits notable short-term spikes reflecting immediate market responses to specific climate events such as major storms or floods, whereas the TRI often retains elevated connectivity, reflecting sustained policy-related uncertainty.

Furthermore, around 2020, the noticeable increase in connectedness aligns closely with the economic uncertainties brought by COVID-19 and the launch of green recovery initiatives such as the European Union's Next Generation EU plan (as the primary financial engine for the European Green Deal). These initiatives significantly heightened market sensitivity to climate risks. Additionally, the pronounced short-term volatility in the TRI suggests that sudden policy shifts in energy transition, especially affecting countries such as the UK and Germany due to their substantial renewable energy sectors, lead to increased market volatility. The stronger short-term impact of the TRI observed here is consistent with the findings of Campiglio *et al*. (2019), who argued that transition risks disproportionately affect fossil-fuel-intensive sectors.

In conclusion, the effects of the TRI and PRI result in significant differences in countries' responses to climate risks. The high short-term impact of the TRI suggests that sudden changes in energy transition policies increase market volatility. Countries such as the UK and Germany are more sensitive to energy transition policies, making them more vulnerable to systemic risks. In contrast, countries such as Switzerland and France appear more resilient to climate risks by exhibiting a more stable structure in the long run.

Figure 3: Net pairwise directional connectedness (total, short-term and long-term)



Source: Authors' own elaboration

The general findings of this study are similar to those of An *et al*. (2022), considering the distinction between short-term and long-term effects. Additionally, unlike studies such as Tran *et al*. (2023) and Bats *et al*. (2024), which claimed that physical risks have more substantial effects on financial markets than transition risks, this study has also reached more potent effects of transition risks, similarly to Bouri *et al*. (2023b). Country-specific findings further support the literature: Germany's net transmitter role in 2016–2020 reflects its proactive climate policies, confirming the findings of Antoniuk and Leirvik (2024) on climate policy impacts. Similarly, the UK's net transmitter role after 2020 aligns with Brexit-driven independent climate policies, consistent with the findings of Wu and Wan (2023), who linked cross-country risk spillovers to economic conditions.

6. Conclusion

This study provides further evidence on the transmission of climate risks to financial markets. We investigated the connectedness of major European markets with climate risks, using quantile connectedness and quantile time-frequency connectedness approaches. We provided a detailed analysis of how financial markets respond to climate risks across different market conditions and time dimensions using physical and transition risk indices. The findings suggest that the effects of the TRI and PRI on market indices are asymmetric and more pronounced when market conditions are weak or volatile. The German (DAX) and French (CAC 40) indices exhibit high connectivity during periods of crisis or uncertainty, suggesting that these markets are more sensitive to climate risks. In particular, the German and UK (FTSE 100) indices were more likely to act as transmitters of shocks due to the TRI effect, suggesting that energy transition policies increase volatility in these countries. In contrast, Italy (FTSE MIB) and Switzerland (SMI) exhibited a relatively more resilient profile to climate risks, generally displaying a more balanced connectedness structure.

Looking at the short-term and long-term connectedness components, it is observed that climate risks generally have stronger impacts on market indices in the short term and that these impacts significantly affect market dynamics. The high volatility of the TRI in the short term, especially in the UK and Germany, reveals that energy transition policies have immediate and strong impacts on these markets. In the long run, on the other hand, connectivity rates decline significantly and market interconnectedness weakens over time. This suggests that countries such as Switzerland are more resilient to climate risks in the long run. In conclusion, the responses of European financial markets to climate risks differ depending on countries' energy transition policies and economic structures. The TRI increased market volatility in the short run, making the UK and Germany more susceptible to systemic risks.

In contrast, France, Switzerland and Italy have been more resilient in the long run and less affected by climate risks. We conclude that European markets do not exhibit a homogeneous response to climate risks and that differences across countries lead to a diversity in systemic risks. These findings indicate that European financial markets do not respond uniformly to climate risks and that factors such as economic structure, energy policies and market dynamics shape the transmission mechanisms of climate risks on financial markets. In particular, transition risks can potentially increase short-term market volatility and trigger systemic financial risks. Countries such as the UK and Germany are among the most affected by the uncertainty surrounding energy transition policies and act as net transmitters of climate risks to other markets. This underscores the fact that policy uncertainty can heighten financial instability, emphasizing the need for regulatory frameworks to become more predictable. Our findings highlight that managing the energy transition process is crucial for environmental sustainability and plays a vital role in ensuring financial market stability. The fact that countries such as France, Switzerland and Italy exhibit more stable market dynamics suggest that implementing energy transition policies gradually and predictably can mitigate market shocks. In this context, enhancing collaboration between policymakers, investors and regulatory institutions is essential to minimize the financial market fluctuations caused by the energy transition process. Furthermore, our findings suggest that financial policy frameworks addressing climate risks should be tailored to individual countries' unique economic and financial structures. To mitigate short-term market volatility stemming from transition risks, regulators should implement climate-sensitive stress tests, while investors should develop portfolio strategies that incorporate a higher share of low-carbon assets. Additionally, to reduce the long-term effects of physical climate risks, investments in infrastructure should be increased and climate-friendly financial instruments should be promoted.

This study provides a detailed analysis of how European financial markets respond to climate risks; however, it has certain limitations. Firstly, the physical and transition risk indices used in this study are constrained by the available datasets; future research should explore alternative data sources and risk measures. Additionally, while the quantile connectedness approach captures the sensitivity of market conditions, structural models or alternative econometric methods could be employed to establish causality more definitively. Lastly, future studies should incorporate datasets covering longer time horizons to better understand the long-term transformations driven by climate risks on financial markets.

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Conflicts of interest: The authors hereby declare that this article was neither submitted nor published elsewhere.

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