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Investor sentiment and dynamic connectedness in European markets: insights from the covid-19 and Russia-Ukraine conflict

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Abstract

The primary objective of this study is to explore the dynamic relationships between equity returns or volatility and sentiment factors in European markets during both the periods preceding the COVID-19 pandemic, the COVID-19 itself, and the Russia-Ukraine war. We achieve this by applying the network methodology initially introduced by Diebold & Yilmaz (2014), along with its extensions based on realized measures and generalized forecast error variance decomposition, as proposed by Baruník & Křehlík (2018) and Chatziantoniou et al. (2023). Additionally, we investigate how the global sentiment factor influences the overall connectedness index by employing a quantile-on-quantile approach, following the methods outlined by Sim & Zhou (2015) and Bouri et al. (2022). To conduct our analysis, we utilize daily-frequency data encompassing the period from January 1, 2011, to December 31, 2023, covering the entirety of the COVID-19 pandemic in 2020 and the Russia-Ukraine conflict in 2022 across six European stock indices. Our primary discovery is the interconnectedness of both returns and sentiment. Furthermore, our results indicate that during the COVID-19 and Russia-Ukraine war, there is a notable increase in volatility spillovers among the analyzed stock indices, driven by the heightened interconnectedness between stock market returns.

Keywords: Investor sentiment, dynamic spillover and connectedness, European financial markets, COVID-19, Russia-Ukraine war

JEL: G11; G12; G14; G40

Non-Technical Summary

This study investigates the role of investor sentiment—defined as investors' psychological attitudes and reactions to market conditions that deviate from responses based purely on rational, fundamental factors—in influencing fluctuations within European stock markets. The focus lies on the ways in which sentiment affects stock prices and market volatility, particularly during high-stress periods like the COVID-19 pandemic and the Russia-Ukraine conflict. This research sheds light on the transmission dynamics of sentiment-induced shocks and their differential effects during stable versus crisis periods across a network of interconnected markets.

Two core research questions drive this study: first, the impact of investor sentiment on European stock markets, and second, how the influence of sentiment changes in stable versus crisis periods. To address these questions, we apply a network-based framework developed by Diebold & Yilmaz (2014). This approach allows for the identification and tracking of sentiment-driven shocks—sudden changes in sentiment that ripple across multiple markets. By analyzing these interconnections, the study reveals how sentiment fluctuations in one market can influence others. Furthermore, the study employs a quantile-on-quantile (QQ) technique to examine the relationship between extreme changes in sentiment and corresponding extreme movements in stock prices and volatility. This technique enables a nuanced view of tail dependencies, which illustrate how extreme sentiment levels affect market dynamics under different conditions, particularly during times of crisis.

Findings indicate a high degree of interconnectedness among European stock markets, where a shock in one market can propagate to others, with this interdependence becoming notably stronger during crises. During periods such as the COVID-19 pandemic and the Russia-Ukraine conflict, the study observes a significant increase in volatility spillovers, highlighting the substantial role that investor sentiment plays in amplifying market fluctuations. This interconnectedness is more pronounced in crisis periods than in stable times, emphasizing heightened sensitivity to sentiment-driven factors in times of increased uncertainty.

Additionally, the study reveals that investor sentiment can serve as a predictor of future market returns and volatility. Positive or negative shifts in sentiment tend to transcend national borders, impacting stock prices in other European markets even when local economic conditions remain unchanged. This finding underscores the role of investor sentiment as a key driver of market behavior across regions, especially during episodes of heightened uncertainty.

Overall, this research emphasizes the importance of investor sentiment in maintaining financial stability, highlighting the potential for sentiment as an early indicator of market instability. For policymakers, monitoring sentiment trends could provide valuable insights into the potential for contagion effects and aid in devising measures to counteract systemic risks within interconnected European financial markets.

1 Introduction

Most research on investor sentiment—defined as investors' psychological attitudes and reactions to market conditions that deviate from responses based purely on rational, fundamental factors—has primarily focused on its impact within domestic markets. However, only a limited number of studies have expanded this analysis to encompass international markets (Schmeling 2009, Beckmann et al. 2011, Baker et al. 2012). Similarly, relatively few efforts have been made to explore the interconnectedness of investor sentiment across different market regions, as seen in the works of Bai (2014), Bathia et al. (2016), Tiwari et al. (2021), Plakandaras et al. (2020), and Borgioli et al. (2024).

This gap is particularly significant for European policymakers, as understandanding the cross-border spread of investor sentiment is essential for maintaining financial stability in Europe's diverse and interconnected financial landscape. The transmission channels and vulnerabilities associated with financial shocks across borders can have profound implications for the stability of European financial markets. Consequently, there is a pressing need for a deeper investigation into sentiment interdependencies within this region.

The field of financial research on contagion focuses on identifying the pathways through which shocks propagate within asset markets, as explored in studies such as Forbes & Rigobon (2001) and Forbes (2012). Two key mechanisms explain this propagation: spillover effects and interdependence. Forbes (2012) defines spillover effects as a significant increase in connections between countries or markets following a shock, such as a financial crisis, in a specific country or market. In contrast, they describe interdependence as the presence of strong links between two countries or financial markets that exist both during pre-crisis and crisis periods. Existing research emphasizes the importance of distinguishing between contagion—the atypical transmission of shocks between countries via channels like trade and finance—and the ordinary transmission of shocks. This distinction is critical for policymakers seeking to develop interventions that prevent the misinterpretation of market linkages during periods of financial instability and reduce the risk of systemic contagion.

In financial literature, the concepts of contagion, spillover, and interdependence are frequently employed to analyze the simultaneous movements of stock markets. However, in this study, we depart from this convention by focusing on the potential connections between asset markets driven by sentiment-related shocks. Specifically, we evaluate these network connections through the lens of investor beliefs (i.e. sentiment), and investigate how they contribute to the formation of stronger associations in returns or volatility across different European countries. Understanding these dynamics is essential for policymakers, as it provides insight into the broader impact of sentiment shocks on the financial system. This knowledge is crucial for designing targeted regulatory and macroprudential measures aimed at containing financial risks.

Building on this foundation, our research examines the spread of sentiment across major European countries during periods of exogenous shocks, such as the COVID-19 pandemic and the Russian aggression against Ukraine (hereafter referred to as the "Russia-Ukraine conflict"). This area has received relatively little attention in the literature to date. Understanding how sentiment propagates through European economies is crucial for ensuring coordinated and effective responses to financial market disruptions. As highlighted by the study conducted by Tiwari et al. (2021), the interdependence of sentiments among economies is usually evident. Even when there is no change in sentiment at the national level, a particular economy can still experience the positive or negative repercussions of sentiment due to the interconnectedness in our globally influenced world. Moreover, shifts in local sentiment—whether positive or negative—can create ripple effects that amplify their impacts on national economies, further underscoring the importance of studying these dynamics.

Consequently, it becomes imperative for policymakers to consider the implications of these spillover effects when designing interventions. The strength and direction of these effects will inform whether policies should aim to counteract adverse consequences of negative sentiment spillovers or sustain the positive effects of improved sentiment. In this context, our study aims to compare various quantile characteristics and the dynamic spillover effects in the correlations between sentiment shocks and stock returns across six European countries: Spain, France, Germany, Italy, United Kingdom, and Netherlands. Indeed, numerous empirical studies on contagion and spillover effects have been dedicated to identifying such interconnections. These studies are situated within two parallel and complementary research approaches: the factor model, as seen in the works of Dungey* et al. (2005), Dungey & Martin (2007), Dungey et al. (2011), Dungey & Gajurel (2014), and the network connectedness approach pioneered by Diebold & Yilmaz (2009, 2012, 2014). However, these aspects reveal contrasting factors not only in terms of their theoretical underpinnings, such as testing versus measurement, but also in their procedural outlines, as highlighted by Diebold & Yılmaz (2015). One significant advantage of the Diebold and Yilmaz framework is that the resulting network is both directed and weighted, offering an estimation of the magnitude of bilateral spillover effects, as explained by Ando et al. (2022).

As a result, our framework is built upon the foundation laid by Diebold & Yilmaz (2012, 2014) and relies on forecast error variance decomposition (FEVD) within an underlying vector autoregression (VAR) framework applied to a specific series, which could be returns, volatility, or sentiment. We adhere to the established body of research and employ a modified version of the Diebold-Yilmaz technique, as introduced by Chatziantoniou et al. (2023). This approach combines the Time-Varying Parameter Vector Autoregression (TVP-VAR) model, as presented by Antonakakis et al. (2020), with the spectral approach as outlined by Baruník & Křehlík (2018). Consequently, our utilization of TVP-VAR connectedness in the frequency domain offers several advantages. Firstly, it addresses the limitations of the conventional approach, which relies on rolling sample analysis and can result in data loss while being susceptible to outliers. Secondly, it allows for the differentiation of connectedness effects across short, medium, and long time horizons. Additionally, we complement this analysis with a quantile-on-quantile examination, enabling us to estimate multiple quantiles for both variables, specifically examining the connectedness of returns/volatility and sentiment.

The primary contribution of this paper revolves around the empirical methodologies we employ. Specifically, our research explicitly identifies the sources and recipients of shocks within a network of returns, volatility, or sentiment using the Time-Varying Parameter Vector Autoregression (TVP-VAR) based connectedness model in the frequency domain. This approach goes further by uncovering the evolving directional spillover risk between these series across various time intervals, as described by Chatziantoniou et al. (2023). Moreover, we introduce the quantile-on-quantile (QQ) method, which enables us to investigate the tail dependence structures in diverse market conditions, whether characterized as bullish or bearish, as demonstrated by Bouri et al. (2022). By providing insight into tail dependencies, this study offers valuable information for policymakers when designing tools that can address extreme market events and mitigate their systemic implications within the European financial system.

The paper is organized as follows. Section 2 provides a review of the existing literature concerning spillover effects, interdependence effects, and the channels through which sentiment factors are transmitted. Section 3 presents an overview of the data utilized in our study, while Section 4 outlines the empirical methodology employed. Section 5 offers an analysis and interpretation of the pertinent empirical findings. Lastly, Section 6 provides the conclusions.

2 Literature review and Hypotheses

Numerous studies have highlighted the importance of contagion and spillover effects in financial markets. The extensive literature on financial integration and liberalization has primarily focused on understanding interactions among various financial markets. In recent years, increasing attention has been given to the simultaneous movement of asset prices across global markets, as evidenced by the works of Bekaert & Harvey (1997), Ng (2000), Joshi (2011), Gupta & Guidi (2012), Balli et al. (2015), Dedi & Yavas (2016), Jebran et al. (2017), Hung (2019), and Niyitegeka & Tewari (2020). Furthermore, as highlighted by Bae et al. (2003), contagion holds significance in policymaking and can be anticipated based on prior information. Therefore, developments in one country are perceived as informative in shaping asset prices in another country, often grounded in real and financial ties between economies. Stock prices in one country can be influenced by changes in another country beyond what can be attributed to economic fundamentals. Such cross-border influences underscore the limitations of analyzing financial markets in isolation and necessitate a global perspective on market behaviors. This dynamic structure challenges traditional models, calling for frameworks that address both domestic and international risks. These cross-market movements emphasize the need for adaptive policy frameworks that account for global financial linkages.

Consequently, phenomena like overreactions, speculative activities, and noise can cross national borders, as observed by Lin et al. (1994). In contemporary financial markets, investors increasingly consider not only domestic information but also also data and signals from other exchanges when making trading decisions. This shift is a consequence of the growing globalization of financial markets, facilitated by the movement of goods and capital, as well as the relatively unrestricted flow of information. Therefore, there is a growing need to systematically comprehend the connectivity and correlation between diverse financial markets. This interdependence underscores the importance of cross-market analysis to design effective trading strategies, risk management protocols, and policy interventions. As financial shocks propagate rapidly across borders, understanding these linkages becomes essential for mitigating systemic risk. Key studies in this regard include those conducted by Koutmos & Booth (1995) and Zhou et al. (2012).

The investigation of spillover effects forms a cornerstone of financial research, particularly within the broader domain of volatility studies. As per Tsay (2005), modeling volatility offers a straightforward approach to conducting risk management calculations and plays a significant role in the process of asset allocation, particularly within the framework of mean-variance analysis. Volatility spillover, as conceptualized by Patnaik (2013) and Brooks (2019), captures the sensitivity of one market's volatility to fluctuations originating in another market. In simpler terms, it signifies the extent to which a market's volatility is affected by information and uncertainties originating from other markets. King & Wadhwani (1990) highlight that errors occurring in one market can be transmitted to other markets, as investors assess and analyze price alterations across different countries. Consequently, this pricing information holds value for other investors who are willing to pay for it. For instance, a transaction conducted in London may create a perception that the information driving price adjustments is relevant in New York and Tokyo, as illustrated by Kutlu & Karakaya (2021). Consequently, specific errors or shifts in one market can propagate to other markets, resulting in increased volatility. However, immediate recognition of an error in a country's market mechanism by other markets may not always be guaranteed. Moreover, unless there are restrictions in place to prevent the covariance structure from evolving over time, any observed correlation between exchanges can be deemed consistent with an asset pricing model that adheres to the efficient market hypothesis.

Additionally, Lee & Kim (1993) highlighted how periods of heightened volatility, particularly in the US, strengthen linkages among global equity markets. Their findings align with contemporary observations that market interdependencies intensify during periods of financial stress, necessitating dynamic models to account for these evolving relationships. This underscores the procyclical nature of financial systems, where stress amplifies co-movements, challenging the assumptions of diversification benefits during crises. Quantifying these relationships not only aids in understanding market behavior but also supports regulatory efforts to maintain stability in interconnected financial environments.

The literature has extensively explored the interconnections between different financial markets employing three primary empirical approaches: first, cointegration analysis on stock market indices (Vector Error Correction, VEC): this approach examines the integration of stock market indices. Second, multivariate GARCH modeling (MGARCH - Multivariate Generalized Autoregressive Conditional): this approach employs sophisticated modeling techniques to analyze the interrelationships among various financial markets. Third, models that measure connectivity through forecast error variance decomposition (FEVD): this method focuses on understanding connectivity by decomposing forecast error variances. Given the breadth of research on these topics, our study narrows its focus to exploring connectivity within equity markets, specifically those of European countries, with the United Kingdom serving as the central economic actor in each investigation. Europe's markets are particularly susceptible to these spillover effects due to their high degree of financial integration, shared regulatory frameworks, and tightly coupled economic policies. This vulnerability is exacerbated by the region's exposure to both global shocks and intra-European dynamics, highlighting the need for region-specific risk assessments. These characteristics not only facilitate rapid cross-border transmission of financial shocks but also potentially amplify volatility during periods of market stress, making European economies more vulnerable to global and regional disturbances.

The existing literature also categorizes volatility spillovers into three distinct groups. First, bidirectional volatility spillover between stock markets: this entails the exchange of volatility between stock markets in both directions. Second, one-way volatility flow from one stock market to another and vice versa: this refers to the unidirectional transmission of volatility from one stock market to another and vice versa. Third, the absence of persistent volatility spillover: as indicated by Ngo (2019), there are instances where volatility spillover does not persist.

Considering the insights drawn from the above discussions, we propose the following below hypothesis.

Hypothesis 1: *A linkage exists, encompassing both returns and volatility, among European markets.*

The second aspect of spillover effects pertains to the propagation of sentiment across financial markets. Numerous studies have highlighted the critical role of sentiment in explaining stock price fluctuations, as demonstrated by Zhou (2018), Ding et al. (2019), DeVault et al. (2019), Gao & Martin (2021), Chen et al. (2021), and Birru & Young (2022). For the purposes of this paper, sentiment is defined as investors' psychological attitudes and reactions to market conditions that deviate from responses based purely on rational, fundamental factors. This definition emphasizes that sentiment encompasses the emotional and behavioral responses that may lead to market outcomes inconsistent with strict fundamental analysis.

Despite these insights, most research has concentrated on domestic financial markets, examining the impact of sentiment within a specific market. The transnational dimension of sentiment transmission has received relatively less attention in the literature. This discrepancy raises an important question: does sentiment travel across borders, and can an overarching sentiment influence individual national markets? Exploring cross-border sentiment flows is particularly relevant in the context of Europe, where integrated financial systems amplify the potential for behavioral contagion. Such an analysis can reveal the underlying drivers of sentiment spillovers and their impact on regional stability.

Beckmann et al. (2011) highlighted that foreign sentiment can significantly influence domestic market returns, underscoring the importance of considering this dimension when assessing spillover effects, particularly if these sentiments contain elements of irrationality, as noted by Karolyi (2003). The concept of sentiment co-movement is introduced and tested by Baker et al. (2012). In their study, the authors create annual sentiment indexes for six developed markets, including Canada, France, Germany, Japan, the UK, and the US. They further disaggregate these indexes into one global sentiment index and six local sentiment indexes. Their findings highlight the pivotal role of the global sentiment index as a contrarian predictor of market returns at the national level. Given that this is the sole evidence of sentiment co-movement, it is important to investigate the mechanisms that might explain the transmission of this factor in international or european markets.

The literature review has also highlighted several pertinent channels that could reveal the mechanisms by which the sentiment factor is transmitted, as evident in studies by Beckmann et al. (2011), Baker et al. (2012), Bai (2014), Hudson & Green (2015), and Gao et al. (2020). Among these channels, two mechanisms stand out through which global sentiment disseminates across international financial markets. Firstly, foreign investors' business activities could impact the sentiment of domestic investors, resembling the correlated business behavior seen among international and institutional investors, as exemplified by Kamara et al. (2008) and Karolyi et al. (2012). Secondly, investor sentiment can traverse national boundaries through information-sharing channels like word-of-mouth, the internet, and the media, as observed in the works of Hong et al. (2004), Tetlock (2007), and Baker et al. (2012). These mechanisms are largely consequences of market integration, as further explored by Bekaert et al. (2013) and Carrieri et al. (2013).

In a similar vein, Hudson & Green (2015) identify four channels through which investor sentiment contagion can occur: (i) If investors in one country express optimism about investing in another country, it can lead to increased investment in that particular country's stocks. (ii) Optimism among a country's investors can result in a broader trend of investors moving toward riskier assets, including international ones. (iii) When foreign investors hold a positive outlook on their own economy, it can lead domestic investors to also be optimistic about their local economy due to the economic interlinkages between the two, with foreign sentiment indirectly affecting domestic stock prices through national sentiment. (iiii) The fourth channel aligns with the concept expressed by Gao et al. (2020), wherein sentiment in a foreign country can directly influence sentiment in the home country due to the herding behavior of noisy trading. Through this channel, it affects stock prices as residents of the countries of origin become more or less optimistic and trade accordingly. This multifaceted contagion highlights the complexity of international sentiment transmission.

Furthermore, it is well-established that social interactions, such as word of mouth, can influence sentiment and investment decisions, as noted in the studies by Shiller et al. (1984), Lin et al. (1994), and Brown et al. (2008). While investors from different countries may not be physically close to each other, online message boards have a global reach and have been proven to impact sentiment and commerce, as indicated by Sabherwal et al. (2011). Additionally, foreign sentiment can take on a local character when there is a relatively high proportion of foreign ownership of locally listed stocks, as discussed by Hudson & Green (2015). These observations further substantiate the interplay between local and international sentiment.

Based on these arguments, we formulate the following hypothesis.

Hypothesis 2: *The sentiments specific to different European financial markets are interconnected.*

Moreover, in the past three decades, crises have occurred with regularity. As noted by Corsetti et al. (2005) and Reinhart & Rogoff (2008), these recent crises bear similarities to historical crises. One of the key commonalities during crises is the general increase in financial market volatility, which tends to affect all markets, as highlighted by Diebold & Yilmaz (2012). Rigobon (2003) examines the stability of transmission mechanisms among 36 stock markets during three major international financial crises, i.e., Mexico in 1994, Asia in 1997, and Russia in 1998. Meanwhile, Bekaert et al. (2013) compare price movements before and during crises and discover limited evidence of contagion from US markets to global equity markets during these crises. However, they do note the presence of contagion from domestic equity markets to individual domestic equity portfolios.

In a recent study, Fernández-Rodríguez & Sosvilla-Rivero (2020) discovered that the level of volatility interconnectedness fluctuates over time, notably surging during periods characterized by rising economic and financial instability. In this study, we investigate whether the interrelationships in returns and sentiments vary over time, particularly in response to the turbulence caused by the Global health crisis and the Russia-Ukraine war. Our objective is to assess the extent of connections among European financial markets and indicators during non-crisis periods and to determine if this differs during times of crisis. Consequently, we elaborate the following hypothesis.

Hypothesis 3: *The transmission of returns and sentiments varies over time in response to the COVID-19 and Russia-Ukraine crises.*

Additionally, Baker et al. (2012) introduce and validate the concept of sentiment co-movement. In their research, they formulate comprehensive sentiment indexes encompassing six developed markets, i.e., Canada, France, Germany, Japan, the UK, and the US. These indexes are further deconstructed into a global sentiment index and six local sentiment indices. Their findings underscore the pivotal role of the global sentiment index as an effective contrarian predictor of market returns at the national level. Furthermore, Aissia (2016) presents evidence that total investor sentiment significantly predicts returns in the French market and that stock excess returns are influenced by both domestic and foreign sentiment. This dual influence of sentiment underscores the interconnectedness of global markets.

Building on these findings, we aim for the first time to explore whether the global sentiment factor can explain the transmission of stock return spillovers within European markets. Specifically, we assess whether the global sentiment index captures changes in market interconnectedness during times of financial instability as well as periods of relative calm. This approach allows us to evaluate the role of sentiment in influencing the degree of integration and risk-sharing across European markets. Consequently, we elaborate the below hypothesis.

Hypothesis 4: *The global sentiment factor in Europe serves as an indicator for predicting stock market returns.*

Finally, we build upon the research conducted by Baker et al. (2012) and Aissia (2016) by investigating whether the global sentiment factor in Europe can account for the transmission of stock return spillovers. As a result, we put forward the following hypothesis:

Hypothesis 5: *the global sentiment factor in Europe is an indicator for forecasting the interconnectedness of stock market returns or volatilities.*

3 Data

Data and Sample for stock returns

This study focuses on three different series related to returns, volatility, and sentiment within six European markets. The data for this analysis is sourced from Thompson Reuters DataStream, which supplied equity market indices for the majority of European countries. Our study utilizes daily data from aggregate stock indices of six European countries' stock markets: IBEX 35 in Spain, CAC 40 in France, DAX 30 in Germany, FTSE MIB in Italy, AEX in the Netherlands, and FTSE 100 in the U.K. The data covers the period from January 1st, 2011, to December 31st, 2023. We followed the selection of European markets as defined by Baker et al. (2012) and relied on the criteria provided by Dow Jones, the FTSE Group, Russell, and S&P to choose these specific countries. Our dataset consists of 3,392 daily observations for each returns series. We opted to conclude the data collection at December 2023 to account for the potential impact of the subsequent Russia-Ukraine war in 2022 and 2023, along with focusing on the COVID-19 pandemic between 2020 and 2022. The choice of the starting date is primarily dictated by data availability for the constructed sentiment index.

To ensure data stationarity, we transformed every stock index at time t into a stock index return. The daily returns, denoted as $R_{j,t}$, are computed as the proportion of log returns relative to the closing price $P_{j,t}$, which is represented as follows:

$$R_{i,t} = \ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right) \times 100 \tag{1}$$

However, similar to the approach taken in Eiling et al. (2012), we employ local market currency returns, which are essentially fully hedged returns. It's worth noting that Eiling et al. (2012) emphasize that currency risk is not a factor in these fully hedged returns. In Figure 1, we can observe the daily performance of the analyzed equity indices from the stock market. It's worth mentioning that all the observed return series experienced significant declines during the early parts of 2020 and 2022, followed by substantial recoveries thereafter.

We decided to employ a market-based variance measure, which is created using the daily returns of the market index, as suggested by French et al. (1987) and Schwert & Seguin (1990). This choice is made instead of utilizing unobservable conditional variance measures like latent-variable approaches such as GARCH and stochastic-volatility models. Following the recommendation of French et al. (1987), we computed the monthly variance of market returns by summing the squared daily returns and doubling the summation of adjacent returns' products. As per French et al. (1987), we calculate the variance of monthly returns using the following method:

$$\sigma^2_{m,t} = \left[\sum_{i=1}^{N_t} r^2_{i,t} + 2\sum_{i=1}^{N_t-1} r_{i,t}r_{i+1,t}\right] \tag{2}$$

Where there are N daily returns, denoted as $r_{i,t}$, within month t. Nonetheless, it's important to highlight that the calculation of monthly volatility depends on N_t, which represents the count of trading days within each month. Notably, some months have more trading days than others. To address this, a straightforward adjustment involves computing monthly volatility based on the specific number of trading days in each month. Each volatility series encompasses data from January 2011 to December 2023, comprising a total of 156 data points.

Figure 2 displays the time-series data of monthly realized variances for each observed variable spanning from 2011 to 2023. It is evident that the highest levels of realized variances occurred during the early-2021 and 2023 periods, coinciding with the turbulent times of the COVID-19 pandemic and the Russia-Ukraine conflict. This trend is consistently observed across all European stock indices, which is unsurprising given that these indices are based on the market capitalizations of major companies. In fact, the surge in volatility within European markets underscores how quickly global equity markets reacted to negative news related to the COVID-19 and the Russia-Ukraine war, leading to increased risk and uncertainty. Consequently, this had an impact on investor sentiment, ultimately influencing stock market prices.

Data and Sample for investor sentiment

The literature has employed various metrics to gauge investor sentiment. In their 2006 study, Baker and Wurgler utilized principal components analysis to create an index amalgamating several sentiment-related variables. These include the stock turnover, dividend premium, a set of IPO-related measures[1] (the number of IPOs, average IPO first-day returns, and the equity share in new issuances), and the discount on closed-end funds. This index, hereafter referred to as the BW index, has been adopted in multiple subsequent studies, including Baker & Wurgler (2006, 2007) and Baker et al. (2012), where it has been recognized as an appropriate sentiment measure[2]. A modified version of this index, tailored for the European context, is one of the measures employed in this study to examine sentiment effects.

Given that our focus is on European countries, whereas the BW index was developed for the US

[1]The absence of consistent and harmonized IPO data in European markets, due to fragmented reporting standards and varying levels of IPO activity across countries, makes the direct application of such metrics unfeasible. Additionally, the reliance on bank financing over public equity reduces the relevance of IPO measures for capturing investor sentiment in this context.

[2]Additional information about the BW index can be found on Wurgler's website.

market, this study incorporates a composite index for the six specific countries of interest: France (SENT FR), Germany (SENT GE), Spain (SENT SP), Italy (SENT IT), Netherlands (SENT NL), and the UK (SENT UK), as recommended by Baker et al. (2012). For these countries, investor sentiment is estimated using country-specific factors, including turnover, the volatility premium (Baker & Wurgler 2006, 2007, Baker et al. 2012), and the consumer confidence index (Schmeling 2009, Lemmon & Portniaguina 2006).

The first two variables align with those used in the BW index, while the third variable aligns with that used by Schmeling (2009) and Lemmon & Portniaguina (2006). These variables are considered due to their association with the level of investor sentiment. Baker & Stein (2004) identify turnover as a sentiment indicator because in a market constrained by short-selling, high liquidity indicates the prevalence of a class of irrational investors who fail to respond appropriately to order flow information, resulting in an overvalued market. High turnover indicates positive investor sentiment and, consequently lower expected returns. Jones (2002) also demonstrates a link between liquidity shifts and diminished future returns in the overall market. In our study, "Turnover (TURN)" is calculated as the natural logarithm of the raw turnover ratio, adjusted for trends using a five-year moving average[3]. Turnover serves as a proxy for the behavior of investors driven more by sentiment than by fundamental valuation. As specified, high turnover is interpreted as a signal of increased speculative activity, often fueled by heightened optimism or excitement among investors. Conversely, low turnover may indicate a lack of enthusiasm or pessimism in the market.

Baker et al. (2012) used the volatility premium, which is a proxy for relative investor demand between high and low periods of volatility. Conceptually, it is similar to that of the dividend premium, which is a proxy for relative investor demand between dividend-paying and non-paying stocks. These two variables are negatively correlated. High volatility stocks tend to be small stocks with low growth potential and dividend non-paying stocks, the demand for which increases with investor sentiment. For a set of countries including three of the six markets analyzed in this study, together with Canada and Japan, Baker et al. (2012) use the volatility premium to replace the dividend premium, which is inappropriate in countries where dividends are uncommon. In this study, the "volatility premium (VP)", is calculated by taking the logarithm of the average book-to-market

[3] This ensures the measure captures sentiment-driven deviations rather than structural changes in market activity.

(BTM) ratio of highly volatile stocks (the top 30%) and less volatile stocks (the bottom 30%). The volatility premium captures the relative valuation of highly volatile stocks versus less volatile ones. Sentiment often drives risk-taking behavior, with optimistic investors favoring riskier, high-volatility stocks. By examining the book-to-market (BTM) ratio between these groups, the VP provides a nuanced, sentiment-sensitive indicator of how investors price risk under different market conditions.

Lastly, the consumer confidence index (CC)[4] (Schmeling 2009) is published by the European Commission on a daily basis for each member state. This index specifically captures household spending and savings data and investors' perceptions of the economic factors involved. The main advantage of this measure is that extended sets of data are available for practically all countries, enabling cross-country comparison. Another positive feature is its independence of market trading. As a result, this variable provides a macro-level sentiment measure that complements the micro-level variables.

We compute a sentiment index for each country based on the three aforementioned variables, following the same approach as Baker & Wurgler (2006). Initially, we estimate the first principal components of these three proxies and their respective lags. This results in a preliminary index with six loadings, with the variable either included in t or $t-1$, depending on which one exhibits the stronger correlation with the first-stage index. The first principal component for France explains 55.597% of the total variance, while the one for Germany explains 55.985%, Spain's accounts for 73.998%, Italy and Netherlands consider for 58.479% and 67.152%, respectively, and the UK's explains 41.654% of the explained variance. This suggests that the initial factors capture a significant portion of the shared variance among the three measures. The sentiment index coefficients for each country are as follows:

$$\text{SENT FR}_t = 0.514\text{CC}_t - 0.374\text{TURN}_{t-1} + 0.547\text{VP}_{t-1} \tag{3}$$

$$\text{SENT GE}_t = 0.510\text{CC}_t + 0.587\text{TURN}_{t-1} + 0.306\text{VP}_{t-1} \tag{4}$$

[4]Reflecting how optimistic or pessimistic individuals are about the economy and financial markets. The consumer confidence index is a macroeconomic sentiment indicator that reflects the overall mood of households regarding the economy. Unlike micro-level variables like turnover or volatility premium, it captures broad-based psychological and economic factors influencing investor behavior. Its daily availability from the European Commission ensures consistent, up-to-date sentiment measures across member states.

$$\text{SENT SP}_t = 0.447\text{CC}_t - 0.407\text{TURN}_t + 0.403\text{VP}_{t-1} \tag{5}$$

$$\text{SENT IT}_t = 0.390\text{CC}_t - 0.522\text{TURN}_t + 0.213\text{VP}_{t-1} \tag{6}$$

$$\text{SENT NL}_t = 0.386\text{CC}_t - 0.310\text{TURN}_t + 0.229\text{VP}_{t-1} \tag{7}$$

$$\text{SENT UK}_t = 0.635\text{CC}_t + 0.578\text{TURN}_{t-1} + 0.411\text{VP}_{t-1} \tag{8}$$

As the analysis necessitates a comprehensive sentiment indicator for the entire European context, we employ the identical principal component analysis methodology to construct a unified composite index encompassing all six countries, labeled as SENT EU. All four countries exhibit notable and positive correlations, and this index accounts for 50.295% of the explained variance. The resulting index scores for each country are as follows:

$$\text{SENT EU}_t = 0.270\text{SENT UK}_t + 0.367\text{SENT GE}_t + 0.387\text{SENT FR}_t + 0.410\text{SENT SP}_t +$$

$$+0.425\text{SENT IT}_t + 0.476\text{SENT NL}_t \tag{9}$$

Hence, Figure 3 displays the sentiment series extracted from each market, offering an overview of how the sentiment factor evolved throughout our study period. A consistent trend is noticeable in terms of the sentiment factor's level during the COVID-19 pandemic and the Russia-Ukraine conflict. It is evident that there was a substantial decline in the sentiment factor during the crisis and uncertainty times around 2021 and 2023.

Nevertheless, Table 1 provides the data for the diverse series under examination, encompassing returns and sentiment metrics. The existing body of empirical research regarding financial contagion and spillover effects has indicated that outcomes can be influenced by the selection of data periods and crisis dates, as noted by Dungey* et al. (2005) and Brière et al. (2012). Many correlation-based studies in this domain often depend on externally determined crisis dates, such as those defined by the World Bank or NBER. However, in this paper, we adopt an approach where crisis and non-crisis periods related to the COVID-19 pandemic and the Russia-Ukraine conflict are determined endogenously. We employ the Iterative Cumulative Sum of Squares (ICSS) algorithm, which is based on the CUSUM test, to identify structural changes in the variance of individual return series, following the methodology outlined by Inclan & Tiao (1994) and Sansó et al. (2004). This approach was initially used to detect crisis periods by Wang & Nguyen Thi (2013).

Thus, we opt to delineate different phases by applying the structural break test. Our analysis reveals three distinct phases: the pre-crisis period (before 17/03/2020), the COVID-19 pandemic crisis period (spanning from 17/03/2020 to 23/02/2022), and the Russia-Ukraine war crisis period (extending from 24/02/2022 to 31/12/2023). It's worth noting that the dates of structural breaks closely align with those reported by the World Bank and the recession dates identified by NBER.

Preliminary analysis

Tables 2 and 3 provide an overview of statistical information for various aspects of the stock market, including returns, volatility, and sentiment indices, categorized into three time periods: the entire period, the period before the crisis related to the COVID-19 pandemic and the Russia-Ukraine war, and the period after the pandemic and war crisis. We observe positive average returns across all the data sets except for the Italian stock index. The highest mean returns are found in the UK and Germany, both at 0.026, while Italy shows relatively close mean returns of around -0.003. Variance is highest for DAX30r and CAC40r at 1.908 and 1.824, respectively, followed by FTSE MIBr at 1.666, indicating a higher level of market risk. Additionally, all return series exhibit left skewness and positive kurtosis, suggesting non-normal distributions with fat tails. This implies that the returns are not normally distributed, as confirmed by rejection of the normality hypothesis at the 1% level (Jarque & Bera 1980).

Furthermore, we can see that all realized volatility series exhibit right skewness and are significantly non-normally distributed. When comparing data from the pre-COVID-19 and war crisis periods and post-COVID-19 and war crisis periods (Table 3), most series show a decrease in mean returns, except for FTSE 100r, which remains constant. Variance increases notably during and after the COVID-19 and war crisis (Part a), especially for France and the UK, rising from 1.686 and 0.996 (Part a) to 2.053 and 1.539, respectively. Analyzing the three data periods for the six European stock index returns, we observe that log-return series have a positive mean in the entire dataset but exhibit higher standard deviations and fatter tails during the COVID-19 and war crises. Sentiment indices (Table 2 Part b) generally have negative means, except for the UK, Italy and the Netherlands. Remarkably, all sentiment indices are significantly leptokurtic, except for the Italian sentiment, which is significantly platykurtic, indicating a distribution with negative excess kurtosis.

Ensuring that the variables remain stable over time is crucial for obtaining consistent estimates. In this study, we utilize the Elliot-Rothenberg-Stock (ERS) test (Elliott et al. 1996) to assess whether unit roots exist in the time series data for each variable. As presented in Table 2, the null hypothesis is consistently rejected at the 1% significance level across all series, i.e., returns, volatility, and sentiment, and time periods. Furthermore, the weighted portmanteau test (Fisher & Gallagher 2012) suggests that there is autocorrelation in all the series, supporting our decision to model the interrelationships among these series using a TVP-VAR approach with a time-varying variance-covariance structure, as shown in Table 2 and Table 3. It is worth noting that the asymmetric nature of the data and the rejection of the normality assumption may indicate the presence of non-linearity in the studied series. Additionally, the Q statistic from Fisher & Gallagher (2012) demonstrates that heteroscedasticity is present in all the retained series.

To investigate the transmission of cross-market risk, we examine the correlations between different series of returns and sentiment indicators. The correlation findings, as presented in Table 4, Parts a and d, suggest the presence of a positive relationship among equity market index returns. Particularly, when looking at the major stock markets, there is a strong positive correlation among them, except for FTSE MIBr, which exhibits a lower correlation with the others. This observation holds true for sentiment indicators as well.

To study the the COVID-19 pandemic and Russia-Ukraine conflict crises impact the correlations between financial assets, we analyze the correlation matrix before and after the COVID-19 pandemic and Russia-Ukraine conflict, as shown in Table 4, parts b and c. These results reveal that all correlations between returns increased during the COVID-19 and war crises. For example, in the case of the UK and France, the correlation increases from 0.266 before the COVID-19 and war crisis to 0.415 after the COVID-19 and war crisis. A similar pattern is observed in the sentiment indicator correlations, as displayed in Table 4, parts e and f. During the COVID-19 and war crisis period, European markets like the UK, Spain, Netherlands, Germany, and France exhibit notably stronger correlations with other markets. Even the Italian market shows increased correlations, although to a lesser extent. For instance, the correlation between Italy and the UK shifts from -0.004 before the COVID-19 and war crisis to 0.442 after the COVID-19 and war crisis.

4 Methodology

Our empirical examination comprises two main phases. Initially, we introduce the Diebold & Yılmaz (2015) approach and its expanded versions, which gauge interconnectedness by evaluating the changing associations among decomposed series components, namely returns, volatility, and sentiment. Subsequently, we examine the connections between interconnectedness either in returns or volatility and sentiment, utilizing quantile-on-quantile regression.

Analysis utilizing a model-based approach to study spillovers

Challenging the empirical evaluations of the 1997 Asian crisis and the 2007 Great Recession, Diebold & Yılmaz (2015), in their book, emphasize the significance of the concept of "connectivity" as a contributing factor in explaining financial contagion phenomena. They introduce a novel analytical framework for conceptualizing and gauging connectivity at various levels, primarily focusing on financial markets. This emphasis is because of the pivotal role of financial markets in understanding activities such as risk management, portfolio allocation, and asset valuation. Furthermore, this approach does not attempt to identify the source of connectivity but considers it an inherent aspect.

The foundation of this analytical framework lies in the examination of entities such as assets, asset classes, companies, countries, markets, financial institutions, etc., that engage in interactions within a network. These interactions are quantified through a VAR/VECM model, employing the generalized decomposition of the forecast error variance (GEFVD). This approach allows for the assessment of not only connectivity but also exposure and impact in response to a shock. The breakdown of variance through this method yields multiple measures of connectivity, encompassing static, dynamic, and directional aspects. Diebold & Yilmaz (2009, 2012, 2014), referred to as "DY" hereafter, introduced a model for quantifying the transmission of returns or volatility, employing the variance decomposition approach. In essence, their method revolves around breaking down the forecast error variance at a specified time horizon (H-step-ahead) for each of the N variables within an N-dimensional VAR model.

This representation enables us to scrutinize the portion of the forecast error variance for variable i (where $i = 1, 2, \ldots, N$) attributable to shocks in variable j (where $j = 1, 2, \ldots, N; i = j$) and aggregate these metrics to construct spillover indices. Furthermore, Diebold & Yilmaz (2012, 2014) refined this approach by leveraging the generalized VAR framework developed by Pesaran & Shin (1998). Consequently, this updated analytical framework facilitates the dynamic decomposition of variance, which was not considered in the Cholesky factorization method employed in Diebold & Yilmaz (2009).

Consider a VAR (Vector Autoregressive) model applied to the variable Y_t:

$$Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + \epsilon_t, \quad \text{with} \quad \epsilon_t \sim (0, \Sigma_\epsilon) \tag{10}$$

In this context, Y_t represents an N-dimensional vector denoted as $(Y_{1t}, Y_{2t}, \ldots, Y_{Nt})$. The matrix ϕ_i represents the $N \times N$ coefficient matrix, and ϵ_t represents the error vector, which is assumed to be independently and identically distributed, following a distribution with mean 0 and covariance matrix Σ. In this study, Y_t represents a vector corresponding to returns, volatilities, or sentiment indices for each of the chosen European markets. The moving average representation, specifically MA(∞), can be expressed as follows:

$$Y_t = \sum_{i=1}^{\infty} \theta_i \epsilon_{t-i} = \psi(L)\epsilon_t, \quad \epsilon_t \sim (0, \Sigma_\epsilon) \tag{11}$$

In this context, $\psi(L)$ signifies an $N \times N$ matrix of infinite-lag polynomials for coefficients. The forecast error at a horizon of H is expressed as:

$$\xi_t(H) = Y_{t+H} - E(Y_{t+H} \mid Y_t, Y_{t-1}, Y_{t-2}, \ldots) = \sum_{i=1}^{H-1} \theta_i \epsilon_{t+H-i} \tag{12}$$

The variance decomposition of forecast errors for the ith variable, as outlined in Pesaran & Shin (1998)'s generalized framework, is defined as:

$$\zeta_{ij}^{g}(H) = \frac{\left(E[\xi_{i,t}^2(H)] - E\left[\xi_{i,t}(H) - E[\xi_{i,t}(H) \mid \epsilon_{j,t+1}, \ldots, \epsilon_{j,t+H}]\right]^2\right)}{E[\xi_{i,t}^2(H)]} = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' \theta_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \theta_h \Sigma \theta_h' e_i)},$$

$$i, j = 1, 2, \ldots, N \tag{13}$$

Here, $\zeta_{ij}^{g}(H)$ represents the percentage reduction in the forecast error variance for variable i over an H-step horizon when considering the future shocks of variable j, and e_i is a selection vector with zeros in all elements except for a 1 in the ith position.

The scaled Generalized Error Forecast Variance Decomposition (GEFVD), denoted as $\zeta_{ij}^{g}(H)$, can be understood as the impact of a shock in variable j on variable i and can be expressed as follows:

$$\zeta_{ij}^{g\dagger}(H) = \frac{\zeta_{ij}^{g}(H)}{\sum_{k=1}^{K} \zeta_{ik}^{g}(H)} = \frac{\zeta_{i\to j}^{g}(H)}{\sum_{j=1}^{N} \zeta_{i\to j}^{g}(H)} \tag{14}$$

Inherent to its design, $\sum_{j=1}^{N} \zeta_{ij}^{g\dagger}(H) = 1$ and $\sum_{i,j=1}^{N} \zeta_{ij}^{g\dagger}(H) = N$. The matrix describing $N \times N$ spillovers for Y_t at an H-step-ahead horizon can be formulated in the following manner:

$$\Lambda_H = \begin{pmatrix} \zeta_{11,H}^{g\dagger} & \zeta_{12,H}^{g\dagger} & \cdots & \zeta_{1N,H}^{g\dagger} \\ \zeta_{21,H}^{g\dagger} & \zeta_{22,H}^{g\dagger} & \cdots & \zeta_{2N,H}^{g\dagger} \\ \vdots & \vdots & \ddots & \vdots \\ \zeta_{N1,H}^{g\dagger} & \zeta_{N2,H}^{g\dagger} & \cdots & \zeta_{NN,H}^{g\dagger} \end{pmatrix} \tag{15}$$

Using the parameter Λ_H as a basis, Diebold & Yilmaz (2014) establish the following measurements. Through the normalization of the element within the GFEVD matrix represented by Λ_H, the comprehensive spillover index $\vartheta^g(H)$ is computed using the subsequent formula:

$$\vartheta^g(H) = \frac{\sum_{i=1,j=1,i=j}^{N} \zeta_{ij}^{g\dagger}(H)}{\sum_{i,j=1}^{N} \zeta_{ij}^{g\dagger}(H)} \times 100 = \frac{\sum_{i=1,j=1,i=j}^{N} \zeta_{ij}^{g\dagger}(H)}{N} \times 100 = \left(1 - \frac{\mathrm{Tr}\{\zeta_{ij}^{g\dagger}(H)\}}{N}\right) \times 100 \quad (16)$$

The term $\vartheta^g(H)$ can be described as the mean spillover from all other markets to a particular asset, excluding the impact of the market on itself due to lags. The overall directional connectedness from other markets to the variable i (denoted as $\psi_{i\leftarrow j}^{g}(H)$), which quantifies the spillovers experienced by market i from all other markets j when $i = j$, is articulated as follows:

$$\psi_{i\leftarrow j}^{g}(H) = \frac{\sum_{j=1,i=j}^{N} \zeta_{ij}^{g\dagger}(H)}{\sum_{j=1}^{N} \zeta_{ij}^{g\dagger}(H)} \times 100 \quad (17)$$

Similarly, the relevant metrics that gauge the complete directional connectedness towards other markets resulting from a shock in variable i (denoted as $\psi_{i\rightarrow j}^{g}$) can be expressed as follows:

$$\psi_{i\rightarrow j}^{g}(H) = \frac{\sum_{j=1,i=j}^{N} \zeta_{ji}^{g\dagger}(H)}{\sum_{j=1}^{N} \zeta_{ji}^{g\dagger}(H)} \times 100 \quad (18)$$

By calculating the difference between the total directional connectedness directed towards other markets (18) and the total directional connectedness originating from other markets (17), we derive the NET total directional connectedness $\psi_i^{g\dagger}(H)$. This measure can be understood as the impact that variable i exerts on the analyzed network. The computation of the NET total directional connectedness is as follows:

$$\psi_i^{g\dagger}(H) = \psi_{i\rightarrow j}^{g}(H) - \psi_{i\leftarrow j}^{g}(H) \quad (19)$$

The net spillover of returns, volatility, or sentiment, as outlined in (19), offers a concise view of how each equity market, in net terms, contributes to the variance in returns, volatility, or sentiment observed in other equity markets. If $\psi_i^{g\dagger} > 0$ ($\psi_i^{g\dagger} < 0$), it indicates that variable i serves as a net transmitter (receiver) of shocks, signifying that variable i is playing a driving (driven) role in the network. Furthermore, we compute the net pairwise directional connectedness (NPDC), which provides insights into the mutual interactions between two variables, demonstrating how variable i

affects variable j or vice versa:

$$\psi_{ij}^{g\dagger}(H) = \left[\frac{\zeta_{ij}^{g\dagger}(H)}{\sum_{k=1}^{N} \zeta_{ik}^{g\dagger}(H)} - \frac{\zeta_{ji}^{g\dagger}(H)}{\sum_{k=1}^{N} \zeta_{jk}^{g\dagger}(H)} \right] \times 100 \tag{20}$$

In this research, $\psi_{ij}^{g\dagger}(H)$ is essentially the contrast between the overall shocks transmitted from market i to j and the total volatility shocks transmitted from j to i.

Following the methodology introduced by DY, which assesses spillovers in the time domain, Baruník & Křehlík (2018), referred to as BK, utilize the Fourier transform to analyze changes in connectedness across different frequency ranges. They employ spectral variance decompositions to extract spillover effects in the frequency domain. BK introduces frequency-dependent connectedness by utilizing a comprehensive spectral representation of variance decomposition. To achieve this, they use the Fourier transform to categorize dynamics into three distinct frequency components: short-term, mid-term, and long-term. The frequency response function $\Psi(e^{-iw}) = \sum_{h=0}^{\infty} \Psi_h e^{-ihw}$ is derived from the Fourier transformation of the coefficient Ψ_h, where $i = \sqrt{-1}$. The generalized causation spectrum across different frequencies $\omega \in (-\pi, \pi)$ is defined as:

$$f(\omega)_{j,k} = \frac{\sigma_{kk}^{-1} \left| \left(\Psi(e^{-iw}) \Sigma \right)_{j,k} \right|^2}{\left(\Psi(e^{-iw}) \Sigma \Psi'(e^{+iw}) \right)_{j,j}}, \tag{21}$$

In this context, $f(\omega)_{j,k}$ denotes the segment of the spectrum of the jth variable at a particular frequency ω that can be attributed to shocks in the kth variable.

To calculate the comprehensive variance decomposition within a specific frequency range ω, as per Baruník & Křehlík (2018), they adjust the $f(\omega)_{j,k}$ values by the frequency's proportionate contribution to the variance of the jth variable. This adjustment is carried out using the following weighting function:

$$\Gamma_j(\omega) = \frac{\left(\Psi(e^{-iw}) \Sigma \Psi'(e^{+iw}) \right)_{j,j}}{\frac{1}{2\pi} \int_{-\pi}^{\pi} \left(\Psi(e^{-i\lambda}) \Sigma \Psi'(e^{+i\lambda}) \right)_{j,j} d\lambda}, \tag{22}$$

Baruník & Křehlík (2018) emphasize that in economic contexts, the focus typically lies in evaluating connectedness over short, medium, or long-term periods rather than isolating it at a single specific frequency. Consequently, to align with economic reasoning more effectively, it is more practical to operate with frequency bands, which they define as the variance of forecast errors occurring across a continuous range of frequencies. Therefore, for a given frequency band represented as $d = (a, b)$ where a and b fall within the range $(-\pi, \pi)$ and a is less than b, the generalized variance decompositions within this frequency band d are expressed as:

$$\Theta_{jk}(d) = \frac{1}{2\pi} \int_a^b \Gamma_j(\omega) f(\omega)_{jk} dw \tag{23}$$

Likewise, the scaling of the generalized variance decomposition is applied within the frequency range represented by d as:

$$\Theta^{g\dagger}_{jk}(d) = \frac{\Theta_{jk}(d)}{\sum_k \Theta_{jk}(\infty)} \tag{24}$$

Here, $\Theta^{g\dagger}_{jk}(d)$ denotes the spillover effects between the jth and kth variables within the specified frequency band d. In line with the approach introduced by Baruník & Křehlík (2018), the connectedness within this frequency band d is defined as:

$$C^F_d = 100 \times \left(\frac{\sum \Theta^{g\dagger}(d)}{\sum \Theta^{g\dagger}(\infty)} - \frac{\mathrm{Tr}\{\sum \Theta^{g\dagger}(d)\}}{\sum \Theta^{g\dagger}(\infty)} \right) \tag{25}$$

A measure of C^F_d approaching unity indicates a strong level of connectivity within the spectral band d. Likewise, the total directional spillover index for "within to" and "within from" can also be expressed as:

To Spillovers on frequency band d:

$$C^F_{\cdot\leftarrow i}(d) = \frac{\sum_{j=1, i=j}^{N} \Theta^{g\dagger}_{ji}(d)}{N} \times 100 \tag{26}$$

$C^F_{\cdot\leftarrow i}(d)$ measures the extent to which a market (where $i = j$) contributes to another market, denoted as i, within a specific spectral band d.

From spillovers on frequency band d:

$$C^F_{i\leftarrow\cdot}(d) = \frac{\sum_{i=1, i=j}^{N} \Theta^{g\dagger}_{ij}(d)}{N} \times 100 \tag{27}$$

As noted earlier, the directional spillovers (within from) gauge the impact of one market (where

$i = j$) on another market, referred to as i, within a defined spectral band, denoted as d.

We introduce a novel framework for frequency connectedness based on Time-Varying Parameter Vector Autoregressive (TVP-VAR) models, building upon the frequency approach developed by Baruník & Křehlík (2018) and the time-domain connectedness approach by Antonakakis et al. (2020). This approach integrates the methodologies presented by Diebold & Yilmaz (2014) and Koop & Korobilis (2014). We adopt this methodology to address several limitations, including (i) the arbitrary selection of rolling-window size, leading to highly volatile parameters, (ii) the loss of observations, and (iii) sensitivity to outliers, as highlighted by Antonakakis et al. (2020) and Korobilis & Yilmaz (2018). Additionally, the frequency connectedness approach proposed by Baruník & Křehlík (2018) enables us to distinguish between short-term, medium-term, and long-term connectedness effects. Then, the TVP-VAR model of order p can be outlined as follows:

$$y_t = \Phi_t Z_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma_t) \tag{28}$$

$$\text{vec}(\Phi_t) = \text{vec}(\Phi_{t-1}) + \xi_t, \quad \xi_t \sim N(0, \Xi_t) \tag{29}$$

Here, Z_{t-1} represents an $np \times 1$ vector consisting of lagged values $(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-P})$, while $\Phi_t = (\Phi_{1t}, \Phi_{2t}, \ldots, \Phi_{pt})$ is an $n \times np$ coefficient matrix with $n \times n$ coefficient sub-matrices denoted as Φ_{it} (where $i = 1, 2, \ldots, p$). The error terms ϵ_t and ξ_t are vectors following a normal distribution with dimensions of $n \times n$ and $n^2p \times n^2p$, respectively, representing time-varying variance-covariance matrices denoted as Σ_t and Ξ_t. By applying the Wold representation theorem, we can express the TVP-VAR process as a Time-Varying Moving Average (TVP-VMA(∞)) process:

$$y_t = \sum_{i=1}^{p} \Phi_{it} y_{t-i} + \epsilon_t = \sum_{j=1}^{\infty} \Psi_{jt} \epsilon_{t-j} \tag{30}$$

The connectedness approach relies on two fundamental concepts: Generalized Impulse Response Functions (GIRF) and Generalized Forecast Error Variance Decompositions (GFEVD) (Koop et al. 1996, Pesaran & Shin 1998), which are rooted in the time-varying coefficients and time-varying variance-covariance matrices obtained from the TVP-VAR model. The GFEVD can be understood as the impact of a shock in variable j on variable i, expressed in relation to the forecast error variance, denoted as $\phi^{g}_{ij,t}(H)$, at a forecasting step H. Its normalized counterpart, represented as $\phi^{g\dagger}_{ij,t}(H)$, can be formulated as follows:

$$\phi^{g}_{ij,t}(H) = \frac{(\Sigma_t)^{-1}_{jj} \sum_{h=0}^{H} \left((\Psi_h \Sigma_t)_{ij,t} \right)^2}{\sum_{h=0}^{H} (\Psi_h \Sigma_t \Psi'_h)_{ii}}, \quad \phi^{g\dagger}_{ij,t}(H) = \frac{\phi^{g}_{ij,t}(H)}{\sum_{j=1}^{n} \phi^{g}_{ij,t}(H)} \tag{31}$$

By employing the normalization process, we obtain the following result: $\sum_{i=1}^{N} \phi^{g}_{ij,t}(H) = 1$ and $\sum_{j=1}^{N} \sum_{i=1}^{N} \phi^{g\dagger}_{ij,t}(H) = N$.

In line with the approaches of Diebold & Yilmaz (2012), Baruník & Křehlík (2018), Antonakakis et al. (2020) and Chatziantoniou et al. (2023) establish the connectedness metrics using the TVP-VAR model in the following manner: They introduce the Net Pairwise Connectedness (NPDC) as:

$$NPDC_{ij,t}(H) = \phi^{g\dagger}_{ij,t}(H) - \phi^{g\dagger}_{ji,t}(H) \tag{32}$$

The total directional connectedness **TO others**:

$$TO_{it}(H) = \sum_{i=1, i=j}^{N} \phi^{g\dagger}_{ji,t}(H) \tag{33}$$

The total directional connectedness **FROM others**:

$$FROM_{it}(H) = \sum_{i=1, i=j}^{N} \phi^{g\dagger}_{ji,t}(H) \tag{34}$$

The net total directional connectedness:

$$NET_{it}(H) = TO_{it}(H) - FROM_{it}(H) \tag{35}$$

And the total connectedness index (TCI):

$$TCI_{it}(H) = N^{-1} \sum_{i=1}^{N} TO_{it}(H) = N^{-1} \sum_{i=1}^{N} FROM_{it}(H) \tag{36}$$

To compute these connectedness metrics in the frequency domain, Chatziantoniou et al. (2023)

utilize equation (24) in conjunction with various measures outlined in equations (32) to (36). This allows them to examine the connection between frequency domain metrics from Baruník & Křehlík (2018) and time-domain measures from Diebold & Yilmaz (2009, 2012, 2014):

$$NPDC_{ij,t}(H) = \sum_d NPDC_{ij,t}(d), \quad TO_{it}(H) = \sum_d TO_{it}(d), \quad FROM_{it}(H) = \sum_d FROM_{it}(d)$$

$$NET_{it}(H) = \sum_d NET_{it}(d), \quad TCI_i(H) = \sum_d TCI_i(d) \tag{37}$$

In line with the methods introduced by Antonakakis et al. (2020) and Chatziantoniou et al. (2023), we determine the lag order (p) using the Schwartz Bayesian Criterion (SBC). Specifically, we set the lag order for the returns dataset to 2, for volatility to 1, and for sentiment to 1. We calculate the Forecast Error Variance (FEV) matrices for a forecasting period of 10 days when analyzing return series. The choice of the forecast horizon length is contingent on the underlying assumption regarding the time horizon of asset market connections.

The model proposed by Baker et al. (2012)

In their model, Baker et al. (2012) break down investor sentiment into two components: local sentiment and global sentiment. They posit the existence of a single global investor who participates in all markets, along with six local investors. Their findings suggest that global sentiment acts as a counterintuitive predictor of returns at the country level. To quantify global sentiment, Baker et al. (2012) create a composite global sentiment index[5]. Specifically, they define global sentiment as the leading principal component derived from a Principal Component Analysis (PCA) applied to these proxy indicators. Additionally, they generate six local sentiment indices, which are determined as the residuals from regressing the country sentiment indices against the global sentiment. The Baker et al. (2012) model can be expressed as follows:

$$R_{\mathrm{MKT},c,t} = a + b\mathrm{SENT}_{t-1}^{\mathrm{Global}} + c\mathrm{SENT}_{c,t-1}^{\mathrm{Local}} + \nu_{c,t} \tag{38}$$

[5]From five indicators, namely: the premium of volatility (PVOL), the average return on the first day of initial public offerings (RIPO) over the year, the count of initial public offerings (NIPO), and trading volume (TURN).

Where $R_{\mathrm{MKT},c,t}$ represents the market's return, denoted as c at time t, $\mathrm{SENT}_{t-1}^{\mathrm{Global}}$ refers to the global sentiment at time $t-1$, and $\mathrm{SENT}_{c,t-1}^{\mathrm{Local}}$ refers to the local sentiment c at time $t-1$.

In our research, we establish a single global European sentiment measure and six local sentiment measures corresponding to the six European countries under examination. Specifically, we employ comprehensive sentiment indexes to assess the interconnections among the various sentiment measures. Meanwhile, global European sentiment is utilized to investigate whether investor sentiment serves as a predictor of return spillovers. To achieve this, we adopt a quantile-on-quantile methodology.

Regressions based on quantiles within quantiles

The quantile-on-quantile (QQ) modeling technique can be credited to the pioneering work of Sim (2015) and Sim & Zhou (2015), who were the first to introduce this method for analyzing the impact of oil price shocks on stock returns. The QQ approach can be viewed as an extension of conditional quantile regression, which allows us to investigate how a predictor affects different quantiles of a response variable. This approach combines nonparametric estimation and quantile regression. Nonparametric estimation, specifically local linear regression, was initially introduced by Cleveland (1979) and Stone (1977). It is typically used to estimate the local influence of a specific quantile of an independent variable on the dependent variable. Local linear regression is employed to address the dimensionality issue often encountered in nonparametric models. Conditional quantile regression (QR), on the other hand, represents a broader form of linear regression introduced by Koenker & Bassett Jr (1978). Unlike standard linear regression, QR is employed to estimate the impact of an independent variable on various quantiles of the dependent variable.

Thus, by combining these two approaches, it becomes possible to model the relationship between the quantiles of the independent variable and the quantiles of the dependent variable. This innovative approach can provide more comprehensive insights into complex relationships between variables than traditional techniques like OLS (Ordinary Least Squares) and standard quantile regression. Furthermore, QQ has demonstrated its effectiveness in cases where the relationship is intricate and consistently delivers results. Considering this perspective, the QQ approach becomes especially valuable for investigating tail dependence structures under various market conditions: normal market conditions (associated with middle quantiles), bullish market conditions (linked to higher quantiles), and bearish market conditions (associated with lower quantiles) (as discussed in Chang et al. (2020), Sim & Zhou (2015) and Bouri et al. (2022)).

Consequently, we aim to examine the potential influence of the sentiment factor on the interconnections between returns and volatility. In alignment with the approach outlined by Bouri et al. (2022), the QQ model is constructed based on the subsequent nonparametric quantile regression framework:

$$TCI_t = \beta^{\theta}(\text{Sentiment}_t) + \mu_t^{\theta} \tag{39}$$

Here, TCI_t denotes the overall connectedness index of returns or volatility at time period t, computed using equation (37). Sentiment signifies the global European sentiment index at time period t, while θ represents the θth quantile. The error term, denoted as μ_t^{θ}, possesses a zero θ-quantile. The standard quantile regression model in equation (39) enables us to investigate how the impact of the investor sentiment index varies across different quantiles of TCI returns or volatilities.

However, this model has limitations because the term $\beta^{\theta}(.)$ is tied to the θth quantile of TCI alone and does not account for the quantile of investor sentiment. Therefore, our focus is on examining the relationship between the θth quantile of TCI and the τth quantile of sentiment, denoted as P^{τ}. This involves analyzing equation (39) in the vicinity of P^{τ} through a local linear regression approach. Since $\beta^{\theta}(.)$ is not known, we approximate this function using a first-order Taylor expansion of $\beta^{\theta}(.)$ around P^{τ}, resulting in:

$$\beta^{\theta}P_t \approx \beta^{\theta}(P^{\tau}) + \beta^{\theta'}(P^{\tau})(P_t - P^{\tau}) \tag{40}$$

In this context, $\beta^{\theta'}$ represents the partial derivative of the function $\beta^{\theta}(P^{\tau})$ concerning P. It is important to emphasize that the parameters within equation (40), namely $\beta^{\theta}(P^{\tau})$ and $\beta^{\theta'}(P^{\tau})$, are characterized by dual indexing involving both θ and τ. Taking this into account, Sim (2015) and Bouri et al. (2022) redefine $\beta^{\theta}(P^{\tau})$ and $\beta^{\theta'}(P^{\tau})$ as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$, respectively. Consequently, equation (40) can be reformulated as:

$$\beta^{\theta}P_t \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(P_t - P^{\tau}) \tag{41}$$

Thus, by replacing equation (41) into (39), we derive:

$$S_t = (\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(P_t - P^\tau))^* + \mu_t^\theta \tag{42}$$

The component $(^*)$ within equation (42) represents the θth quantile of TCI. In contrast to the typical conditional quantile function, equation (42) elucidates the comprehensive dependence pattern between the θth quantile of TCI and the τth quantile of the sentiment variable. This is accomplished by considering the relationship between their respective distributions, as the parameters β_0 and β_1 are doubly indexed based on both θ and τ.

The estimated values of the parameters P_t^*, P^τ, $\hat{\beta}_0$, and $\hat{\beta}_1$ within equation (42) can be determined by solving the following equation:

$$\min_{b_0, b_1} \sum_{i=1}^{n} \rho_\theta \left[S_t - b_0 - b_1(P_t^* - P^\tau)\right] K\left(\frac{F_n(P_t^* - \tau)}{h}\right) \tag{43}$$

In this context, ρ_θ represents the quantile loss function, defined as $\rho_\theta = (\theta - I(\mu < 0))$, where $K()$ denotes the kernel function. The Gaussian kernel is employed to assign weights to results around P^τ, and this is done based on a bandwidth parameter, denoted as h. It's worth noting that Sim (2015) highlighted that these weights are inversely proportional to the distance, expressed as $F_n(P_t) = \frac{1}{n}\sum_{k=1}^{n} I(P_t < P^\tau)$, where I is a standard indicator function. To precisely assess different frequencies of sentiment shocks and TCI returns or volatility, we consider a specific bandwidth parameter value of $h = 0.05$. This choice is made to appropriately weight the observations in the vicinity of the quantiles, as suggested by Sim (2015) and Bouri et al. (2022).

5 Empirical Findings

In this section, we showcase the key findings derived from various connectedness models that operate in both the time and frequency domains. Additionally, we include a supplementary analysis employing quantile-on-quantile regression, as applied in our research. We begin by presenting the average dynamic connectedness in the frequency domain, focusing on returns or volatility and sentiment, utilizing the framework outlined by Chatziantoniou et al. (2023). Furthermore, we analyze the extreme behavior and tail dependence of sentiment shocks on stock returns across different distributional levels, utilizing the quantile-on-quantile approach. Our study goes deeper by exploring connectedness during both crisis and non-crisis periods in relation with the COVID-19 pandemic and Russia-Ukraine conflict.

Average dynamic connectedness

Table 5 provides a summary of the estimations for the average dynamic connectedness metrics for each dataset, namely returns, realized volatility, and sentiment. These metrics are generated using the TVP-VAR model in the frequency domain. The Total Connectedness Index (TCI) quantifies the average influence of a variable on all the other variables in the network. It can be interpreted as the percentage of the forecast error variance of variable i that can be explained by the shocks originating from all other non-i variables within the network. When this measure is relatively high, it suggests that the interconnection within the network, and consequently the market risk, is elevated. This means that a shock in one variable will have a significant impact on others. Conversely, a low TCI value indicates that most of the variables are relatively independent of each other, signifying that a shock in one variable will not trigger adjustments in the other variables. This, in turn, results in lower market risk. However, the TCI represents the collective variance of forecast errors for Europe that can be accounted for by the interconnectedness of shocks across European countries. As presented in Table 5, the average connectedness index (TCI) for the entire sample period is quite similar, standing at approximately 68.65% for returns, 69.68% for volatility, and 65.50% for sentiment. This implies that, on average, around 69% of returns are influenced by spillover effects from other markets, about 69% of realized volatility is impacted by spillover volatility from other assets, and approximately 65% of the sentiment factor is affected by spillover effects from other sentiment markets.

These values provided in Table 5 for the entire sample period can be further broken down into results for the short-term and long-term periods. For instance, looking at the diagonal element under the column labeled FTSE 100r, we observe that 45.72% of the connectedness represents the impact of its own shocks to expectations. Specifically, this breaks down into 37.16% in the short run and 8.56% in the long run. In contrast, the off-diagonal elements reveal how returns, volatility, and sentiment spread from one market to another within the entire network. In summary, the main diagonal elements correspond to self-contribution (i.e., idiosyncratic effect), while all the off-diagonal elements reflect contributions either "from" or "to" other markets.

Looking at Table 5, Part a, we can observe that the average value is 68.65%. This can be further broken down into 52.61% attributed to the short-term and 16.04% attributed to the long-term (TCI for returns). This breakdown suggests that connectedness is primarily influenced by developments, or the transmission of shocks, in the short-term (52.61%). However, when examining the results for realized volatility and sentiment, we find that they are primarily influenced by the long-term, with values of 45.69% and 61.09%, respectively. This finding indicates that more than fifty percent of the total variance in forecast errors for Europe can be explained by the interconnectedness of shocks across European countries, while the remaining part can be attributed to idiosyncratic shocks. This result is in close alignment with the findings of Fernández-Rodríguez & Sosvilla-Rivero (2020), who studied returns and stock exchanges for seven influential countries (US, Euro Area, Japan, Canada, Switzerland, UK, Australia) from 1980 to 2018. They found that 56.01% of the total variance in forecast errors is explained by shocks across markets, while 43.99% is due to idiosyncratic shocks. However, it's worth noting that our result differs from the 78.3% reported by Diebold & Yilmaz (2014) for US financial institutions and the value of 97.2% found by Diebold & Yilmaz (2012) for international financial markets.

Our discovery highlights a robust interconnection among markets, a phenomenon that can be attributed to the substantial financial integration prevailing among different European economies. Specifically, the increased financial market integration among European Union (EU) economies, fostered by the European monetary union, aligns with earlier research findings such as Kim et al. (2005), Cappiello et al. (2006), Hardouvelis et al. (2006), and Mylonidis & Kollias (2010). This outcome provides supporting evidence for our hypothesis H1, which posits a significant interconnectedness in stock returns among European markets. Furthermore, the TCI reveals that among European economies, the United Kingdom (FTSE 100r) stands out as the most influential market, acting as a net transmitter with the highest contribution of 14.31% to other developed markets. Following is the CAC40r, contributing approximately 10.92% to other European countries. Specifically, FTSE 100r has net spillover effects of 10.82%, 10.64%, 11.16%, 1.35%, and 20.31% to AEXr, DAXr, CAC40r, FTSEMIBr, and IBEX35r, respectively. In contrast, Italy is the least influential country, serving as a net receiver with a contribution of -36.73% to other markets.

Regarding frequency analysis, the network appears to process information at varying speeds. The UK market, for instance, exhibits a slower processing rate, primarily driven by long-term dynamics (8.36%). In contrast, the French market predominantly transmits return spillovers in the network on a shorter time scale, contributing 8.19% from the short run. However, when considering the category "from others" (FROM), France stands out as the most susceptible to external shocks, with a vulnerability of 64.20%, closely followed by Germany at 63.82%. In contrast, Italy is recognized as the least vulnerable stock market in terms of external shocks originating from other European economies, with a vulnerability of 46.01%. Notably, the UK market also displays lower vulnerability, as its connectedness from other European countries amounts to 54.28%. We illustrate these results in Figure 4a by graphing them based on the net pairwise directional connectedness values, as determined using the methodology outlined by Chatziantoniou et al. (2023).

In Table 5 Part b, we can observe that the TCI for realized volatility is 69.68%, which is quite similar to the TCI for returns. Concerning the influence of frequency bands, the average connectedness index is predominantly affected by long-term dynamics, constituting 23.99% for the daily-frequency band and 45.69% for the low-frequency band. Additionally, the primary net transmitter within this network is the Netherlands (AEXv), contributing an average of 13.75%, closely followed by the United Kingdom with a contribution of 13.35%. Conversely, the most notable net recipient in this network is the Italian stock market, exhibiting an average value of -37.26%. Notably, the lowest spillover of volatility is from FTSEMIBv to FTSE 100v at 3.61%, while the highest is from CAC40v to AEXv at 22.03%. We can observe the transmission of volatility in Figure 4b.

The findings presented in Table 5 Part c reveal a robust interconnectedness among the sentiment indices. The total connectedness index (TCI) for the entire sample period stands at approximately 65.50%, i.e., comprising 4.41% for the high band and 61.09% for the low band, and it closely resembles the TCI observed for realized volatility. This implies that 65.5% of the overall variance in sentiment forecast errors across the European countries can be attributed to the interplay between sentiment indices, with the remaining 34.5% arising from unique shocks specific to each European country. Furthermore, the influence of sentiment spillover is primarily rooted in the long term. Consequently, we affirm hypothesis H2 of our study, which posits that investor sentiments across various European financial markets are mutually dependent. Furthermore, it is worth mentioning that the Italian sentiment index, followed by the French and German sentiments, exhibit a net receiving position, with respective values of -22.12%, -10.18%, and -7.7%. Conversely, Spanish sentiment, followed by UK sentiment, serves as the primary source of sentiment spillover, contributing 82.39% and 76.29%, respectively. An intriguing observation is that German and French sentiments experience more significant external shocks from other sources, with percentages of 77.57% and 72.20%, respectively. These findings are clearly represented in Figure 4c, illustrating the interconnectedness of sentiment indices among the European countries, as per the methodology by Chatziantoniou et al. (2023).

Total dynamic connectedness

In this section, we establish a connection between the changing patterns of interrelatedness among various variables and significant economic occurrences, as discussed by Balcilar et al. (2021). Our objective is to determine whether the varying degrees of interconnection observed in different time segments are linked to these events. To accomplish this, we conduct an examination of the evolving measures of different series, including returns, realized volatility, and sentiment, in a dynamic context.

Compared to the average Total Connectedness Index (TCI), as depicted in Figure 5, we observe that the TCI, indicated by the black-shaded region, fluctuates within the range of approximately 19% to 75% for returns, 65% to 77% for realized volatility, and 56% to 80% for the sentiment factor over the entire sample period based on the TVP-VAR model. Our dynamic analysis of the network's evolution in Figure 5 goes beyond examining the overall TCI; it also dissects the TCI into short-term (red-shaded area) and long-term (green-shaded area) components.

In Figure 5a, it is evident that the overall TCI for returns is notably influenced by significant events and displays varying magnitudes (black-shaded area). There are distinct spikes observed, particularly in early 2012 and early 2015, as well as more recently between 2019 and 2022. The first substantial increase in TCI occurs in mid-2014, coinciding with the FTSE 100 plummeting by 22.6%

in a single trading session, and a similar event in the Italian market. A second spike emerged in the early 2015, coinciding with the U.K. stock market downturn as described by Quinn & Turner (2020). Additionally, the peak in the average TCI in 2015 can be attributed to a political event as discussed in Chatziantoniou et al. (2023).

Thirdly, we observe sporadic rises around 2017-2018 followed by a decline around 2020 in the TCI, before a further drop after 2021. Notably, the total dynamic connectedness reaches exceptionally high levels during and after the COVID-19 pandemic and Russia-Ukraine conflict (2020-2023), with the highest peak surpassing 75%. Subsequently, the TCI experienced a downward trend, reaching its lowest point in early 2021, which corresponds to the second outbreak of the COVID-19 pandemic. A new upward trend emerges afterward, with connectedness predominantly ranging between 68% and 72% between 2021 and 2022. There is also a further drop after 2023, related to the continuing aggressive launch of the Russia-Ukraine war.

Regarding the results of net total connectedness, particularly in relation to the decomposition of total return spillovers in the frequency domain, it is worth noting that during the COVID-19 pandemic and Russia-Ukraine conflict, total spillovers are primarily driven by the short-term component. This suggests that shocks are processed and transmitted over a short period, aligning with the findings of Ding et al. (2021). By the COVID-19 pandemic and Russia-Ukraine war, the European index had lost much of its peak value.

Moving on, we analyze the results regarding the dynamic interconnection of realized volatility, which are illustrated in Figure 5b. Similar to what we observed in the network of returns, we once again notice a substantial peak in dynamic total connectedness, particularly around the 2017-2018 and 2021-2023 periods. However, in Figure 5b, it is evident that the values of the Total Connectedness Index (TCI) fluctuate within the range of 67% to 78% for nearly the entire duration and stabilize slightly only after 2018. It is important to note that the spillover of volatility is primarily driven by the long-term component, which refers to the response to shocks at low frequencies. This observation could imply an increase in long-term uncertainty and systemic risk, as discussed by Baruník & Křehlík (2018).

Our particular focus lies in examining the dynamic transmission of the sentiment index, as illustrated in Figure 5c. In this context, the results regarding sentiment demonstrate more prominent peaks and valleys. Two significant events stand out distinctly. The initial peak corresponds to the 2017-2018 period, while the subsequent peak aligns with the COVID-19 pandemic and Russia-Ukraine war (2020-2023), with the highest peak exceeding 78%. However, it is noteworthy that long-term connectedness played a dominant role in shaping the underlying dynamics of the sentiment index. Notably, the majority of the total connectedness within the network can be attributed to the low-frequency range. This indicates that shocks are processed and transmitted over an extended period, potentially leading to fundamental shifts in investors' expectations. This observation aligns with the research of Wang et al. (2022) and Huang et al. (2023). These findings suggest that heightened uncertainty exerts prolonged effects on the sentiment index.

We conduct additional investigations using a TVP-VAR model in the time domain, as described by Antonakakis et al. (2020). This analysis is performed for two distinct sub-periods, namely the period before and after the COVID-19 pandemic and Russia-Ukraine conflict. The primary goals of this analysis are twofold. Firstly, it aims to validate the presence of a potential time-varying pattern of interconnectedness. Secondly, it seeks to pinpoint the factors responsible for explaining this dynamic behavior. The empirical findings for these sub-periods are presented in Table 6 and Table 7.

In this research, our main emphasis is on examining the impact of the COVID-19 pandemic and Russia-Ukraine war between 2020 and 2023 on the interconnections within sentiment. The results presented in Table 6 and 7, reveal a disparity in the Total Connectedness Index (TCI) between the period preceding the crisis and the period following it. The TCI increases from 56.98% to 61.81%. This discovery indicates that during the crisis period of COVID-19 and war, there is a higher level of interconnectedness among sentiments across different European countries. Consequently, we affirm the second part of our hypothesis, H3, which posits that the spillover of sentiment is more pronounced during pandemic and war crises.

Subsequently, we examine the outcomes related to net connectedness, with a particular focus on examining the impact of the COVID-19 pandemic and Russia-Ukraine war between 2020 and 2023 on the interconnectedness of returns. As illustrated in Table 7, highlights a notable contrast in the Total Connectedness Index (TCI) between the crisis and non-crisis periods related to COVID-19 and war. It increases from 51.44% to 65.83%. This result underscores that during the crisis period, there was a significant degree of synchronization among European financial markets. Consequently, the interlinkage of shocks across different European countries accounts for 65.83% of the total variance in the network's forecast error.

However, it is noteworthy that in both the post-COVID-19 and war and pre-COVID-19 and war periods, the FTSE 100 and the IBEX35 sentiment indices play a pivotal role as the primary sources of sentiment transmission, accounting for 21.38% and 45.76% during the post-COVID-19 and war period and 6.08% and 43.09% during the pre-COVID-19 and war period, respectively. Conversely, Italy appears less susceptible to sentiment shocks originating from other countries in both non-crisis and crisis periods, with figures of 37.36% and 50.12%, respectively.

Regression model conducted by Baker et al.(2012)

We present the findings pertaining to the Baker et al. (2012) model in Table 8. In Table 8, the second column indicates that the coefficient linked to the global European sentiment index is both negative and statistically significant, in line with our expectations. Specifically, a one-unit increase in the standard deviation of global European sentiment corresponds to an 8.82% decrease in total sentiment for European markets. Additionally, as per Baker et al. (2012), we conducted two separate regressions for the entire period, one including the United Kingdom in the sample and one excluding it. The estimated coefficients affirm that sentiment impacts markets even when the United Kingdom is excluded from the analysis. Consequently, we confirm our hypothesis H4, which posits that global European sentiment predicts total sentiment. This hypothesis is pivotal for justifying the utilization of global European sentiment in studying its effects on market return connectivity.

However, the results in Table 8 demonstrate that the coefficient associated with the local European sentiment index is not statistically significant. This outcome may be explained by the fact that country-level sentiment indices are predominantly influenced by global European sentiment. To deepen our analysis, we proceeded to estimate the Baker et al. (2012) model during two distinct periods: the COVID-19 pandemic in 2020-2021 and the Russia-Ukraine conflict period in 2022-2023.

The results in Table 8 reveal that the coefficient associated with global European sentiment increases during the COVID-19 pandemic and the Russia-Ukraine conflict periods compared to the non-COVID-19 and war period, shifting from -12.05% to -25.29% and -15.18%, respectively. Intriguingly, local European sentiment becomes a significant index during both the COVID-19 pandemic and the Russia-Ukraine conflict, with an estimated coefficient of -9.05% and -4.18%. This finding underscores a strong relationship between global European sentiment and local European sentiment during times of deterioration.

Regression of quantile with quantile

We present the results of our QQ (Quantile on Quantile) analysis using data from the Baker et al. (2012) regression. In our approach, we initially estimate a linear regression model as represented by Equation (39) to investigate how TCIs (Total Connectedness Index) respond to changes in the global European investor sentiment index. Employing a monthly frequency and the Ordinary Least Squares (OLS) regression framework, we find a statistically significant coefficient of -0.041. This outcome indicates that global European investor sentiment has a negative impact on stock return connectedness. Consequently, the transmission of stock returns between European markets increases with investor pessimism and decreases with investor optimism. This finding confirms our hypothesis H5, which posits that investor sentiment plays a role in explaining the connectedness of returns in European markets.

We propose that the adverse effect of sentiment on return connectedness can be attributed to an increase in risk aversion driven by positive future expectations. This, in turn, boosts portfolio concentration and, as a result, reduces cross-border capital flows, leading to an increase in the interconnectedness of financial market returns during periods of pessimism and a decrease during periods of optimism. We contrast our findings with those of Bouri et al. (2022), who were the pioneers in employing the QQ framework to investigate the link between investor sentiment and the interconnectedness of returns and volatility in financial markets. In their study, they utilize a happiness index as a gauge of investor sentiment optimism. They discover that when estimating the Total Connectedness Index (TCI) for returns, the coefficient associated with investor sentiment exhibits a positive direction, while it displays a negative direction when estimating the TCI for return volatility.

Additionally, to gain a comprehensive understanding of the conditional relationship between normal and extreme states of the TCI and global investor sentiment, we utilize the QQ approach to assess these relationships across various quantile levels. As previously discussed, the QQ approach delves into tail dependence structures under different market conditions, including typical market conditions, i.e., middle quantiles, bullish or expansionary market conditions, i.e., higher quantiles, and bearish or recessionary market conditions, which may correspond to crisis periods, i.e., lower quantiles.

Figures 6a and 6b depict the outcomes of the QQ model, which examines the association between global European sentiment and the Total Connectedness Index (TCI) of stock market returns in the European countries, as well as their volatility. While the findings generally align with those obtained from the linear regression analysis, the relationship between sentiment and market risk demonstrates a change in direction at extreme quantiles. Specifically, Figure 6a illustrates that investor sentiment negatively influences the interconnectedness of stock market returns within the middle quantiles of sentiment. However, it becomes evident that this relationship turns positive when sentiment reaches extremely high values. This discovery implies that extreme shifts in sentiment, whether positive or negative, can significantly impact risk spillovers, whereas the negative effect of sentiment is confined to the middle quantiles of TCI when sentiment is moderate.

Consequently, these results underscore the importance for investors and portfolio managers to closely monitor sentiment shocks in both directions, as such shocks can have substantial implications for risk and contribute to the spillover effects on global returns in European markets. In summary, our results demonstrate a robust connection between global European investor sentiment and the interdependence of returns in the financial stock markets of the European nations. Notably, the influence of global European sentiment on return spillovers exhibits asymmetry, particularly when sentiment values are exceptionally high.

6 Conclusion

In this study, we investigate the phenomenon of spillover in stock returns and sentiment indexes within the European financial markets from January 2011 to December 2023. We employ the theoretical framework for decomposing the variance of forecast error initially introduced by Diebold

& Yilmaz (2012, 2014) and extended by Chatziantoniou et al. (2023). Our findings reveal pronounced spillovers in both returns and sentiment indexes, and this interdependence is attributed to the high level of financial integration among the various markets in European countries.

However, we observe that the overall connectedness within our network fluctuates significantly over time, particularly during periods of crisis. Notably, strong interconnections are identified between both market returns and sentiment indexes during the COVID-19 pandemic and Russia-Ukraine conflict in 2020-2023. Another finding from our research reaffirms the significant influence of the UK market on European returns and sentiment indexes. Specifically, sentiment trends in the UK market play a pivotal role in shaping sentiment across other markets and countries in Europe, consequently affecting returns in European equity markets.

Additionally, our results regarding Italy suggest that Italy may attract investor attention during risk-off cycles. Italy appears to be less susceptible to sentiment shocks originating from other European countries, both in non-crisis and crisis periods in relation to COVID-19 and the war. Consequently, portfolio managers should exercise caution with strongly interconnected markets in the event of deteriorating sentiment.

Nevertheless, our findings, as revealed through the quantile-to-quantile approach, demonstrate that the transmission of stock returns between markets tends to rise or fall in response to investor pessimism or optimism within the central quantiles. However, it is noteworthy that this relationship takes a positive turn when sentiment values reach extremely high levels. This observation suggests that extreme sentiment shocks in either direction have a positive impact on the interconnectedness of returns.

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Figure 1: Daily stock return

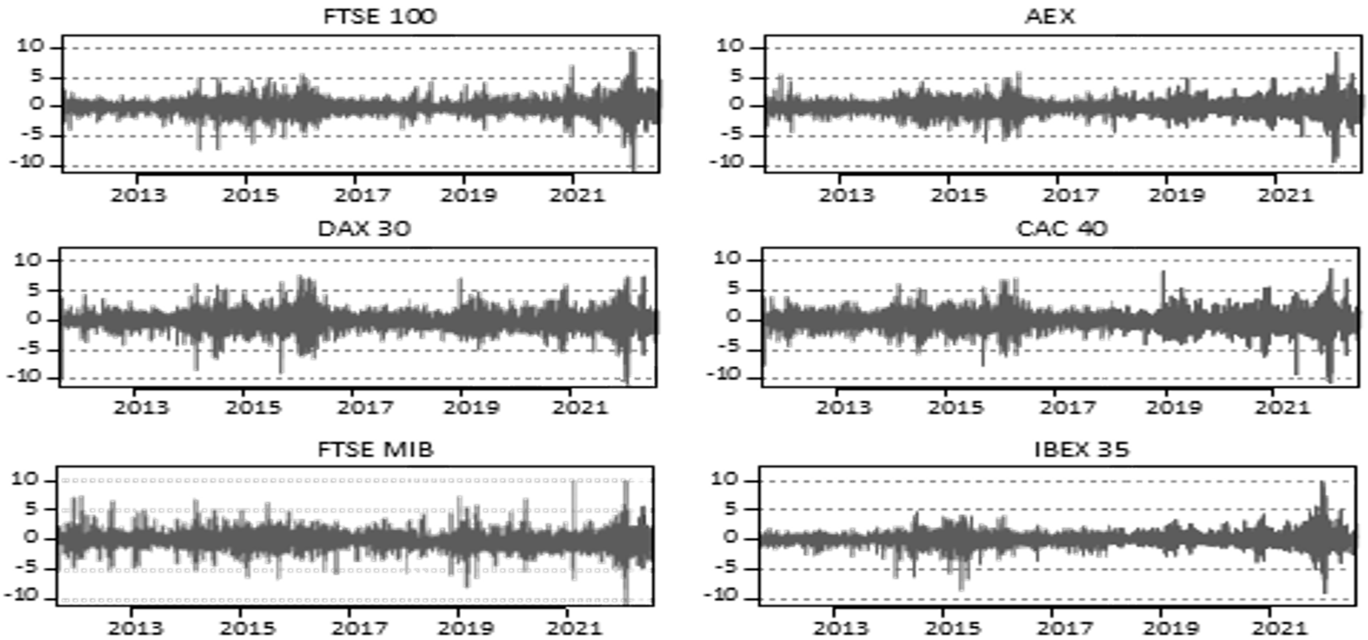


Figure 2: Monthly realized volatility

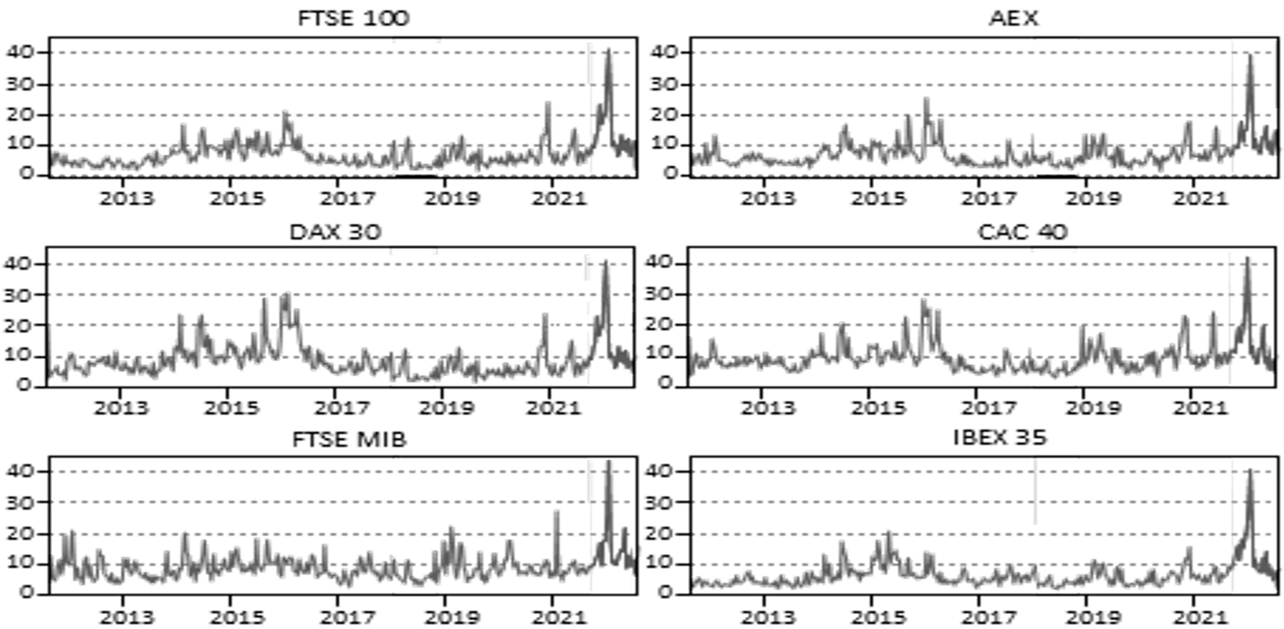


Figure 3: Monthly Sentiment index

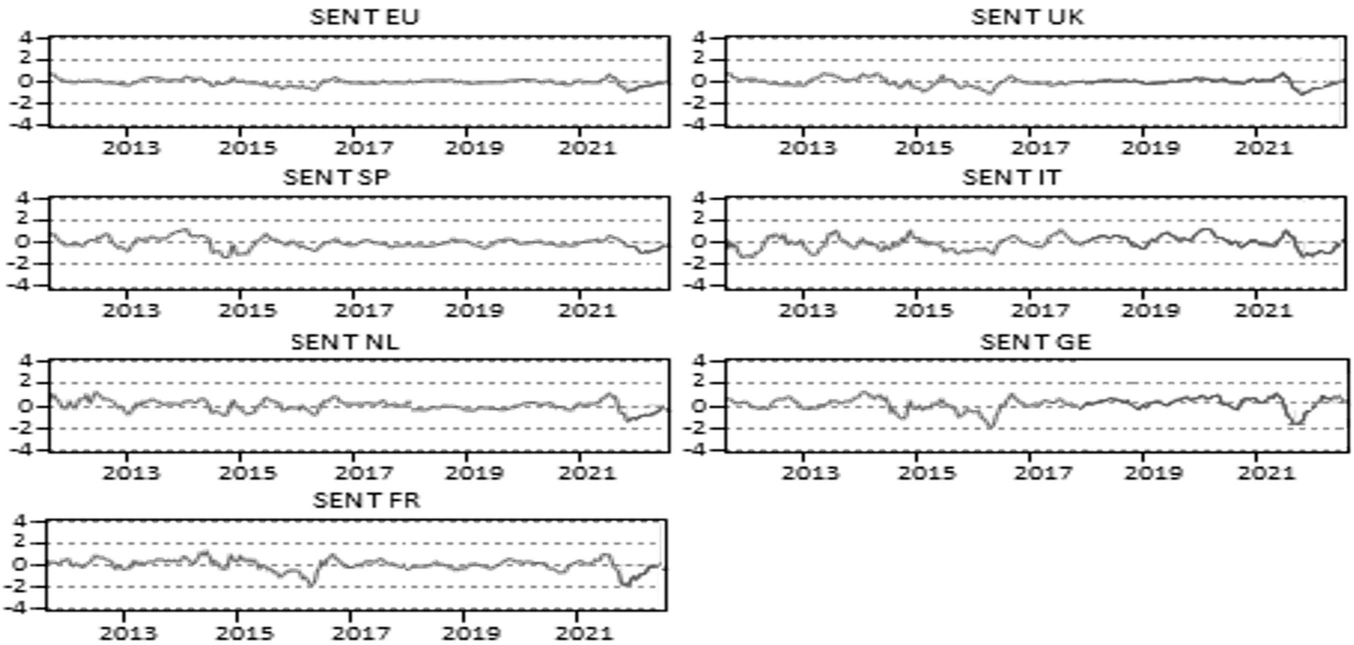
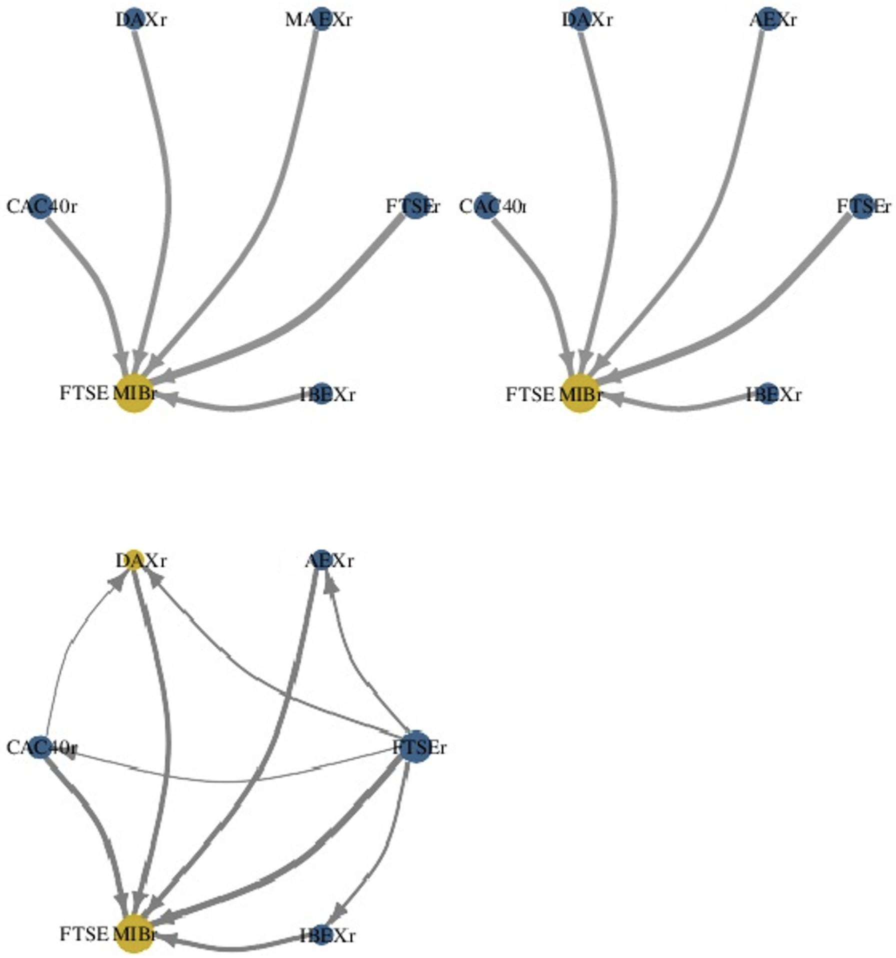
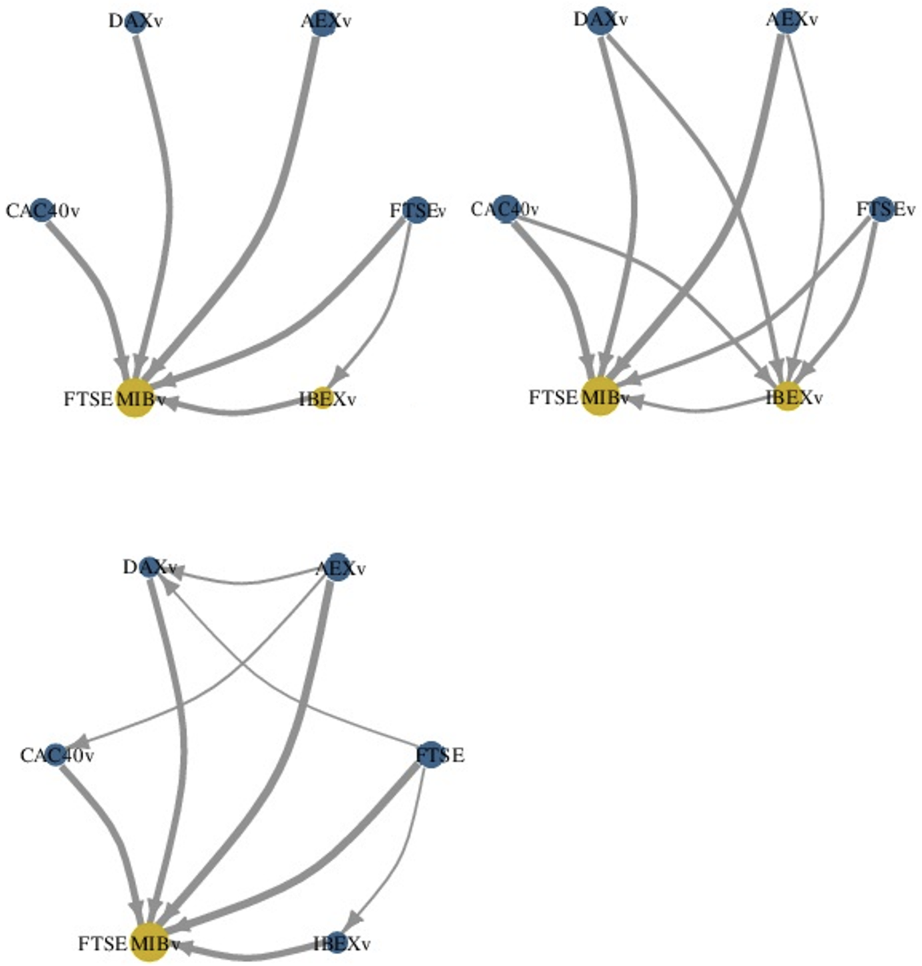


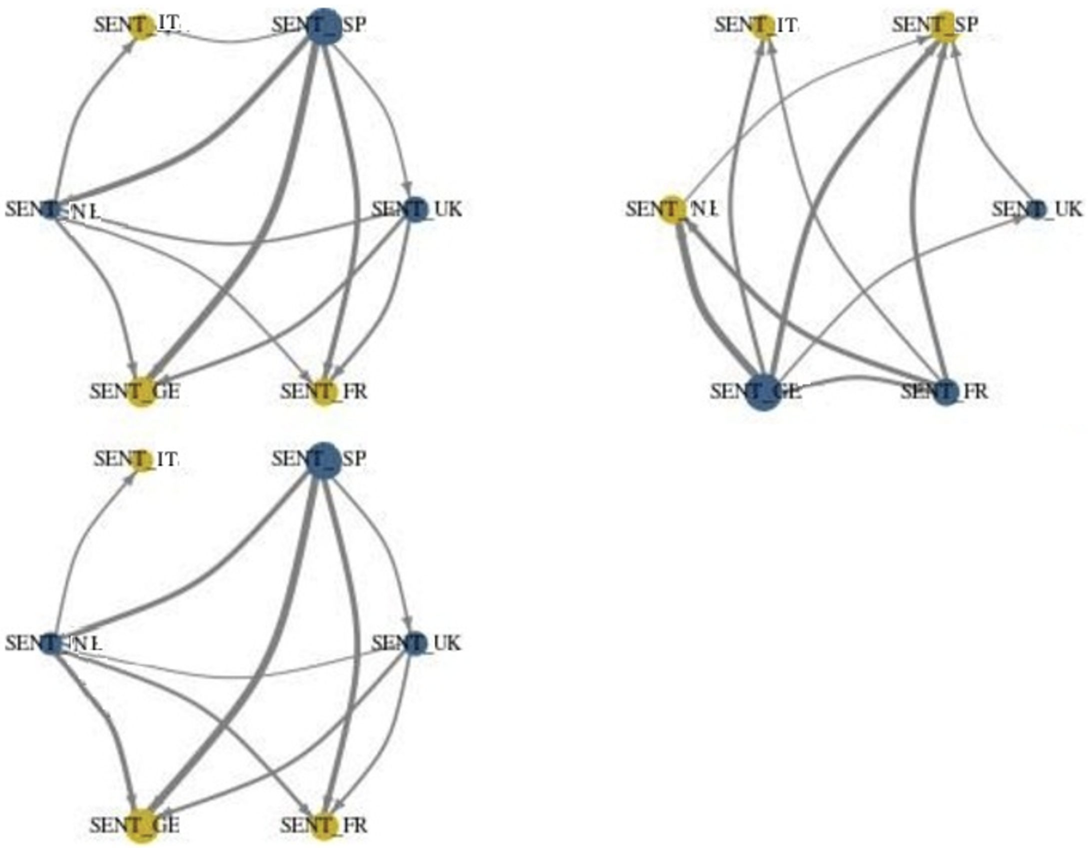
Figure 4: Network Connections for Returns, Volatility, and Sentiment



(a) Network Interconnectedness for return

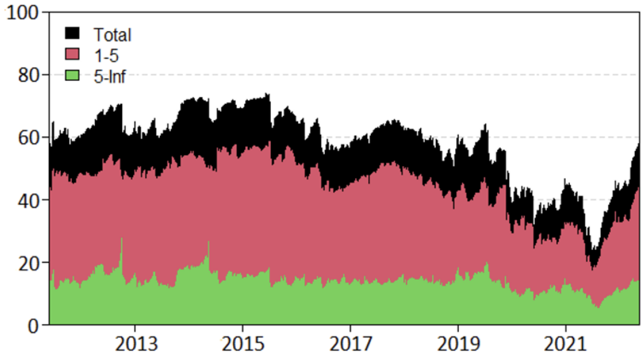


(b) Network Interconnectedness for volatility

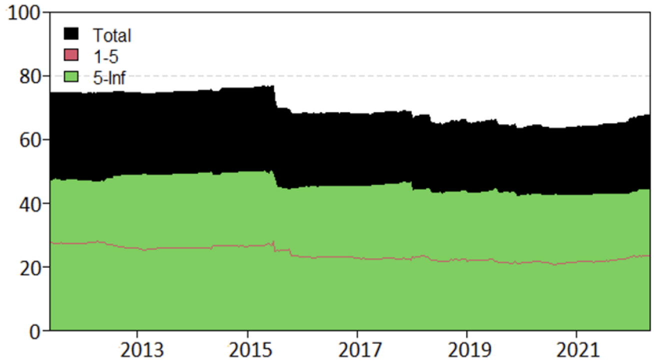


(c) Network Interconnectedness for sentiment

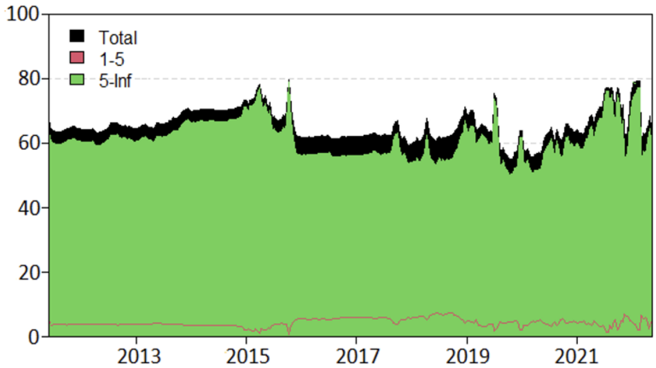
Figure 5: Total dynamic connectedness



(a) Total dynamic connectedness index (TCI) for return

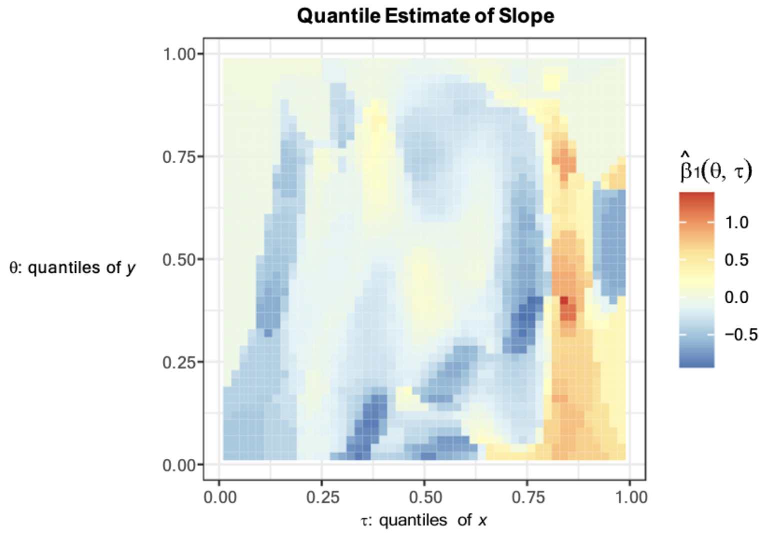


(b) Total dynamic connectedness index (TCI) for volatility

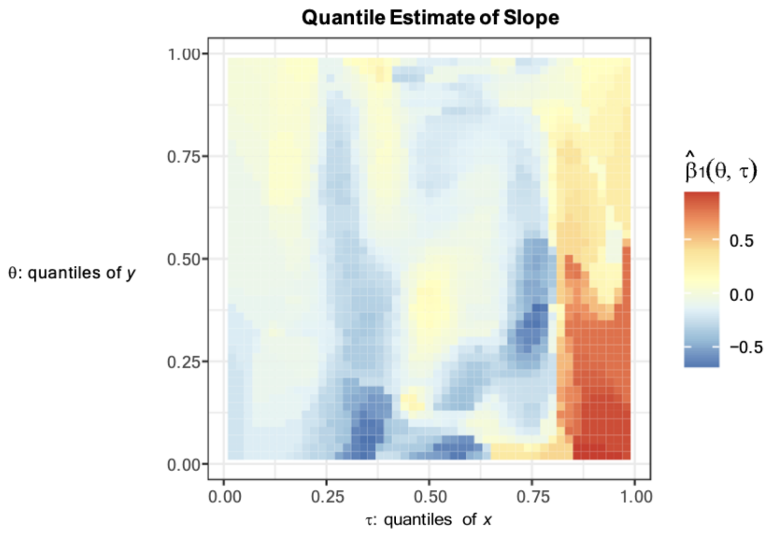


(c) Total dynamic connectedness index (TCI) for sentiment

Figure 6: Estimates of quantile slopes $\hat{\beta}_1(\theta, \tau)$ pertaining to the connectedness of returns or volatility



(a) Estimates of quantile slopes related to the interconnectedness of returns



(b) Estimates of quantile slopes related to the interconnectedness of volatility

Table 1: Stock Market and Sentiment Indices from 2011 to 2023

Country	Index	Period	Obs.	Freq.
Part 1: Stock market indices				
UK	FTSE 100	01.01.2011 to 31.12.2023	3,392	Daily
NL	AEX	01.01.2011 to 31.12.2023	3,392	Daily
GE	DAX	01.01.2011 to 31.12.2023	3,392	Daily
FR	CAC 40	01.01.2011 to 31.12.2023	3,392	Daily
IT	FTSE MIB	01.01.2011 to 31.12.2023	3,392	Daily
SP	IBEX 35	01.01.2011 to 31.12.2023	3,392	Daily
Part 2: Sentiment indices				
EU	SENT EU	01.01.2011 to 31.12.2023	156	Monthly
UK	SENT UK	01.01.2011 to 31.12.2023	156	Monthly
NL	SENT NL	01.01.2011 to 31.12.2023	156	Monthly
GE	SENT GE	01.01.2011 to 31.12.2023	156	Monthly
FR	SENT FR	01.01.2011 to 31.12.2023	156	Monthly
IT	SENT IT	01.01.2011 to 31.12.2023	156	Monthly
SP	SENT SP	01.01.2011 to 31.12.2023	156	Monthly

Table 2: Summary statistics for stock returns, market volatility, and sentiment indicators across six prominent stock markets in Europe

Part a. Market returns for Full period

	FTSE 100r	AEXr	DAXr	CAC40r	FTSE MIBr	IBEX 35r
Mean	0.026	0.013	0.026	0.014	-0.003	0.020
Variance	1.2	1.177	1.908	1.824	1.666	0.958
Skewness	-0.270***	-0.135***	-0.193***	-0.078***	-0.207***	-0.729***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	9.472***	6.455***	5.198***	4.979***	6.211***	11.227***
	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)
JB	26820.945***	12438.165***	8095.845***	7394.849***	11548.172***	38191.868***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-40.651***	-30.473***	-30.017***	-41.093***	-33.779***	-27.087***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q.20	59.723***	68.388***	20.971***	44.527***	25.776***	51.361***
	(0.000)	(0.009)	(0.000)	(0.000)	(0.001)	(0.000)
Q^2.20	5251.804***	4772.254***	3278.324***	3076.697***	3257.912***	5567.686***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Part b. Sentiment index of Europe and Local for Full period

	SENT EU	SENT UK	SENT SP	SENT IT	SENT NL	SENT GE	SENT FR
Mean	-0.001	0.002	-0.006	0.002	0.034	-0.004	-0.021
Variance	0.065	0.136	0.207	0.359	0.218	0.353	0.291
Skewness	-0.493***	-0.464***	-0.098	-0.097	-0.232*	-1.116***	-1.013***
	(0.000)	(0.001)	(0.462)	(0.467)	(0.085)	(0.000)	(0.000)
Kurtosis	1.077***	0.601**	0.477*	-0.629***	0.142	2.005***	1.716***
	(0.003)	(0.046)	(0.092)	(0.001)	(0.484)	(0.000)	(0.000)
JB	29.116***	16.700***	3.634	5.922*	3.185	123.066***	96.391***
	(0.000)	(0.000)	(0.163)	(0.052)	(0.203)	(0.000)	(0.000)
ERS	-1.404	-2.208**	-2.181**	-4.016***	-2.790*	-3.032***	-4.676***
	(0.161)	(0.028)	(0.030)	(0.000)	(0.006)	(0.003)	(0.000)
Q.10	857.813***	927.238***	946.773***	904.589***	774.835***	866.155***	868.751***
	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)
Q^2.10	518.103***	576.747***	713.968***	503.300***	548.311***	667.427***	605.532***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Part c. Volatility for Full period

	FTSE 100v	AEXv	DAXv	CAC40v	FTSE MIBv	IBEX 35v
Mean	7.311***	7.417***	9.537***	9.473***	9.097***	6.462***
Variance	20.091***	17.067***	26.717***	22.455***	19.463***	16.905***
Skewness	2.909***	2.762***	2.021***	2.303***	2.953***	3.260***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	14.112***	13.171***	5.786***	8.629***	18.719***	17.858***
	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)
JB	3194.185***	2796.268***	682.848***	1311.502***	5281.506***	4954.445***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-4.299***	-4.612***	-1.885*	-2.643***	-3.591***	-3.257***
	(0.000)	(0.000)	(0.060)	(0.009)	(0.000)	(0.001)
Q.20	551.372***	424.358***	485.000***	372.343***	135.360***	633.034***
	(0.000)	(0.009)	(0.000)	(0.000)	(0.001)	(0.000)
Q^2.20	55120.734***	195.746***	281.337***	207.656***	55.602***	296.039***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)

Note: The p-values are presented within parentheses, with asterisks (***, **, *) indicating significance levels at 1%, 5%, and 10%. The tests conducted include: Skewness: Assessed using the D'Agostino (1970) test. Kurtosis: Evaluated using the Anscombe & Glynn (1983) test. JB: Normality test based on the Jarque & Bera (1980) method. ERS: Unit-root test as per Elliott et al. (1996). Q.20, Q^2.20, and Q^2.10: Weighted portmanteau tests following the Fisher & Gallagher (2012) approach.

Table 3: Summary statistics for stock returns, volatility, and sentiment indicators across six prominent stock markets in Europe before and after the Covid-19 pandemic and Russia-Ukraine conflict

Part a. Market returns before Covid-19 pandemic and Russia-Ukraine conflict

	FTSE 100r	AEXr	DAXr	CAC40r	FTSE MIBr	IBEX 35r
Mean	0.026*	0.016	0.030	0.020	-0.010	0.028**
	(0.083)	(0.294)	(0.144)	(0.307)	(0.590)	(0.035)
Variance	0.996***	1.079***	1.887***	1.686***	1.499***	0.799***
Skewness	-0.130***	-0.136***	-0.342***	-0.157***	-0.031	-0.709***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.398)	(0.000)
Ex.Kurtosis	3.970***	3.239***	4.418***	3.036***	2.881***	6.356***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	2943.946***	1965.355***	3718.344***	1732.515***	1544.014***	7888.844***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-31.873***	-23.690***	-23.196***	-31.814***	-26.529***	-20.272***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q 20	26.448***	45.242***	24.315***	29.823***	29.774***	28.586***
	(0.001)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Q² 20	1090.989***	2263.829***	2159.425***	1765.546***	502.273***	704.752***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Part b. Market returns after Covid-19 pandemic and Russia-Ukraine conflict

	FTSE 100r	AEXr	DAXr	CAC40r	FTSE MIBr	IBEX 35r
Mean	0.026	0.008	0.020	0.004	0.008	0.005
	(0.269)	(0.706)	(0.463)	(0.894)	(0.755)	(0.812)
Variance	1.539***	1.342***	1.942***	2.053***	1.944***	1.221***
Skewness	-0.383***	-0.130***	0.046	0.023	-0.408***	-0.710***
	(0.000)	(0.006)	(0.331)	(0.627)	(0.000)	(0.000)
Ex.Kurtosis	12.333***	9.682***	6.424***	7.002***	9.216***	13.624***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	17100.314***	10505.546***	4623.279***	5491.631***	9587.430***	21015.847***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-8.223***	-11.125***	-18.129***	-14.382***	-5.141***	-10.760***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q 20	51.420***	40.766***	21.691***	35.478***	6.783	78.351***
	(0.000)	(0.000)	(0.008)	(0.000)	(0.842)	(0.000)
Q² 20	2427.217***	1989.185***	1202.878***	1212.178***	1806.370***	2971.485***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Part c. Volatility before and after Covid-19 pandemic and Russia-Ukraine conflict

	Before						After					
	FTSE 100v	AEXv	DAXv	CAC40v	FTSE MIBv	IBEX 35v	FTSE100v	AEXv	DAXv	CAC40v	FTSE MIBv	IBEX 35v
Mean	7.153***	7.343***	9.550***	9.363***	8.908***	6.326***	7.575***	7.541***	9.515***	9.657***	9.414***	6.690***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variance	12.832***	14.124***	26.354***	18.016***	12.696***	11.490***	32.342***	22.129***	27.544***	30.044***	30.832***	26.057***
Skewness	1.664***	1.853***	1.699***	1.859***	1.005***	1.946***	3.056***	3.423***	2.529***	2.517***	3.444***	3.558***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	4.178***	4.454***	3.210***	4.228***	1.111***	5.146***	12.432***	17.609***	9.768***	9.942***	18.459***	17.502***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	244.859***	288.113***	187.497***	272.156***	45.267***	357.258***	983.488***	1829.279***	620.099***	636.407***	1989.514***	1829.382***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-2.190**	-3.070***	-1.585*	-1.926**	-2.635***	-1.463*	-0.164	0.161	-0.015	-0.080	-0.027	0.190
	(0.030)	(0.002)	(0.115)	(0.050)	(0.009)	(0.145)	(0.870)	(0.872)	(0.988)	(0.937)	(0.979)	(0.850)
Q 20	396.710***	249.155***	384.650***	237.831***	60.754***	320.377***	114.706***	84.649***	114.448***	94.467***	39.646***	157.284***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q² 20	153.530***	121.121***	278.889***	164.843***	32.624***	137.501***	65.069***	32.842***	55.261***	40.835***	12.635	63.855***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.258)	(0.000)

Part d. Sentiment index before and after Covid-19 pandemic and Russia-Ukraine conflict

	Before						After					
	SENT UK	SENT SP	SENT IT	SENT NL	SENT GE	SENT FR	SENT UK	SENT SP	SENT IT	SENT NL	SENT GE	SENT FR
Mean	0.010	0.040	-0.103**	0.159***	0.094**	0.069*	-0.004	-0.065**	0.145***	-0.136***	-0.136***	-0.148***
	(0.733)	(0.293)	(0.013)	(0.000)	(0.027)	(0.070)	(0.894)	(0.018)	(0.006)	(0.001)	(0.007)	(0.001)
Variance	0.156***	0.280***	0.330***	0.191***	0.341***	0.278***	0.110***	0.101***	0.365***	0.207***	0.342***	0.282***
Skewness	-0.159	-0.206	0.070	-0.333*	-0.895***	-1.070***	-1.187***	-0.398*	-0.373*	-0.085	-1.574***	-1.077***
	(0.356)	(0.231)	(0.681)	(0.056)	(0.000)	(0.000)	(0.000)	(0.053)	(0.069)	(0.670)	(0.000)	(0.000)
Ex.Kurtosis	-0.186	-0.033	-0.573**	-0.231	1.310***	-1.799***	2.313***	0.073	-0.420	-0.972***	2.713***	1.965***
	(0.722)	(0.884)	(0.038)	(0.604)	(0.006)	(0.001)	(0.001)	(0.644)	(0.303)	(0.040)	(0.000)	(0.002)
JB	1.080	1.371	2.787	3.980	39.380***	62.519***	62.700***	3.647	4.179	-5.560*	98.557***	48.504***
	(0.583)	(0.504)	(0.248)	(0.137)	(0.000)	(0.000)	(0.000)	(0.161)	(0.124)	(0.062)	(0.000)	(0.000)
ERS	-1.718*	-2.022***	-3.651***	-2.681***	-2.577***	-3.283***	-3.842***	-2.364***	-2.980***	-3.518***	-2.762***	-3.993***
	(0.088)	(0.045)	(0.000)	(0.008)	(0.011)	(0.001)	(0.000)	(0.020)	(0.003)	(0.001)	(0.007)	(0.000)
Q 20	627.397***	632.585***	544.641***	391.010***	568.754***	557.023***	468.697***	520.939***	491.579***	469.168***	414.471***	442.845***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q² 20	292.594***	469.903***	267.824***	149.950***	326.979***	316.846***	387.199***	373.320***	273.697***	502.451***	361.055***	348.361***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: The p-values are presented within parentheses, with asterisks (***, **, *) indicating significance levels at 1%, 5%, and 10%. The tests conducted include: Skewness: Assessed using the D'Agostino (1970) test. Kurtosis: Evaluated using the Anscombe & Glynn (1983) test. JB: Normality test based on the Jarque & Bera (1980) method. ERS: Unit-root test as per Elliott et al. (1996). Q.20, Q2.20, and Q2.10: Weighted portmanteau tests following the Fisher & Gallagher (2012) approach.

Table 4: Correlation Matrix for stock returns, sentiment indicators across six prominent stock markets in Europe for the full period and before and after the Covid-19 pandemic and Russia-Ukraine conflict

Part a. Stock returns for the Full period

	FTSE 100r	AEXr	DAXr	CAC40r	FTSEMIBr	IBEX35r
FTSE 100r	1.000					
AEXr	0.494***	1.000				
DAXr	0.528***	0.759***	1.000			
CAC40r	0.512***	0.836***	0.836***	1.000		
FTSEMIBr	0.115***	0.272***	0.246***	0.264***	1.000	
IBEX35r	0.709***	0.505***	0.493***	0.499***	0.198***	1.000

Part b. Stock returns before Covid-19 and war

	FTSE 100r	AEXr	DAXr	CAC40r	FTSEMIBr	IBEX35r
FTSE 100r	1.000					
AEXr	0.264***	1.000				
DAXr	0.264***	0.475***	1.000			
CAC40r	0.266***	0.563***	0.553***	1.000		
FTSEMIBr	0.071***	0.145***	0.152***	0.147***	1.000	
IBEX35r	0.434***	0.291***	0.278***	0.279***	0.105***	1.000

Part c. Stock returns after Covid-19 and war

	FTSE 100r	AEXr	DAXr	CAC40r	FTSEMIBr	IBEX35r
FTSE 100r	1.000					
AEXr	0.388***	1.000				
DAXr	0.404***	0.620***	1.000			
CAC40r	0.415***	0.661***	0.752***	1.000		
FTSEMIBr	0.068***	0.157***	0.146***	0.153***	1.000	
IBEX35r	0.524***	0.373***	0.362***	0.374***	0.111***	1.000

Part d. Sentiment indices for Full period

	SENT EU	SENT UK	SENT SP	SENT IT	SENT NL	SENT GE	SENT FR
SENT EU	1.000	–	–	–	–	–	–
SENT UK	0.837***	1.000	–	–	–	–	–
SENT SP	0.500***	0.658***	1.000	–	–	–	–
SENT IT	0.569***	0.315***	0.129**	1.000	–	–	–
SENT NL	0.686***	0.722***	0.674***	0.369***	1.000	–	–
SENT GE	0.747***	0.740***	0.563***	0.423***	0.718***	1.000	–
SENT FR	0.780***	0.633***	0.443***	0.514***	0.651***	0.817***	1.000

Part e. Sentiment indices before Covid-19 and war

	SENT EU	SENT UK	SENT SP	SENT IT	SENT NL	SENT GE	SENT FR
SENT EU	1.000	–	–	–	–	–	–
SENT UK	0.520***	1.000	–	–	–	–	–
SENT SP	0.480***	0.506***	1.000	–	–	–	–
SENT IT	0.455***	-0.004	0.042	1.000	–	–	–
SENT NL	0.470***	0.460***	0.529***	0.194***	1.000	–	–
SENT GE	0.460***	0.421***	0.486***	0.250***	0.460***	1.000	–
SENT FR	0.485***	0.263***	0.272***	0.349***	0.291***	0.528***	1.000

Part f. Sentiment indices after Covid-19 and war

	SENT EU	SENT UK	SENT SP	SENT IT	SENT NL	SENT GE	SENT FR
SENT EU	1.000	–	–	–	–	–	–
SENT UK	0.460***	1.000	–	–	–	–	–
SENT SP	0.390***	0.479***	1.000	–	–	–	–
SENT IT	0.420***	0.442***	0.181***	1.000	–	–	–
SENT NL	0.450***	0.690***	0.430***	0.397***	1.000	–	–
SENT GE	0.490***	0.599***	0.247***	0.370***	0.614***	1.000	–
SENT FR	0.510***	0.616***	0.438***	0.459***	0.649***	0.612***	1.000

Note: *, **, *** represent significance levels at 10%, 5%, and 1%, respectively.

Table 5: Average dynamic connectedness and TVP-VAR frequency domain

Part a							
	FTSE 100r	**AEXr**	**DAXr**	**CAC40r**	**FTSE MIBr**	**IBEX 35r**	**FROM**
FTSE 100r	**45.72 (37.16)[8.56]**	10.82 (8.77)[2.05]	10.64 (8.60)[2.04]	11.16 (9.01)[2.15]	1.35 (1.12)[0.23]	20.31 (16.51)[3.81]	54.28 (44.00)[10.28]
AEXr	12.05 (8.57)[3.48]	**37.54 (29.94)[7.59]**	17.15 (13.74)[3.42]	21.71 (17.41)[4.30]	2.10 (1.76)[0.34]	9.45 (6.81)[2.64]	62.46 (48.28)[14.18]
DAXr	12.81 (9.38)[3.43]	17.30 (13.50)[3.79]	**36.18 (29.03)[7.15]**	22.97 (17.86)[5.11]	2.09 (1.70)[0.39]	8.65 (6.37)[2.29]	63.82 (48.81)[15.01]
CAC40r	11.36 (8.22)[3.14]	20.73 (16.65)[4.08]	21.54 (17.33)[4.21]	**35.80 (28.74)[7.06]**	2.04 (1.68)[0.36]	8.53 (6.26)[2.27]	64.20 (50.13)[14.07]
FTSE MIBr	10.79 (7.61)[3.18]	8.75 (6.01)[2.73]	8.83 (6.13)[2.70]	9.36 (6.46)[2.90]	**53.99 (42.62)[11.36]**	8.29 (5.69)[2.60]	46.01 (31.90)[14.11]
IBEX 35r	21.58 (16.17)[5.40]	10.19 (7.85)[2.34]	9.08 (6.99)[2.09]	9.93 (7.59)[2.33]	1.70 (1.32)[0.38]	**47.52 (36.37)[11.15]**	52.48 (39.92)[12.56]
TO	68.59 (49.95)[18.64]	67.78 (52.79)[15.00]	67.24 (52.78)[14.46]	75.12 (58.33)[16.80]	9.29 (7.57)[1.71]	55.24 (41.62)[13.61]	**TCI**
NET	14.31 (5.95)[8.36]	5.32 (4.51)[0.81]	3.42 (3.97)[-0.55]	10.92 (8.19)[2.73]	-36.73 (-24.32)[-12.40]	2.76 (1.70)[1.05]	**68.65 (52.61)[16.04]**
Part b							
	FTSE100v	**AEXv**	**DAXv**	**CAC40v**	**FTSE MIBv**	**IBEX 35v**	**FROM**
FTSE 100v	**28.97 (9.93)[19.04]**	17.93 (5.47)[12.45]	16.14 (5.01)[11.13]	15.75 (5.24)[10.51]	3.61 (1.67)[1.94]	17.61 (5.58)[12.03]	71.03 (22.97)[48.06]
AEXv	17.80 (5.46)[12.34]	**25.84 (9.90)[15.94]**	17.93 (6.03)[11.91]	20.60 (7.75)[12.85]	5.72 (2.92)[2.80]	12.11 (3.92)[8.19]	74.16 (26.08)[48.08]
DAXv	17.31 (4.66)[12.64]	19.54 (5.56)[13.98]	**26.70 (9.08)[17.63]**	21.03 (6.70)[14.33]	3.91 (1.99)[1.92]	11.52 (3.71)[7.80]	73.30 (22.63)[50.67]
CAC40v	16.87 (5.02)[11.85]	22.03 (7.38)[14.65]	20.34 (6.88)[13.46]	**25.36 (9.52)[15.83]**	4.58 (2.40)[2.17]	10.82 (3.61)[7.21]	74.64 (25.30)[49.34]
FTSE MIBv	11.15 (3.37)[7.78]	14.50 (5.78)[8.72]	10.99 (4.19)[6.80]	12.31 (5.03)[7.28]	**40.54 (25.02)[15.53]**	10.51 (3.36)[7.15]	59.46 (21.71)[37.74]
IBEX 35v	21.25 (7.49)[13.77]	13.92 (5.13)[8.79]	13.48 (4.56)[8.01]	12.46 (5.07)[7.38]	4.38 (2.09)[2.29]	**34.51 (13.72)[20.80]**	65.49 (25.24)[40.25]
TO	84.38 (26.00)[58.37]	87.91 (29.32)[58.57]	78.88 (27.56)[51.31]	82.15 (29.79)[52.36]	22.20 (11.08)[11.13]	62.56 (20.18)[42.38]	**TCI**
NET	13.35 (3.03)[10.32]	13.75 (3.24)[10.51]	5.58 (4.94)[0.64]	7.51 (4.49)[3.02]	-37.26 (-10.64)[-26.62]	-2.93 (-5.06)[2.13]	**69.68 (23.99)[45.69]**
Part c							
	SENT UK	**SENT SP**	**SENT IT**	**SENT NL**	**SENT GE**	**SENT FR**	**FROM**
SENT UK	**35.51 (3.25)[32.27]**	22.10 (1.31)[20.79]	6.51 (0.35)[6.16]	13.29 (1.29)[12.01]	12.76 (1.22)[11.53]	9.84 (0.76)[9.08]	64.49 (4.49)[59.56]
SENT SP	16.35 (1.54)[14.81]	**45.17 (3.70)[41.47]**	6.26 (0.17)[6.09]	11.48 (1.03)[10.45]	10.68 (0.95)[9.73]	10.06 (0.79)[9.27]	54.83 (4.49)[50.34]
SENT IT	10.76 (0.54)[10.22]	9.51 (0.24)[9.27]	**43.47 (5.67)[37.80]**	12.78 (0.42)[12.36]	12.61 (0.55)[12.06]	10.87 (0.48)[10.39]	56.53 (2.24)[54.29]
SENT NL	16.46 (1.61)[14.85]	17.35 (1.13)[16.23]	7.31 (0.40)[6.91]	**32.63 (4.57)[28.06]**	13.70 (1.54)[12.16]	12.54 (1.17)[11.38]	67.37 (5.84)[61.53]
SENT GE	16.88 (0.80)[16.07]	19.34 (0.48)[18.86]	7.06 (0.023)[6.83]	15.58 (0.69)[14.90]	**22.43 (2.52)[19.91]**	18.71 (1.66)[17.05]	77.57 (3.86)[73.70]
SENT FR	15.84 (0.73)[15.11]	14.09 (0.63)[13.46]	7.27 (0.29)[6.98]	14.88 (0.81)[14.07]	20.12 (2.62)[17.50]	**27.80 (3.95)[23.85]**	72.20 (5.08)[67.12]
TO	76.29 (5.23)[71.07]	82.39 (3.79)[78.60]	34.41 (1.43)[32.97]	68.01 (4.23)[63.77]	69.87 (6.89)[62.98]	62.02 (4.86)[57.15]	**TCI**
NET	11.80 (0.30)[11.51]	27.56 (-0.70)[28.26]	-22.12 (-0.80)[-21.32]	0.64 (-1.61)[2.25]	-7.70 (3.03)[-10.73]	-10.18 (-0.21)[-9.97]	**65.50 (4.41)[61.09]**

Note: This table reports the variance decompositions for the estimated TVPVAR model in frequency domain addressing different European stock market returns, realized volatility and sentiment. Values in parentheses () and brackets [] represent short and long term frequency connectedness, respectively. The diagonal elements (in black) are the own variance, while the offdiagonal entries are the pairwise directional connectedness. The row sums to TO and column sums to FROM. The NET row is the difference between TO and FROM. The TCI row at the bottom is the total connectedness index in the system.

Table 6: Time-domain TVP-VAR analysis of interconnectedness for sentiment indicators, stock returns, and volatility across six prominent stock markets in Europe before and after the Covid-19 pandemic and Russia-Ukraine conflict

Part a. Dynamic Connectedness in Sentiment for Pre-covid-19 and War

	SENTUK	**SENTSP**	**SENTIT**	**SENTNL**	**SENTGE**	**SENTFR**	**From**
SENTUK	**45.77**	24.88	3.22	10.65	9.35	6.14	54.23
SENTSP	16.00	**56.62**	3.38	10.95	6.62	6.43	43.38
SENTIT	7.94	7.50	**62.64**	10.17	6.18	5.57	37.36
SENTNL	17.76	17.56	6.39	**42.29**	8.23	7.77	57.71
SENTGE	17.65	22.47	4.70	18.54	**19.50**	17.14	80.50
SENTFR	16.25	16.72	3.94	15.38	16.41	**31.30**	68.70
TO	75.61	89.14	21.63	65.68	46.79	43.04	341.90
NET	21.38	45.76	-15.73	7.97	-33.71	-25.66	**TCI**
NPDC	1.00	0.00	5.00	2.00	4.00	3.00	56.98

Part b. Dynamic Connectedness in Sentiment for Post-covid-19 and War

	SENTUK	**SENTSP**	**SENTIT**	**SENTNL**	**SENTGE**	**SENTFR**	**From**
SENTUK	**35.82**	23.82	5.04	16.60	10.01	8.71	64.18
SENTSP	11.45	**57.67**	6.96	9.54	8.13	6.24	42.33
SENTIT	8.68	10.01	**49.88**	11.66	11.95	7.82	50.12
SENTNL	19.60	20.19	4.76	**34.77**	11.68	9.01	65.23
SENTGE	17.81	17.65	5.59	19.08	**20.98**	18.89	79.02
SENTFR	13.17	13.75	6.07	16.23	20.74	**30.05**	69.95
TO	70.71	85.42	28.42	73.10	62.52	50.67	370.84
NET	6.53	43.09	-21.71	7.87	-16.50	-19.28	**TCI**
NPDC	1.00	0.00	5.00	2.00	3.00	4.00	61.81

Note: The table contains a decomposition of forecast error variance computed for the sentiment factors for six main European market. Elements in the off-diagonal entries are the PAIRWISE directional connectedness, while the diagonal elements (in black) are the sentiments' own variance. The terms "FROM" and "TO" indicates the measure of the directional connectedness that a given variable i receives the shocks from all other variables j, following Eq.(34) and the directional connectedness that a given variable i transmits its shock to all other variables j, following Eq. (33), respectively. The NET row at the bottom is the difference between TO and FROM following Eq.(35). NPDC means the net pairwise directional connectedness following Eq.(32). TCI indicates the total connectedness in the system following Eq (36).

Table 7: TVP–VAR connectedness in time domain for returns and volatility (Pre- and Post-covid-19)

Return for Pre-covid-19 and War

	FTSE100r	AEXr	DAXr	CAC40r	FTSEMIBr	IBEX35r	From
FTSE100r	**51.97**	8.84	8.48	8.78	0.98	20.95	48.03
AEXr	10.94	**42.09**	15.41	21.55	1.88	8.13	57.91
DAXr	12.72	15.81	**40.20**	21.31	1.79	8.17	59.80
CAC40r	10.03	20.62	19.64	**40.46**	1.75	7.51	59.54
FTSEMIBr	8.37	6.99	6.81	7.15	**63.86**	6.82	36.14
IBEX35r	22.01	8.26	7.46	8.06	1.44	**52.76**	47.24
TO	64.07	60.52	57.81	66.84	7.84	51.58	308.65
NET	16.04	2.61	-2.00	7.30	-28.30	4.34	**TCI**
NPDC	0.00	2.00	4.00	1.00	5.00	3.00	51.44

Return for Post-covid-19 and War

	FTSE100r	AEXr	DAXr	CAC40r	FTSEMIBr	IBEX35r	From
FTSE100r	**36.36**	13.79	13.96	14.62	1.76	19.51	63.64
AEXr	13.77	**30.46**	20.10	22.19	2.15	11.34	69.54
DAXr	13.22	19.80	**29.97**	25.25	2.27	9.50	70.03
CAC40r	13.30	21.17	24.43	**28.82**	2.32	9.96	71.18
FTSEMIBr	14.33	11.15	11.66	12.58	**40.02**	10.26	59.98
IBEX35r	21.17	13.14	11.69	12.68	1.95	**39.37**	60.63
TO	75.79	79.04	81.83	87.32	10.45	60.57	395.00
NET	12.15	9.50	11.80	16.14	-49.52	-0.06	**TCI**
NPDC	3.00	2.00	1.00	0.00	5.00	4.00	65.83

Volatility for Pre-covid-19 and War

	FTSE100v	AEXv	DAXv	CAC40v	FTSEMIBv	IBEX35v	From
FTSE100v	**35.36**	13.49	11.72	10.12	2.76	26.55	64.64
AEXv	13.61	**31.54**	13.77	20.71	8.55	11.83	68.46
DAXv	11.91	19.46	**29.34**	18.39	5.28	15.62	70.66
CAC40v	11.73	24.49	17.93	**29.11**	5.79	10.95	70.89
FTSEMIBv	4.61	12.43	5.71	5.94	**65.69**	5.62	34.31
IBEX35v	21.75	11.46	11.64	7.55	1.88	**45.72**	54.28
TO	63.60	81.33	60.77	62.71	24.26	70.57	363.24
NET	-1.04	12.87	-9.89	-8.18	-10.05	16.29	**TCI**
NPDC	4.00	3.00	1.00	2.00	0.00	5.00	60.54

Volatility for Post-covid-19 and War

	FTSE100v	AEXv	DAXv	CAC40v	FTSEMIBv	IBEX35v	From
FTSE100v	**25.85**	18.00	13.31	14.42	6.83	21.60	74.15
AEXv	18.01	**22.98**	15.35	18.15	9.34	16.17	77.02
DAXv	17.00	19.12	**22.35**	18.76	7.79	14.96	77.65
CAC40v	17.15	20.87	18.04	**21.48**	7.87	14.60	78.52
FTSEMIBv	13.75	16.27	11.13	12.50	**30.95**	15.41	69.05
IBEX35v	21.99	15.86	11.57	12.34	7.58	**30.65**	69.35
TO	87.90	90.12	69.40	76.16	39.42	82.74	445.74
NET	13.74	13.10	-8.24	-2.36	-29.63	13.40	**TCI**
NPDC	13.74	13.10	-8.24	-2.36	-29.63	13.40	74.29

Note: The table contains a decomposition of forecast error variance of the TVP–VAR model addressing different stock market returns and volatility for six main European markets. Elements in the off-diagonal entries are the pairwise directional connectedness, while the diagonal elements (in bold) represent the own variance (or volatility) of the series. The terms “FROM” and “TO” indicate, respectively, the directional connectedness received from and transmitted to all other variables (see Eq. (34) and (33)). The NET row shows the difference between TO and FROM (Eq. (35)). NPDC denotes the net pairwise directional connectedness (Eq. (32)), and TCI indicates the total connectedness in the system (Eq. (36)).

Table 8: Regression analysis using Baker et al. (2012) model for sentiment indicators across six prominent stock markets in Europe

$$R_{MKT,c,t} \;=\; a \;+\; b\,\mathrm{SENT}^{EU}_{t-1} \;+\; c\,\mathrm{SENT}^{Local}_{t-1} \;+\; v_{c,t}$$

Coefficients	SENT^{EU}_{t-1}		$\mathrm{SENT}^{Local}_{t-1}$		$\mathbf{R^2}$
	b	$[p(b)]$	c	$[p(c)]$	
Part a : Full period					
Including UK	-0.08824	[0.001]	-0.06836	[0.605]	0.84%
Excluding UK	-0.08903	[0.002]	-0.06380	[0.647]	0.83%
Part b : Pre-covid-19 and war					
Including UK	-0.12055	[0.000]	-0.03661	[0.179]	0.65%
Part c : Post-covid-19					
Including UK	-0.252915	[0.049]	-0.090563	[0.024]	0.72%
Part d : Post-Russia-Ukraine conflict					
Including UK	-0.1518	[0.055]	-0.04186	[0.074]	0.88%

Note: The regression results of the Baker et al. (2012) model. In Part a, (1) the sample includes monthly country-level index returns between 2010 to 2022 in six European countries. In Part a, (2), the sample excludes UK data. The first and third column show the results from (38) for SENT^{EU}_{t-1} et $\mathrm{SENT}^{Local}_{t-1}$ respectively, the second and fourth columns show the clustered p-values are in brackets and the last column tabulate the R^2. Part a reports results for the full sample period while Part b, c and d report results respectively during the non-Covid-19 and Russia-Ukraine conflict, the Covid-19 pandemic period and the Russia-Ukraine conflict period.

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