Investigating Systemic Risk with Co-occurrence Networks

Studies from the fields of sovereign bond and energy markets

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Doktori értekezés

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Expression of gratitude

To Kriszti

At the culmination of this academic endeavor, I am deeply grateful for the multitude of influences that have guided and shaped this thesis. First and foremost I am very thankful for my supervisor, Zsuzsa Huszar who provided a tremendous amount of help to make the content of this dissertation happen. I also owe gratitude to Zsolt Bihary, who have been my supervisor in the first two and a half years of my studies and provided countless analytical support.

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This doctoral dissertation represents the culmination of an extensive research journey, presented in a format that adheres to conventions typical of scientific finance writing - an article-based thesis. In contrast to the traditional monograph, this work is structured around three distinct articles, each intended for submission to esteemed academic journals. Together, these articles form a comprehensive exploration of co-occurrence network-based systemic risk, making a significant contribution to the existing body of knowledge in this field.

The decision to pursue an article-based dissertation was driven by a desire to disseminate research findings in a manner consistent with prevailing academic practices. This format not only enables the dissemination of research outcomes through rigorous peer-reviewed publications but also serves to enhance the visibility and impact of the research, facilitating meaningful engagement with the broader academic community and policy-makers.

The focal point of the dissertations are three research articles which are framed by the introduction and the conclusion to provide foundation knowledge, contextualization and discussion of further research based on the research findings. Each of the three articles represents a distinct investigation within the broader research domain. While they can stand alone as individual contributions, they are interconnected by common research themes: systemic risk and network models.

The articles within this dissertation are the product of original ideas and personal intellectual contributions. However, to align with established academic conventions, the collective pronoun 'we' is utilized instead of 'I' in the articles. This linguistic choice is made to reflect the collaborative nature of the research process, acknowledging the active participation of senior coauthors during the publication phase.

This journey is a testament to our commitment to advancing knowledge and fostering innovation in the field of systemic risk analysis.

CHAPTER

I

INTRODUCTION

This thesis aims to educate about the different facets of systemic risk, that emanate from multiple sources, including the financial sector and the energy market, and potentially others that are yet to be identified.

Systemic risk, a critical concept in the field of finance and economics, refers to the potential for a disturbance or shock to propagate through interconnected financial institutions and markets, leading to widespread disruptions and potentially catastrophic consequences for the entire financial system and economy. Systemic risk, as the term suggests, poses a threat to the entire financial system and, by extension, to the broader economy that can be detrimental, especially in a concentrated market. It differs fundamentally from the well-understood systematic risk, which relates to market-wide factors such as interest rates and economic cycles. While systematic risk is characterized by a certain degree of predictability and is amenable to quantitative measurement, systemic risk is marked by its elusive nature.

Unlike systematic risk, the sources, implications, and characteristics of systemic risk remain shrouded in ambiguity, and continuously evolve, much like the global financial markets themselves. The roots of systemic risk can be traced back to the intricate web of relationships and dependencies within mainly the financial sector, but other markets as well. This interconnectedness not only facilitates the transmission of shocks but also creates a scenario where the failure of a single institution could trigger a domino effect, causing a cascade of failures across the system. The interconnectedness is also prevalent at the country levels within the EU, or the USA dominance in the financial sector.

In light of these challenges and knowledge gaps, this thesis contributes to the ongoing discourse surrounding systemic risk. By investigating its sources, implications, and characteristics, we seek to shed light on this elusive risk and explore the development of tools for its measurement. As we traverse the terrain of systemic risk in both known and potentially unidentified sources, our objective is to equip financial professionals, regulators, and policymakers with a more nuanced understanding of this complex risk and the means to mitigate its detrimental effects on the global economy.

The inherent fragility of the international economic and financial system was made evident by the 2008 Global Financial Crisis (GFC). A genuine real economy shock became a systemic financial event that affected a large number of (mostly financial) firms and had significant social and public consequences because of the financial industry's size, interconnection, opacity, and complexity. To comprehensively understand systemic risk, it is essential to adopt a holistic perspective on diverse economic systems, which incorporates the internal and external feedback dynamics that lie at the heart of financial systemic events.

As of today, there is still no consensus about the definition of systemic risk. In an early study on measuring systemic risk with econometric models, Billio et al. (2012) (p. 536) say: *"... although most regulators and policymakers believe that systemic events can be identified after the fact, a precise definition of systemic risk seems remarkably elusive... "*. According to the European Central Bank (ECB), systemic risk is a risk of financial instability: *"...so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially."* (ECB (2010), p. 129). Others concentrate on more particular mechanisms, including negative externalities (Financial Stability Board (2009)), information disruptions (Mishkin et al. (2009)), imbalances (Caballero (2010)), asset bubbles (Rosengren et al. (2010)), contagion (Moussa (2011)), feedback behavior (Kapadia et al. (2012)), correlated exposures (Acharya et al. (2017)) and event probability (Montagna et al. (2020)). Anabtawi and Schwarcz (2011) (p. 1351) define systemic risk as *"...the risk that a localized adverse shock, such as the collapse of a firm or market, will have repercussions that negatively impact the broader economy."* which can be regarded as a broad definition. By this means, systemic risk is not restricted to a single industry or type of corporation and relates to an impact on the entire economy.

The lack of agreement about systemic risk, suggests that likely more than one risk measure is required to adequately account for the financial system's complexity and adaptability. Despite increased attention, it is still challenging to define and assess the concept of systemic risk (Hansen (2013)). To evaluate systemic risk, several theoretical frameworks have been proposed. Some studies measure tail interdependence between assets market indices (Adrian and Brunnermeier (2011); Acharya et al. (2017)) or on estimating the threat carried on by interconnectedness (Diebold et al. (2008); Billio et al. (2012)). Other approaches (Basel Committee (2011); Hollo et al. (2012)) aggregate several market indicators to determine the system's level of stress, taking into account the multidimensionality of systemic risk. Last but not least, a class of popular models uses microstructural approaches, in which interactions between agents are individually modeled, to describe a complex system and investigate the spread of financial contagion via various channels in response to an exogenous initial shock (Allen and Gale (2000); Gai and Kapadia (2010); Acemoglu et al. (2012); Montagna and Kok (2016); Nyman et al. (2021)). Since the Global Financial Crisis (GFC), defining, characterizing, and measuring systemic risk has remained a contentious issue in financial economics and econometrics. The multifaceted nature of systemic risk defies a universal definition. Equally challenging is the development of robust quantitative methodologies to measure it. In this dissertation, a comprehensive exploration of systemic risk is undertaken from various angles, aiming to contribute to this ongoing discourse and provide valuable insights into its intricate complexities.

After this very brief summary of the concept of systemic risk, the rest of this thesis is structured as follows. In Chapter II, a short review is given on the interpretation of systemic risk in the context of the financial industry. In Sections II.1.3 and II.2 this context is broadened to the market of sovereign bonds and energy assets.[1] Section II.3 provides an overview of different financial networks, while Section II.3.3 introduces the usage of the econometric models utilized in Chapters III, IV and V.

In Chapter III, we examine the sovereign yield curve network of 12 developed countries by analyzing the term structure of interest rates using a decomposition model. The connections between latent yield curve factors across countries are measured using a suitable cointegration model, revealing differences during global and local crises. The Chapter also explores the role of US latent factors, network density variations during crises, and the relationship between central banks' decisions and the dominance of the US yield curve in the network.

Chapter IV investigates the volatility transmissions within the European energy industry across different production segments. Analyzing the period from October 2006 to June 2022, the research identifies notable internal volatility spillovers, particularly originating from Upstream companies. The study demonstrates that Downstream and Midstream segments can also transmit volatility under specific circumstances. Remarkably, prominent Russian Integrated Oil Gas (IOG) firms shifted from being volatility absorbers to significant transmitters post-2022 due to geopolitical events, potentially causing systemic instability.

[1] In sections II.1, II.1.3 and II.2, only those literature is presented that is not part of the later body of this thesis.

In Chapter V, we examine energy risk's systemic nature and its regional impact. Analyzing 24 European Economic Area countries, we explore the links between energy price fluctuations, equity market behavior, and volatility using various methods. Findings highlight major sources of volatility, energy shocks' influence on equity markets, and increased risk from green energy sources. It also reveals Central and Eastern European market sensitivity to energy shocks during currency depreciation against the Euro. Chapter VI provides future research ideas, focusing on climate risk and asset pricing models, then lastly Chapter VII concludes.

CHAPTER

II

LITERATURE REVIEW ON SYSTEMIC RISK AND NETWORK MODELS

II.1 Systemic risk from the financial sector

Due to the substantial influence that issues in the banking industry may have on the larger financial system, the idea of systemic risk was first introduced in the field of banking. Initially, the phrase *"systemic risk"* was used to refer to threats to the overall stability of the financial system, such as the possibility of widespread failures and disruptions. The phrase *"too big to fail"* originated with the GFC and expresses the idea that some banks are so enormous and essential to the economy's operation that their failure would have serious systemic repercussions. In this section, the basic concepts of banking-related systemic risk are introduced to understand the theoretical background and set the scope to be broadened in Sections II.1.3 and II.2.

Jackson and Pernoud (2021) make a distinction between two types of interbank dependencies that may lead to systemic risk. First is when a change in the value of one bank ripples across the system and has wide-ranging effects. A change in the value of bank i impacts bank j, this then affects the values of the banks connected to j and so on. The majority of the financial contagion literature focuses on this type of risk.

The existence of several equilibria and the potential for a change in equilibrium are the sources of the second category of systemic risk. Interdependencies can result in self-fulfilling feedback effects wherein changes in beliefs become realized, even in the absence of any change in the fundamentals.

The first kind of systemic risk describes how a change in fundamentals might formally propagate across the banking system and how much equilibrium values change in response to an initial change in fundamentals while maintaining the equilibrium being constant. On the other hand, the second type of systemic risk captures shifts between equilibria. A contagion-based crisis can be caused by a change in fundamentals, however, what triggers an equilibrium shift is less clear.

II.1.1 Financial contagion

A cascade of insolvencies is a classic example of contagion. A bank's investments provide minimal returns, leaving it unable to pay its loans. As those liabilities are not paid for, the balance sheets of other institutions go worse, which causes some of them to go bankrupt. As more become insolvent, others' values are further diminished, which has a domino effect on the system.

Early models of counterparty risk include Rochet and Tirole (1996); Allen and Gale (2000) model the behaviors of banks and depositors. Banks can exchange some of their ex-ante deposits as insurance against shocks. Banks with extra liquidity can provide it to banks that need it. However, these transactions can lead to financial instability and contagion when a shock occurs that is either unexpected, impacts several institutions, or the banking system is improperly connected. In these cases, illiquidity may cascade as a result of liquidity drawn by one bank from another.

Less direct contagion is caused by externalities in asset values. When a bank experiences insolvency, it frequently needs to hold *fire sales* when substantial quantities of assets are prematurely sold. These dumpings lower the value of these asset prices, which eventually lowers the portfolio values of other institutions that hold such assets. Kiyotaki and Moore (1997)), Cifuentes et al. (2005), Gai and Kapadia (2010), Capponi and Larsson (2015) and Greenwood et al. (2015) emphasize how this might cause others to bankrupt and sell their assets, creating a downward spiral. Through simulations, Cifuentes et al. (2005) and Gai and Kapadia (2010) show how fire sales can amplify the spread of counterparty risk. They take into account financial networks that provide two different kinds of links between banks: obligations on balance sheets and price effects whenever a bank is required to deleverage its portfolio. They then investigate how the network structure of interbank commitments, namely its density, affects the probability of contagion. This is not only a theoretical concern, there is evidence that two banks are considerably more likely to be counterparties if their portfolios have a higher correlation, showing that institutions that are connected via financial obligations also tend to be more connected through commonality in exposures (Elliott et al. (2021)).

Exposure similarities open the door for another type of contagion called *"guilt by similarity"*. People are skeptical of the solvency of other banks that resemble bankrupt ones. Such contagion is made feasible by connected portfolios across banks and uncertainty over the value of fundamentals and/or the portfolio structures. Given the incomplete understanding of those portfolios, banks draw conclusions that may or may not be validated in hindsight. The fact that banks are members of a complicated financial network with an imperfectly known structure makes this type of inference-based contagion worse. Caballero and Simsek (2013) show that cautious banks may take precautionary measures more frequently than needed and refrain from lending money to each other during a crisis, because of the complex interbank cross-exposure system.

II.1.2 Multiple Equilibria

Even in the absence of a shift in fundamental values, systemic risk can arise. When a financial network allows for many equilibrium states, a simple change in beliefs might cause the system to abruptly switch between states, with actual economic repercussions. These belief changes can arise from inferences, that reflect real underlying correlations, but they could also arise via sunspots (Shell (1989)), bubbles (Brunnermeier and Oehmke (2013)), or exogenous events that can be conditioned upon by investors (Angelini et al. (1996)). The fundamental principle is that, in the case of many equilibria, the equilibrium that actually holds relies on what people anticipate.

The conventional form of bank runs and panics belongs to this category of systemic risk, in which behavior becomes self-fulfilling. This risk arises from the banks' core function of converting short-term deposits into long-term illiquid investments, which renders banks inherently fragile institutions: if enough depositors withdraw their money before the bank realizes its investments, the bank will be unable to repay them all and default (Reinhart and Rogoff (2009)). Diamond and Dybvig (1983) demonstrate how depositors might cause a bank to become bankrupt by withdrawing their funds. This is an inefficient situation since a depositor's decision on investment relies on how other depositors behave. When investments are complementary, multiple equilibria can exist because the assumptions about how assets will be valued might become self-fulfilling and fear becomes contagious.

Not only might depositors and outside investors experience fear and reduce their investments, but banks themselves may also do so. Banks may have second thoughts about how financially viable many businesses will be due to economic uncertainty. This might get out of control because banks may reduce their capital if they anticipate a recession thus demanding higher interest rates. This might result in a spiraling situation and perhaps a total credit freeze. The absence of investment worsens the conditions of companies and financial intermediaries, making them worse investments, which then justifies the withdrawal. As a result, this type of freeze can be self-fulfilling and still be a problem even if there are no changes in the fundamentals that drive the assumptions (Bebchuk and Goldstein (2011)). This was present in the freeze of overnight lending between 2007 and 2009 (Brunnermeier (2009); Diamond and Rajan (2011)).

Financial contracts between banks have the potential to set off a chain reaction of defaults as bank values are linked due to interbank contracts. The chance of one bank defaulting on its obligations might reduce the value of other banks and have a domino effect back on the original bank, self-fulfilling the failure. They appear in any system of exposures between banks for which there are multiple equilibrium values for interbank claims (Elliott et al. (2014); Roukny et al. (2018); Jackson and Pernoud (2020)). Such cascades are not only transfers that are not done; they also result in real economic losses, and the multiplicity of equilibria has an impact on efficiency when there are costs connected with bankruptcy.

Fire sales may result in many equilibria and a self-fulfilling deterioration of the financial system. The investment model of Krishnamurthy (2010) allows multiple equilibria to coexist and exhibit various degrees of liquidation and price levels. Caballero and Simsek (2013) take into account a model that includes both fire sales and cross exposures across banks. They demonstrate that there may be an equilibrium where contagion is restrained and prices remain fair, as well as an equilibrium where banks adopt conservative measures that result in fire sales, low market prices, and worse contagion.

Naturally, all the above-mentioned forms of systemic risk are present and interact at the same time.

II.1.3 Systemic risk on the sovereign bond market

Among other things, the Global Financial Crisis sparked worries about the fragility of the debt markets. In Europe, this was aggravated by the European Sovereign Debt Crisis (ESDC) and the potential systemic risk impact of a sovereign default on other European debt markets. Therefore, it is not surprising that the majority of the systemic risk-related papers target this region from this era. As the perception of systemic risk is typically linked to how an asset's or financial institution's financial distress affects other assets or the entire financial system, it is closely related to how failures spread from one asset or institution to another or to the system as a whole. The vast majority of articles discussing systemic risk on the sovereign bond markets use this idea of systemic risk and take into account the effects of a potential sovereign debt default in one country on all other markets for sovereign bonds (Reboredo and Ugolini (2015)).

II.1.3.1 Risk spillover within the spread and return of European government bonds

One strand of the literature on sovereign systemic risk includes articles that look at the co-movements and factors that influence changes in government bond spreads or returns, such as credit risk, exchange rate fluctuations, particular news, rating shifts, and even the likelihood that some nations will leave the eurozone. Depending on whether they focus on the GFC or the ESDC, they can be further divided.

Manganelli and Wolswijk (2009) emphasize that there is a positive relation between short-term interest rates and the euro area government bond spreads. Haugh et al. (2009) show that bond yield spreads in the euro area may be explained in part by differences in fiscal policies, especially as they relate to their impact on future deficits and the debt service ratio. Investigating bond spreads compared to both US and German bonds, Von Hagen et al. (2011) claim that a small number of macroeconomic and financial variables reliably account for the majority of the spreads' behavior. Moreover, markets penalize fiscal imbalances much more strongly since the GFC. Borgy et al. (2011) come to similar conclusions by estimating the joint dynamics of eight euro area government bond yield curves making use of three common euro area macro factors and one latent fiscal factor for each country. They conclude that fiscal factors are the main determinants in the increase of yield spreads since 2008.

De Santis (2014) separates aggregate risk, country-specific risk, spillover risk and contagion risk. The aggregate risk is driven by changes in monetary policy, global uncertainty and risk aversion, while the country-specific risk is related to changes in default probabilities on the sovereign debt, the ability to raise funds in the primary market and liquidity factors in the secondary market. De Santis (2014) also claims that separating liquidity risk, spillover risk and contagion risk from aggregate risk is required to make proper policy decisions in terms of central bank interventions. Beetsma et al. (2013) focus on the PIIGS (Portugal, Italy, Ireland, Greece, Spain) countries and find that bad news spill over from PIIGS countries onto non-PIIGS countries, affecting the bond spreads. Afonso et al. (2015) suggest that the set of financial and macro spreads' determinants in the euro area is rather unstable but generally becomes richer and stronger in significance as the crisis evolves. Silvapulle et al. (2016) proposed a semi-parametric copula model in a bivariate case to evaluate tail dependence parameters and the joint distribution of yield spreads. The approach for contagion showed a significant increase in tail dependence from the pre-crisis (1999 - 2008) to the post-crisis (2008 - 2013) periods.

II.1.3.2 Risk spillover from the European government bond market to other financial areas

The other strand of this literature implicates the European debt crisis on the financial industry. Alter and Schüler (2012) evaluate the connection between sovereign default risk and domestic banks. They contend that while government and bank credit risk interconnectedness varies among countries, it is homogeneous within the same country. Through the use of assets, collateral, and rating channels, De Bruyckere et al. (2013) investigate the contagion between bank and government default risk in Europe. They discover that banks with poor capital buffers, lousy funding structures, and less conventional banking operations are most prone to risk spillovers. The study of Perego and Vermeulen (2016) focuses on the Eurozone asset markets and provides evidence on the importance of macroeconomic factors on stock, bond and stock-bond correlation.

Mink and De Haan (2013) analyze the impact of highly volatile Greek bonds on European bank stock prices in 2010. They note that PIIGS assets are particularly vulnerable to news on the Greek bailout. Using impact analysis on news, Bhanot et al. (2014) examines how changes in Greek sovereign yield spreads affect stock returns in the banking industry. Their analysis indicates that news events lead to spillovers in excess of increases in domestic interest rates and higher funding costs. Similarly, Pragidis et al. (2015) study the contagion of the spread of government bonds on the stock market during the Greek financial crisis and acknowledge that it is not straightforward to reject or accept the contagion hypothesis since there are many potential channels for contagion.

While researchers focus mainly on the links between sovereign yields of European economies, more recently papers targeting other geographic regions appeared. In Chapter III, a few examples are mentioned, however, it is safe to say, that papers targeting the European area are in the majority. Chapter III provides an analysis that focuses on developed economies worldwide thus providing an extension to the existing body of literature.

II.2 Systemic risk from energy sector

The energy market is one of the most crucial parts of the economic system, and in recent years, energy prices have become more volatile with high risk and significant uncertainty (Ji and Zhang (2019)). As a result, such volatility has a major impact on the real economy and indirectly threatens the stability of the financial system, even creating a systemic danger to the world's financial markets. In the context of energy market-related studies, systemic risk is mainly associated with the propagation of price and volatility shocks in the financial system (Lautier and Raynaud (2012)). The cross-market risk contagion in the energy system, particularly during times of turbulence, has received a lot of attention since the GFC. Risk spillover between different energy markets, risk spillover to different commodities markets, and risk spillover to different stock markets are the three primary strands of energy-related spillovers.

II.2.1 Risk spillover within different energy markets

In an early study, Hammoudeh et al. (2003) investigate WTI, gasoline and heating oil to determine the volatility spillover between future and spot prices. They claim that both spot and futures prices have bi-directional causal links, but the spot prices have the most spillover effects. Papież and Śmiech (2015) assess the dynamics of the integration process of the international steam coal prices and look into how particular coal prices have changed in relation to this market's supply and demand structure. Lin and Li (2015) investigate the global crude oil and natural gas markets and find that while US gas prices are decoupled from oil due to natural gas market liberalization and shale gas growth, European and Japanese gas prices are cointegrated with Brent oil prices. Exploring the impact of uncertainties (economic policy, financial markets and energy markets) on energy prices Ji et al. (2018b) suggest that there generally exists negative dependence between energy returns and changes in uncertainty.

Using MSCI energy indices of 21 major economies, Singh et al. (2019) show that return spillover is significant and is more prevalent in some nations. However, this behavior alters during times of crisis. In the global crude oil system, where Brent and WTI play the major roles in risk transmission, China's crude oil futures act as a net risk receiver, claims Yang et al. (2021). Gong et al. (2021) look into four major energy commodities (crude oil, natural gas, heating oil, and gasoline) and find that the main net transmitters of information about volatility risk are the crude oil and heating oil futures, while the main net receivers are the gasoline and natural gas futures.

II.2.2 Risk spillover between energy and other commodity markets

The literature on risk spillover from energy assets to other commodities is very rich. Two groups of commodities are often examined against energy commodities, from which the first one is precious and industrial metals. In the case of metals, the interconnection between energy prices and industrial and precious metals could be explained since an increment in oil, gasoline, coal and gas prices results in an increase in production costs, passing through to the final metal prices (Hammoudeh and Yuan (2008)).

Upon investigating safe haven characteristics of precious metals, Shahzad et al. (2019) claim that the safe haven function of each precious metal can change depending on how well or poorly it protects against downward or upward oil shocks. Guhathakurta et al. (2020) examine how oil price shocks affect various metal commodities over time and their implications for investment choices. During particular oil price regimes, they provide portfolio decisions. Umar et al. (2021b) explores the dynamic connectedness of industrial and precious metals to crude oil shocks. They conclude that there are more differences between the net dynamic connectedness of the metal markets analyzed in terms of return than volatility. Mensi et al. (2020) examine co-movements, risk spillovers, and portfolio implications between precious metals and main energy futures price returns and volatility. They demonstrate that, regardless of market conditions, gold and oil are net contributors to volatility while the other assets are net recipients of risk.

The second type of commodities that are in the scope of energy-related studies (and mainly crude oil) are the agriculture commodities. In general, there are three ways to establish links between crude oil and agricultural prices. First, a significant percentage of the cost of agricultural goods is attributable to the use of commercial nitrogen fertilizers and other production-related inputs, which indirectly links the price of these products to the price of energy (Esmaeili and Shokoohi (2011); Mensi et al. (2017b)). Second, as agriculture got more industrialized, it used more fuel, chemicals, and fertilizers, which made it an energy-intensive sector of the economy (Zhang and Qu (2015); Hasanov et al. (2016)). Third, due to a sharp increase in oil costs, renewable energy, particularly biofuels, has been expanding quickly (Ji and Fan (2012); Nazlioglu et al. (2013); El Montasser et al. (2015); Hasanov et al. (2016)).

In an earlier study, Du et al. (2011) discover evidence of volatility spillover among crude oil, corn, and wheat markets, explained by tightened interdependence between crude oil and these commodity markets induced by ethanol production. Luo and Ji (2018) investigate the realized volatility connectedness of US crude oil futures and five of China's agricultural commodity futures. The findings support the presence of volatility spillover from the US crude oil market to Chinese markets, even though the scale of the spillover is modest. Shahzad et al. (2018) find evidence of spillovers from oil to agricultural commodities that intensify during financial turmoil. On the contrary Umar et al. (2021a) state that a set of agricultural commodities are transmitters (canola and corn) while others are receivers (orange juice, lean hog, sugar and rubber). In a related study, Balcilar et al. (2021) come to a similar conclusion, claiming that crude oil, grains, livestock, sugar, and soybean oil are the transmitter commodities while corn, lean hogs, soybeans, cattle, and wheat are the main receivers of shocks.

II.2.3 Risk spillover between energy and equity markets

There is conflicting evidence in the empirical literature on the effects of oil price shocks and stock market returns about how oil price changes affect stock prices. The influence of oil prices on stock returns may be classified as positive, negative, or null, as well as the effect of oil price volatility on the volatility of stock market returns.

Hammoudeh and Li (2005) claim that there is an inverse relation between oil prices and stock returns in oil-exporting countries and US oil-sensitive industries. Similarly, Ghouri (2006) observe a negative connection between WTI and US monthly stock positions. Basher and Sadorsky (2006) and Hammoudeh and Choi (2007) provide evidence of the adverse impacts of oil prices on stock markets for developing countries. The analysis of Nandha and Faff (2008) on the connections between oil prices and 35 global industrial sectors reveals that, except the oil and gas sectors, all industries had negative effects from rising oil prices. Driesprong et al. (2008) discover evidence of high predictability and a negative and statistically significant association between oil prices and stock returns using data for 48 developed and developing countries. These findings are consistent with the idea that investors underreact to information about oil prices. Narayan and Sharma (2011) look at the relationship between the price of oil and stock returns for companies listed on the NYSE and discover that the impact of the oil price varies depending on the sector, that there are lag effects consistent with the investors' underreaction hypothesis, and that the intensity of the impact on firm returns varies with firm size.

Given that oil future returns and volatility have a negative and positive impact on industry returns, respectively, Elyasiani et al. (2011) offer evidence at a sectoral level that oil price movements are asset price risk factors. Miller and Ratti (2009) provide evidence of a negative long-run impact of the global price of crude oil on international stock markets that can momentarily alter. Zhu et al. (2011) further establishes that there is bidirectional long-run Granger causality between crude oil prices and stocks for both OECD and non-OECD countries. Tiwari et al. (2018) look at nine Indian equities sectors and discovers that in eight of them, there are inverse relationships between oil prices and equity returns. The carbon sector is the only one that is immune to oil price risk.

Besides linear models, Aloui and Jammazi (2009), Chen (2010) and Reboredo (2010) study nonlinearities in the relationship between crude oil shocks and stock markets. They come to the same conclusion that oil has a negative effect on the mean and the volatility of stock returns in some regimes. Jammazi (2012) also look at how components of the oil price (obtained through wavelet decomposition) relate to overall stock market returns and discover that crude oil shocks temporarily restrained expanding stock market phases. Using non-linear Autoregressive Distributed Lag cointegration methodology, Badeeb and Lean (2018) show weak negative linkages between oil price changes and the Islamic composite index.

A positive association between oil prices and stock market returns has been also shown in several research. For instance, El-Sharif et al. (2005) conduct a study on the relationship between crude oil prices and equity values in UK oil and gas companies with a result of a positive linkage. Narayan and Narayan (2010) discover a significant positive effect of oil on Vietnamese stock prices. Using Seemingly Unrelated Regression (SUR) methods, Arouri and Rault (2012) document a positive impact of oil price increases on stock prices in Gulf Cooperation Council (GCC) countries. According to Mollick and Assefa (2013), crude oil prices have a positive impact on the US stock returns but only from mid-2009. Reboredo and Rivera-Castro (2014) finds positive interdependence between oil and stock prices in Europe and the USA since the onset of the GFC. Ma et al. (2019) investigate the interconnectedness between WTI oil price returns and the returns of listed firms in the US energy sector and detect positive relations.

Many publications also offered evidence for the independence of oil and stock market returns. Henriques and Sadorsky (2008), for example, who examine the connection between alternative energy stock prices, technology stock prices, oil prices as well as interest rates, claims that shocks to oil prices had only a weak impact on the alternative energy companies. Apergis and Miller (2009) investigate how structural shocks affected stock market returns for a sample of eight nations and discover that oil market shocks had little to no effect on stock market returns. Looking into GCC countries, Al Janabi et al. (2010) found evidence of no Granger causality for oil prices and stock price indices. Broadstock and Filis (2014) investigate the effect of oil price shocks both on the US and Chinese equity markets, and claim that while China is resilient to oil price shocks, the USA is not. By investigating clean energy firms, Bondia et al. (2016) finds that from crude oil, there is no causality running towards prices of alternative energy stock prices in the long run. Looking into clean energy stock indices and crude oil prices, Dawar et al. (2021) provide insignificant connections during bullish episodes (but find strong negative effects in bearish periods).

The oil-stock market volatility link was examined by Hammoudeh et al. (2004), who employ generalized autoregressive conditional heteroskedasticity (GARCH) models to show that oil volatility decreases the volatility of stocks in the downstream industry, but increases it for companies in the upstream sector. Aloui et al. (2008), find that oil price changes had causal effects on stock market volatility in six developed countries. Hammoudeh et al. (2010) study the effect of oil price changes on stock return volatility, finding a positive effect for increases in return volatility for sectors that use oil intensively, a negative effect for oil-related sectors and a negative and asymmetric effect for all sectors. Vo (2011) studies the volatility of stock and oil future markets using a multivariate stochastic volatility model, reporting evidence of time-varying correlation, volatility persistence and a positive effect for volatility innovation in one market on the other. Tsuji (2018) examies volatility spillovers and financial risks among oil futures and oil and gas sector equity returns of the US, Canada, Australia, and Russia. Their results suggest that there are unidirectional and bidirectional volatility spillovers between oil futures and oil equities and mostly bidirectional volatility spillovers among oil equities.

As the above-mentioned summary suggests, the literature on systemic risk in the field of energy assets is very extensive. However, it is less common to investigate the effects neither on sovereign level nor on company level. Chapter IV examines the volatility spillover between major European energy companies, while Chapter V provides an analysis of oil and natural gas-related risk spillover within European countries. It is also noteworthy that Europe is underrepresented in the literature hence this thesis provides a multifold contribution to the literature.

II.3 Measuring systemic risk with network models

Financial networks are intricate systems where several institutions or assets are connected to one another in a variety of ways. The notion that financial interdependencies lead to systemic hazards is highlighted by all models, notwithstanding differences in the nature of the financial network. The sources of systemic risk may thus be measured, predicted, and tracked using a formal model of financial networks.

II.3.1 Interbank networks

The connections and interdependence between financial institutions (banks) are represented by interbank networks. First and foremost, institutions are linked through financial contracts. To smooth out idiosyncratic liquidity variations and meet deposit requirements, institutions lend to and borrow from each other. They also work together on investment opportunities and operate in chains, repackaging and reselling assets among themselves. A significant portion of the literature focuses on these networks of interdependencies (Allen and Gale (2000); Eisenberg and Noe (2001); Elliott et al. (2014); Acemoglu et al. (2015a); Diem et al. (2020)).

Second, despite the absence of direct transactions between financial institutions, similarity across their exposures causes their values to be interrelated. This can be examined via a network in which the correlation between the portfolios of two institutions is captured by a (weighted) connection between them (Acharya et al. (2007); Allen et al. (2012); Diebold and Yılmaz (2014); Cabrales et al. (2017), Elliott and Golub (2022)).

A bank's vulnerability to value declines or defaults from additional sources increases as it adds counterparties, which tends to raise the risk of cascading events. Holding the overall exposure of a bank constant, however, distributing that exposure over a greater number of counterparties reduces the bank's exposure to any particular counterparty, hence reducing the risk of contagion. Elliott et al. (2014) separates two fundamental aspects of the interconnectivity between financial institutions to study these two forces: the number of partners each institution has, referred to as the network's "*density*" and the percentage of a bank's portfolio that is held in contracts with other institutions, referred to as the network's "*integration*".

According to Gai and Kapadia (2010) and Haldane (2013), financial networks exhibit a paradoxical characteristic of being "*robust yet fragile*". Banks rely on each other through lending and liquidity provision, which helps to distribute risk. This allows individual institutions to be less vulnerable to liquidity or portfolio shocks. The impact of those shocks is shared among various counterparties. This type of diversification effectively reduces the likelihood of any single institution's failure. Financial networks are considered robust for this reason. Despite diversification, large shocks can still cause institutions to fail. In such cases, interdependencies can spread the shock more extensively. There are nuances to consider based on the specific model and the types of contracts established between institutions (Allen and Gale (2000); Gale and Kariv (2007); Gai and Kapadia (2010); Elliott et al. (2014); Acemoglu et al. (2015b)). The property of being robust yet fragile means that a network can be better than an other one in certain situations but can be a poorer choice in others.

Acemoglu et al. (2015b) focus on networks of unsecured interbank debt, and study how a shock to a bank's returns propagates through the network. There are two types of shock regimes that they differentiate between, shocks that can be absorbed by the excess liquidity in the system, and those that cannot. Under the former regime, interdependencies reduce the possibility of contagion. The ideal network structure for resisting contagion is the complete network, where each bank's liabilities are evenly distributed among all other banks. This leads to maximal risk sharing and a minimal expected number of defaults. On the other hand, if the shocks are greater than the overall excess liquidity in the system, interdependencies make it easier for the shocks to spread.

In a different model, one in which interdependencies between banks represent the correlation in their investments, Cabrales et al. (2017) emphasizes the importance of the size of shocks. They take into account a collection of ex-ante identical banks, each having debt due to outsiders and access to a risky project. The returns on these projects may be affected by unpredictable events that occur independently among different banks. If a bank is unable to cover its debt to outsiders, it defaults and incurs some costs due to distress. By exchanging claims on each other's projects, banks have the opportunity to diversify their portfolios. For example, the connection from bank i to bank j captures the claim that bank i has on the return of j's project. Links in their model, therefore, indicate portfolio correlation between banks rather than any kind of interbank obligation. When it comes to managing risk, the trade-off is the same as it is in the model of Acemoglu et al. (2015b). Having more links between parties can lead to better risk sharing, but it also means being exposed to more potential sources of risk. The optimal network structure to minimize the number of defaults depends on how the shocks are distributed.

One challenge with financial networks is the existence of significant asymmetries, particularly the presence of a core-periphery structure, which can impact the risk of contagion. Large core banks can be resilient to modest shocks, however, when faced with enormous shocks they can fail catastrophically, especially when those shocks are correlated. This was what loomed in 2008. There is further research that supports the idea that heterogeneity makes a substantial difference. Simulations by Gai et al. (2011) demonstrate how the degree of concentration in networks of interbank claims affects the spread of contagion. Teteryatnikova (2014) demonstrates how the network becomes more robust by creating a negative correlation between nearby institutions. According to theoretical findings by Glasserman and Young (2015), in a particular class of networks, contagion is greatest when banks are heterogeneous in size and the shock originates at a large central bank.

By employing the above-mentioned network models, researchers regulators and policymakers can gain deeper insights into the critical nodes and linkages that contribute to the potential failure of a financial institution. Analyzing the structural patterns and dynamics of these networks aids in identifying potential sources of contagion and formulating effective risk management strategies. As such, a comprehensive understanding of the interactions and dependencies within networks can serve as a cornerstone for building more resilient and stable systems in the face of potential crises.

II.3.2 Co-occurrence networks

In several circumstances, financial entities are not necessarily related via direct interactions (such as flows of money, holdings of shares or financial exposures) but via some form of co-occurrence, which may be indirect, such as commonality, similarity or correlation (Bardoscia et al. (2021)). A common type of co-occurrence network is a network with nodes that represent financial entities described by some empirical time series (for example, stocks traded in a financial market) and whose links are weighted by the measured correlation (Tumminello et al. (2005), Kremer et al. (2019)) or causality (Billio et al. (2012)) between the corresponding time series.

The analysis of these types of financial networks has shown that co-occurrence can reveal higher-order properties that are not immediately evident or predictable from the intrinsic properties of nodes. Data-driven clustering of assets can improve the performance of standard factor models for risk modeling and portfolio management (Antonakakis et al. (2018); Guhathakurta et al. (2020); Mensi et al. (2020)). In general, because shocks on portfolios can propagate to their owners, the existence of non-obvious groups of correlated financial assets can have important consequences for shock propagation.

Various characteristics of co-occurrence networks require special caution and can make their analysis more complicated than that of other types of networks. First, although other types of networks are typically sparse, one-mode projections obtained from empirical co-occurrence can be very dense (Billio et al. (2012)) and often do not contain zeros (Diebold and Yılmaz (2014); Härdle et al. (2016)), in which case, they do not immediately result in a network. This property has led to the introduction of several filtering techniques aimed at sparsifying those matrices while retaining the strongest connections.

Second, in the presence of heterogeneous entities, the same measured value of similarity might correspond to very different levels of statistical significance for distinct pairs of nodes. For this reason, simply imposing a common global threshold on all co-occurrences is inadequate, and alternative filtering techniques are required (Verma et al. (2019)). These approaches found that financial entities belonging to the same nominal category can have very different connectivity properties in the network (Bartesaghi et al. (2020)). An open question is the theoretical justification for the choice of the embedding geometry wherein the network is constructed.

Third, in general, all entries of empirical similarity matrices tend to be shifted towards large values, as a result of an overall relatedness existing across all nodes, as, for example, a common market trend (Laloux et al. (1999)). The network representation only seeks to depict true linkages, but this global phenomenon hides them.

Finally, the measurement of co-occurrence networks is intrinsically prone to the curse of dimensionality. With n the number of time series and m the length of those time series, to measure with statistical robustness the $n(n-1)/2$ entries of a correlation or similarity matrix one needs $m \geq n$, that is, a sufficiently large number of temporal observations (or nodes in the other layer of the bipartite network) in the original data to avoid dependency and statistical noise. Unfortunately, increasing m for a given set of n nodes is often not possible in practice, for instance, because one would need to consider a period so long that nonstationarities would unavoidably kick in, making the measured correlation unstable and not properly interpretable.

The above complications lead to the requirement of a comparison with a proper null hypothesis that controls simultaneously for node heterogeneity, for a possible 'obfuscating' global mode and for 'cursed' noisy measurements. An important caveat here is that, in co-occurrence networks, the model necessarily has mutually dependent links. This arises from the fact that, if node i is positively co-occurring with node j, which is, in turn, positively co-occurring with node k, then nodes i and k are typically also positively co-occurring. Therefore, naively using those null models introduces severe biases in the statistical analysis of co-occurrence networks.

II.3.3 Methodological framework

II.3.3.1 The Toda-Yamamoto model

The Toda and Yamamoto (1995) model (T-Y hereafter), has emerged as a significant tool for researchers seeking to explore complex causal relationships in economic data. This model extends the traditional Granger causality test to handle non-stationary time series data, making it particularly valuable for understanding dynamic interdependencies between economic variables. Although originally it is an econometric model, Fig. II.1 highlights that the method is particularly popular in environmental science and energy-related journals as well, due to the characteristics of time series occurring in these fields.

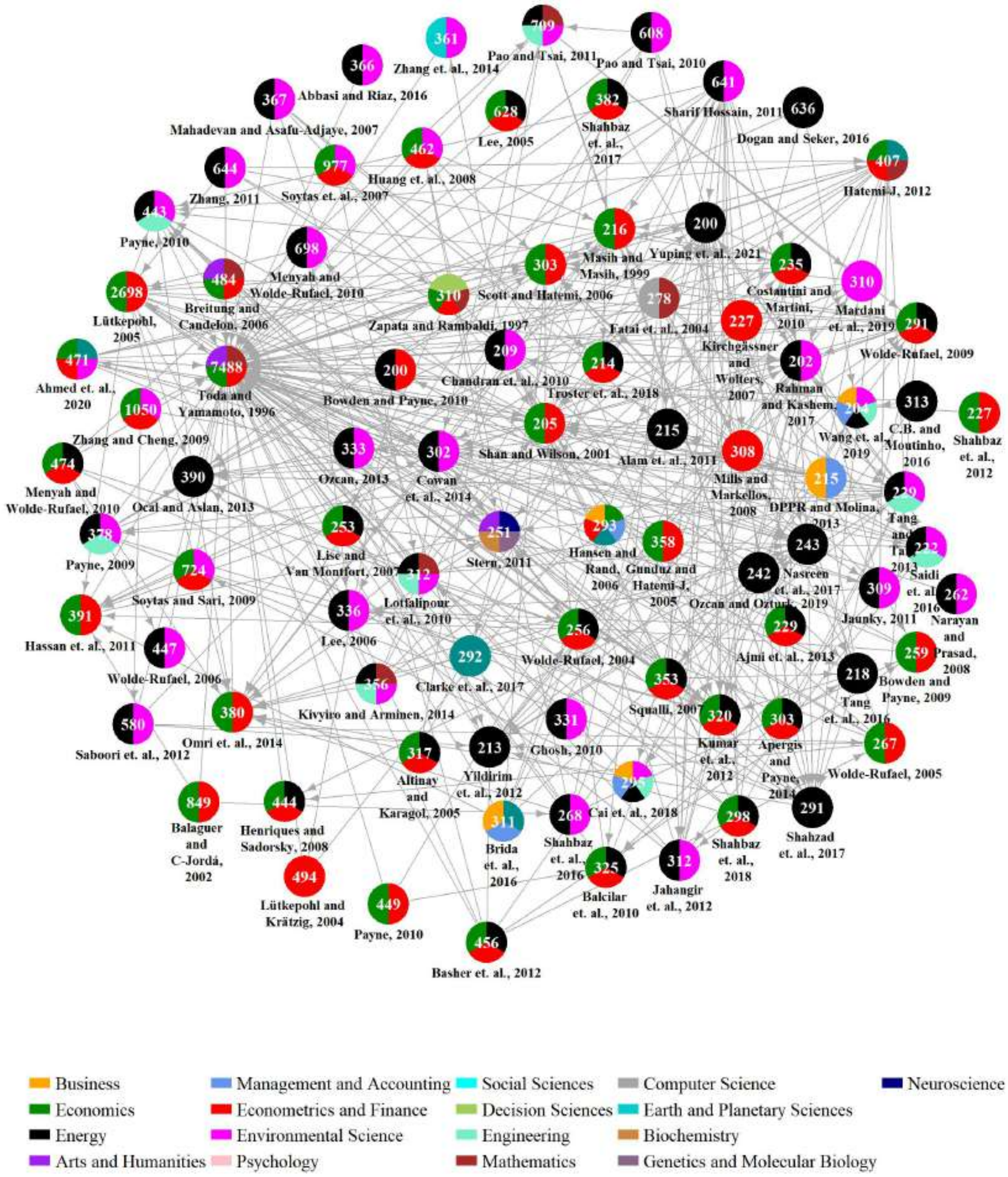


Fig. II.1. The citation network of Toda and Yamamoto (1995), as of July 2023

Note: A node represents a citing article, the number in the node stands for the number of citations of that given article according to Scopus, as of July 2023. An arrow between two nodes indicates the direction of the citation, and the colors of the nodes indicate the main fields of the hosting journal according to Scimago. Only those articles are represented that are cited at least 200 times, as of July 2023.

In an unconstrained VAR context, the traditional Granger causality tests rely on the presumption that the underlying variables are stationary, or integrated of order zero. The stability criterion of the VAR is intended to be broken if the time series are non-stationary. As a result, the χ^2 (Wald) test statistics for Granger causality, which are used to check the combined significance of all other lagged endogenous variables in VAR equations, are no longer valid. Investigating cointegration in the case of non-stationary time series is necessary, and if found, the vector error correction model should be used in place of the unconstrained VAR. No test for the long-run relationship is used if the series are not integrated of order $\mathrm{I}(1)$ or are integrated of different orders. On the other hand, using unit root and cointegration tests may have low power compared to the alternative. Therefore, they can be misplaced and may suffer from pre-testing bias (Toda and Yamamoto (1995); Pesaran and Shin (1998)).

To address some of these issues, Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) introduce the modified Wald (MWALD) test for restriction on the parameters of the VAR(p), where p is the lag length of the VAR system. According to their method, the greatest order of integration (d^{max}) is added to the system's correct order (p), and the VAR$(p + d^{max})$ is then computed without taking into account the coefficients of the most lagged d^{max} vector. Toda and Yamamoto (1995) confirm that regardless of whether the process is stationary, around a linear trend, or whether it is cointegrated, the Wald statistic converges in distribution to a chi-square random variable with degrees of freedom equal to the number of the removed lagged variables.

The T-Y approach is unique in that it eliminates the possible bias brought on by unit roots and cointegration tests by not requiring pre-testing for the system's cointegrating characteristics (Zapata and Rambaldi (1997); Clarke and Mirza (2006)). It suggests using augmented level VAR modeling to test for causality in a system that may be integrated and cointegrated (of arbitrary orders), allowing for the long-run information that is frequently overlooked in systems that first require differencing and pre-whitening (Clarke and Mirza (2006); Rambaldi and Doran (1996)). The test statistic (MWALD) is valid as long as the order of integration of the process does not exceed the true lag length of the model (Toda and Yamamoto (1995)).

However, besides its appealing characteristics, the T-Y approach has some weaknesses as well. The method suffers some loss of power because the VAR model is intentionally over-fitted (Toda and Yamamoto (1995)). Kurozumi and Yamamoto (2000) also warn that for small sample size, the asymptotic distribution may be a poor approximation to the distribution of the test statistic.

II.3.3.2 The Diebold-Yilmaz spillover index

The spillover indices of Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), Diebold and Yılmaz (2014) (D-Y hereafter) is a popular method for measuring total interdependence or "connectedness" in a dynamic system of random variables. The D-Y index became one of the cornerstones of the literature studying systemic risk, and it has been widely used in policy (e.g., ECB (2021); IMF (2023)) and industry to assess systemic risk in financial markets. Although the D-Y index is a relatively young method, as Fig. II.2 points out, Diebold and Yılmaz (2014) is widely cited, especially in the fields of Economics, Econometrics and Finance. This section provides a brief oversight of the history and usage of the framework, Sections IV.3.2 of Chapter IV and V.4 of Chapter V provide a complete description.

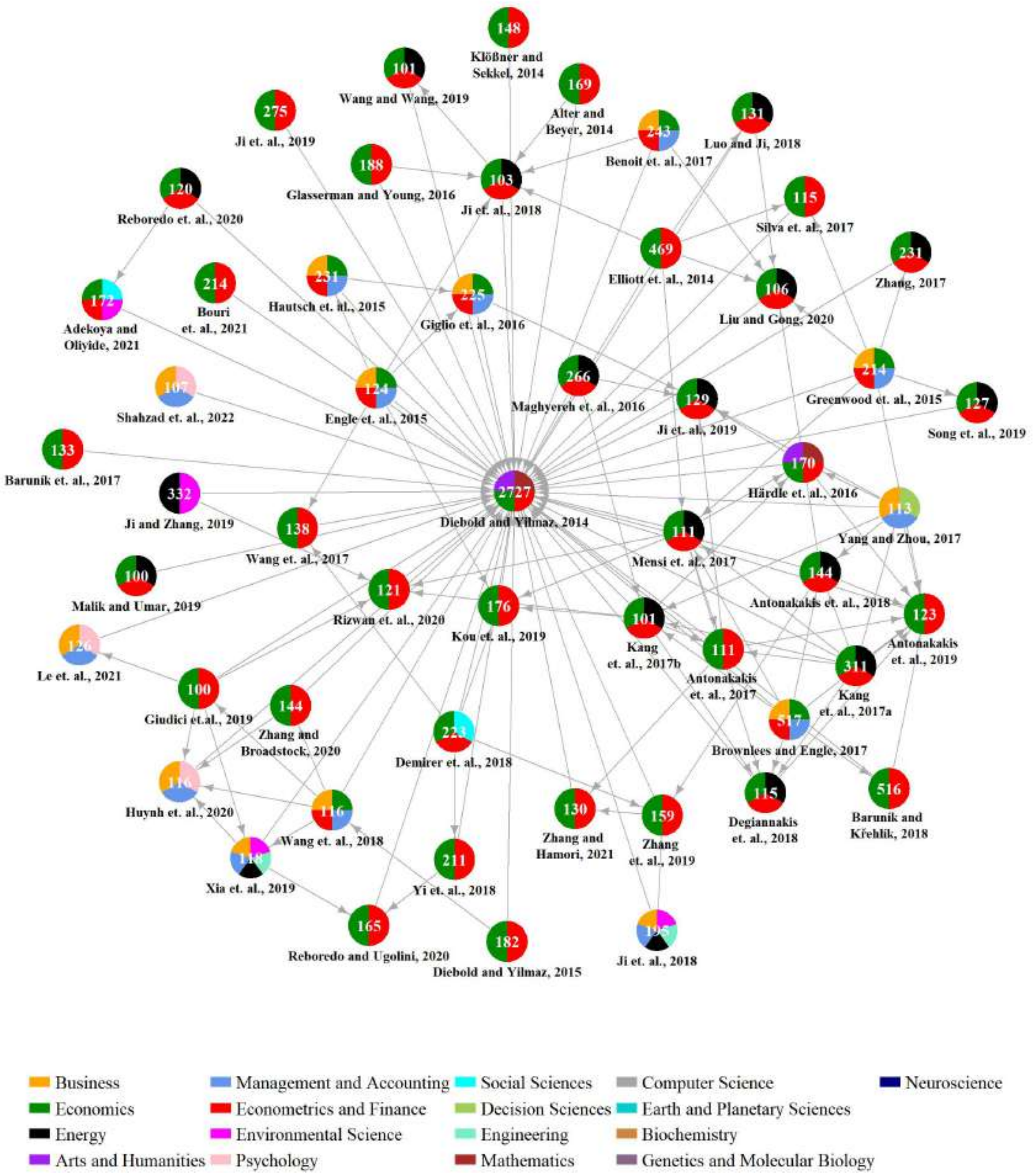


Fig. II.2. The citation network of Diebold and Yılmaz (2014), as of July 2023

Note: A node represents a citing article, the number in the node stands for the number of citations of that given article according to Scopus, as of July 2023. An arrow between two nodes indicates the direction of the citation, and the colors of the nodes indicate the main fields of the hosting journal according to Scimago. Only those articles are represented that are cited at least 100 times, as of July 2023.

In Diebold and Yilmaz (2009) the volatility spillover metric which is based on Forecast Error Variance Decomposition (FEVD) coming from a Vector AutoRegressive model introduced by Sims (1980). Variance decomposition measures how exactly the H step ahead forecast error variance of a variable i can be attributed to the innovation of another variable j, thereby creating an intuitive method for measuring the spillover of volatility. In this form of the procedure two limitations encounter, one of which is that the VAR method uses Cholesky factor identification, so the results depend on the order of the variables. The second is that only the spillover index for the entire population can be calculated, not between constituent pairs.

Diebold and Yilmaz (2012) eliminate both limitations using a generalized VAR model built on the results of Koop et al. (1996) and Pesaran and Shin (1998), getting a process which is nonsensitive to the order of variables. This method allows correlated shocks assuming the normality of error distribution. Thus, the shocks to each variable are not orthogonal. The generalized spillover index (Diebold and Yilmaz (2012)) is based on the contribution to a variable's forecast error variance coming from all other variables' shocks in the system - the "spillover" inherent in the system. Going from low-dimensional to high-dimensional environments, Diebold and Yılmaz (2014), Diebold and Yilmaz (2015) and Demirer et al. (2018) study the connectedness of financial institutions within the USA, across the Atlantic, and across the globe, respectively.

There are various interpretations of D-Y's generalized measures of total spillover in extant studies. For example, Diebold and Yılmaz (2014) (p 126) interpret the generalized total spillover from others as "*...the share of volatility shocks received from other financial firm stocks in the total variance of the forecast error for each stock.*" In the context of bond yield volatilities of eleven European countries, Fernández-Rodríguez et al. (2015) (p 340) claim to "*...obtain a value of 54.23% for the total volatility spillover index among the eleven countries under study, indicating that slightly more than half of the total variance of the forecast errors during the sample is explained by shocks across countries, whereas the remaining 45.77% is explained by idiosyncratic shocks.*" Numerous other papers (and this thesis as well) similarly interpret the generalized total spillover from others to variable i as the percent of the forecast error variance of variable i that can be explained by the shocks of all other $non - i$ variables in the system.

As per Diebold and Yilmaz (2023) it is easy to comprehend why the D-Y connectivity assessment has become so popular. The approach is straightforward and compelling, integrating classic "*econometric modeling thinking*" with contemporary "*network and Big Data thinking*", putting the pieces together to go to entirely new places. It is based on variance decompositions, which are well-known and easy to use, and it is supported by the innovative discovery that "*a variance decomposition is a network*" which makes a connection between the apparently separate VAR literature and the network literature. Therefore, network methods that easily scale to large dimensions offer significant assistance in summarising and visualizing connections as determined by variance decompositions.

CHAPTER

III

THE IMPACT OF CRISIS PERIODS AND MONETARY DECISIONS OF THE FED AND THE ECB ON THE SOVEREIGN YIELD CURVE NETWORK

Chapter III is based on the work of Badics et al. (2023). Minor modifications are made to align with the dissertation format.

III.1 Introduction

Over the past few decades interlinkages between global financial markets increased due to the fundamentals, regulatory convergence, and growing international trade. Globalization and surging connectedness led to a higher likelihood of local and global crises. Furthermore, during turbulent periods the strength of connections sharply increases, and risk spills over across markets and asset classes, as it happened during the Dotcom Bubble, the Global Financial Crisis of 2007–2009, the European Sovereign Debt Crisis, or the recent Covid-19 Pandemic. Examining financial systems is crucial for investors and other market participants too because a shock and a crisis in one market can affect the return and volatility of another market and infect the decision-making for portfolio risk management. For this reason, it is essential for regulators to monitor the rapid changes, understand the network dynamics on different levels, and identify the key participants of financial networks. During the last few years, motivated by these episodes of crises, the connections between financial markets have been widely investigated in academia, especially from a network perspective (Diebold and Yilmaz (2009), Billio et al. (2012)).

To examine financial networks, several approaches have appeared in the literature since the Global Financial Crisis. On the theoretical side, Gai and Kapadia (2010), Gai et al.

(2011), Elliott et al. (2014), Acemoglu et al. (2015b) and Glasserman and Young (2015) analyze the effects of financial contagion on risk. On the empirical side, there are various ways to quantify connectedness. In the last decade, the widespread methods are the Granger causality (Billio et al. (2012)), Conditional Value at Risk (CoVaR) (Adrian and Brunnermeier (2011)), Systemic Expected Shortfall (SES) and Marginal Expected Shortfall (MES) (Acharya et al. (2012)), and the spillover measure based on Forecast error variance decompositions (FEVD) from Vector autoregressive (VAR) model, shown by Diebold and Yilmaz (2009), Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014). These techniques are frequently used to examine networks in various asset classes, such as equities (Bernal et al. (2014), Vỳrost et al. (2015), Billio et al. (2016), BenSaïda (2019)), bonds (Antonakakis and Vergos (2013), Reboredo and Ugolini (2015), Corsi et al. (2018)), currency rates (Bubák et al. (2011), Antonakakis (2012), Ji et al. (2019)) or commodity prices (Kang et al. (2017a), Ji et al. (2018a), Umar et al. (2021d)). The Granger and FEVD-based frameworks have the benefit over CoVaR and MES approaches in that they can better analyze the network on different levels (pairwise, subsystem and total connectedness, Diebold and Yılmaz (2014)). The Granger causality and the Diebold-Yilmaz (D-Y) approaches are extensively used in the network literature (Barigozzi and Brownlees (2019)).

The network-related econometrics frameworks are increasingly evolving (Baruník and Křehlík (2018), Demirer et al. (2018)). Despite the high number of recent connectedness-related articles and the widespread methods, the deeper structure of the networks (analyzing on different levels) has been investigated by far fewer. In addition to that, only a few studies (Hautsch et al. (2015), Sedunov (2016), Nucera et al. (2016), Hué et al. (2019)) try to identify the key participants of the financial networks and. Although there is a large body of both theoretical (Gai and Kapadia (2010), Gai et al. (2011)) and empirical (Diebold and Yilmaz (2012), Alter and Beyer (2014), Bouri et al. (2021)) literature focusing on differences between calm and turbulent periods, the comparison of different crises has only come into focus in recent years (e.g. Mensi et al. (2018), Gunay (2021), Batten et al. (2022), Jebabli et al. (2022), Jana et al. (2022), Baumöhl et al. (2022)).

The majority of the network-related literature focuses on equities and fewer papers turn attention toward sovereign bonds. Given that two recent crises, which had serious, cross-county impacts, have been closely related to the fixed-income market (namely, the Subprime and the European Sovereign Debt Crises), a study that focuses on sovereign yield curves is essential. While researchers focus mainly on the links between sovereign yields of European (Antonakakis and Vergos (2013), Fernández-Rodríguez et al. (2015)) or Asian (Gabauer et al. (2022)) countries, only a few studies explore the connections between the most developed (Umar et al. (2022), Berardi and Plazzi (2022)) markets. Additionally, the most developed sovereign bond markets have significant influences on the yield curves of other countries, as shown by Ahmad et al. (2018) and Stona and Caldeira

(2019).

In this paper, to address the gap in the empirical literature, we calculate the yield curve factors (Level, Slope, and Curvature) of 12 developed sovereigns based on the model of Diebold and Li (2006) and investigate the connectedness among them from 1998 to 2021. Our examination covers cross-factor relations as well, and we use the Toda-Yamamoto (Toda and Yamamoto (1995)) causality test to handle cointegrated time series. We are particularly interested in investigating the density of networks during calm and turbulent periods. To deeper understand the structural changes and identify the key participants in the sovereign yield curve network, we analyze the connections on factor, country, and node level. In addition, in analyzing the nodes' connections, we examine the relation between the monetary policy decisions and the sovereign yield curve network. We explore links between the easing and tightening decisions by the Fed and ECB, and the time-varying dominance of the key participants in the sovereign yield curve network.

The contribution of this paper to the existing literature is fourfold. First, to our knowledge, we are the first to adopt the Toda-Yamamoto (Toda and Yamamoto (1995)) causality test to examine a large network of sovereign yield curves over an extended period of time. While the Time-Varying Parameter Vector Autoregression (TVP-VAR) model recently suggested choice for network analysis (Rossi (2005), Rossi and Wang (2019)), our choice of the Toda-Yamamoto model (T-Y hereafter) is motivated by its simplicity and flexibility (see Rambaldi and Doran (1996)), alleviating complications that may arise from using TVP-VAR with cointegrated series. The T-Y causality test is applicable regardless of whether a series is $\mathrm{I}(0)$, $\mathrm{I}(1)$, or $\mathrm{I}(2)$ are cointegrated or not cointegrated in any arbitrary order. The procedure avoids the bias associated with unit roots and cointegration tests (Rambaldi and Doran (1996); Zapata and Rambaldi (1997); Clarke and Mirza (2006)), as it does not require pre-testing of the cointegrating properties of the system. Consistent with earlier studies (e.g., Cavaliere et al. (2010); Engsted and Tanggaard (1994); Hall et al. (1992); Wilms and Croux (2016)), we also provide evidence of numerous cointegrated time-series yield curve pairs using Engle-Granger (Engle and Granger (1987)) and Johansen (Johansen (1988)) tests. To address potential limitations of T-Y model, and account for potentially time-varying parameters in the network, we use 750-day estimation moving window estimation during the sample period.

Second, using a large sample of sovereign yield curves, from 12 countries over 23 years, we consider Level, Slope, and Curvature factors using the Diebold and Li (2006) model.[2] We explore cross-connections between sovereign yield curve factors and show evidence of a significant amount of linkage between the Level Slope and Curvature subnetworks. We identify the key participants in the sovereign yield curve network and find that the US factors dominate as key network participants throughout the sample, in each subperiod,

[2]Our model is a close network approach, containing only yield curve factor data, as we focus on the endogenous relationships. Therefore omitted variable bias might occur.

with some variation across time. These results extend the findings of other recent yield curve papers (e.g., Cavaca and Meurer (2021); Umar et al. (2021c); Umar et al. (2022) and Gabauer et al. (2022)) who examine spillover effects among networks created from Level, Slope and Curvature factors only and do not identify the top nodes in the system.
Third, we provide several unique insights by analyzing the deeper structure of our network showing the followings: (1) the two global crises have more dense networks, than the local ones;[3] (2) US latent factors act as key participants in our network, however, their contribution is time variant; (3) cointegrated relationship between Canada and the USA results in the Canada being co-driver in the network during in crises periods.
Lastly, we contribute to the literature about the spillover effect of monetary policy decisions (e.g., Hofmann and Takáts (2015); Kearns et al. (2018); Albagli et al. (2019); Lakdawala et al. (2021); Miranda-Agrippino and Ricco (2021); Jarociński (2022) and Miranda-Agrippino and Nenova (2022)) and provide insights for monetary policy discussions. We also extend the scope of the earlier sovereign yield curve studies as we inspect the dynamics of the key participants' dominance in the network and connect these dynamics to the monetary policy decisions. Specifically, by analyzing the influence of the easing and tightening decisions by the Fed and the ECB on the key participants of the sovereign yield curve network we find that the dominance of the US factors peaks if the Fed leads the rate hike cycle and reaches its minimum when the interest rate cycle is led by the ECB. We provide insights for the more exposed market participants to prepare for the expected impacts of US intervention potentially better. We also highlight the potential structural breaks in crisis and tranquil periods, by showing that Canada is effectively an extension of US monetary policy impact during crisis periods, highlighting the importance of close trade partner relations.
The rest of this paper is structured as follows. In Section III.2 we review the literature on the sovereign yield curve networks, in Section III.3 we discuss the methodology for extracting the latent factors with the Diebold-Li model and we introduce the T-Y model. In Section III.4 the data is presented, in Section III.5 we discuss our empirical results and in Section III.6, we conclude and present the policy implications.

III.2 Literature review

There are two families of articles investigating links among sovereign bonds. The first one examines the market integration and comovements between short and long-term yields of international bonds. The second one estimates the connectedness among sovereign yields or yield curve factors with network-based econometric methods.

[3]We examine the Dotcom Bubble (DCB), the Global Financial Crisis (GFC), the European Sovereign Debt Crisis (ESDC), and the Covid-19 Pandemic (C19). From these, we consider the GFC and the C19 Pandemic as global, while the other two as local crises. It is revealed that the two global crises have more connection counts, than the local ones.

An overview of existing literature on the bond market reveals that there are only two pioneer studies that analyze the connectedness of international bond markets from a network view, without using the last 10 years' network-based econometrics methodologies. In an early paper, Sander and Kleimeier (2003) investigate connections among Asian sovereign bond spreads with Gragner-causality during four episodes of Asian crises. They show that the Asian crisis changed causality patterns on a regional base. Christiansen (2007) examine the volatility spillover between the US and European sovereign bond markets using a GARCH model. Results indicate volatility spillover from the US to European bond markets, but not vice versa.

Since the GFC network-based methodologies have gained popularity. Antonakakis and Vergos (2013) examine the spillover in the sovereign yield spread among Eurozone countries using measures developed by Diebold and Yilmaz (2012) and find that more than 60% of the variances are explained by spillovers from other countries. Gómez-Puig and Sosvilla-Rivero (2013) analyze the time-varying nature of Granger causal relationships between the yields on 10-year government bonds issued by five EMU countries. In a similar study Gómez-Puig and Sosvilla-Rivero (2016), using sovereign bond yield spreads of ten central and peripheral countries to examine the dynamic evolution of Granger causality network connections. Both studies document peaks of linkages during the ESDC. Claeys and Vašíček (2014) measure the direction of the linkages of the sovereign bond market among sixteen European Union countries, using a factor-augmented version of the D-Y model. They show that spillover effects from other countries dominate the domestic fundamental factors for EMU countries' sovereign yields. Fernández-Rodríguez et al. (2015) investigate 10-year yield volatility spillovers in eleven Eurozone countries using the D-Y framework. They document that more than half of the total variance of the forecast errors is explained by systemic shocks. A year later in Fernández-Rodríguez et al. (2016) study the time-varying integration of EMU bonds with the same framework. Contrary to previous empirical studies, they find a significant decrease in connectedness during the crisis period. Reboredo and Ugolini (2015) use conditional value-at-risk (CoVaR) to measure systemic risk in European sovereign bond markets around the ESDC. They find that prior to the crisis, the markets were all coupled, while after that, the risk decreased for the affected countries. Bernal et al. (2016) use the same methodology to analyze the risk spillovers within the EMU and examine the impact of Economic Policy Uncertainity to the net connections. They find that uncertainty has an impact to country-level spillovers which is stronger for key countries. Using Diebold-Yilmaz-based structural vector autoregressions, De Santis and Zimic (2018) examine the bond market connectivity among the 10-year sovereign yields of 12 developed countries. They document that connectedness among sovereign bond yields declined during the 2008-2012 period due to financial fragmentation. Chatziantoniou and Gabauer (2021) concludes the same while examining the financial risk synchronization of 11 EMU members' government bond yields with a time-varying parameter Diebold-Yilmaz model. They document fragmentation during the ESDC and find that core countries spillover risk shocks to periphery countries. Hamill et al. (2021) investigate the network connectivity of the European sovereign bond markets and compare the different variants of D-Y frameworks. They document that the Lanne-Nyberg dynamic connectedness model provides an accurate indication of the GFC. In a recent study, Benlagha and Hemrit (2022) investigate the impact of Economic Policy Uncertainty (EPU) on the connectedness among G7 sovereign bond yields. They find that EPU affects the connectedness of long-term yields but is insignificant for short-term yield spillovers. Berardi and Plazzi (2022) investigate the connectedness between the yield curve components of four developed countries after they decompose the nominal yields into the sum of expectations, the term premium, and the convexity term. They find that the USA indicates the strongest spillovers in long-term yields.

While the above-mentioned studies investigate the linkages among government bond yields in the last few years, another strand of literature analyze yield curve factor connectedness among sovereign markets.

Sowmya et al. (2016) are the first to investigate linkages across latent factors of yield curves using D-Y framework in a sample of four developed and seven emerging Asian economies. They find that the regional influence is higher in Slope and Curvature factors among the Asian countries. In a recent paper, Umar et al. (2021c) study connectedness of 11 Eurozone countries and document that the core countries are net transmitters while the peripheral countries are net receivers. Cavaca and Meurer (2021) examine the spillover between yield curve factors of the United States and four South American countries. They prove that the degree of spillover is highest for the Slope subnetwork, followed by the Level and the Curvature. Gabauer et al. (2022) explore the spillover of yield curve factors across the Asia-Pacific sovereign bond markets with a time-varying parameter D-Y model. They find that the highest market connectedness is in the Level subsystem followed by the Slope and Curvature subnetworks. Umar et al. (2022) examine the connectedness between the Level, Slope, and Curvature factors individually. They conclude that France and Germany are the transmitters whereas the UK and Japan are the net receivers for all the yield curve components' networks.

We briefly summarize and highlight the gaps in the literature in A.1. As of today, a large number of connectedness studies use VAR-based Diebold-Yilmaz frameworks despite the concern that the application of the VAR model on cointegrated time series can lead to spurious connections. A notable exception is Cavaca and Meurer (2021)'s work where the authors try to handle this problem within the estimation of the network model. However, unlike the Vector Error Correction Model (VECM)-based (D-Y) approach, which relies on the variables being integrated in the same order for cointegration analysis, the T-Y model does not require such an assumption. Although there is a large number of recent sovereign bond connectedness-related studies, deep structural network analysis, examination networks at multi-levels (analyzing on different levels), is scarce. The papers analyze the network either on node- or on factor level. Lastly, while a number of bond market works compare tranquil and turbulent periods without specific distinction in crisis periods, comparing different crisis periods and exploring the network behavior of key market players are underrepresented in the literature.

III.3 Methodology

Our approach consists of two steps. First, the Diebold and Li (2006) methodology is used to decompose the yield curve into latent and economically meaningful factors. Next, we quantify the significant causality relations between the different yield curve components using the Toda and Yamamoto (1995) model. We describe both of these processes in the next subsections.

III.3.1 The Nelson-Siegel yield curve model and the Diebold-Li decomposition

Nelson and Siegel (1987) (N-S hereafter) suggest a flexible, parsimonious, exponential components framework that has the ability to capture a variety of frequently observed yield curve shapes (forward sloping, inverse, humped) and allows for a clear interpretation of the estimated factors. Diebold and Li (2006) (D-L hereafter) extend the N-S approach, by allowing the dynamic change of the latent factors. A central feature of the model is that these factors can be interpreted as the Level, Slope, and Curvature as proven by Diebold et al. (2006), Mumtaz and Surico (2009), Mönch (2012), Koopman et al. (2010) and Christensen and Rudebusch (2012). Following N-S and D-L, we assume that these components include the majority of the information in the term structure of the yield curve. The D-L model offers an adaptable structure and has a wide applicability in any market (Yu and Zivot (2011), Xu et al. (2019), Bredin et al. (2021)).
The observed yield curve can be described with the following equation:

$$y_\tau = \beta_1 + \beta_2 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} \right) + \beta_3 \left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau} \right) \tag{III.1}$$

where y_τ denote yields for τ maturity, β_1, β_2 and β_3 are the Level, Slope, and Curvature parameters respectively, and λ is a parameter that controls the shapes of loadings for the D-L factors (especially for Curvature). The β_i parameters have an economic meaning: β_1 (Level) represents the long end of the yield curve, β_2 (Slope) is the short-term component, while β_3 (Curvature) mimics the middle interval. The Level factor applies equally to all maturities. Some of the articles focus on the Level and Slope factors only, however, De Pooter (2007), Almeida et al. (2009) and Ullah et al. (2015) draw attention to the importance of the third factor, therefore we involve Curvature in our analysis.

We estimate the latent factors using the two-step procedure on a daily basis proposed and applied by Diebold and Li (2006). We use simple ordinary least squares (OLS) on every day to extract the time-varying latent Level, Slope, and Curvature factors. Following Diebold and Li (2006), Bianchi et al. (2009), Koopman et al. (2010) and Van Dijk et al. (2014) we set the λ parameter at 0.06093 such that the Curvature factor attains its maximum at τ= 30 months.

III.3.2 The Toda-Yamamoto model

The T-Y model is a popular causality testing approach, introduced by Toda and Yamamoto (1995). Over the past few years several network-based studies applied the T-Y model to handle cointegrated time series (Gündüz and Kaya (2014), Bratis et al. (2020), Nazlioglu et al. (2020)). As T-Y point out, the classic Granger causality test (Granger (1969)) obtained by a VAR model on cointegrated time series can lead to spurious connections (Dolado and Lütkepohl (1996), Zapata and Rambaldi (1997), Pittis (1999)). The T-Y approach eliminates this shortcoming by introducing a modified Wald test (MWald) which has restrictions on the parameters of the VAR(p) model. The test is based on a χ_p distribution, where $p' = p + d^{max}$. The order of VAR is increased artificially, p gets increased by d^{max} which is the maximal order of the integration. Then, a VAR with an order of $(p + d^{max})$ is estimated, where the last d^{max} lag coefficient is ignored. A VAR$(p + d^{max})$ model is described by Equations (III.2) and (III.3):

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \delta_{1i} Y_{t-i} + \sum_{j=p+1}^{d^{max}} \alpha_{1j} Y_{t-j} + \sum_{j=1}^{p} \theta_{1j} X_{t-j} + \sum_{j=p+1}^{d^{max}} \beta_{1j} X_{t-j} + \omega_{1t} \tag{III.2}$$

$$X_t = \alpha_1 + \sum_{i=1}^{p} \delta_{2i} Y_{t-i} + \sum_{j=p+1}^{d^{max}} \alpha_{2j} Y_{t-j} + \sum_{j=1}^{p} \theta_{2j} X_{t-j} + \sum_{j=p+1}^{d^{max}} \beta_{2j} X_{t-j} + \omega_{2t} \tag{III.3}$$

where α, δ, θ, and β are model parameters, p is the optimal lag of the original VAR model, ω_{1t} and ω_{2t} are the errors of the VAR model, and d^{max} is the maximal integration order in terms of the T-Y model. The hull hypothesis states that the lagged values of Y_t do not significantly contribute to explaining changes in X_t ($H_0 : \beta_{1j}$ for all $j = 1, 2, \ldots, p + d^{\max}$). Hereby based on (III.2), there is a Granger causality between X and Y, if $\beta_{1j} \neq 0$. In the same way, based on (III.3), Granger causality is observable between Y and X, if $\beta_{2j} \neq 0$.

From the VAR$(p + d^{max})$ model, the T-Y model is realized in three steps:

- Perform d^{max} ordered stationarity tests on all of the time series by applying ADF (Augmented Dickey-Fuller test), KPSS (Kwiatkowski-Phillips-Schmidt-Shin test), and PPE (Phillips-Perron test) tests individually or in combination.

- Determine the optimal lag, (p) with the maximal consistency of the AIC (Akaike's Information criterion), BIC (Bayesian Information Criterion), the HQ (Hannan-Quinn criterion), or the LR (Likelihood Ratio test) criteria.

- With the application of the upper-mentioned parameters, rejecting the Granger test between X and Y at a given significance level (usually 1%), means a causality relation in Toda-Yamamoto terms. Bivariate rejection suggests a mutually causal relation between the variables.

III.4 Data

Following Sowmya et al. (2016), Hamill et al. (2021), Umar et al. (2022) and Stenfors et al. (2022), we collect daily data from twelve developed countries. We select sovereigns with the highest GDPs and liquid bond markets, resulting in the sample dataset: Australia, Canada, Switzerland, Germany, Spain, France, Great Britain, Italy, Japan, South Korea, the Netherlands, and the United States of America.[4] Similarly to Antonakakis and Vergos (2013), Sowmya et al. (2016), Byrne et al. (2019), Umar et al. (2022) and Gabauer et al. (2022), we collect the zero-coupon sovereign bond yields from Bloomberg. The specific yield curves and the corresponding tickers are listed in Table A.2 in the Appendix. We consider 15 maturities[5] to obtain the yield curve factors of the term structure for each country as Umar et al. (2021c) and Umar et al. (2022) and we extend the analysis of Sowmya et al. (2016), Cavaca and Meurer (2021) and Gabauer et al. (2022) who use shorter terms only. The time period is from September 30, 1998, to December 31, 2021. Our sample spans over various business cycle phases and major turbulent periods too. Based on Byrne et al. (2019) and Bouri et al. (2021) we cover the following crisis periods:[6]

- The Dotcom Bubble (DCB): 03/10/2000 - 12/02/2001
- The Global Financial Crisis (GFC): 09/15/2008 - 07/21/2010
- The European Sovereign Debt Crisis (ESDC): 11/21/2010 - 03/13/2013
- The Covid-19 Pandemic (C19): 01/20/2020 - 12/31/2021

[4]The countries are frequently referred to by the three-letter shorthand created by the OECD so henceforth we use AUS, CAN, CHN, DEU, ESP, FRA, GBR, ITA, JPN, KOR, NLD, and USA.

[5]3, 6, 12, 24, 36, 48, 60, 72, 84, 96, 120, 180, 240, and 360 months

[6]Start dates and end dates of such crises are linked to global events, described in A.3 in the Appendix. Our results are robust to the choice of the selected dates. The results of this robustness analysis are not reported here but are available from the authors upon request.

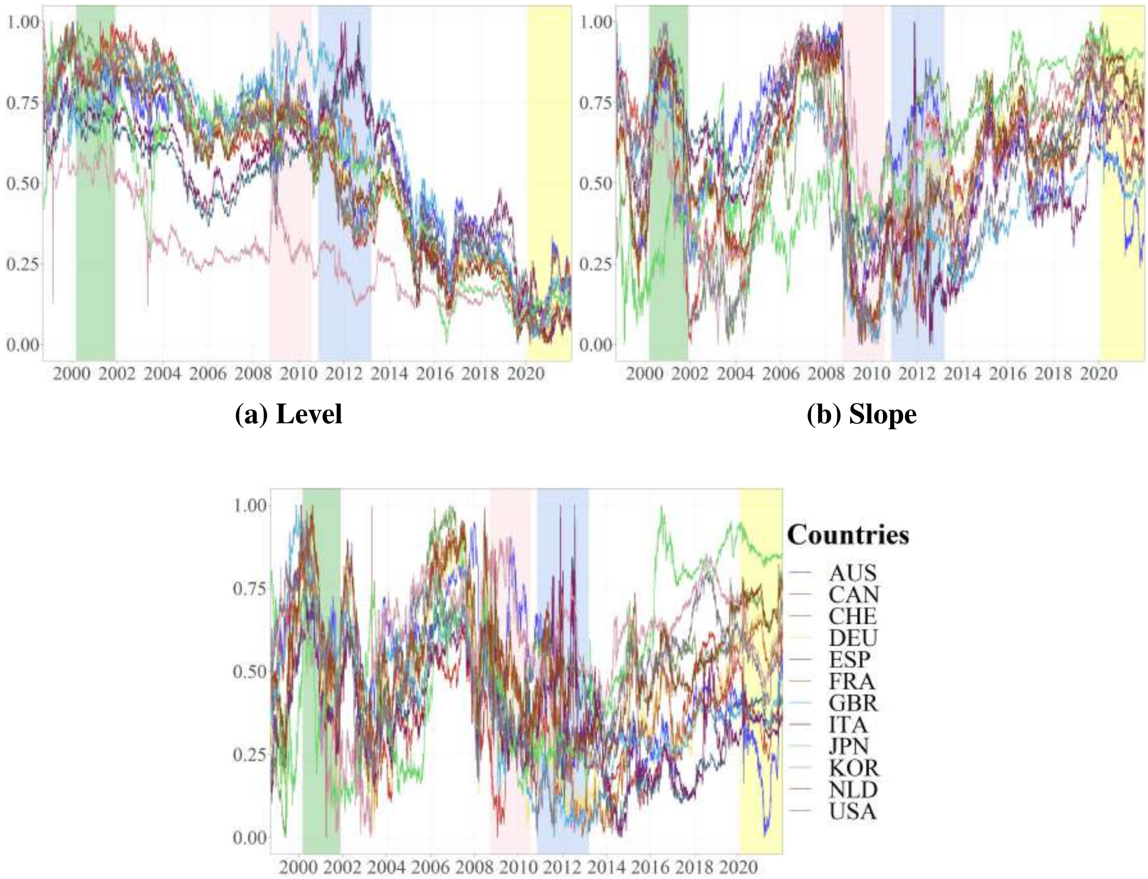
and two longer calm periods (CALM1, CALM2) between these crises.[7] According to our best knowledge, we are the first to examine the characteristics of four different crises on the bond market. We differentiate between global (GFC, C19) and local (DCB, ESDC) crises, as GFC and C19 are worldwide events as opposed to the other crises (DCB and ESDC) which primarily affect one country or a region.

The zero-coupon sovereign bonds are denominated in local currency and we use these yields for two reasons. As per Cavaca and Meurer (2021), debt in local currency better represents the different interest rate cycles of the economy and the domestic monetary policy. Additionally, according to Sowmya et al. (2016), local currency denominated bonds have better liquidity than debt issued in US dollars.

Descriptive statistics for the 1-, 5-, 10- and 30-year nodes of each country's yield curve are provided in Table A.4 of the Appendix. The yield curve characteristics are in line with the findings of previous studies (Sowmya et al. (2016), Cavaca and Meurer (2021)). The normalized time series of the D-L factors are shown in Fig. III.1 in which, DCB is depicted in green shading, GFC is denoted with red, ESDC is represented with blue, and C19 is marked with yellow.

Fig. III.1 sheds light on several stylized facts. Level factors decline and converge across countries during the examination period. Evans and Marshall (2007) find evidence from the USA market that macro shocks shift the level factor of the yield curve, which is visible in our sample too, during the GFC and ESDC in III.1a. Slope time series show countercyclical behavior and comoves across countries. As per Diebold et al. (2006), the curvature factor has only weak links with the macroeconomic fundamentals thus trends or cyclicality are less specific for this factor.

[7]CALM1: 12/03/2001 - 09/14/2008; CALM2: 03/14/2013 - 01/19/2020. Before the Dotcom Bubble, there is an additional calm period (CALM0), due to the rolling window estimation in the dynamic analysis we don't provide results from this era. The timeframe between GFC and ESDC is very short, therefore we do not consider it as a separate subperiod.



(a) Level **(b) Slope**

(c) Curvature

Fig. III.1. Normalized time series of Level, Slope, and Curvature factors

Notes: The green area denotes the DCB, the red-shaded area shows the GFC, the blue field represents the ESDC and the yellow area the C19 period.

The descriptive statistics of the estimated D-L factors are represented in Table III.1. The average Level factors are positive in all cases, with South Korea having the highest values and Japan the lowest. The mean Slope is negative for all countries, which refers to the typical upward-sloping shape of the yield curves. In absolute terms, Italy has the highest Slope, while Australia has the lowest. The average Curvature is also negative, highest for Italy and lowest for Great Britain (in absolute terms).

Table III.1
Descriptive statistics of the yield curve factors

Factor	Average	Std. dev.	Minimum	Maximum	Jarque-Bera t-stat.	P value
Australia						
Level	4.87	1.50	1.06	7.71	540.29	0.00***
Slope	-1.11	0.99	-4.14	0.97	85.24	0.00***
Curvature	-2.15	1.90	-6.80	2.93	205.41	0.00***
Canada						
Level	3.94	1.56	0.70	6.62	404.33	0.00***
Slope	-1.83	1.37	-5.35	0.58	364.08	0.00***
Curvature	-2.18	1.94	-6.27	4.83	400.29	0.00***
Switzerland						
Level	2.19	1.56	-0.79	4.63	528.09	0.00***
Slope	-1.60	0.94	-4.10	-0.06	543.73	0.00***
Curvature	-2.71	1.49	-7.25	1.05	30.68	0.00***
Germany						
Level	3.35	1.98	-0.55	6.56	542.63	0.00***
Slope	-1.84	1.11	-4.69	0.22	234.39	0.00***
Curvature	-3.51	1.73	-6.81	0.96	256.80	0.00***
Spain						
Level	4.54	1.73	0.75	8.56	397.05	0.00***
Slope	-2.78	1.52	-7.35	-0.07	282.06	0.00***
Curvature	-4.01	2.09	-8.75	3.90	115.59	0.00***
France						
Level	3.72	1.80	0.11	6.63	575.05	0.00***
Slope	-2.15	1.17	-4.85	0.16	241.96	0.00***
Curvature	-3.98	1.90	-8.08	0.57	47.29	0.00***
Great Britain						
Level	3.69	1.37	0.47	5.77	764.03	0.00***
Slope	-1.39	1.73	-5.40	3.21	233.43	0.00***
Curvature	-1.82	3.58	-8.79	8.77	93.08	0.00***
Italy						
Level	4.83	1.43	1.43	7.90	481.67	0.00***
Slope	-3.01	1.39	-6.36	-0.24	196.68	0.00***
Curvature	-4.19	1.96	-8.74	4.06	142.96	0.00***
Japan						
Level	1.79	0.91	-0.03	3.57	599.64	0.00***
Slope	-1.43	0.75	-3.30	-0.09	318.65	0.00***
Curvature	-3.72	1.44	-6.54	-0.95	508.30	0.00***
South Korea						
Level	6.13	2.49	1.88	17.23	842.90	0.00***
Slope	-3.00	1.58	-7.85	0.10	169.56	0.00***
Curvature	-4.17	3.00	-14.38	2.67	1961.09	0.00***
The Netherlands						
Level	3.45	1.97	-0.36	7.01	539.12	0.00***
Slope	-1.95	1.14	-4.89	0.20	237.11	0.00***
Curvature	-3.30	1.57	-8.40	0.74	180.26	0.00***
USA						
Level	4.39	1.45	0.96	6.98	383.47	0.00***
Slope	-2.44	1.72	-5.71	0.91	311.13	0.00***
Curvature	-3.61	2.68	-10.35	3.27	197.93	0.00***

*Notes: This table reports the descriptive statistics of latent factors for each country extracted from the Diebold-Li model. Jarque-Bera tests the normality of the distribution. Rejection of null hypothesis at 1%, 5%, and 10% levels are denoted by ***, **, and * respectively.*

We employ the Jarque - Berra test statistics for the normality test, which is always rejected. Furthermore, the ADF and KPSS unit-root tests for stationarity are applied. The

Level time series is stationary for Korea and the USA, the Slope for Japan, and Curvature for Australia and Italy on a 99% confidence level, according to the ADF test. According to the KPSS test, neither of the time series is stationary. The first difference is stationary for all time series based on the two tests. The results of the ADF and KPSS tests are in the Appendix in Table A.5.

Pairwise Engle-Granger (Engle and Granger (1987)) and Johansen (Johansen (1988)) tests are used to determine cointegrations before using the first differences for further analysis. The ratios of the cointegrated time series, grouped by factors, are shown in Table III.2.

Table III.2
The ratio of cointegrated time series pairs based on the Engle-Granger and Johansen tests, aggregated by the yield curve factors

	Level	Slope	Curvature
Level	83.3%	41.7%	86.1%
Slope	16.0%	65.0%	90.3%
Curvature	23.6%	61.1%	91.7%

(a) Engle-Granger test

	Level	Slope	Curvature
Level	68.1%	88.9%	83.3%
Slope	88.9%	88.9%	59.0%
Curvature	83.3%	59.0%	37.5%

(b) Johansen test

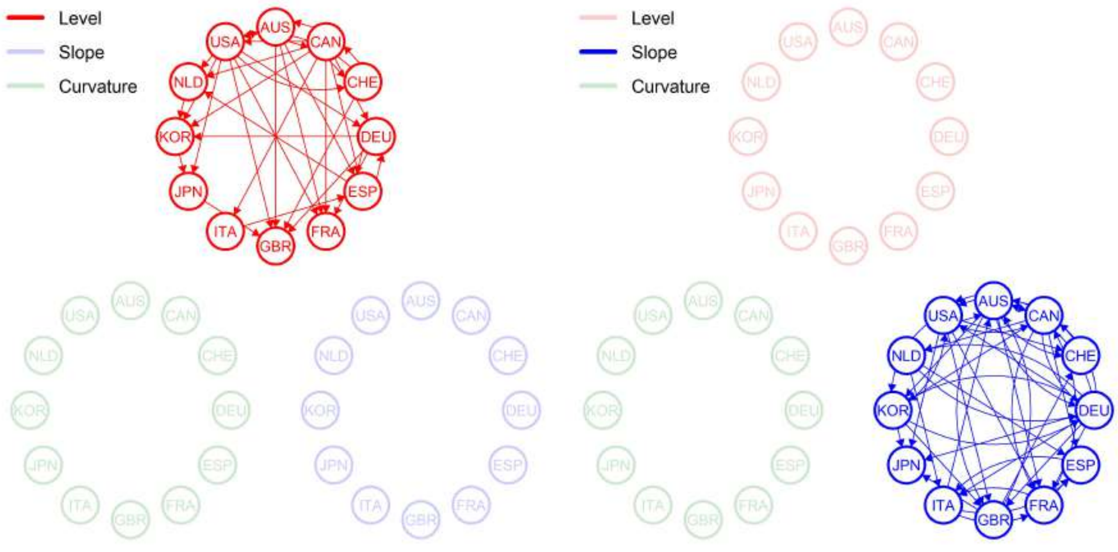
Notes: Instead of the 36 × 36 matrix which we obtain from the pairwise Engle-Granger and Johansen tests, we show only the subsystems-based aggregated values in this table

Tables III.2a and III.2b provide a high ratio of cointegrated connections, for example, the Level-Curvature subsystem is greater than 80% in both cases. Based on Table III.2 and Table A.5 of the Appendix, applying the T-Y model is required because the time series are not stationary in the same order and the ratio of cointegrated time series is high.

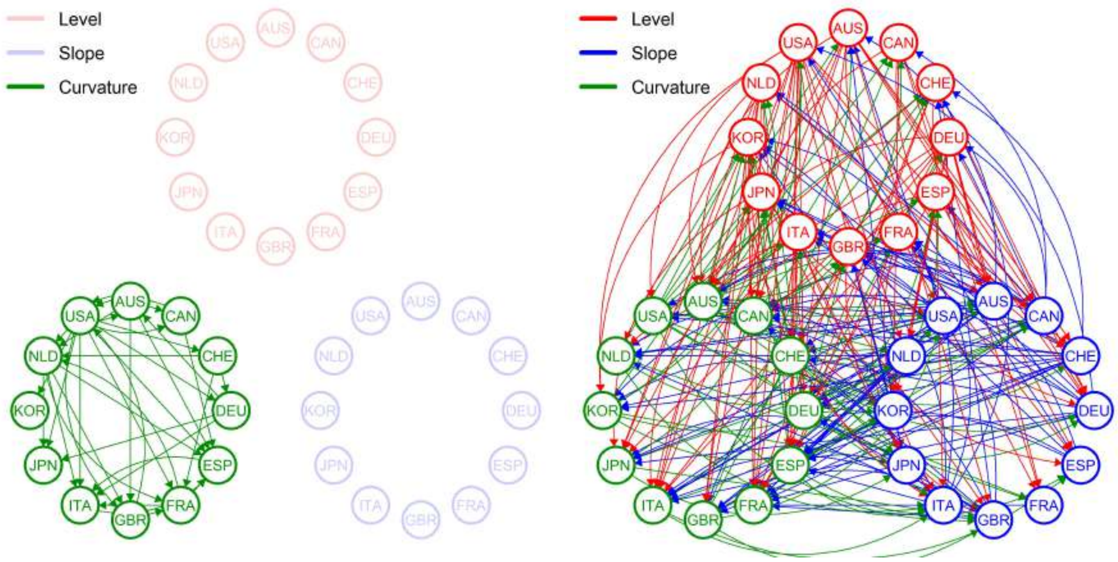
III.5 Results

III.5.1 Static, full-sample connectedness analysis

Following Antonakakis and Vergos (2013), Claeys and Vašíček (2014), and Fernández-Rodríguez et al. (2015), we begin our analysis with a static investigation on a factor level. We measure the connections within the Level, Slope, and Curvature subsystems, and identify the cross-relations among them. Fig. III.2 displays the causal linkages at a 1% level of significance, separated by subnetworks. The figure shows connections estimated by the Toda-Yamamoto procedure, using all the available data.



(a) Level subnetwork **(b) Slope subnetwork**



(c) Curvature subnetwork **(d) Cross connections**

Fig. III.2. Causality relations within subnetworks, estimated by static Toda-Yamamoto model

Notes: Level factors are displayed in red, Slopes in blue, and Curvatures in green. An arrow between two factors indicates the direction of causation, and the color of the arrow indicates the source factor. Time series are differentiated at a maximum of one time, and the ideal lag time is chosen based on the AIC. For Level factors, 34; for Slope, 47; and for Curvature, 36 connections are significant from the possible $132 = (12 \times (12 - 1))$. *In the case of cross-connections, 258 are significant from the possible* $864 = (1260 - 3 \times 132)$. *For total connections, 375 links are significant from the possible* $1260 = (36 \times (36 - 1))$.

The Slope network has the highest density of the three subsystems with 35.61% of the potential relations being significant. It is followed by Curvature (27.27%), then Level (25.76%). The findings of Sowmya et al. (2016), Umar et al. (2021c), Umar et al. (2022) and Gabauer et al. (2022), who all claim that Level subsystem has the largest spillover effect, followed by Slope, and Curvature, are in contrast with ours. However, according to Cavaca and Meurer (2021), the Slope is the most connected subnetwork, which is supported by our findings. In addition to the different country set and the sample length, the other reason for the different results could be the T-Y model, which is suitable for filtering out spurious connections in the case of highly cointegrated systems (compared to the widely used VAR-based D-Y spillover index which is applied in the above-mentioned papers).

We also analyze the cross-connections among the yield curve components, for further insights. Altogether 258 significant cross-connections are defined, about 29.86% of the total 864 possible edges. From these connections, 95 (36.8%) originate from Slope-, 92 (35.3%) from Level-, and 72 (27.9%) from Curvature nodes. Altogether 258 significant cross-connections can be defined, which is 29.86% of the total possible edges of 864. From these, 95 (36.8%) originate from Slope, 92 (35.3%) from Level, and 72 (27.9%) from Curvature nodes. Based on Table III.3a, on factor level, the Curvature has the most incoming edges, while the Slope has the most outgoing ones. The Level has the least incoming links while it is second in the list of outgoings. The Curvature subnetwork has the least outgoing edges, and in this sense, it is the least connected, which is in line with the findings of Dewachter and Lyrio (2006).

Table III.3
The number and distribution of the significant connections defined in the system

	Level	Slope	Curvature	Outgoing
Level	34	43	48	125
Slope	33	47	62	142
Curvature	34	38	36	108
Incoming	101	128	146	375

(a) Number of connections, grouped by factors

	Level	Slope	Curvature	Outgoing
Level	25.8%	29.9%	33.3%	29.8%
Slope	22.9%	35.6%	43.1%	33.8%
Curvature	23.6%	26.4%	27.3%	25.7%
Incoming	24.0%	30.5%	34.8%	29.8%

(b) Distribution of connections, grouped by factors

Notes: In the diagonal, we divide the connections by $132 = (12 \times (12 - 1))$*, since this is the maximum definable relation in the subnetworks. Between two subsystems this number is* $144 = (12 \times 12)$*, we scale the upper and lower triangular by this. The values in the summarized row and column are divided by* $420 = (132 + 144 + 144)$*. The total definable connections in the network are* $1260 = (420 \times 3)$*, we divide 375 by this.*

Fig. III.2d and Table III.3 highlight that the connections between different subsystems are not negligible. The cross-factor connections are 68.8% of the defined causality relations (258 out of 375).

Although Figs. III.2 and III.3 provide information about the subsystems of the factors, these are not sufficient to draw conclusions about the main economics drivers behind the network. To extend the factor level-based analysis in the next subsection we examine our sovereign yield curve network on a country and a node-wise level too.

III.5.1.1 Country-level analysis and the key participants of the network

Despite the high number of recent connectedness-related articles, there are limited insights about the different levels, changes in density and key participants (i.e., dominant factors). In this section, we use the net (outgoing-incoming) and sum connections to identify the core countries of the system, as shown in Table III.4.

Table III.4
Net and sum connections throughout the study period, aggregated by countries, ordered by net connections

Country	Net connections	Sum connections
USA	**45**	89
DEU	**18**	74
AUS	16	80
CAN	11	69
CHE	9	51
NLD	2	58
KOR	-8	56
GBR	**-13**	59
ESP	-16	58
ITA	-18	60
JPN	**-22**	44
FRA	-24	50

Aggregating the connections on a country level, the United States and Germany are at the top of the list. Our results align with the findings of Umar et al. (2022) and Berardi and Plazzi (2022) but we also consider cross-factor connections. They also claim that Japan and Great Britain are net importers of shock and hereby we confirm this statement.

Table III.4 only provides an aggregated overview on a country level, however, to deeper understand our network, and identify the key participants, it is useful to aggregate on a node-level too, as they are driven by different economic effects. None of Sowmya et al. (2016), Cavaca and Meurer (2021) or Gabauer et al. (2022) carry out this examination (as far as we know, we are the first to investigate this on the bond market), so hereby we extend their results. Nodes with the most connections are shown in Table III.5. The first quarter of the table represents the summarized relations, whereas the subsequent columns show the nodes with the highest numbers of separate incoming and outgoing connections. For finding the dominating participants in our network we use net (outgoing-incoming) connections which is an accurate measurement according to Barigozzi and Brownlees (2019).

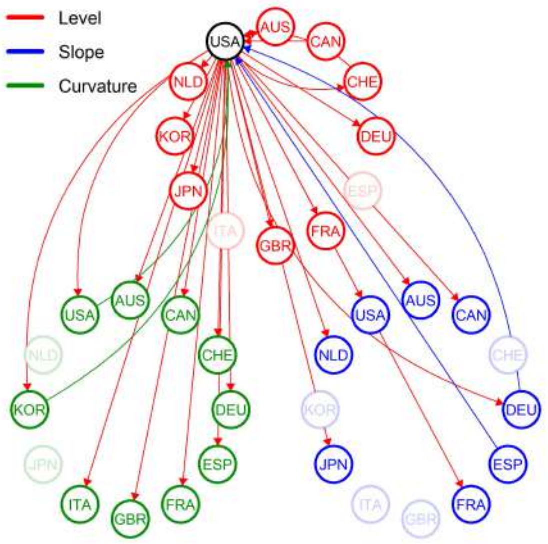
Table III.5 highlights that in our network, the Slope factor of Canada has the most connections overall, at 32, from which 19 arrows originate and 13 come in. In a previous study,

Table III.5
Key country factors having either the most of summarized, incoming, outgoing or netted edges

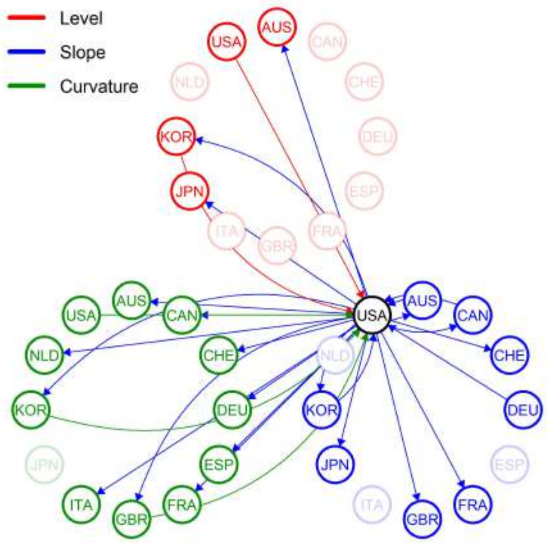
Top 5 Sum				Top 5 Incoming		Top 5 Outgoing		Top 5 Net	
Node	Total	In	Out	Node	In	Node	Out	Node	Net
CAN S	32	13	19	ESP C	20	USA L	25	USA L	19
USA L	31	6	25	ITA C	19	USA C	22	USA C	15
AUS C	30	12	18	FRA C	18	USA S	20	USA S	11
AUS S	29	13	16	KOR L	14	CAN S	19	DEU L	9
DEU S	29	11	18	ITA S	14	DEU S	18	CAN L	8

Umar et al. (2022) find that Noth-American countries have the most net connections in all subsystems. On 10-year Treasury bond yields, the results of Umar et al. (2020) show that the USA is the most dominant, followed by Canada, then the European countries. These findings are in line with our results, except we consider cross-connections too, in addition, in our case, all three factors of the USA lead the list of net connections.

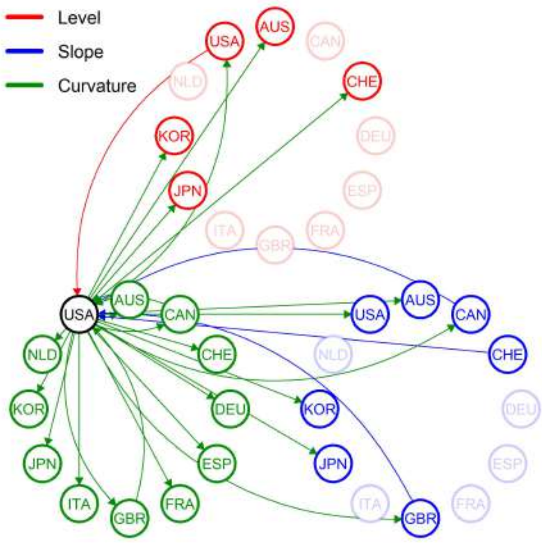
To better comprehend the role of the USA sovereign yield curve in the network, we analyze the node-wise connections of the three factors. The connections of the USA Level, Slope, and Curvature components are highlighted in Fig. III.3. The graphs support the statement of Table III.5, while the US factors have few incoming connections, they have many outgoing ones. It is also visible that all three factors have numerous cross-connections (56.2% of the defined edges) which further emphasizes the importance of such relations.



(a) USA Level



(b) USA Slope



(c) USA Curvature

Fig. III.3. Role of the USA nodes in the system, estimated by static Toda-Yamamoto model

Notes: Level factors are displayed in red, Slopes in blue, and Curvatures in green. An arrow between two factors indicates the direction of causation, and the color of the arrow indicates the source factor. Time series are differentiated at a maximum of one time, and the ideal lag time is chosen based on the AIC. For USA Level factors, 31 (44.29%); for Slope, 29 (41.43%); for Curvature 29 (41.43%) connections are significant from the total possible $70 = (2 \times (12 + 12 + 11))$. *Cross-connection ratios are 67.7% for Level, 62.1% for Slope and 38.0% for Curvature.*

The USA is not only dominant on a country level, as shown by Table III.4, but on a node-wise level as well. Based on these outcomes, we conclude that relying on a static connectedness analysis, the US yield curve factors are the key participants of our the network. After the full-sample investigation, we examine the network behavior in turbulent (global and local crises) and tranquil periods.

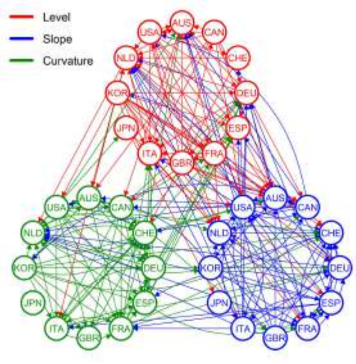
III.5.2 Connectedness during different subperiods of the study horizon

The effects of crises on the sovereign yield curve networks are well documented in the empirical literature (Claeys and Vašíček (2014), Reboredo and Ugolini (2015)), however, it is less common to compare different crises.[8] We examine the sovereign yield curve network in the crisis periods on different levels (yield curve factor, country, and node-wise) in a static way, then we investigate the networks in four previously discussed turbulent and tranquil periods to understand the differences between the global (GFC, C19) and local (DCB, ESDC) crises.

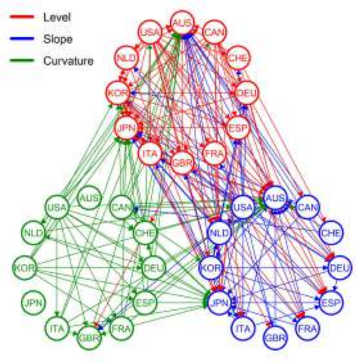
To deeper understand the different crises, we perform a static connectedness analysis on six separate time periods. Fig. III.4 shows the periods introduced in Section III.4, of which four are turbulent (2 globals and 2 locals) and two are calm.[9]

[8]Previous articles such as Antonakakis and Vergos (2013), Fernández-Rodríguez et al. (2015), Fernández-Rodríguez et al. (2016), Hamill et al. (2021), Chatziantoniou and Gabauer (2021) and Umar et al. (2022) examine calm and turbulent periods, using a time frame that includes the Global Financial Crisis and the European Sovereign Debt Crisis while Karkowska and Urjasz (2021) and Umar et al. (2022) extend the investigation window to involve the Covid-19 pandemic as well. However, these papers only compare calm and turbulent periods with a dynamic model, and we widen their research twofold.

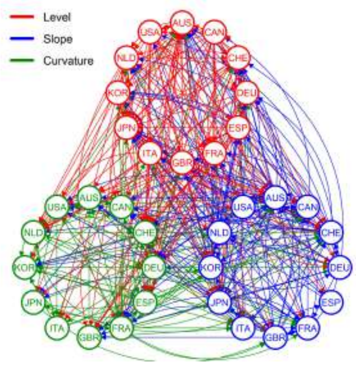
[9]These periods range in length (DCB: 451 days, CALM1: 1770 days, GFC: 483 days, ESDC: 603 days, CALM2: 1787 days, C19: 510 days), so to maintain consistency, we first averaged the time span of the crises (512 days) and then pick such lengthy sets from the calm periods randomly (CALM1: 01/13/2004 - 12/28/2005; CALM2: 05/06/2014 - 04/20/2016). Our results are robust to the choice of the selected dates.



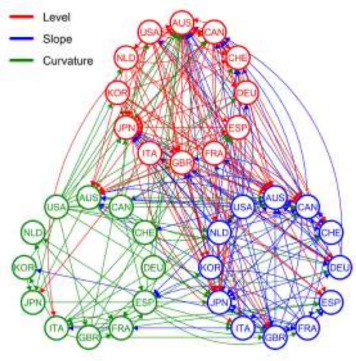
(a) Dotcom Bubble



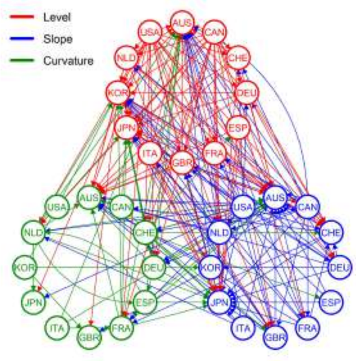
(b) Calm period 1



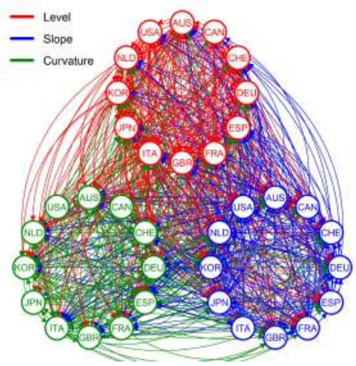
(c) Global Financial Crisis



(d) European Sovereign Debt Crisis



(e) Calm Period 2



(f) Covid-19 Pandemic

Fig. III.4. Network connectedness in different subperiods, estimated by static Toda-Yamamoto model

Notes: Level factors are displayed in red, Slopes in blue, and Curvatures in green. An arrow between two factors indicates the direction of causation, and the color of the arrow indicates the source factor. Time series are differentiated at a maximum of one time, and the ideal lag time is chosen based on the AIC. Number of connections in DCB: 236, in CALM1 (sample): 206, in GFC: 414, in ESDC: 234, in CALM2 (sample): 225, in C19: 763.

Fig. III.4 highlights that C19 (763) and GFC (414) provide the networks with most connections, followed by DCB (236) and ESDC (234). The ratio of cross-connections is the following in each subperiod: DCB: 39.9%, CALM1: 57.8%, GFC: 62.6%, ESDC: 62.0%, CALM2: 62.7%, C19: 65.0%. These results further emphasize the importance of investigating cross-factor linkages.

The number of significant connections is higher in the two global crises (GFC, C19) than in local ones (DCB, ESDC), or calm periods. Fernández-Rodríguez et al. (2016), Chatziantoniou and Gabauer (2021) and Karkowska and Urjasz (2021) all find that in crisis periods the spillover is higher in the sovereign bond markets, which is in line with our results. We extend the contribution of the latter studies, by showing that while the density difference between calm periods and local crises is rather small, it is significantly larger during the two worldwide crises.

Similarly to the full-sample investigation, after identifying the density structures of the different time frames on yield curve factor level, we determine the countries that are responsible for the significant causal relations within the networks. The net connections for each subperiod, averaged by countries, are shown in Table A.7.

Except for the DCB period, the USA is the dominant country in each subperiod.[10] On a country level, the USA is the main exporter and Japan the main importer of interest rate shocks (apart from the cases of DCB and C19, when Japanese net connections add up to zero), which further emphasizes the findings of Berardi and Plazzi (2022).

To achieve a deeper understanding of the role of the key participants in the sovereign yield curve network during the selected periods, we aggregate the connections by nodes. Table III.6 outlines the role of Level, Slope, and Curvature factors for the twelve countries. As far as we are aware, ours is the first paper that examines the roles of latent yield curve factors in calm, local and global crisis periods.

Table III.6

Factors being net transmitters or net receivers of causality connections during the six sub-periods

	Level							Slope							Curvature						
	Whole period	DCB	CALM1	GFC	ESDC	CALM2	C19	Whole period	DCB	CALM1	GFC	ESDC	CALM2	C19	Whole period	DCB	CALM1	GFC	ESDC	CALM2	C19
AUS	+	-	-	-	-	-	-	+	-	-	+	-	-	-	+			-	-	-	-
CAN	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	+	+	+	+	+	+
CHE	+		+	-	-	+	+	+	-	+	-	-	-	-	+	-	+	-		+	-
DEU	+	-	-	+	+	+	+	+	-		-	-	+	-	+	+	+	+	+	+	-
ESP	+	-		+	+	+		-	+	-	+	-	+	+	-	-	+	-	+	+	-
FRA	+	+	+	+	+	+	+	-		-	-	+	+	-	-	+	+	+	-	+	-
GBR	-	+		+			+	+	+		+	-	-	-	-	-	-	-	+	-	
ITA		-	-	+	+	+	+	-	+		-	+	+	+	-	+	+	-	+	+	-
JPN	-	+	-	-	-	-	-	-	-	-	-	-	-	+	-			-	-	-	+
KOR	-	+	+	+	+	-	-	-	+	+	+	+	+	-	-	+	+	-		+	-
NLD	+	-	+	+	+	+	+	+	-	-	+	+	+	-	-	-	+	-	-	+	-
USA	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+

Notes: **+** *signs indicate that the factor is a net transmitter in the given period, while* **-** *signs indicate that the factor is a net receiver.*

Considering the first column, we conclude that the majority of Level and Slope factors are net providers (7 out of 12 in both cases), while Curvatures are usually net recipients (8 out of 12) of causality relations. Based on Table III.6 the USA is the only country where all the three yield curve factors net connections are positive during each subperiod.[11] Table

[10] At the end of the '90s, South Korea (and other Southeastern Asian countries) went through a serious financial crisis and its consequences are felt during the 2000-2001 horizon which overlaps with the Dotcom Bubble in the US (Kihwan (2006)). Most of the net connections of South Korea in this period are due to the Level factor (15) which originates from the Bank of Korea's monetary policies described in Coe and Kim (2002) and Chung and Kim (2002).

[11] In addition to the US factors, the Canadian Level and Slope have a high impact on the network for the majority of the time frame and Canada also can be found in a high position in the different subperiods in Table A.7. Greenwood-Nimmo et al. (2015) document that since Canada is a member of the North

III.6 confirms our previous statement, besides the US factors being the dominant nodes on the whole study period we claim that they are the key participants in every identified subperiods as well.

III.5.3 Dynamic, rolling-window-based connectedness analysis

Running a static analysis may not capture perfectly the cyclical and structural changes in the dynamics of the network and we are keen on exploring the potential changes in the network on different levels and the key participants through the examination horizon. Thus after the static examination, we perform a dynamic analysis of the sovereign yield curve network, similar to Sowmya et al. (2016), Cavaca and Meurer (2021), Umar et al. (2021c), Umar et al. (2022) and Gabauer et al. (2022).[12] We estimate 1064 different models as we roll the estimation window by one business week (5 days) through our sample. In Fig. III.5 the purple, cyan, and grey lines represent the ratios of total significant connections, summarized edges in the three subnetworks, and the cross-connections, respectively compared to the maximum number of possible linkages.

American Free Trade Agreement (NAFTA), it can be an indicator for being net positive in most cases.

[12]There is no exact rule to chose the sufficient window size and based on Arce et al. (2013) and Papana et al. (2017) we choose a rolling window method with 750 days. This can be seen as three years with 250 business days. In subsection A.2 of the Appendix, we extend our analysis with window sizes of 500 and 1000 days. Furthermore, we perform a Granger causality test, with a rolling window size of 750 days, as an additional robustness check.

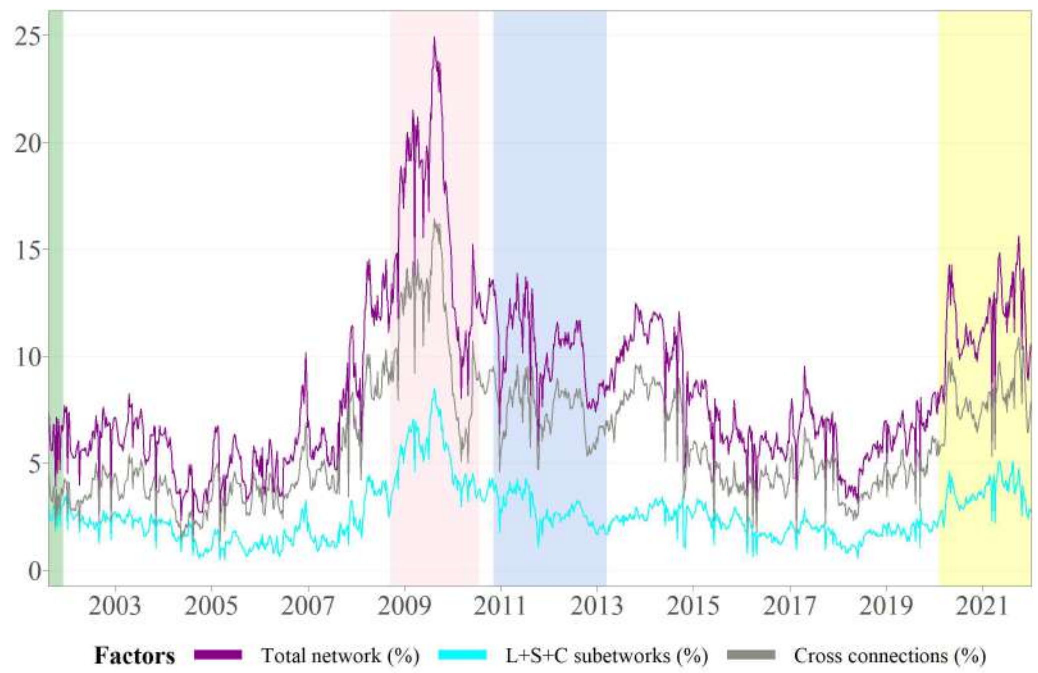


Fig. III.5. Summarized connection ratios during the study period, estimated by dynamic Toda-Yamamoto model

Notes: Window size of 750 days and a lag determined by the AIC. The green area denotes the Dotcom Bubble, the red-shaded shows the Global Financial Crisis, the blue field represents the European Sovereign Debt Crisis, and the yellow covers the Covid-19 period. The purple line indicates the ratio of total significant connections, the cyan represents the summarized edges in the three subnetworks, and the grey line is the time series of the cross-connection ratios, compared to the maximum number of possible edges.

The behavior of the three time series is very similar, and all of them peak during the GFC, and the C19 outbreak. In the empirical literature, there is general agreement that connectedness rises during turbulent times. The DCB and the ESDC cannot be viewed as a global phenomenon, thus the graphs in Fig. III.5 do not indicate an upward tendency during these times. While Diebold and Yilmaz (2009), Billio et al. (2012) and Diebold and Yilmaz (2015) find this evidence for stocks, Antonakakis and Vergos (2013), Fernández-Rodríguez et al. (2015), Sowmya et al. (2016), Fernández-Rodríguez et al. (2016), Ahmad et al. (2018), Chatziantoniou and Gabauer (2021), Karkowska and Urjasz (2021), Hamill et al. (2021), Chatziantoniou and Gabauer (2021) and Umar et al. (2022) all exhibit the same on the bond markets. However, none of these studies differentiate between local and global crises (as far as we know, we are the first to investigate this on the bond market) so hereby we extend their results.
The average summarized connections for each subperiod are shown in Table III.7.

Table III.7
Average connection count by types during the six sub-periods - 750 days long window size

	Whole period	DCB	CALM1	GFC	ESDC	CALM2	C19
L+S+C	32.4	34.2	24.3	67.4	35.1	25.9	44.9
Cross connections	75.5	43.4	54.3	139.7	93.1	65.9	100.3
All connections	108.0	77.6	78.6	207.1	128.2	91.8	145.3

Table III.7 demonstrates that as the Level, Slope, and Curvature subnetworks get denser, cross-connections also increase during times of crisis.[13] Fig. III.5 and Table III.7 jointly show that the magnitude of cross-connections is around twice the combined number of connections in the yield curve factor subnetworks. Our dynamic analysis supports the results of the earlier studies of Sowmya et al. (2016), Cavaca and Meurer (2021), Umar et al. (2021c), Umar et al. (2022) and Gabauer et al. (2022), but we complete them with cross-connections between the Level, Slope and Curvature subnetworks.

III.5.4 The shift in the dominance of US factors across the study horizon

There is growing evidence in the empirical literature that US market shocks play a special role in international asset market comovements and Fed monetary policy affects the global bond market. Hofmann and Takáts (2015) are the first who document economically and statistically significant spillovers from the US short and long-term interest rates to advanced economies' government yields. In an influential paper Miranda-Agrippino and Rey (2020) study how the existence of a 'Global Financial Cycle' shapes the global financial spillovers of US monetary policy shocks. Lakdawala et al. (2021) also document that the Fed's communication on uncertainty regarding future actions is an additional, new monetary policy instrument through which the Fed can influence global financial conditions.

Empirical evidence on the effects of ECB policies on international government bonds is less clear (Jarociński (2022)). Kearns et al. (2018) find significant spillovers from ECB announcements and Curcuru et al. (2018) document that US and European government bond yields also co-move around these actions. Jarociński (2022) complete these results while he documents that spillovers of ECB interest rate shocks are smaller because they are conditional on the integration of European interest rates. Contrary to these findings, Miranda-Agrippino and Nenova (2022) document comparable magnitudes of spillovers related to the two central bank's monetary policy decisions. Based on these results, it is worth examining how the Fed and ECB monetary policy decisions affect the key participants of a sovereign bond-related network as well.

[13] A detailed view of the average edge counts by countries in these six periods is available in Table A.6 in the Appendix.

Hofmann and Takáts (2015), Albagli et al. (2019), Miranda-Agrippino and Rey (2020), Lakdawala et al. (2021) all emphasize that the Fed exerts a significant impact on the rest of the world's fixed-income market through its monetary policy, which presents itself in a dominant role at the yield-curve factor level in our network. However, as evidenced by the lead-lag effect of the Fed's interest rate politics, based on Kearns et al. (2018), Jarociński (2022) and Miranda-Agrippino and Nenova (2022) this dominance can vary over time. Therefore we also examine the ECB monetary policy decisions.

In subsections III.5.1 and III.5.2 we show that the US factors are the key participants in our network, considering the whole time frame, as well as each subperiod. Upon further examination of the time series of these connections, based on Fig. A.3, we discover that these yield curve factors are the key participants of the system from a dynamic perspective too. Fig. A.3 highlights that the dominance of the US factors is time-varying; therefore, further economic drives can be behind these nodes' dynamics. Since monetary policy decisions have a great impact on the evolution of the yield curve, it is useful to investigate the linkage between the Fed's and ECB's easing and tightening decisions and the dominance of US factors.

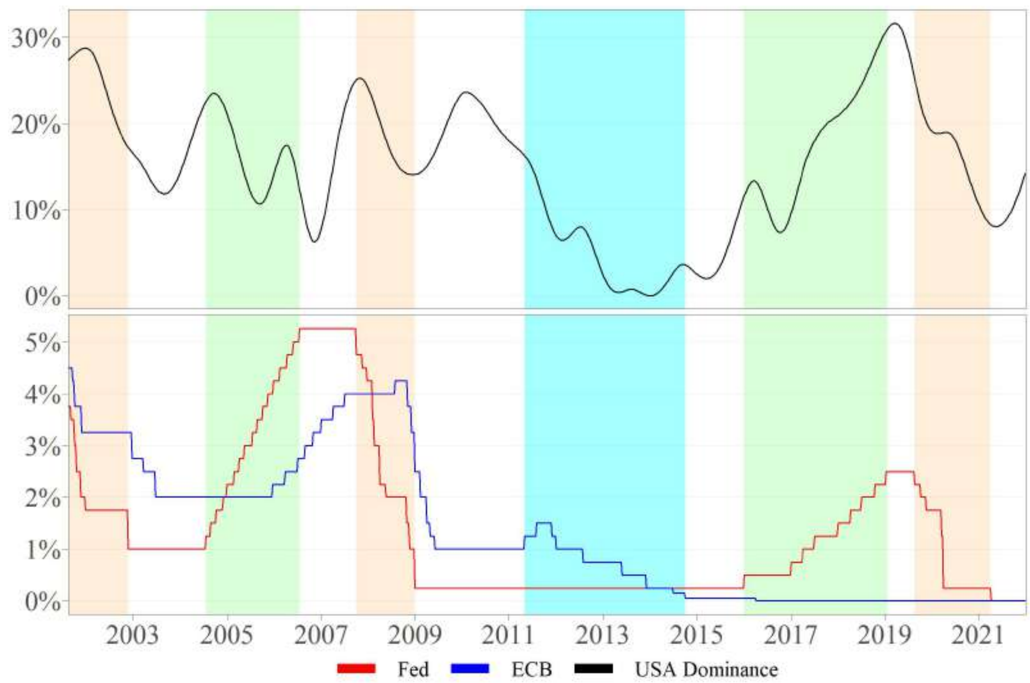


Fig. III.6. Dynamic dominance of US factors, estimated by dynamic Toda-Yamamoto model

Notes: Window size of 750 days and a lag determined by the AIC, smoothed by cubic spline method. The orange areas denote the Fed interest rate cut, the green-shaded parts show Fed interest rate hikes and the cyan field represents the period when ECB leads the interest rate cycle. The red line stands for the Fed rates over time, while the blue represents ECB rates. The black line is the dynamic ratio of summarized outgoing USA edges and the total number of outgoing edges, smoothed by a cubic spline.

In the lower part of Fig. III.6 the time series of the policy rates set by the Federal Reserve (Fed, red line) and the European Central Bank (ECB, blue line) are visible.[14] Orange shading represents those periods when Fed cuts interest rates, while during green shading, Fed raises interest rates. Additionally, with cyan filling, the only period is noted when the ECB changes rates while the Fed does not. The upper part of Fig. III.6 represents the ratio of the outgoing USA connections (Level, Slope, Curvature summarized) compared to the aggregated outgoing connections of the entire network. Fig. III.6 shows that the Fed, in general, leads the ECB and this phenomenon is in line with the hypothesis that the Fed is the leader of the interest rate cycle. According to Brusa et al. (2020), the Fed is the global central bank and generally leads the other central banks in setting monetary policy. Fig. III.6 highlights that the US dominance decreases in the sovereign yield curve network when Fed cuts rates. Furthermore, its dominance reaches the global minimum when the interest rate cycle is led by the ECB (during the years 2011-2014). Based on Fig. III.6, during interest rate hiking cycles, the dominance of the US factors also change, however, from 2016 to 2019, the dominance increased sharply, while a slight decrease is experienced between 2004 and 2006.

III.6 Concluding remarks

This study investigates the network of sovereign yield curves of 12 developed countries. We decompose the term structure of the interest rates into the Level, Slope, and Curvature factors using the dynamic Nelson-Siegel (Nelson and Siegel (1987)) model as in Diebold and Li (2006). The connections between the latent yield curve across countries are measured using the Toda and Yamamoto (1995) method, which is suitable for cointegrated time series. Our examination also covers cross-factor relations. For deeper understanding the structural changes and identify the key participants in the sovereign yield curve network, we analyze the connections on factor, country, and node levels too. Our timeframe lasts over a 23-year long interval; therefore, we can compare two global (GFC and C19) and two local (DCB and ESDC) crises.

When considering the whole time period, the Slope subnetwork has the most connections of the three subsystems followed by Curvature and Level. Additionally, we claim that there is a significant amount of linkage between the three subnetworks on factor level, so cross-connections are not negligible. The number of total connections in the network increases during turbulent periods. During the two global crises (GFC and C19) the sovereign yield curve network is denser than in the two local (DCB, ESDC) cases. We found that the USA factors are the key participants in our network, considering the whole time frame, as well as each subperiod and the dynamic analysis too, but this behavior is

[14] The rates for the Fed and ECB are collected from `https://fred.stlouisfed.org` and `https://www.ecb.europa.eu` respectively.

time-varying. Although the dominance of the USA factors is independent of the characteristics of the subperiod (whether it is a calm, local or global crisis) it is affected by the Fed's and ECB's monetary policy decisions. The dominance of the US factors peaks if the Fed leads the hiking cycle and reaches its minimum when the interest rate cycle is led by the ECB.

Our results are relevant for academics, central bankers, and policymakers by providing insights into the behavior of sovereign yield curve networks during turbulent and tranquil periods. Our findings related to Fed and ECB monetary policy decisions are important for central bank policymaking. Identifying the key participants provides insights into the dynamics of the market. Specifically, monitoring the activities of these players can aid policymakers' assessment of the market conditions, identify potential risks, and detect any deviation from tranquil periods that may impact market stability. All network participants have linkages with various financial institutions and other asset classes, locally and globally. Policymakers need to be aware of these connections to assess systemic risk and the potential for contagion in times of market stress. Overall, our results about the influence of the Fed and the ECB, the two key players, can be useful for policymakers in smaller economies for managing their macroeconomic and monetary policy decisions. Essentially smaller economies have to be aware of their network exposure to key players to be prepared. Identifying the important players can help policymakers anticipate and mitigate the likely spillover effects emanating from disruptions or shocks from the key participants.

CHAPTER

IV

DYNAMIC VOLATILITY TRANSFER IN THE EUROPEAN OIL AND GAS INDUSTRY

Chapter IV is based on the work of Huszár et al. (2023a). Minor modifications are made to align with the dissertation format.

IV.1 Introduction

Today, the oil and natural gas industry plays a critical role in the global economy and the everyday life of citizens who rely on oil and gas for work, transportation, heating and nourishment, among others. The processes, systems and companies involved in producing and distributing oil and gas are increasingly complex, capital-intensive and continuously evolving with technological innovations (CRS Report (2021)). Due to the high entry barriers, the industry is characterized by an oligopolistic structure where governments often have direct or indirect involvement in the management of these strategically and economically important national companies. The involvements are non-negligible since these national oil companies (NOCs) controlled over $3 trillion in assets in 2019 and produced much of the world's oil and gas, while their operations are often non-transparent to the public (IMF (2019a)). With the recognition of energy risk as a new source of systemic risk, (e.g., Jang et al. (2020); Caporin et al. (2023); Yang and Hamori (2021)) there have been an increasing number of studies into oil price behaviors in relation with equity markets, debt markets and political uncertainty (e.g., Kang et al. (2017b)).

It is important to understand the link between oil and gas markets. First, the supply and demand dynamics of all energy commodities are interconnected (Al-Maamary et al.

(2017)). Second, as a number of companies are involved in both exploration and production of oil and gas, their financial performance can be influenced by the performance of both commodities simultaneously (George et al. (2016)). While traditionally Brent, WTI, and natural gas prices are strongly correlated, gas prices seem to have decoupled recently, as government policies and environmental regulations have preferential treatment towards natural gas. For example, the European Union (EU)'s energy strategy change with a shift towards gas as a "green alternative" from oil (SPGlobal (2022)) and diversification of the energy supply chain, increasing reliance on US and other non-European energy sources call for examination of oil and gas prices together.

Globally, a few oil-rich countries are the dominant players in the oil and gas industry. While the US energy sector is privatized and therefore data is readily available, it is not the case for non-US companies (IMF (2019a)). Thus energy studies tend to focus on the US market (e.g., Antonakakis et al. (2018); Zhao (2020)), in particular, studies on renewable energy and clean energy sources (Ferrer et al. (2018)). Apart from the US, the European continent is also a big player in the energy sector. Although the European Union produced 1.9 million Tera Joule (TJ) worth of natural gas in 2020 (Eurostat (2023)), it remained heavily dependent on external energy, with an over 80% increase in natural gas dependence ([import - export] / inland demand). The top gas exporters to the EU are Russia (23.3%), Norway (22.7%), Ukraine (10.2%) and Belarus (8.9%) (Eurostat (2023)).

Even without external disruptions such as Russia's war on Ukraine (Council of Europe (2023)), energy prices can be highly volatile because of the slow production/distribution process and the limited number of large production players (who can collude on supply and engage in price setting). While there are hopes that in the long run, the use of nuclear power, renewables and alternative energy sources can be exploited to reduce carbon emissions and improve energy security throughout Europe, in the short term the end users are largely dependent on traditional oil and gas producers (IMF (2022b)).

In this study, we focus on the European energy market where the impact of environmental and geopolitical risks on stability and sustainability are of growing concern, especially since the start of Russia's war on Ukraine. Specifically, we investigate the volatility spillover among crude oil, natural gas, unleaded gasoline prices and the stock prices of major European oil and gas companies over the period from October 2006 to June 2022. We separate our sample into different industry segments, namely Upstream, Midstream, Downstream and Integrated Gas and Oil, to analyze the flow of volatility throughout the production and distribution process.

The economics and financial literature often distinguish between fundamental versus financial excess volatility. Fundamental excess volatility of different economic entities can be interconnected through the supply chain of goods, services (including technology) and capital flows. These effects are known in the literature as spillovers (Masson (1999)), interdependence and interconnectedness (Forbes and Rigobon (2002); Forbes (2012)), or fundamental-based contagion (Kaminsky and Reinhart (2000)). On the other hand, financial contagion is defined as shocks that could trigger crises elsewhere and spread to all or most of the system participants (Masson (1999)).

In the empirical literature, various methods have been used to measure connectedness. For example, Granger causality network by Billio et al. (2012), Conditional Value at Risk (CoVaR) by Liu et al. (2022), Marginal Expected Shortfall (MES) by Acharya et al. (2012) and VaR-GARCH model by Arouri et al. (2012). In the last decade, Diebold and Yilmaz (2012)'s generalized spillover index (D-Y spillover index, hereafter), using generalized forecast error variance decomposition, has gained traction in risk transmission analysis, particularly in energy sector analysis. In extensions for the model, for example, Antonakakis et al. (2023) and Ghosh et al. (2023) examine volatility transmissions, using time-varying parameter VAR variant of the connectedness approach.

The popularity of the DY model can be attributed to its intuitiveness and flexibility, suitable for network analysis even in market turbulence and transition. Specifically, the model considers the dynamic nature of volatility, allowing for changing market conditions and accounting for the interaction between the market (or the network) participants. In addition, the approach can distinguish between directional spillovers, aiding the identification of the main source of potential systemic risk. The net spillover matrix is a popular tool for representing systematically important elements within a set of companies or assets.

We adopt the D-Y spillover index for our analysis of volatility transmission across the European energy industry in relation to oil and natural gas prices. Our contribution to the literature is threefold. First, to the best of our knowledge, our work is the first comprehensive analysis of the volatility transmission dynamics across all major European oil and natural gas companies. Covering more than 90 percent of the total market capitalization of the European energy sector and close to 20 years, from 2003 to 2022. The existing literature covers only a handful of major oil companies (e.g., Antonakakis et al. (2018)), and over shorter periods. Our time series coverage includes three exogenous shock periods, namely the 2008 Global Financial Crisis (GFC), the European sovereign debt crisis (ESDC), and the Covid-19 pandemic (C19).

Second, while previous studies examine volatility transmission across individual energy companies across normal and stress periods, we provide a full network approach view. By including all major European energy network participants, we seek to display the most significant net connections (i.e., edges in the network) and provide key insights into the vulnerable points of the system.

Third, by differentiating across Upstream, Downstream, Midstream, and Integrated Oil and Gas segments along the production line, we identify the emission mechanism for the idiosyncratic volatility spillover shocks in the context of European companies and identify system fragility points during stressful conditions. We note that the energy market has exposure to external impacts, such as weather, political decisions, wars, and pandemics.

System instability can arise from various sources, such as Russia's war on Ukraine which has adversely affected the publicly traded European energy companies, many of which are in the IOG segment. Since the start of the war in February 2022, the IOG segment has become a significant volatility transmitter. This evidence is rather alarming since prior to the Russian conflict, the IOG segment serves as volatility receivers and absorbers and supports system stability.

In summary, this paper provides new insights into the volatility transmission mechanism in the European oil and gas industry with a unique network approach, highlighting various causes of system shifts, and showing how different types of shocks (e.g., demand, supply and uncertainty) affect various groups of the energy supply chain participants.

The rest of the paper proceeds as follows. Section IV.2 reviews the relevant literature. Section IV.3 presents the research methodology followed by data description. Section IV.4 provides the full sample and subsample results. Section IV.5 concludes.

IV.2 Literature review

The interconnectedness of the energy commodity and the equity market has attracted much research attention over the years. Earlier studies focus on the connection between oil prices and overall stock returns, providing various conclusions. Using US stock data and crude oil prices, Sadorsky (1999), Jones and Kaul (1996) and Kling (1985) find an inverse relationship, while Chen et al. (1986) find insignificant results. Huang et al. (1996), on the other hand, examine the relationship between oil futures and US stocks and conclude that while price movements of oil futures have no impact on aggregate equity market indexes, they do influence specific stocks. In a follow-up work, Sadorsky (2001) find results that support the inverse relationship between stock returns and oil price by using interest rates and foreign exchange rates as additional explanatory variables.

In addition to the numerous studies into the linkages between oil prices and stock returns, (e.g.,Cuñado and de Gracia (2003); El-Sharif et al. (2005); Kilian (2009); Wang et al. (2013)), there were studies on the volatility relationship across the commodity markets (including oil) and the equity market. Mostly aggregated stock market indices are considered in studies evaluating the link between oil and stock market volatility in the USA (e.g., Phan et al. (2016); Arouri et al. (2011a)) and in major oil producing countries (Arouri et al. (2011b)).

Phan et al. (2016) document positive contemporaneous relationship between trading volume, price volatility and bid-ask spread, using crude oil, E-mini NASDAQ and S&P 500 index futures data. While Maghyereh et al. (2016) analyze the connections between oil and equity indices across 11 countries, their insights into European companies remain limited. Thus, a comprehensive analysis of major European oil and gas companies will be a material contribution to the literature.

Despite the numerous extant studies on the spillover between crude oil and the stock market, there are relatively few studies on natural gas and financial markets. Ewing et al. (2002) analyze the volatility spillover between oil and natural gas markets using the GARCH model, while Zhang (2017) investigate the spillover effect of the stock market volatility index for crude oil and natural gas markets. Zhang et al. (2020)study the return and volatility spillover from commodity and utility sectors to equity indices in North America and Europe. Their results show that, compared to natural gas, crude oil has a greater volatility spillover on the utility stock indices. Dai and Zhu (2022) document the return volatility spillover and the dynamic connectedness of WTI crude oil futures, natural gas futures, and the Chinese stock market indices. They find a high interdependence among all analyzed asset classes and a sharp increase in the total volatility spillover under major crisis events.

Malik and Umar (2019) show that aggregate stock market indices may mask the heterogeneity of responses to oil price volatility in the different sectors. They examine the transmission of volatility shocks between oil prices and five US major sectors and find significant volatility transmission between the oil market and some of the examined sectors. Arouri et al. (2012) investigate the volatility transmission between oil and stock markets in Europe and the US, at a sectoral level and show significant volatility interaction between oil and stock market sectors. Arouri et al. (2012) show that for Europe, the transmission of volatility is much more apparent from oil to stocks than from stocks to oil.

Using information from the Dow Jones Stoxx Europe 600 index and seven DJ Stoxx sector indices, Arouri et al. (2012) report significant volatility spillovers between oil prices and sector stock returns. Sadorsky (2012) on the other hand, analyzes the volatility spillovers between oil prices and the US clean energy and technology sectors, and finds that clean energy sector prices are more highly correlated with technology sector volatility than with oil price volatility. In a related study, Ferrer et al. (2018) measure the volatility and return spillover between oil prices and the returns of the green energy sector in the US. They find that crude oil price is not a key driver of the stock market performance of renewable energy companies. In the context of the Chinese market, Wang and Wang (2019) investigate the volatility spillover between WTI and 11 Chinese equity sectors.

To our knowledge, only a handful of recent papers investigate the volatility spillover at the individual stock level in relation to oil and gas prices. Antonakakis et al. (2018) examine the volatility spillovers and co-movements among oil prices and stock prices of major oil and gas corporations. They find significant volatility spillover effects between oil, and oil and gas companies with BP, Chevron, Exxon, Shell, and Total being the major net transmitter. Corbet et al. (2020) test for the existence of volatility spillovers and co-movements among energy-focused corporations during the outbreak of the Covid-19 pandemic. They find positive and economically meaningful spillovers from falling oil prices to both renewable energy and coal markets. Wu et al. (2021) investigate the risk connectedness using a Value-at-Risk (VaR) measure within a network comprising the top 20 global energy companies. Their results show that the dynamics are mainly driven by the US stock market volatility and investors' sentiment over the full sample, while energy market risks and exchange rate movements exert significant but short-term influences. Only a handful of studies (e.g., Antonakakis et al. (2018); Corbet et al. (2020); Wu et al. (2021)) examine the oil and gas industry at the firm level. However, these studies either combine the analysis of energy commodity firms, such as coal, electric utility and renewable energy companies, or examine only a few key market players globally, or focus only on the US market. Overall, this study widens the research scope of Corbet et al. (2020) by focusing on European oil and natural gas companies, providing more insights into the sustainability and stability of the European energy market which is an acute concern for decision makers globally after 2022, with the start of Russia's war on Ukraine.

IV.3 Data and Research Methodology

IV.3.1 Data

As this study focuses on the European Energy market, including a representative sample of all the firms belonging to *Energy - Fossil Fuels* business sector from Thomson Reuters Refinitiv. The sample is restricted to the companies with primary exchange listing is on European Exchange in the *Energy - Fossil Fuels* business sector, based on the Refinitiv Business Classification (TRBC).[15] From each subsector, daily stock price, trading volume and market capitalization data are collected for the largest companies. Specifically, we collect information about 40 companies from the six relevant industry groups as follows:

- *Oil and Gas Exploration and Production*
- *Oil and Gas Drilling*
- *Oil Related Services and Equipment*
- *Oil and Gas Transportation Services*
- *Oil and Gas Refining and Marketing*
- *Integrated Oil and Gas*

Following the convention in the energy literature (e.g., Kang et al. (2017b); Ewing et al. (2018)), we distinguish across firms based on being active in the Upstream, Midstream, and Downstream segments of the oil and gas industry as:

[15] Alternative classification of companies, using the Global Industry Classification Standard (GICS), is also performed. This grouping is slightly different based on GICS, and due to the lack of data, only seven-element company groups can be created. The summary of the corporates is described in Table B.2 in the Appendix. There is no major difference in the results regardless of the classification standard.

- *Firms in Oil and Gas Exploration and Production & Oil and Gas Drilling* → Upstream
- *Firms in Oil and Gas Transportation Services & Oil Related Services and Equipment* → Midstream
- *Firms in Oil and Gas Refining and Marketing* → Downstream
- *Firms with a mix of business, active in upstream, midstream, and downstream activities* → Integrated Oil and Gas (IOG)

From each of the four different industry segments, we choose the 10 largest European exchange-listed corporations (as of June 2022) with some further constraints. Specifically, we require daily continuous stock market coverage from October 24, 2006, until the end of the sample period or until the liquidation (delisting) of the company. The start of the sample period is restricted by our data access with an intent to provide a current picture of the industry including all major players as of 2022. GALP was listed on October 24, 2006, while ROSN went public in July of the same year. The finalized sample period is from October 24, 2006, to June 30, 2022. The sample is restricted to liquid stocks, defined as stocks where the number of zero daily volatility exceeds 20% of the observations. The start of the sample is two years of the financialization of the energy market (see Irwin and Sanders (2011)) so it is unlikely to affect our analysis.

Table IV.1

Summary of the sample firms by industry segments of Upstream, Midstream, Downstream and IOG, based on the TRBC industry classification

Ticker	Company Name	Exchange	Industry group	Capitalization
Integrated Oil and Gas				
SHEL	Shell	UK	Integrated Oil and Gas	205 631
TTEF	TotalEnergies	France	Integrated Oil and Gas	141 241
EQNR	Equinor	Norway	Integrated Oil and Gas	113 235
GAZP	Gazprom	Russia	Integrated Oil and Gas	103 229
ROSN	Rosneft	Russia	Integrated Oil and Gas	58 363
ENI	Eni	Italy	Integrated Oil and Gas	50 832
LKOH	Lukoil	Russia	Integrated Oil and Gas	41 347
SIBN	Gazprom Neft	Russia	Integrated Oil and Gas	28 593
SNGS	Surgutneftegaz	Russia	Integrated Oil and Gas	11 618
TATN	Tatneft	Russia	Integrated Oil and Gas	12 702
Sum				**766 789**
Upstream				
NVTK	Novatek	Russia	Oil & Gas Exploration and Production	40 117
LUNE	Orron Energy	Sweden	Oil & Gas Exploration and Production	12 906
HBR	Harbour Energy	UK	Oil & Gas Exploration and Production	4 106
DNO	DNO	Norway	Oil & Gas Exploration and Production	1 680
TLW	Tullow Oil	UK	Oil & Gas Exploration and Production	901
MAUP	Maurel and Prom	France	Oil & Gas Exploration and Production	1 002
SQZ	Serica	UK	Oil & Gas Exploration and Production	801
CNE	Capricorn Energy	UK	Oil & Gas Exploration and Production	743
TETY	Tethys Oil	Sweden	Oil & Gas Exploration and Production	256
PHARP	Pharos Energy	UK	Oil & Gas Exploration and Production	124
Sum				**62 637**
Midstream				
TENR	Tenaris	Italy	Oil Related Services and Equipment	18 588
SRG	Snam	Italy	Oil & Gas Transportation Services	18 135
ENAG	Enagas	Spain	Oil & Gas Transportation Services	5 620
VOPA	Vopak	Netherlands	Oil & Gas Transportation Services	3 306
VLLP	Vallourec	France	Oil Related Services and Equipment	2 965
SUBC	Subsea 7	Norway	Oil Related Services and Equipment	2 907
SBMO	SBM Offshore	Netherlands	Oil Related Services and Equipment	2 735
TRNF	Transneft	Russia	Oil & Gas Transportation Services	2 723
EUAV	Euronav	Belgium	Oil & Gas Transportation Services	2 691
FLUX	Fluxys Belgium	Belgium	Oil & Gas Transportation Services	359
Sum				**60 028**
Downstream				
BP	BP	UK	Oil & Gas Refining and Marketing	97 670
NESTE	Neste	Finland	Oil & Gas Refining and Marketing	32 991
REP	Repsol	Spain	Oil & Gas Refining and Marketing	22 689
OMVV	OMV	Austria	Oil & Gas Refining and Marketing	17 660
GALP	GE SGPS	Portugal	Oil & Gas Refining and Marketing	9 485
PKN	PKN Orlen	Poland	Oil & Gas Refining and Marketing	6 723
MOLB	MOL	Hungary	Oil & Gas Refining and Marketing	5 730
ROSNP	OMV Petrom	Romania	Oil & Gas Refining and Marketing	5 319
RUBF	Rubis	France	Oil & Gas Refining and Marketing	2 880
LTS	Grupa Lotos	Poland	Oil & Gas Refining and Marketing	2 832
Sum				**203 980**

Note: Market capitalization is expressed in million €.

Table IV.1 summarizes our sample of 40 European energy companies with relevant available data by industry segments, covering 91.7% of the total market capitalization of the European oil and gas industry. 98.6% of the market capitalization of IOG companies, 60.4% of the Upstream segment, 69.4% of the Midstream segments, and 92.2% of the Downstream segment.

We complement our daily stock market database with commodity information, including daily exchange-listed futures information on ICE Europe Brent Crude Oil (Brent), the Dutch TTF Natural Gas (NG), and the ICE Europe Low Sulphur Gasoil (Gasoil). We also include equity market information, namely the FTSE All World Index (FTSEALL) daily returns. These latter assets are considered external in our network analysis.

We define asset i price volatility as the absolute return $V_{it} = |ln(P_{it}) - ln(P_{(it-1)})|$ where P_{it} is the daily closing price of asset i on day t. Descriptive statistics of the volatility series are reported in Table IV.2. Daily volatilities of the series are presented in Figs. B.1 - B.5 in the Appendix. Our choice of volatility measures is motivated byForsberg and Ghysels (2007), who show that absolute returns are good volatility predictors, as they have good population performance, low sampling errors and are robust to jumps.[16]

[16]In robustness checks, results are also replicated with GARCH(1,1) model (see Figs. B.13 - B.17).

Table IV.2
Descriptive statistics of realized volatilities of the selected companies and the external assets

Name	Mean	Median	St. dev.	Min.	Max.	Skew.	Kurt.	Jarque-Bera	ADF	Obs.
Integrated Oil and Gas										
SHEL	0.012	0.008	0.013	0	0.194	3.755	29.301	0.16***	-8.15***	4 092
TTEF	0.012	0.009	0.013	0	0.182	3.806	27.758	0.14***	-9.23***	4 092
EQNR	0.013	0.01	0.014	0	0.195	2.674	14.768	0.04***	-8.09***	4 092
GAZP	0.014	0.01	0.019	0	0.363	6.184	71.857	0.91***	-8.28***	4 092
ROSN	0.015	0.01	0.02	0	0.451	7.517	112.242	2.19***	-9.16***	4 092
ENI	0.012	0.008	0.014	0	0.234	4.435	40.979	0.30***	-8.69***	4 092
LKOH	0.014	0.009	0.018	0	0.258	4.689	39.041	0.27***	-8.22***	4 092
SIBN	0.013	0.008	0.017	0	0.31	4.842	44.282	0.35***	-7.92***	4 092
SNGS	0.015	0.01	0.02	0	0.374	5.97	69.215	0.84***	-8.77***	4 092
TATN	0.017	0.011	0.021	0	0.354	4.898	45.566	0.37***	-8.56***	4 092
Upstream										
NVTK	0.016	0.011	0.019	0	0.302	4.467	39.026	0.27***	-9.04***	4 092
LUNE	0.018	0.011	0.066	0	4.02	55.455	3371.658	1940***	-3.89**	4 092
HBR	0.024	0.016	0.032	0	0.855	9.026	170.717	5.02***	-10.15***	4 092
DNO	0.024	0.016	0.028	0	0.612	4.833	61.024	0.65***	-10.03***	4 092
TLW	0.023	0.016	0.034	0	1.264	14.352	452.31	35.02***	-10.58***	4 092
MAUP	0.016	0.011	0.018	0	0.306	3.021	22.536	0.09***	-8.84***	4 092
SQZ	0.024	0.016	0.032	0	0.882	7.995	159.506	4.38***	-13.07***	4 092
CNE	0.018	0.013	0.02	0	0.346	4.311	39.681	0.28***	-9.86***	4 092
TETY	0.02	0.014	0.022	0	0.31	3.783	27.717	0.14***	-12.14***	4 092
PHARP	0.019	0.013	0.023	0	0.423	4.348	42.201	0.32***	-9.16***	4 092
Midstream										
TENR	0.016	0.012	0.017	0	0.241	3.192	20.142	0.08***	-9.28***	4 092
SRG	0.01	0.007	0.01	0	0.213	4.382	52.184	0.50***	-10.87***	4 092
ENAG	0.011	0.008	0.011	0	0.16	3.144	22.142	0.09***	-10.86***	4 092
VOPA	0.012	0.008	0.013	0	0.168	3.301	20.638	0.08***	-11.09***	4 092
VLLP	0.023	0.016	0.025	0	0.388	3.502	26.156	0.13***	-10.21***	4 092
SUBC	0.019	0.014	0.02	0	0.237	2.652	13.013	0.03***	-8.50***	4 092
SBMO	0.016	0.011	0.018	0	0.282	3.915	29.245	0.16***	-10.20***	4 092
TRNF	0.016	0.01	0.021	0	0.325	4.891	44.008	0.35***	-8.77***	4 092
EUAV	0.018	0.013	0.018	0	0.165	2.201	7.649	0.01***	-10.19***	4 092
FLUX	0.009	0.006	0.01	0	0.151	2.807	19.227	0.07***	-12.88***	4 092
Downstream										
BP	0.012	0.008	0.014	0	0.217	3.636	28.442	0.14***	-8.38***	4 092
NESTE	0.016	0.011	0.016	0	0.213	2.774	14.214	0.04***	-10.28***	4 092
REP	0.014	0.01	0.015	0	0.171	3.063	16.904	0.06***	-8.15***	4 092
OMVV	0.015	0.011	0.016	0	0.213	3.517	23.925	0.11***	-9.35***	4 092
GALP	0.014	0.01	0.016	0	0.221	3.345	22.144	0.09***	-9.20***	4 092
PKN	0.016	0.012	0.015	0	0.134	1.782	5.6	0.01***	-10.49***	4 092
MOLB	0.014	0.01	0.015	0	0.162	2.97	15.782	0.05***	-8.24***	4 092
ROSNP	0.013	0.008	0.016	0	0.162	3.279	17.915	0.06***	-8.92***	4 092
RUBF	0.011	0.008	0.012	0	0.125	2.729	12.015	0.03***	-9.69***	4 092
LTS	0.016	0.012	0.016	0	0.17	2.108	8.439	0.02***	-11.11***	4 092
External assets										
Gasoil	0.015	0.01	0.016	0	0.332	4.753	52.546	0.49***	-9.53***	4 092
FTSEALL	0.007	0.004	0.008	0	0.1	3.712	23.283	0.10***	-7.60***	4 092
NG	0.021	0.012	0.03	0	0.479	5.183	45.08	0.36***	-9.64***	4 092
Brent	0.016	0.011	0.018	0	0.309	4.209	41.809	0.31***	-7.58***	4 092

*Note: Jarque-Bera statistics are expressed in millions. The 1%, 5%, and 10% significance levels are indicated with ***, **, *, respectively.*

Two stocks, TLW and LUNE, are outliers in terms of maximum value and return volatility. In December 2019, the CEO and the director of explorations of TLW left as the company was facing major problems across its oil and gas exploration fields in Ghana, Uganda, Kenya, and Guyana. Then almost immediately the Covid-19 pandemic struck. As for LUNE, the last day of trading in its shares on Nasdaq Stockholm was June 22, 2022, as it changed its name to Orron Energy after merging its E&P business with Aker BP, to reflect its new status as a pure-play renewables business. Prior to delisting in 2022, LUNE's stock price decreased from 444.1 SEK on June 17 to 10.2 SEK, on June 20, erasing almost 98% of the company's market capitalization.

IV.3.2 The volatility spillover index

To examine spillovers in the volatility of major oil companies' stock prices and commodity prices, we apply the generalized version of the spillover index, introduced in Diebold and Yilmaz (2012). The original D-Y model (Diebold and Yilmaz (2009)) is based on a VAR method (Sims (1980)) with a major focus on the calculation of the Forecast Error Variance Decomposition (FEVD). Variance decomposition measures how exactly the H step ahead forecast error variance of a variable i can be attributed to the innovation of another variable j, thereby creating an intuitive method for measuring the spillover of volatility.

In this form of the procedure two limitations are encountered, one of which is that the VAR method uses Cholesky factor identification, so the results depend on the order of the variables. The second is that only the spillover index for the entire population can be calculated, not between constituent pairs. These shortcomings are eliminated in Diebold and Yilmaz (2012) by using the generalized VAR framework (e.g., Koop et al. (1996)), where the FEVDs are invariant to the ordering of the variables, avoiding the ordering of the variables in the VAR model. This method allows correlated shocks assuming the normality of error distribution. Thus, the shocks to each variable are not orthogonal. Therefore, the sum of the contributions to the forecast error variance is not necessarily or equal to one. Given the goal is to assess the magnitude of the volatility spillovers rather than identifying the causal effects of structural shocks, this appears to be the preferred choice in the present context (Diebold and Yilmaz (2023)).

Under the generalized VAR framework, we consider a covariance-stationary VAR (p) model with N-variable i.e., $Y_t = \sum_{t=1}^{p} \psi_i Y_{t-i} + e_t$, where $e_t \sim i.i.d(0, \Sigma)$ is a $N \times 1$ vector of residuals. The moving average representation of the VAR model takes the form of $Y_t = \sum_{j=0}^{\infty} \psi_i A_j e_{t-j}$ where A_j is an $N \times N$ is a coefficient matrix. A_j follows recursive pattern as $A_j = \psi_1 A_{j-1} + \psi_2 A_{j-2} + ... + \psi_p A_{j-p}$, A_0 is an identity matrix and $A_j = 0$ for $j < 0$. Diebold and Yilmaz (2012) apply a generalized VAR framework to calculate the H-step-ahead generalized forecast error decompositions as follows:

$$\phi_{ij}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h' \Sigma e_i)} \tag{IV.1}$$

where Σ is the (forecasted) variance matrix of e_t error vector, σ_{ii} is the standard deviation of the error term of equation i and e_i is a vector with element i being 1, and the rest is 0. This provides a $\phi(H)$ matrix with dimension $N \times N$, $\phi(H) = [\phi_{ij}(H)]_{i,j=1,\dots,N}$, where all of elements j represents the contribution for the forecast error variance of variable i. The values in the diagonal reflect the contribution of the shocks to variable i to their own forecast error variance, and those outside the diagonal show the cross contribution of the other j variables to variable i. The sum of the elements in each row of the variance decomposition table is not equal to one thanks to the usage of generalized VAR, thus normalization is required for each entry of the variance decomposition table by its row sum as follows:

$$\bar{\phi}_{ij}(H) = \frac{\phi_{ij}(H)}{\sum_{j=1}^{N} \phi_{ij}(H)} \tag{IV.2}$$

so that the decomposition including shocks in each market equals to unity, i.e., $\sum_{j=1}^{N} \bar{\phi}_{ij}(H) = 1$ and total decomposition of all variables sums to N, i.e., $\sum_{ij=1}^{N} \bar{\phi}_{ij}(H) = N$ The total spillover index is computed as follows:

$$TS(H) = \frac{\sum_{ij=1, i\neq j}^{N} \bar{\phi}_{ij}(H)}{N} \cdot 100 \tag{IV.3}$$

The total spillover index explains the spillovers from all the assets to the total FEVD. Similarly, directional spillovers which measure the volatility spillover received by asset i from the universe of markets j is calculated as follows:

$$DS_{i\leftarrow j}(H) = \frac{\sum_{j=1, i\neq j}^{N} \bar{\phi}_{ij}(H)}{N} \cdot 100 \tag{IV.4}$$

and

$$DS_{i\rightarrow j}(H) = \frac{\sum_{j=1, i\neq j}^{N} \bar{\phi}_{ji}(H)}{N} \cdot 100 \tag{IV.5}$$

Finally, the net spillovers from one variable to another for a set of variables are calculated by taking the difference of Eq. IV.4 and IV.5 as

$$NS_i(H) = DS_{i\rightarrow j}(H) - DS_{i\leftarrow j}(H) \tag{IV.6}$$

IV.4 Empirical results

IV.4.1 Static, full sample interconnectedness analysis

We start the analysis of the volatility transmission across European energy companies, oil and gas commodity futures, and a global equity index by investigating their spillover effects. Table IV.3 presents key volatility spillover results for our Energy firms universe, based on the full sample estimation. For brevity, Table IV.3 is only a subset of Table B.1 in the Appendix. Diebold and Yılmaz (2014) report a 78.3% spillover index in their investigation of the financial system, which they consider as very high. In our case the total volatility spillover index is also high, reaching 76.1%, which indicates high interconnectedness among all assets. Our spillover index is higher than that shown by Antonakakis et al. (2018) who study a handful of the world's largest oil and gas companies from 2001 to 2016 and find 69.8% for the D-Y spillover index. In our sample, the largest pair-wise volatility spillovers (colored by magenta) can be detected between Brent→Gasoil (11.9%), HBR→SRG (11.9%) and HBR→CNE (10.7%).

Table IV.3
The strongest pairwise spillovers

	⋯	LUNE	HBR	⋯	TLW	⋯	CNE	⋯	SRG	⋯	FLUX	Gasoil	FTSEALL	⋯	Brent	From
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
LUNE	⋯	97.3	0.2	⋯	0.2	⋯	0.1	⋯	0.0	⋯	0.0	0.0	0.0	⋯	0.0	2.7
HBR	⋯	1.5	47.2	⋯	8.5	⋯	2.9	⋯	0.4	⋯	0.1	1.2	0.2	⋯	2.1	52.8
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
TLW	⋯	1.5	9.4	⋯	54.4	⋯	1.9	⋯	0.3	⋯	0.1	1.0	0.2	⋯	1.6	45.6
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
CNE	⋯	2.2	10.7	⋯	6.9	⋯	20.8	⋯	0.5	⋯	0.1	1.1	0.5	⋯	1.9	79.2
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
SRG	⋯	3.4	11.9	⋯	5.7	⋯	3.5	⋯	9.8	⋯	0.3	1.3	0.5	⋯	2.2	90.2
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
FLUX	⋯	2.1	5.0	⋯	4.2	⋯	2.5	⋯	0.8	⋯	16.9	1.2	0.4	⋯	13.9	83.1
Gasoil	⋯	2.3	7.7	⋯	5.6	⋯	1.5	⋯	0.3	⋯	0.1	17.8	0.5	⋯	11.9	82.2
FTSEALL	⋯	3.7	5.6	⋯	4.1	⋯	3.3	⋯	0.6	⋯	0.1	1.6	3.1	⋯	2.4	96.9
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
Brent	⋯	2.6	9.8	⋯	5.9	⋯	2.1	⋯	0.4	⋯	0.1	9.0	0.5	⋯	17.5	82.5
⋮	⋱	⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋮	⋮	⋱	⋮	⋮
To	⋯	121.2	230.2	⋯	170.4	⋯	90.9	⋯	18.5	⋯	5.7	49.4	20.6	⋯	68.4	**76.1**
Net	⋯	**118.5**	**177.4**	⋯	**124.8**	⋯	**11.7**	⋯	**-71.7**	⋯	**-77.4**	**-32.8**	**-76.3**	⋯	**-14.1**	

Note: This table is a subset of the whole spillover matrix which is represented in Table B.1. TS(10) = 76.1

A participant is either a net volatility transmitter (positive values in the Net row) or receiver (negative values in the Net row), based on the difference between emitted and taken volatilities. The net spillover indices indicate that FLUX (-77.4%) is the largest volatility receiver, followed by FTSEALL (-76.3%). Similarly, we find that Gasoil and Brent are net volatility receivers (with -32.8%, -14.1% values, respectively), suggesting that these commodity volatilities are impacted by the oil and gas companies' volatilities. Antonakakis et al. (2018) and Dai and Zhu (2022) who also find that energy commodities are net volatility recipients. On the other hand, NG is net positive (26.0%) in volatility transmission, which underlines the importance of involving this asset in the investigation. Furthermore, all Downstream companies are net volatility receivers while Upstream companies are net transmitters (except for PHARP). Wu et al. (2021) also find that the Downstream segment is affected the most and the Upstream segment contributes the most to the volatility spillover of the energy system. Although, IOG companies tend to be volatility receivers; four Russian companies are net transmitters. Midstream companies tend to be both volatility takers and emitters. The strongest volatility transmitters are all part of the Upstream segment, namely HBR, TLW and LUNE (177.4%, 124.8% and 118.5% respectively).

Using the connectedness table, it is also possible to construct a matrix containing the pairwise net directional connectedness of all pairs. Fig. IV.1 provides a visual representation of these relations in an informative network graph. An arrow from variable y_i to variable y_j denotes a positive net directional connectedness (in other words, variable y_i explains more to variable y_j than the reverse). The companies are grouped and color-coded by sector. External assets are represented in one circle; however, they do not belong together thus they are colored differently. The colors of the arrows indicate the industry segment of the transmitter participant. Only those edges with the uppermost 5% magnitude of the net spillover are shown. Thicker arrows indicate connections from the top 1%, the strongest pairwise spillover connections.

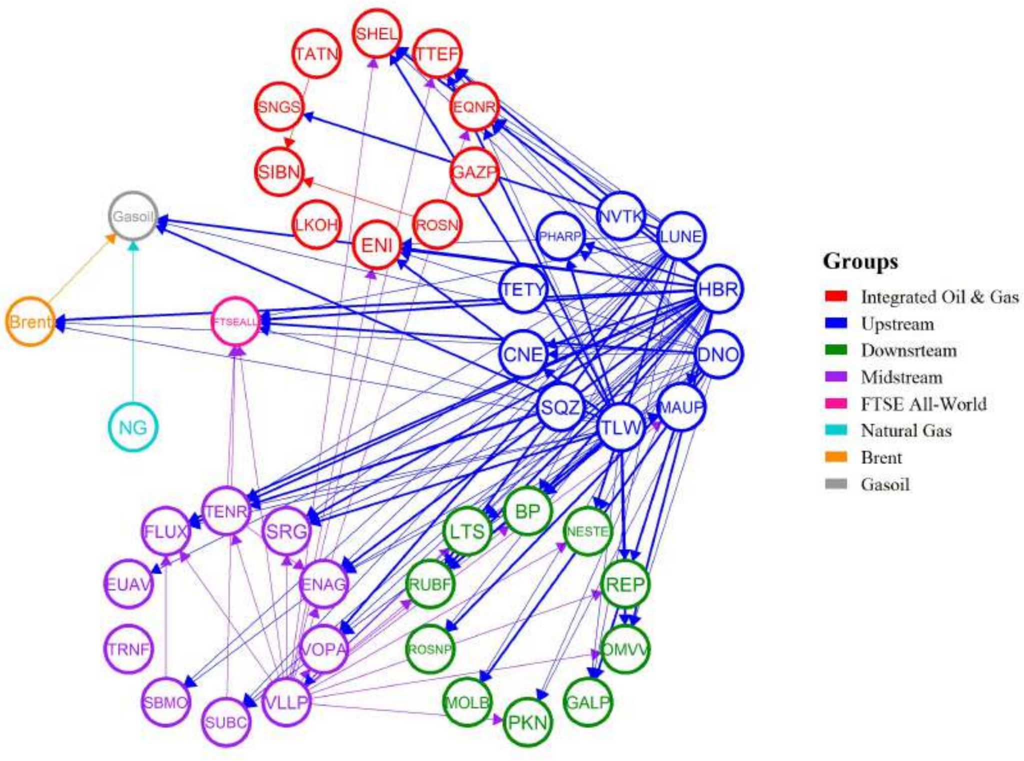


Fig. IV.1. Static, full-sample volatility interconnectedness network

Note: An arrow between two nodes indicates the direction of the spillover, and the color of the arrow indicates the industry segment of the asset that originates from. Thinner lines represent the strongest 5% of connections, while thicker lines show the uppermost 1% of connections. For the figure, we use Lag=3 and H=10 model inputs. TS(10) = 76.1

In Fig. IV.1, the blue colored arrows dominate, indicating that Upstream companies are the primary volatility transmitters in the system. Of the possible 114 arrows, 88 are coming from this group which is 77.2% of all edges. This is followed by the Midstream group with 19.3% then the IOG companies with 1.8%. Natural Gas and Brent both have one outgoing edge which means 0.9% each. Gasoil and FTSEALL have no outgoing edges, nor the whole Downstream sector. The distribution on the receiving side is more even, the Midstream sector takes 34 arrows which are 29.8% of the possible edges, then it is followed by Downstream companies (29.8%), IOG sector (20.2%) and the Upstream firms (7.9%). FTSEALL takes 6.1%, Gasoil takes 4.4% while Brent is responsible for 2.6% of the incoming edges. Natural Gas does not receive any arrow.

There are a few underlying reasons why the Upstream segment is likely the primary source of volatility emission. Companies in this segment are associated with the beginning of the production cycle and are likely to have the strongest connection with oil supply shocks. In this sense, the segment is directly linked to OPEC decisions (see Behrouzifar et al. (2019)). This is in line with the findings of King et al. (2012) who point out that many upstream companies are state-owned and publicly traded firms in this sector must coexist with the related political decisions. They also highlight that in addition to the sector's dependence on the political decision-making process in oil-exporting nations, the world supply of oil is occasionally reduced by war, terrorism, and guerrilla activity that are the result of political instability or conflict.

Despite the large number of connectedness articles, the deeper structure of the networks and the top nodes have been investigated by far fewer. Neither Wu et al. (2021) nor Dai and Zhu (2022) highlight the top nodes in their network analysis, hereby we extend their approach. To find the main drivers of the network, we use the net (out-in) and total connections. Table IV.4 identifies the most vulnerable points of the network, by showing the participants with the most edges. The first four columns provide the aggregated relationships, with subsequent columns representing the nodes having the most incoming and outgoing edges separately.

Table IV.4

European energy market participants with most edges in the network

Top 5 Sum				Top 5 Incoming		Top 5 Outgoing		Top 5 Net	
Node	Total	In	Out	Node	In	Node	Out	Node	Net
HBR	29	0	29	FTSEALL	7	HBR	29	HBR	29
TLW	23	0	23	FLUX	6	TLW	23	TLW	23
DNO	18	0	18	SRG	6	DNO	18	DNO	18
VLLP	18	1	17	ENAG	6	VLLP	18	VLLP	17
LUNE	16	0	16	SHEL	5	LUNE	16	LUNE	16

The participants with the most outgoing and net edges comprise of the same set of companies, HBR, TLW, DNO, VLLP, and LUNE in this order. Of these, only VLLP is from the Midstream segment while the remainder belong to the Upstream segment. Tables IV.3 and B.1 indicate that FLUX, FTSEALL, and SRG are the strongest volatility receivers, considering the spillover index. These nodes also have the highest number of incoming edges (although in a different order, FTSEALL, FLUX, and SRG). They are followed by ENAG and SHEL. The three companies, FLUX, SRG and ENAG, are from the Midstream segment, while SHEL is from the IOG segment.

Table IV.4 and Fig. IV.1 provide three insights. First, there are no such assets, which are volatility receivers and emitters at the same time. Second, the Upstream industry contributes the most to the volatility spillover, with a number of firms (e.g., LUNE, HBR, DNO and LTW) in this group being strong volatility transmitters by having numerous net edges. Third, there is no such industry or external asset on the recipient side, as the incoming edges are more evenly distributed.

IV.4.2 Dynamic, rolling-window-based interconnectedness analysis

While all industries tend to shift over time, this is especially true for the energy industry which has experienced significant changes in recent years with technological innovations and the adaptation of new alternative resources. In addition, the energy sector is sensitive to external demand and supply shocks. To address the dynamics of the European energy market, we investigate the changing connectedness in the network by adopting a rolling-window approach. For the entire sample period with 4 092 observations, the total volatility index is recursively estimated 769 times over time, with each window being 250 days Fig. IV.2 presents the total volatility spillover index over the sample period based on 250-day rolling windows and a 10-day-ahead forecast horizon.[17] It is interesting to note that even though the static total spillover index is estimated to be 76.04% when we examine this index over time, we see that it is mainly above this value and fluctuates between about 73% and 93%. This is another indication that a time-varying approach provides significantly more information for energy market stakeholders, compared to the static analysis.

The investigation horizon contains three periods that the Euro Area Business Cycle Dating Committee considers to be crises.[18] These are the Global Financial Crisis (GFC), the European Sovereign Debt Crisis (ESDC) and the Covid-19 pandemic (C19). Fig. IV.2 below shows the time-series trend in the system, with crisis periods marked with pink, blue, and yellow shading respectively.

[17]As a robustness check, alternative rolling window sizes (500-day and 750-day), forecast horizons (20 and 30-day ahead) and confidence levels (90% and 99%) are also explored. The results are very similar in characteristics and available upon request from the authors.

[18]The data is available at https://eabcn.org/dc/chronology-euro-area-business-cycles

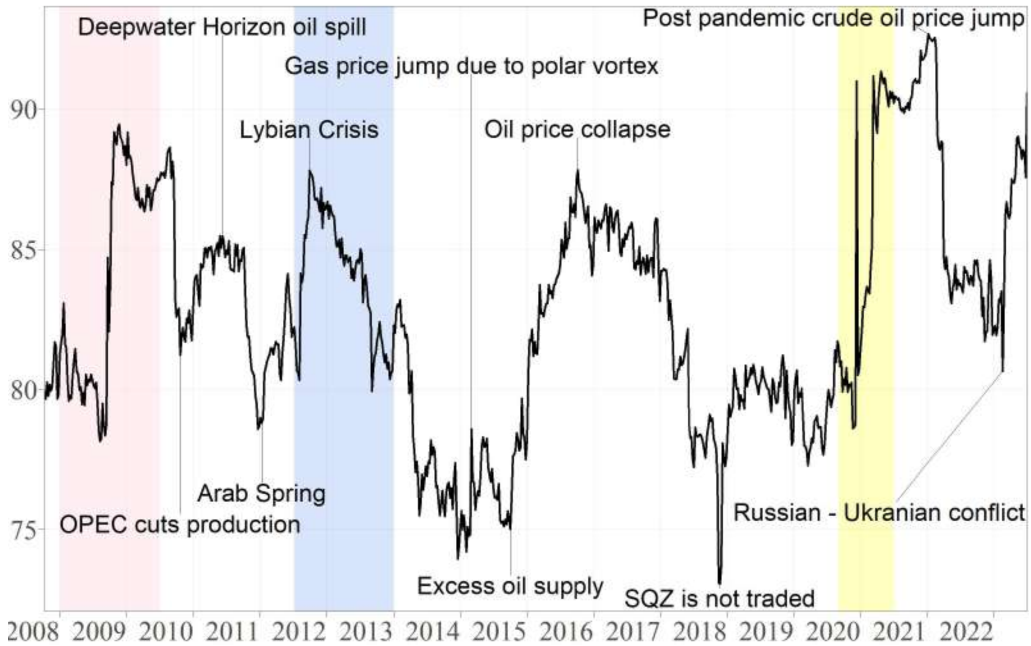


Fig. IV.2. Total volatility spillover [TS(10)] over the observation horizon

Note: The total volatility (100%) is indicated on the left axis. The shaded areas represent various crises periods, namely the GFC: January 1, 2008 - July 1, 2009 (pink area), the ESDC: July 1, 2011 - January 1, 2013 (blue area), and the C19: September 1, 2019 - July 1, 2020 (yellow area). In creating the figure, we used Lag=3 and H=10 as model parameters with a window size of 250 days.

Consistent with Bouri (2015) and Kang et al. (2017a)who study volatility spillover during the GFC, we find that the volatility spillover increases during turbulent periods. However, the spillover effect did not fade out immediately after the end of the GFC but persisted until mid-2010. A plausible explanation for the persistence is the April 2010 Deepwater Horizon oil spill in the Gulf of Mexico that was caused by a BP oil rig.

The second phase of high spillover of about 85% is observed during the period between mid-2011 to 2014 before they collapsed to below 75% at the end of 2014. These spillovers reflect the uncertainty in the energy market due to the 2011 Arab Spring, the Libyan political unrest, the turbulence in Bahrain, Egypt, and Yemen, as well as the Syrian Civil War in the post-2011 period. Additionally, these events overlap with the ESDC, which increased uncertainty in the PIIGS country Figs. B.6 - B.10 show the heightened volatility index values for companies from these countries.

The third phase of increased spillover was evident from 2015 when oil prices hovered around \$50. It is noteworthy that before the oil price declined from mid-2014 to 215, volatility spillovers reached a local minimum. Fantazzini (2016) suggests that there was a negative bubble in 2014 - 2015, which decreased oil price beyond the level justified by economic fundamentals, and which might explain the low volatility spillovers.

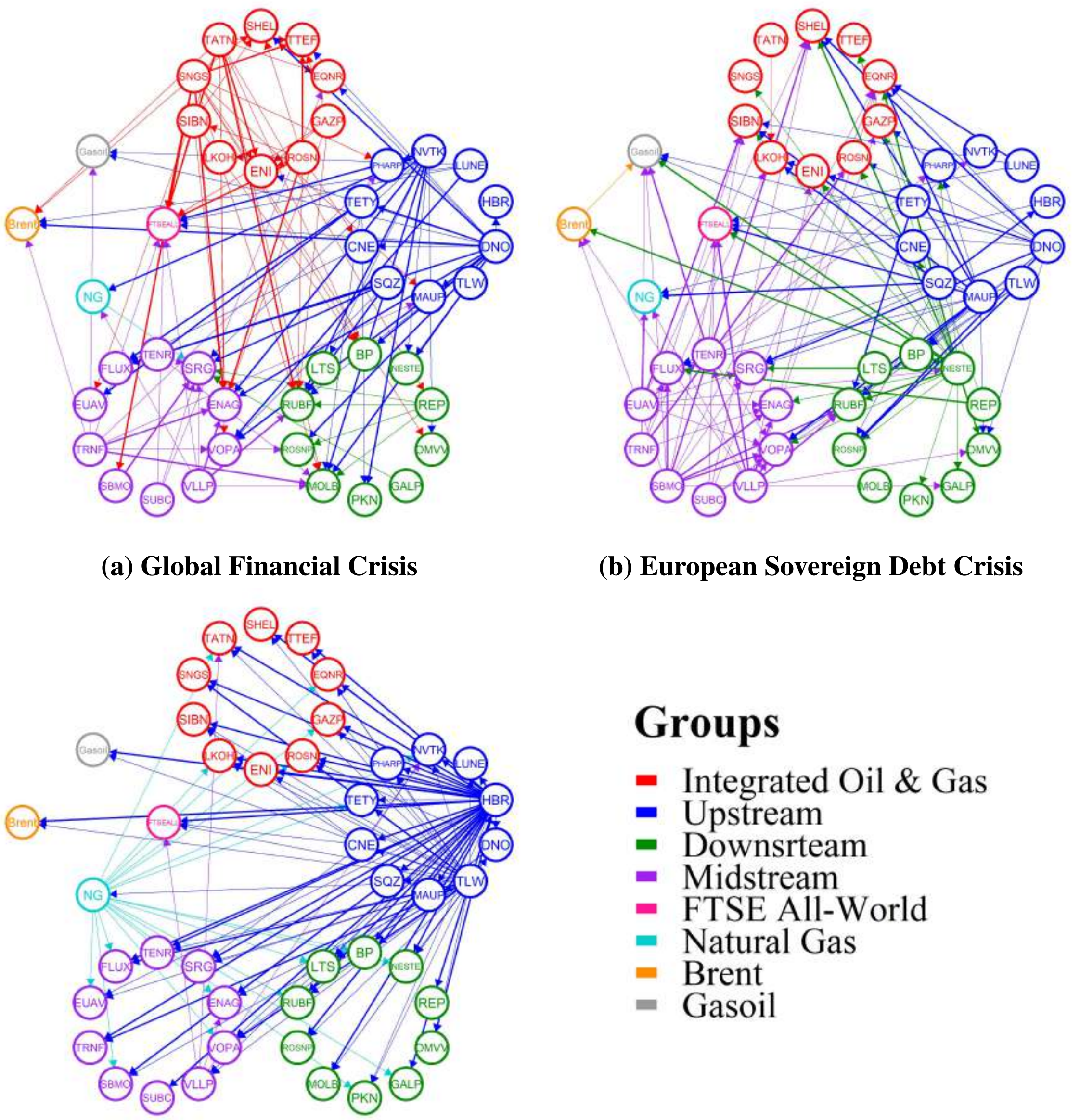
The Covid-19 pandemic paralyzed real economic activity around the world. Oil prices experienced unprecedented decline because of plummeting demand due to reduced economic activity, limited international travel, and implementation of lockdowns. By June 30, 2022, there were over 600 million confirmed Covid-19 cases and 6.5 million confirmed deaths globally. Despite the decline in oil prices, the high spillover index persisted. There are a few publications on volatility spillovers in the oil industry during the Covid-19 pandemic (e.g., Ghorbel and Jeribi (2021); Mensi et al. (2022); Shahzad et al. (2021)) which all show similar results.

In 2022, Russia started an offensive against Ukraine. The eight Russian companies (GAZP, ROSN, LKOH, SIBN, SNGS, TATN, NVTK, and TRNF) within the observed universe accounted for 26.66% of the total market capitalization. The connectedness index is particularly sensitive to these companies. On February 24, 2022, following the start of a full-scale invasion of Ukraine by Russia, the Moscow Exchange (MOEX) suspended trading and foreign clients were banned from selling any securities. On March 23, 2022 it was announced that trading of 33 Russian Ruble securities would resume on March 24 for residents of Russia, but that foreign investors remained restricted to repo and derivative deals. Between February 22, 2022, and June 30, 2022, the MOEX index dropped to 2204.85 from 3084.74. Although Western sanctions further sank the Russian stock market, revenues collected through the oil and gas industries, which accounted for about 40% of the Russian government state budget, remained largely the same (Sturm and Menzel (2022)).

IV.4.3 Spillover effects in crisis periods

Fig. IV.2 indicates that during turbulent periods, the spillover effect increases. The impact of crises on the energy market is well documented in the empirical literature, although it is less common to compare different turbulent periods. Several studies (e.g., Wu et al. (2021)) examine tranquil and turbulent periods, but they focus on the large global energy companies. We provide a more a comprehensive analysis of European energy companies using a network approach based on the D-Y index that is capable of identifying the vulnerable points of the system by displaying the most significant net edges.

To provide additional insights into different market turbulences, we perform a static spillover analysis on three separate turbulent periods, namely the GFC, ESDC, and C19. Figs. VI.1a - IV.3c show that the strongest net volatility transmitters differ across the subsample periods, and different underlying effects move the market during these turbulent periods.



(a) Global Financial Crisis **(b) European Sovereign Debt Crisis**

(c) Covid-19 Pandemic

Fig. IV.3. Network model of volatility spillover in European oil and gas industry in different sub-periods

Note: An arrow between two nodes indicates the direction of the spillover, and the color of the arrow denotes the asset from which it originates. Thinner lines represent the strongest 5% of connections, while thicker lines show the top 1% strongest connections. For the figure, we use Lag=3 and H=10 model inputs. The three crisis periods: the Global Financial Crisis (GFC) from January 1, 2009 to July 1, 2009; the European Sovereign Debt Crises (ESDC) from July 1, 2011 to January 1, 2013; and the Covid-19 pandemic (C19) from September 1, 2019 to July 1, 2020.

The IOG segment becomes a significant volatility emitter during the GFC. This effect can be connected to Russian companies as 36% of the significant edges originate from the six Russian IOG companies. This ratio increases to 52% if NVTK (Upstream) and TRNF (Midstream) are also considered. Political anxieties following the conflict with Georgia and the sharp decline in the price of Urals heavy crude oil (Kuboniwa (2014)) contributed to the 2008 - 2009 subprime crisis in Russia, resulting in the 2008 Russian market crash, wiping out more than $1 trillion in value.

During the Eurozone crisis, the Upstream companies' volatility emission significantly declined and only one Downstream company has been identified as volatility emitters, NESTE. In NESTE's 2012 Annual financial report, the company notes serious intermittent production problems in the main facility and the confounding effects of the escalating Eurozone crisis and the deepening crisis between Iran and the West.[19] While crude oil prices peaked in early spring at $125/bbl amid concerns about a deepening crisis between Iran and the West, the Eurozone recession fears pushed priced back to $90. Midstream companies have also overexpanded their investments in recent years, from 2006 - 2012 investing the double to adapt to the new productions, to build new pipelines for shale productions and to transport Natural Gas Liquids (NGLs). In 2012, it was estimated that another $250 billion in capital investment will be required in the next 20 years in the industry putting extreme pressure on Midstream companies and their investors. This put extreme pressure on Midstream companies and their investors in view of the demand decline due to ESDC and the increase in supply from US shale oil.[20]

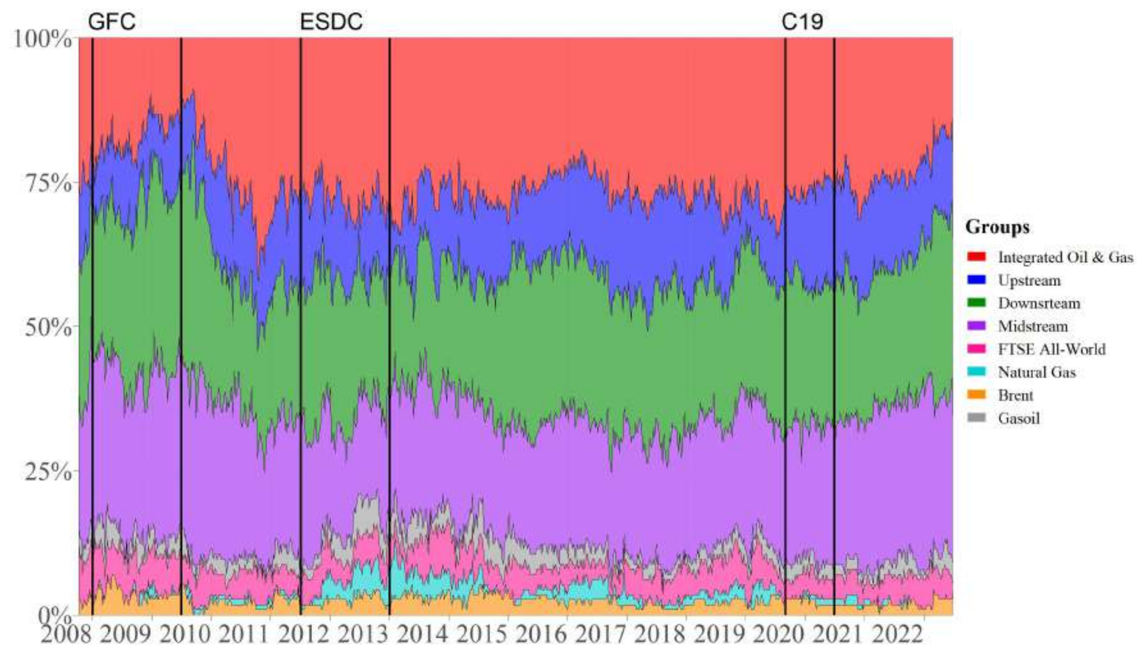
In the C19 period, 89% of the edges originated from three nodes, name HBR, TLW and NG. Global gas demand slumped in Q1 2020 with the implementation of C19 lockdowns. The pandemic hit an already declining gas demand due to historically mild temperatures over the first few months of the year. In February 2020, the TTF month-ahead fell to a 10-year low and in the second quarter, the economic stress pushed prices further down into unchartered territories. With record low prices, even small price movements had a relatively high impact on volatility. The demand slump for NG had an indirect effect on the volatility of HBR and TLW as they have high exposure to gas exploration and extraction.

IV.4.4 Distribution of imported and emitted volatility over time

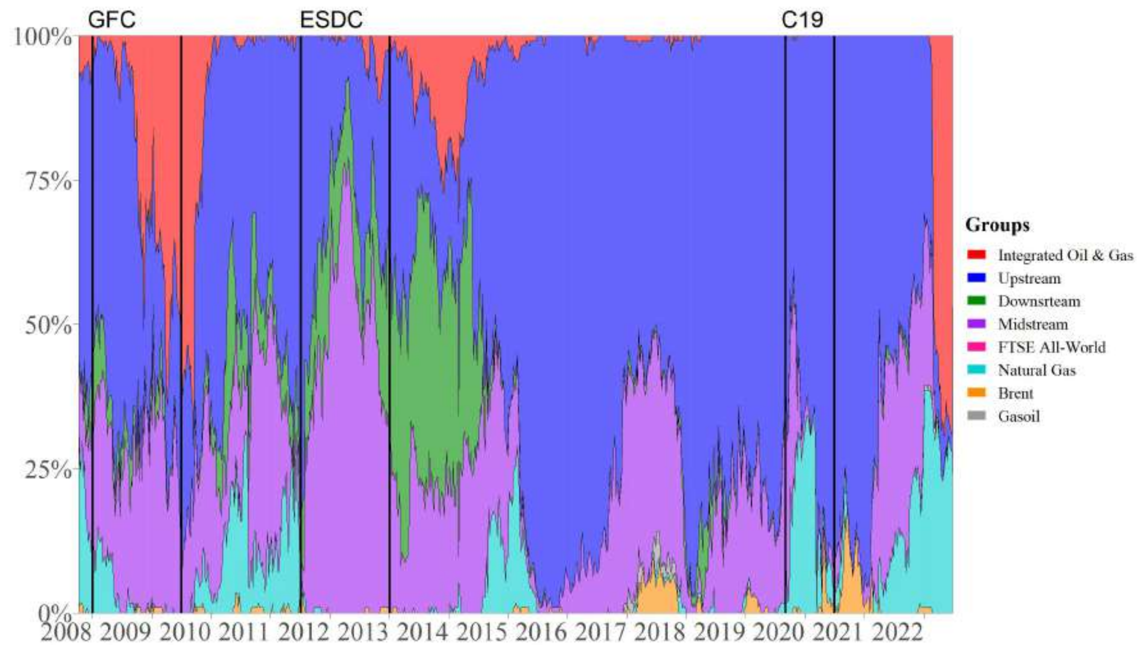
Previously, in the static plot, it was highlighted that volatility import is approximately evenly scattered between the four sets of companies and the external assets receive way less. Fig. IV.4a shows that this statement is persistent in time. It shows the distribution of the most powerful linkages, as seen in the network plot of Fig. IV.1. The same rolling window method is utilized here.

[19] Source: NESTE 2012 Annual report, https://www.neste.com/sites/default/files/attachments/corporate/investors/agm/review_by_the_board_of_directors_2012.pdf

[20] Source: Deloitte, 2012 Deloitte Oil & Gas Conference A new world of opportunity, https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Energy-and-Resources/dttl-ER-The-rise-of-the-midstream.pdf



(a) Distribution of imported volatility from the various energy sectors and commodities, over times



(b) Distribution of emitted volatility from the various energy sectors and commodities, over time

Fig. IV.4. Distribution of imported and emitted volatility over time

Note: Panel (a) displays the distribution of imported volatility over time, while Panel (b) shows the distribution of emitted volatility over time. For both figures, in the model input, we use Lag=3 and H=10, with a window size of 250 days and we display the strongest 5% of edges.

In Fig. IV.4b the persistent presence of blue shaded area and purple shaded area imply consistent volatility emission from the Upstream segment and the Midstream segment, respectively. In addition, various idiosyncratic shocks can be identified. For example, the top section of the graph (with red spikes) shows that the IOG segment becomes a significant volatility importer three times during our sample period. All these cases can be connected to Russian companies. The first spike is identical to the results of Fig. VI.1a during the GFC. The third occasion is the larger Russo-Ukrainian War starting in February 2022.

The steep devaluation of the Russian Ruble that started in the second half of 2014 led to the financial crisis in Russia from 2014 to 2016 (Viktorov and Abramov (2020)). Investors sold off their Russian assets, which further decreased the value of the Ruble and raised concerns of a possible financial disaster. At least two significant causes contributed to the loss of trust in the Russian economy. First is the decrease in oil prices, a significant export for Russia, in 2014 by about 50%. Second is the implementation of international economic sanctions on Russia in response to its annexation of Crimea and the war in Donbas (Frye (2019)).

There are five different idiosyncratic volatility spillover periods driven by Natural gas. According to Growitsch et al. (2015), the volatility of TTF increased during the final quarter of 2007, but it decreased from the first quarter of 2008 to the third quarter of 2009. The change is probably, at least in part, explained by the decline in crude oil prices. The price of gas in continental Europe is frequently index-linked to the price of crude oil (Zhang and Ji (2018)). Brent Crude Oil peaked on July 11, 2008 and reached its local minimum on December 24, 2008. TTF behaves very similarly, with a longer price-decreasing period, it reached the local minimum on September 3, 2009.

Two significant events in 2011 were particularly noteworthy in terms of natural gas supply and consumption. The supply side has been impacted by the revolutions against powerful regimes in the Middle East and in countries of North Africa. These two regions are important natural gas providers to European companies (Del Sarto (2016)). On the demand side, the Fukushima nuclear accident that followed the tsunami that hit Japan on March 11, 2011, had a large impact on the energy discussion in the European Union and the region's projected demand for natural gas (Hayashi and Hughes (2013)). In reaction to widespread protests against nuclear power, politicians started researching alternatives for this electricity generation, with gas acting as an essential safety net.

The third spillover shock connected to natural gas is related to the Crimea annexation period. As a form of political pressure, Russia announced two consecutive price increases for retail gas in Ukraine through Gazprom in April 2014. As a result of the lack of advance payments, tensions increased and on June 16, 2014, Russia cut off the gas supply to Ukraine. An interim deal was struck at the end of March 2015 following several months of negotiations and the assistance of the European Union (Reuters (2015)).

The natural gas market instability was already evident during the Covid-19 pandemic, driven by an initial decline in demand and rapid price rise in the summer of 2021 (Fulwood (2022)). When Russia's aggression against Ukraine in the first few months of 2022 raised concerns about the safety of Europe's gas supply and the unpredictability of gas prices on the continent, the situation deteriorated further. In the first quarter of 2022, the EU spent a projected €78 billion on gas imports, €27 billion of which came from Russia. EU's net gas imports had increased by 10% over this time, while imports of liquefied natural gas (LNG) had increased by 72% year on year (European Commission (2020), European Commission (2020)).

During 2006 - 2022, two discernible Brent-related volatility spillover spikes occurred, the first of which happened in 2017. OPEC and non-OPEC members decided to execute a nine-month production cut on May 25, 2017. Russia, a major non-OPEC oil producer, and OPEC agreed to renew their oil supply curbs through the end of 2018 (Bloomberg (2017)). The spillover became apparent once more in late 2021, this time due to the Omicron form of the Covid-19 virus. The revelation that other European nations are imposing travel restrictions on the UK as it manages a growing wave of the highly transmissible virus added new pressure to demand and spurred a sell-off. The front-month futures price for Brent fell by 12% on November 26 after the World Health Organization classified the SARS-CoV-2 Omicron as a variant of concern. A little more than a month later, oil prices rose on hopes that the omicron virus version would be milder, calming worries about the demand forecast (Reuters (2022b)).

IV.5 Conclusions

This study examines the co-movements and spillovers in volatility between the stock prices of key European oil and gas companies and the prices of oil and gas commodities in the period from October 24 to June 30, 2022. To the best of our knowledge, this is the first empirical study that examines volatility co-movements and spillovers utilizing company-level data from 40 oil and gas companies clustered to distinct segments, in a network setting.

The results of this study offer fresh and distinctive perspectives on this dynamic and continuously evolving sector, as it moves from relying primarily on traditional continental oil to shale oil production and natural gas. We show that the Upstream companies are the major volatility transmitters during our sample period. During the European Sovereign Debt Crisis (ESDC) and the Covid-19 pandemic, the volatility transmission mechanisms were altered. During the ESDC, the volatility emission from the Upstream segment declined even as the Midstream segment came under stress conditions. More importantly, during the Global Financial Crisis and recently with the Ukraine invasion, the IOG companies have become major volatility transmitters. This latter effect is alarming because the large IOG companies traditionally were volatility absorbers and system stability providers.

For investors seeking to diversify across the energy sector, it is critical to understand the companies' vulnerability of companies within the system and to external factors. Our results provide new insights into the key European energy sector network, their overall network risk, and the time-varying network fragility due to external shocks. We believe that the unique insights into the various crisis situations during our sample period offer interesting scenario analysis and information for regulators and policymakers to ensure crisis preparedness. Specifically, the overreliance on traditional oil and gas companies, highlighted by the dominance of the Upstream companies' volatility transmission stresses the pressing need for energy diversification. Europe's ongoing energy crisis management should consider diversification along the supply chain at least as long as alternatives or renewable energy sources are not yet available in large volume to replace the oil and gas energy source.

CHAPTER

V

VOLATILITY SPILLOVER ON EUROPEAN EQUITY MARKETS: DESTABILIZING ENERGY RISK IS THE NEW NORMAL

Chapter V is based on the work of Huszár et al. (2023b). Minor modifications are made to align with the dissertation format.

V.1 Introduction

Oil and natural gas resources are critical for major manufacturing processes and services. This economic and sometimes political importance of energy markets has motivated a growing energy finance literature in recent decades (Hamilton (1983); Herrera et al. (2011); Kilian and Park (2009); Mensi et al. (2021)). The analysis of the impact of energy prices on economic activity is rather complex as it cannot be considered in isolation without also considering feedback from economic activity and growth. On the one hand, low energy prices can fuel production, manufacturing, and investment, which in turn increases demand and eventually energy prices. On the other hand, while in general high economic growth is associated with high energy demand, energy prices increase is inevitable due to low short-term elasticity of supply, potentially resulting in a slowdown in growth. This co-integrated relation between the economy and the energy market has been documented in prior studies (e.g., Zhu et al. (2011)).

In the new millennium, the complexity and volatility of the energy market increased. First, in 2004, with the financialization of the commodity market speculators have gained access to the market (Ding et al. (2021)). More recently, additional sources of volatility have emerged from the pandemic, growing political uncertainty (e.g., Russo-Ukraine war) and growing cybersecurity threats of oil and gas and utility companies.[21] Overall, recent studies have recognized energy market risk as a new source of systemic risk attracting much academic, as well as policy attention.

The first strand of finance-energy market studies primarily examine the influence of energy commodity prices on equity returns (Andreasson et al. (2016); Dutta et al. (2020); Olson et al. (2014)). Their focus varies from the US market, major oil producing countries, key global equity exchanges, and specific regions or countries, such as BRICS and China. Kling (1985), Jones and Kaul (1996), Sadorsky (1999) and Sadorsky (2001) show that a rise in oil price leads to a fall in US stock returns, while Sadorsky (2001) finds a positive relation between oil and Canadian equity prices. There is also evidence of oil prices negatively affecting the equity markets in the Gulf countries (GCC), which is somewhat trivial given the large contribution of oil export to the GDP (e.g., Arouri et al. (2011b); Hammoudeh et al. (2004)).

Aloui et al. (2011) find that oil price shocks negatively affect stock markets in various countries, including the USA, during the Global Financial Crisis. However, there is variation across oil importing and exporting countries, with oil exporters naturally benefiting from oil price increase (e.g., Ramos and Veiga (2013)). Kang and Ratti (2015) document time varying impact of oil shocks on stock returns in the USA. Lin et al. (2014) report mixed results from China where oil price increase is often positively associated with market returns. More recently, Castro et al. (2023) reports consistent evidence of time varying impact of oil price movement on a small sample of European equity markets.

Besides examining return correlation and lead-lag relations, an increasing number of studies investigate the volatility interconnectedness across the commodity markets (including oil) and the equity market. A number of studies examine the US market (e.g., Arouri et al. (2011a); Phan et al. (2016)) and major oil producing countries Arouri et al. (2011b). More recently, Dai and Zhu (2022) provide insights into volatility spillover and the dynamic connectedness of WTI crude oil futures, natural gas futures, in Chinese context. Again, the lack of European coverage is rather evident, as only a few studies examine European equites or European markets. Zhang et al. (2020) study the return and volatility spillover of natural gas, crude oil, and electricity utility stock indices in North America and Europe and show that compared to natural gas, crude oil has a greater volatility spillover on electricity utility stock indices. Castro et al. (2023) also examine the oil price influence on European equity markets and find time varying impact of oil price movements.

Addressing the time varying interconnectedness of equity end energy markets Mensi et al. (2017a) provide an in-depth analysis using variational mode decomposition (VMD) method and static and time-varying symmetric and asymmetric copula functions. The

[21] According to Statista there were 21 attacks on Oil and Gas companies in 2021. A comprehensive list of ransomware attacks on oil and gas, and energy companies is available on: https://www.oilandgasiq.com/digital-transformation/articles/5-big-cyber-security-attacks-in-oil-and-gas.

authors document evidence of tail dependence and show that the stock market's, using European, US, and Canadian equity indices (S&P500, STOXX600, DJPI and TSX) respond to oil price (WTI) change differently in down-markets and in the cross-section the responses also vary because of the country's energy import dependence. The authors suggest that there is increased connectedness because more investors make decisions not only based on fundamental information in stock markets, but also on prevailing information in the oil markets. Ewing and Malik (2010) also report time varying effects, and compute volatility persistence by incorporating endogenously determined structural breaks into a GARCH model, while Salisu and Fasanya (2013) document structural breaks in oil prices in 1990 and 2008.

Interesting, to our knowledge, there are no comprehensive European market study that analyzes contemporaneously a large number of European equity markets in relation to crude oil and natural gas prices, despite the growing European Energy Crisis (IMF (2022a)). The European Economic Area (EEA), with its ambitious net zero emission targets, has been at the forefront of climate change initiatives for years, albeit with limited success. In 2022, the European Parliament (European Parliament (2022)) agreed not to veto the designation of nuclear and gas energy sources as green, as part of its efforts to encourage energy diversification. Due to growing opposition for nuclear energy from the public in Germany and France (Reuters (2023)), gas as a less ”dirty” alternative than oil has been pushed forward across Europe.

Overall European gas demand has been gradually increasing from 1971 to 2017, with declining production in all countries with the exception of Norway (IOGP (2018)), exposing countries to increasing volatile gas prices, which resulted in the adaptation of emergency energy regulations in EU in 2022 (European Council (2022)).

This study aims to examine the economic spillover effect of crude oil and natural gas in Europe. While most energy finance studies focus on oil, we consider the examination of the role of gas increasingly important because of the increasing reliance on this form of energy in EU countries. Specifically, we examine the implications of price change and volatility of energy commodities on equity markets across Europe from March 24, 2003, to December 31, 2022, covering several political and economic turmoil events (e.g., the 2008 Georgian-Russian war, Crimea Annexation, and the ongoing Russian-Ukrainian war (Council of Europe (2008); Council of Europe (2023)). In the cross-section, we include all current and past (EEA) countries, except for a few countries (e.g., Slovakia, Luxembourg, Iceland, Malta) because of data limitations. Our final sample, comprising 24 European economies, provides comprehensive coverage for the EEA.

First, in panel regression setting, we examine the equity market performances of the sample countries, using MSCI index daily returns. We find that crude oil and natural gas prices systematically influence equity markets. We also examine MSCI index volatility in panel regressions. The results show that oil and gas are major volatility contributors and have been increasingly so over the years. More importantly, we find that countries with weak or depreciating domestic currencies are more sensitive to energy shocks. In the final section, we deploy Diebold and Yılmaz (2014), Diebold and Yilmaz (2023) spillover index (D-Y index hereafter) to gain more insights into the spillover effect of energy prices in a closed network of European equity markets, accounting for only volatility transmission and source of volatility within the network.

We provide network analysis for the 2004 EU enlargement, 2005-2008 US Mortgage market run-up to the 2008 Global Financial Crisis, 2009-2012 European Sovereign Debt Crisis, and other subperiods such as, 2013-2015, 2016-2019, 2020, 2021, and 2022 to provide insights into the impacts of network changes. Across the eight subperiod analysis, we find significant differences. During our sample period of 20 years, the primary sources of volatility were initially from economic or political uncertainty. Generally, the key sources of volatility in the European equity markets arise from a specific country, or group of countries, e.g., from Greece during the sovereign debt crisis, from Central and Eastern European countries (CEEC) after the 2004 EU extension, and from Norway during the 2008 oil rout (Jung and Park (2011)).[22] We also note that the volatility spillover effect of oil and gas is potentially an acute issue to consider.

Overall, our study provides three unique contributions by extending the work of Mensi et al. (2017), in several directions. Using a comprehensive sample of European equity indices, we document heterogeneous implications of oil price and gas price shocks not only over time but also across markets. Acknowledging the inelasticity of countries' energy import dependence during our sample period, we show that the cross-sectional variation in the impact of energy shocks on equity market can be related to domestic currency weakness and volatility. Last, we also provide unique pair-wise interconnectedness insights into the European equity market network by deploying the D-Y spillover index (Diebold and Yılmaz (2014)) in subsample analyses, allowing for time variation in our parameter estimates, given the well-known structural breaks in the European economy and oil and natural gas prices. Our results might be also relevant for the understanding of the sensitivity of emerging economies to energy market shocks with weak and/or volatilize domestic currencies. For example, the growing costs of energy has been shown to play a role in the built-up of the economic crisis of Sri Lanka and the 2022 country default (IMF (2019b)).

The rest of the paper is structured as follows. Section V.2 presents the data and the hypotheses development. Section V.3 the first part of the empirical analysis, discusses panel regression analysis of EEA countries domestic equity index returns and volatility. Section V.4, the second part of the empirical analysis, presents our closed networkanalysis using the D-Y spillover index, providing insights about pairwise connections in the network in

[22]There are many oil routs during the last 100 years of history. We specifically refer here to the 2008 oil rout when oil prices declined from $150 to 40 in acourse of 6 months or so.https://capital.com/crude-oil-industry-history-market-trends-trading.

subsections. Last, V.5 concludes.

V.2 Data and Empirical Hypotheses Development

V.2.1 Data and Summary Statistics

In this study, we examine the performance of the European Economic Area (EEA) economies from 3/24/2003 to 12/31/2022.[23] We collect daily MSCI country equity index data from Refinitiv where available for all EU member states and collaborator countries (e.g., Norway, Switzerland), and the former EU member state, the UK. Since MSCI does not provide equity index information for Cyprus, Latvia, Luxemburg, Malta, and Slovakia, these countries are dropped from our analysis, resulting in a sample of 24 countries, covering just about 500 million population out of the 513 million in the entire EEA, or 97.4% of the population based on 2022 Eurostat numbers.

In addition to extensive cross-sectional coverage, we also have extensive time-series coverage, spanning almost 20 years, covering the EU enlargement with CEEC in 2004, the buildup of the US mortgage bubble from 2005 to 2008, the 2008 Global Financial Crisis (GFC) and the 2010 European Sovereign Debt Crisis (ESDC). The sample period also includes the onset of the Covid-19 pandemic in 2020, the recovery in 2021, and the start of Russia's war on Ukraine in 2022.

Our cross-country time-series panel data is unbalanced because of data limitations for some of the newer countries (e.g., countries formed from the former Yugoslavia) and smaller countries. In 2004, only Hungary and Poland, from the CEEC region, had continuous daily coverage from MSCI. We extend our coverage as data becomes available and include Bulgaria, Croatia, Romania, and Slovenia from 2008, Estonia from 2010, Czech Republic from 2013, and Lithuania from 2014, as data becomes available from MSCI. We also include daily domestic currency to EUR exchange rates from the European Central Bank (ECB), measured in the number of domestic currency equivalent to a EUR.

We complement our panel data of daily MSCI index value for 24 European countries with annual value for energy production and energy consumption from Eurostat (see C.1 in the Appendix). From the Eurostat data, for each country, we calculate country-specific energy (total energy, crude oil, natural gas) dependencies by the formula of: $1 - (energyproduction/energyconsumption)$. At the time of our data collection (April 2023), Eurostat had only country specific energy production and consumption data up to 2021 (Eurostat (2022)). The 2022 energy dependence numbers (Eurostat (2022)) were extrapolated using the last 5 years of data, from 2017 to 2021, capturing the shift towards

[23] Our historical data coverage is limited because of our data access (we could not extend our coverage further back in time) and data availability as some of the smaller European countries do not have designated MSCI equity indices.

green alternatives.[24] Unfortunately, the energy dependence information is only available annually and the variable is rather sticky, and because of the low time series variation during the sample period, the country fixed effect effectively already capture the cross-country effect at least during our sample period.

Last, we collect daily commodity price information. Like Wang and Wang (2019), Corbet et al. (2020) and others, we use daily futures prices for commodities, oil, and gas. Daily exchange listed futures price data are collected for ICE Europe Brent Crude Oil (Brent) and the Dutch TTF Natural Gas (Natural Gas) contracts. Additionally, to control for the arrival of new information from different geographic market information, we also include daily Asia Pacific and the US equity indices data from MSCI.

Overall, our final data contains daily energy commodity information for Brent oil prices and TTF gas price in the form of futures prices, daily MSCI index data for all 24 EEA countries are from Refinitiv Eikon. The currency rates and country energy dependence information are from ECB and Eurostat. Variable definitions and summary statistics are presented in Table V.1. $Ret1d$ and $Ret5d$ are the key return measures based on each country's MSCI index value, calculated as the aggregate change. $APlag1d$, $APlag5d$, $USlag1d$ and $USlag5d$ are the previous 1-day and 5-day Asian Pacific and US market index returns, which are likely to influence the European market.

[24]In case of the UK, Eurostat has stopped data coverage for the country in 2019 with Brexit, thus we extrapolate the 2020 - 2022 energy dependence numbers the previous 5 years of data, using a rolling window approach.

Table V.1
Summary Statistics for the Pooled Sample

Variables	Observations	Mean	Std. Dev.	25th perc	Median	75th perc	Min	Max
$cntrcd$	110 740	12.799	6.925	7	13	19	1	24
$Ret1d$	110 740	0	0.017	-0.007	0	0.008	-0.271	0.261
$Ret5d$	110 740	0.001	0.037	-0.016	0.003	0.02	-0.377	0.424
$Lag1dret$	110 740	0	0.017	-0.007	0	0.008	-0.271	0.261
$Lag5dret$	110 740	0.001	0.037	-0.016	0.003	0.02	-0.377	0.424
$APlag1dRet$	110 740	0	0.011	-0.005	0.001	0.006	-0.086	0.093
$APlag5dRet$	110 740	0.001	0.025	-0.012	0.003	0.016	-0.178	0.169
$USlag1dRet$	110 740	0	0.012	-0.004	0	0.006	-0.121	0.117
$USlag5dRet$	110 740	0.002	0.024	-0.009	0.003	0.014	-0.184	0.182
$Brentlag1dRet$	110 740	0	0.023	-0.01	0.001	0.011	-0.244	0.21
$Brentlag5dRet$	110 740	0.002	0.052	-0.024	0.004	0.029	-0.347	0.514
$TTFlag5dRet$	102 343	0.001	0.04	-0.012	0	0.012	-0.32	1
$TTFlag5dRet$	102 377	0.005	0.09	-0.032	-0.002	0.031	-0.484	1.216
$Engdep$	110 740	0.435	0.401	0.313	0.507	0.699	-1	0.912
$TTFvol5d$	102 257	0.064	0.073	0.023	0.043	0.077	0	1.103
$Brentvol5d$	110 620	0.044	0.034	0.024	0.036	0.055	0.002	0.5
$LogFXprice$	110 740	0.842	1.423	0	0	1.577	-0.423	6.065
$FXlag5dRet$	110 740	0	0.006	0	0	0	-0.094	0.099
$FXlag1dRet$	110 740	0	0.006	0	0	0	-0.094	0.099

(a) Summary Statistics for the Pooled Sample

Note: The sample statistics are based on 24 EEA countries from March 24, 2003 to December 30, 2022. $Cntrcd$ is a country indicator used here to show that the sample covers 24 unique countries. $Ret1d$ and $Ret5d$ are future 1-day and 5-day returns on the country's equity market, measured by the change in the country's MSCI Index. $Lag1dRet$ and $Lag5dRet$ are the country's own lagged equity market returns. $APlag1dRet$, $APlag5dRet$, $USlag1dRet$ and $USlag5dRet$ are the lagged 1-day and 5-day MSCI index returns in Asia Pacific and in the USA, respectively. $Brentlag1dRet$, $Brentlag5dRet$, $TTFlag1dRet$, and $TTFlag5dRet$ are the lagged 1-day and 5-day price changes in Brent oil contract and TTF gas contracts, respectively. $Engdep$ is the country's energy dependence, or energy shortfall, measured as $1–energyproduction/energyconsumption$. $TTFvol5d$ and $Brentvol5d$ are the 5-day extreme price volatility for gas and oil, measured as the difference between the last 5-day maximum price and minimum price, divided by the initial price, or the price 5 days ago. $LogFXprice$, is the natural logarithm of the forex rate, the number of domestic currency is needed to buy 1 EUR. $FXlag1dRet$ and $FXlag5dRet$ are the lagged 1-day and 5-day change in the forex rates for a country.[a]

[a] We also use interaction variables of the oil price change and the gas price change variables (e.g., $brent1dlagret$, $brent5dlagret$, $ttf1dlagret$, $ttf5dlagret$) are interacted with the country total energy dependence ($Engdep$) variable

	Observations	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Core EU countries							
Austria	4 957	0	0.019	-0.153	0.143	-0.125	10.538
Belgium	4 957	0	0.015	-0.180	0.142	-0.743	18.209
Germany	4 957	0	0.015	-0.140	0.123	-0.027	11.313
Denmark	4 957	0.001	0.014	-0.126	0.113	-0.157	9.727
Finland	4 957	0	0.016	-0.115	0.123	-0.068	9.064
France	4 957	0	0.015	-0.138	0.126	-0.01	12.154
Netherlands	4 957	0	0.014	-0.114	0.111	-0.044	10.816
Sweden	4 957	0	0.017	-0.138	0.151	0.104	9.781
PIIGS countries							
Spain	4 957	0	0.016	-0.158	0.174	-0.029	13.382
Greece	4 957	0	0.024	-0.222	0.187	-0.163	10.908
Ireland	4 957	0	0.018	-0.140	0.136	-0.330	9.989
Italy	4 957	0	0.017	-0.186	0.131	-0.330	12.458
Portugal	4 957	0	0.015	-0.129	0.125	-0.112	10.439
Countries joined EU after 2004							
Bulgaria	3 756	0	0.016	-0.167	0.12	-1	15.169
Czech Republic	2 609	0	0.013	-0.123	0.077	-0.738	11.902
Croatia	3 756	0	0.013	-0.211	0.261	0.830	81.962
Estonia	3 157	0	0.013	-0.123	0.138	0.064	15.662
Hungary	4 957	0	0.022	-0.184	0.225	0.028	12.856
Lithuania	2 273	0	0.010	-0.136	0.081	-1.326	28.257
Poland	4 957	0	0.019	-0.162	0.153	-0.197	9.360
Romania	3 756	0	0.018	-0.271	0.134	-1.168	24.183
Slovenia	3 756	0	0.013	-0.119	0.099	-0.652	11.125
Ex-EU regions							
United Kingdom	4 957	0	0.014	-0.132	0.13	-0.149	15.195
Norway	4 957	0	0.019	-0.133	0.166	-0.244	10.099
United States	4 957	0	0.012	-0.121	0.117	-0.283	16.260
Asia Pacific	4957	0	0.011	-0.086	0.093	-0.259	9.309
Commodities							
Brent	4 957	0	0.023	-0.244	0.21	-0.202	13.030
TTF	4 668	0.001	0.040	-0.320	0.614	2.877	39.431

(b) Detailed summary statistics of the daily MSCI index returns by countries and the daily price changes in the commodity futures

Note: The panel is an unbalanced panel with shorter time coverage for the Central and Eastern European Countries (CEEC) because of data limitations.

Table V.1 shows that generally, the MSCI equity market indices are well behaved, with some extreme outliers primarily from the eastern EU states. The 1-day and 5-day market returns, Ret1d and Ret5d, with mean zero values, have rather wide ranges from -27% to 26%, and -37% to 42%, respectively, suggesting some extreme movement in some markets. For more insights about the distribution of the return variables, Table V.1b provides summary statistics results by countries. It is also worth mentioning the extremely large price swings in gas (TTF) in 2022 after the start of the Russian conflict, when gas prices increased over 120% in five days temporarily.

V.2.2 Empirical Hypothesis Development

Empirically, the relation between energy prices (proxied by oil and natural gas prices) and economic growth (proxied by stock market performance) are intertwined. Economic growth and precautionary demand pressures drive energy prices up, given the relatively low elasticity of oil and gas supply where production adjustment is a slow process. On the other hand, crude oil and natural gas prices can impact the market and the economy in at least three ways, namely (1) inflation, (2) consumer spending, and (3) market uncertainty. First, higher oil prices can lead to inflation, as the costs of production and transportation increase, and these costs are passed on to consumers. While traditionally higher prices are endogenous and driven by demand, supply shocks due to collusion of producers can also impact prices, as is the case with OPEC interventions in the energy market. Second, higher energy prices and higher volatility, especially when combined with market uncertainty (e.g., Russian-Ukrainian conflict), can lead to reduced consumer spending as people spend more on energy bills and petrol and increase their precautionary savings. Also, higher oil prices can dampen consumption because of higher production costs, lower return on investment, and lower disposable income. Third, crude oil and natural gas prices can induce market volatility, where rising oil prices, signaling recessionary outlook, may trigger mass selloffs on the equity market. Overall, energy price shocks can affect the equity markets by influencing investors' outlook, companies' investment policies and thereby have a significant impact on the economy and the financial well-being of individuals and businesses.

While the energy risk spillover to equity markets is rather intuitive, it has only been tested empirically in a few studies. Given, the ongoing energy market turbulence as a result of the Russia-Ukraine conflict and rising tensions in the Middle East, understanding the energy risk spillover to European economies is of interest to academics, investors and also policymakers. We specifically examine equity market returns and equity market volatility relation with oil and gas price and volatility trends to test four empirical hypotheses.[25]

Empirical Hypothesis 1: Energy prices (oil and gas) influence equity markets across Europe. We have a baseline model with the following specification for Hypothesis 1:

$$Ret_{c,t+1} = \alpha + \beta \cdot \Delta Ener_{t-5,t} + \sum_{j=0}^{l} \gamma \cdot \sum_{j=0}^{l} K + \varepsilon_{c,t+1} \tag{V.1}$$

The dependent variables are the 1-day or 5-day future MSCI market index cumulative returns (in decimal) for a sample of 24 European countries from March 24, 2003, to December 31, 2022. $\Delta Ener$, the change in energy prices, is proxied by changes in Brent and TTF during the previous 5 days. β is the loading on the energy price change. The control vector (K) includes country specific controls, such as the lagged market performance, currency levels, currency movements, and the lagged change in the US and Asian market equity indices. α is the intercept term, γ is a coefficient array for the control variables and ε is the error term.

Hypothesis 1suggests that energy prices impact market performance. The alternative hypothesis is that energy prices are influenced by the market, or that energy prices are irrelevant in the short term because energy price production and consumption can be forecasted with reasonably high accuracy, especially in the traditional crude oil and natural gas seg-

[25] Appendix C.1 provides a short specification about the two-way fixed effect panel regression.

ment. The degree of market sensitivity may change over time, depending on the country's energy exposure and country development as suggested by Mensi et al. (2017a).
While predicting stock market performance and stock market returns may not be of outmost importance for regulators and politicians, equity market volatility tends to make investors jittery and may discourage local and foreign investment. Thus, in Hypothesis 2, we examine the equity market volatility in relation to energy price changes, overall, in Europe. We are concerned with the overall and time-series effect of energy price volatility because of the heightened geopolitical risk from Russia.

Empirical Hypothesis 2: Heightened energy price (oil and natural gas) volatility is associated with higher equity market volatility across Europe.

We test the volatility implications with a similar model as V.1 but we replace the dependent variable with a 5-day market volatility measure:

$$Vol_{c,t+5} = \alpha + \beta \cdot \Delta Ener_{t-5,t} + \sum_{j=0}^{l} \Theta \cdot \sum_{j=0}^{l} K + \varepsilon_{c,t+5} \tag{V.2}$$

In equation V.2, the dependent variable is the 5-day volatility in the MSCI index calculated as the difference between the maximum and minimum values during the 5-day period, scaled by the last day return. Specifically, the $Vol_{c,t+5} = (maxMSCIIndex_{t,t+5} - MinMSCIindex_{t,t+5})/MSCIIndex_t$. The explanatory variables are the same as with Hypothesis 1 and Θ is a coefficient array for the control variables.
Last, with Hypothesis 3, we are concerned with the less developed European economies, who coincidentally are highly exposed in terms of energy import dependence. In this hypothesis, we consider cross-sectional country differences and distinguish across Euro and non-Euro countries and consider energy price volatility in conjunction with exchange rate stability.

Empirical Hypothesis 3: Energy prices (oil and natural gas) influence equity markets volatility more in countries with weakening domestic currencies, since oil and gas contracts are primarily settled in USD or EUR.

We test Hypothesis 3, with the following specification.

$$Vol_{c,t+5} = \alpha + \beta \cdot \Delta Ener_{t-5} + \delta \cdot Int + \gamma \cdot \Delta Ener_{t-5} \cdot Int + \sum_{j=0}^{l} \Theta \cdot \sum_{j=0}^{l} K + \varepsilon_{c,t+5} \tag{V.3}$$

The dependent variable as before with Hypothesis 2, is the equity market volatility. The explanatory variables as before energy prices, and energy price volatilities. The additional new variables in equation V.3 are the country exchange rate stability which we capture with two measures. One is the country exchange rate relative to Euro (Int), using the

$logFXprice$ and the second is the changes in the domestic currency (DOC), measured in change in the number of local currencies needed to buy 1 EUR. δ is the coefficient array for the Int.

Our $FXprice$ measures the number of local currencies equivalent of 1 EUR. To address the skewness of the measure (e.g., that one EUR is less than one GBP, but it is about 400 HUF), we use the natural logarithm of $FXPrice$ in the regression analysis. More importantly, we also include a currency "weakness" measure which captures the change in the number of local currency equivalent to one Euro during the previous week.

In the next section, Section V.3, we test our three empirical hypotheses in a panel regression setting, with 2-way fixed effect and allowing for the clustering of standard errors consistent with the literature to provide overall evidence about the influence of energy prices on equity markets. In Section V.4, we aim to provide a more in-depth insights into the pairwise connections in the network of European equity markets and energy markets, adopting the D-Y spillover index method. In a recent review article, Diebold and Yilmaz (2023) explain that the reasons for the popularity of the Diebold-Yilmaz connectedness measurement is its flexibility in adaptation. Its methodology is simple and attractive, combining traditional econometric modeling with modern network and Big Data thinking. The measurement relies on variance decompositions, with the insight that a variance decomposition can be viewed as a network. Considering our sample as a closed network, ignoring external factors, with the D-Y spillover index we can visualize and summarize pairwise connections, providing insight about potential system fragility concerns, by allowing us the identification of critical nodes.

In network analysis, tranquil and crisis periods are often distinguished because connectedness of asset classes and markets are different during turbulent times (Acemoglu et al. (2015a)). To allow for the flexibility of time variant parameter estimates with identify ex post regimes shifts in Europe, linked to the changes in EU country compositions, the global financial crisis period, as well as the recent Covid-19 pandemic, and Ukraine invasion. With the use of subperiods, we effectively allow for structural breaks in our analysis, thereby addressing the potential time variant parameter concerns with our D-Y approach.

V.3 Empirical Analysis of Energy Risk in European Economies

In this empirical section in 3 parts, we test equity market implications of crude oil and natural gas price movements, specifically price changes and volatility of Brent and TTF. In sub-sections V.3.1 and V.3.2, using a comprehensive panel data set of 24 European countries from 2004 to 2022, and examine MSCI Index returns and volatility in relation with energy price changes (i.e., returns) and energy price shocks (extreme 5-day volatility).

V.3.1 European Market Indices Return Analysis in Relation with Oil and Natural Gas Returns

In Table V.2, we start our regression analysis by examining the impact of MSCI market returns for 24 European countries. To investigate whether oil and gas prices have an influence on equity markets, we estimate Models 1A-3A with 1-day future returns on the MSCI equity index, and Models 1B-3B with 5-day future returns.We find that the coefficients on the lagged 1- and 5-day oil price returns ($Brentlag1dRet$ and $Brentlag5dRet$) are insignificant, except for a positive and significant coefficient on $Brentlag5dRet$ in Models 2A and 2B, indicating a short-term market rally following oil price increases. However, the gas price change variables ($TTFlag1dRet$ and $TTFlag5dRet$) are insignificant in both specifications in which they are included (Models 3A and 3B).

Table V.2
MSCI Country Index Return Regression Analysis

Variables	(Model 1A) Ret1d	(Model 2A) Ret1d	(Model 3A) Ret1d	(Model 1B) Ret5d	(Model 2B) Ret5d	(Model 3B) Ret5d
Lag1DRet	-0.076***	-0.074***	-0.273***	-0.036	-0.035	-0.005
	(-3.35)	(-3.29)	(-14.20)	(-1.04)	(-1.01)	(-0.14)
Lag5DRet			0.281***			-0.046**
			-30.5			(-2.49)
APlag1dRet	-0.170***	-0.166***	-0.100***	-0.044	-0.042	-0.058
	(-5.60)	(-5.54)	(-3.62)	(-0.63)	(-0.61)	(-0.78)
APlag5dRet	-0.011	-0.018	-0.175***	-0.143***	-0.146***	-0.125***
	(-0.62)	(-0.98)	(-9.31)	(-3.63)	(-3.69)	(-2.95)
USlag1dRet	0.214***	0.222***	0.291***	-0.107	-0.104	-0.121
	-6.17	-6.43	-8.62	(-1.34)	(-1.30)	(-1.46)
USlag5dRet	0.206***	0.194***	0.064***	0.134***	0.129***	0.149***
	-9.38	-9.11	-4.30	-2.93	-2.93	-3.16
Brentlag1dRet	-0.003	-0.024*	-0.007	0.033	0.023	0.026
	(-0.28)	(-2.01)	(-0.60)	-1.03	-0.70	-0.73
Brentlag5dRet		0.023***	0.009*		0.010	0.016
		-3.79	-1.74		-0.68	-1.020
TTFlag1dRet			0			-0.010
			(-0.02)			(-0.51)
TTFlag5dRet			0.001			-0.009
			-0.21			(-1.26)
Constant	0.001**	0.001**	-0.016***	0.012***	0.012***	0.021
	-2.32	-2.45	(-3.28)	-8.85	-8.91	-1.24
Observations	110 740	110 740	102 292	110 740	110 740	102 292
R-squared	0.116	0.12	0.304	0.026	0.026	0.025

*Note: The dependent variable is the future 1-day MSCI index return in Models 1A-3A and the future 5-day MSCI index returns in Models 1B-3B, respectively. The explanatory variables are defined in Table V.1. The sample period is from March 24, 2003, to December 30, 2022, covering 24 EEA countries (see the complete list of countries in Table V.1b). The panel is an unbalanced panel with shorter time coverage for the Central and Eastern European Countries (CEEC) because of data limitations. The coefficient estimates with the corresponding robust t-statistics (in parentheses) are reported from panel regression, with time and country fixed effects, with clustered standard errors at time and country dimensions. ***, **, and *, indicate the statistical significance at the 1 percent, 5 percent, and 10 percent levels.*

In Table V.3, we further explore the relationship between MSCI index returns and oil prices in a subsample analysis. We find some evidence that the price of gas became more relevant to equity markets after 2013. Specifically, in the subsample analysis of 2003 - 2012, the coefficient estimate on $Brentlag5dRet$ remains significant and positive in Table V.3 Model 1A, consistent with the results in Table V.2. However, this significance disappears in the later part of the sample period. On the other hand, the coefficient on the $TTFlag5dRet$ variable is significant in the after-2013 subsample in Model 2B.

Table V.3
MSCI Country Index Regression Analysis, Subsample Results

Variables	(Model 1A) Ret1d	(Model 2A) Ret1d	(Model 3A) Ret1d	(Model 1B) Ret5d	(Model 2B) Ret5d	(Model 3B) Ret5d
	Before 2013	***After 2013***	***After 2020***	***Before 2013***	***After 2013***	***After 2020***
Lag1DRet	-0.286***	-0.263***	-0.285***	-0.032	0.024	0.110
	(-11.27)	(-10.88)	(-8.50)	(-0.66)	-0.47	-1.08
Lag5DRet	0.292***	0.267***	0.294***	-0.053	-0.045*	0.034
	-27.59	-21.71	-15.80	(-1.58)	(-1.97)	-0.76
APlag1dRet	-0.090**	-0.087***	-0.153**	-0.058	-0.062	-0.145
	(-2.26)	(-2.95)	(-2.76)	(-0.52)	(-0.73)	(-0.88)
APlag5dRet	-0.221***	-0.129***	-0.151***	-0.166**	-0.070	-0.202**
	(-8.83)	(-6.88)	(-5.45)	(-2.51)	(-1.51)	(-2.19)
USlag1dRet	0.400***	0.180***	0.178***	-0.143	-0.098	-0.152
	-8.30	-5.04	-3.56	(-1.13)	(-0.92)	(-0.95)
USlag5dRet	0.078***	0.046**	0.037	0.207**	0.094*	0.121
	-3.43	-2.62	-1.39	-2.61	-1.80	-1.45
Brentlag1dRet	-0.021	0.002	0.003	0.064	0.006	0.028
	(-0.90)	-0.15	-0.13	-1.04	-0.13	-0.36
Brentlag5dRet	0.019*	0.005	0.011	0.004	0.024	0.040
	-1.86	-0.90	-1.06	-0.13	-1.34	-1.43
TTFlag1dRet	-0.010	0.004	0.003	-0.008	-0.009	-0.012
	(-1.05)	-0.58	-0.46	(-0.26)	(-0.41)	(-0.42)
TTFlag5dRet	0.005	-0.001	-0.002	0.020	-0.019**	-0.017
	-1.24	(-0.44)	(-0.55)	-1.36	(-2.17)	(-1.58)
Constant	-0.009	0	0	-0.006	0.003**	0.003
	(-0.98)	(-0.38)	-0.19	(-0.21)	-2.42	-0.88
Observations	40 030	62 262	18 792	40 030	62 262	18 792
R-squared	0.338	0.277	0.324	0.039	0.016	0.026

*Note: The dependent variable is the future 1-day MSCI index return in Models 1A-3A and the future 5-day MSCI index returns in Models 1B-3B, respectively. The explanatory variables are defined in V.1. The sample period is from March 24, 2003, to December 30, 2022, covering 24 EEA countries (see the complete list of countries in Table V.1b). The panel is an unbalanced panel with shorter time coverage for the Central and Eastern European Countries (CEEC) because of data limitations. The coefficient estimates with the corresponding robust t-statistics (in parentheses) are reported from panel regression, with time and country fixed effects, with clustered standard errors at time and country dimensions. ***, **, and *, indicate the statistical significance at the 1 percent, 5 percent, and 10 percent levels.*

Overall, results from Tables V.2 and V.3 provide some weak evidence that crude oil and natural gas prices are relevant for the equity market performance in Europe during the 2003-2022 sample period, providing support for our first and second hypotheses. One potential explanation for the weak and insignificant results is that we also include lagged US and Asian market information using an MSCI Asian ex-Japan index and the MSCI US index, to control for new economic information released the previous day. Moreover, predicting returns is not the primary objective of this paper. Rather, we aim to demonstrate the economic and political importance of energy risk from an equity market perspective. Therefore, in the next sections, we will focus on equity market volatility instead of returns.

V.3.2 Analysis of the Relation Between European Market Indices Volatility and Oil and Natural Gas Volatility

Table V.4 examines the relationship between equity market volatility and crude oil and natural gas returns, as well as oil and gas price volatility. In Table V.4 Panel V.4a , the dependent variable is the future 5-day MSCI index volatility with the key explanatory variables: the lagged 5-day volatilities in oil and gas prices. In the spirit of Corwin and Schultz (2012), and measure volatility as the difference of the maximum and minimum prices (or index values) during a 5-day window scaled by the relevant lagged 5-day commodity price or index value. Our findings show that, on average, oil price increases tend to be positive news for the equity market and reduce market volatility. However, oil price volatility tends to spill over to equity market volatility and has a significant positive relation with equity market volatility across all model specifications in Table V.4.

Consistent with previous results, we do not find that natural gas prices influence equity market volatility. Nevertheless, we report a significant positive coefficient on the 5-day gas price volatility measures ($TTFvol5d$), indicating a significant positive relation with equity market volatility. Thus, while the level of natural gas prices does not matter for the equity market, the uncertainty in gas prices does.

Specifically interpreting the results from Models 1A through 3A, we find that a 10% increase in the 5-day oil volatility is associated with about 1.1% increase in the country stock market index volatility in the EEA on average from 2003 to 2022. This increase in market risk linked to energy price volatility is mitigated when the volatility increase in oil is associated with an increase in oil price level. These results are economically nonnegligible given that the average equity market index volatility is 2.28%. In Models 2A and 3B, we also find that volatility emanating from natural gas prices further increases market volatility, albeit on a smaller scale. With these results we provide support for our second Hypothesis that the energy price volatility is transmitted to equity markets in Europe.

In Table V.4, Panels V.4b and V.4c, we further examine the influence of oil and gas price volatility on equity market indices in Europe and find that the effect of oil price volatility decreases over time and the natural gas price volatility is mostly transient in our sample, like. Table V.4 Panel V.4b shows that the coefficient on the oil price volatility measure is economically larger and significant than in Panel V.4a, indicating that stronger effect at the 10-day market volatility. Lastly, Table V.4 Panel V.4c shows that the coefficients on the oil price volatility measure are insignificant in Models 3C-3D in recent years, indicating that the oil price impact is short term. The results with the 5-day natural gas price volatility are strongest at the 5-day window, by and large insignificant in at the 10-day (in Table V.4 Panel V.4b) and suggest reversal, decline in market volatility in 20-days.

Table V.4
MSCI Country Index Volatility Analysis with Crude Oil and Natural Gas Price Volatility

Variables	(Model 1A) mscivol5d	(Model 2A) mscivol5d	(Model 3A) mscivol5d	(Model 3B) mscivol5d	(Model 3C) mscivol5d	(Model 3D) mscivol5d
				Before 2013	***After 2013***	***After 2020***
Lag1DRet	-0.030	-0.034	-0.032	-0.041	-0.012	-0.011
	(-1.60)	(-1.64)	(-1.70)	(-1.43)	(-0.53)	(-0.24)
Lag5DRet	-0.070***	-0.074***	-0.068***	-0.055***	-0.074***	-0.068***
	(-5.95)	(-5.95)	(-5.67)	(-3.55)	(-4.69)	(-3.14)
APlag1dRet	0.008	-0.003	0.005	0.009	0.006	-0.001
	(-0.20)	(-0.08)	(0.13)	(0.15)	(0.16)	(-0.01)
APlag5dRet	-0.002	-0.019	-0.001	-0.022	0.021	0.013
	(-0.08)	(-0.83)	(-0.04)	(-0.68)	(0.88)	(0.29)
USlag1dRet	0.004	-0.010	0.002	-0.004	0.012	0.018
	(-0.09)	(-0.23)	(0.04)	(-0.07)	(0.22)	(0.22)
USlag5dRet	-0.051**	-0.068**	-0.049**	-0.067*	-0.041	-0.070
	(-2.34)	(-2.75)	(-2.18)	(-1.84)	(-1.58)	(-1.71)
Brentvol5d	0.106***		0.108***	0.207***	0.079***	0.103***
	(8.12)		(7.85)	(7.61)	(5.29)	(5.14)
Brentlag1dRet	-0.015		-0.015	-0.030	-0.011	-0.024
	(-0.91)		(-0.89)	(-0.86)	(-0.54)	(-0.68)
Brentlag5dRet	-0.033***		-0.036***	-0.043**	-0.031***	-0.040***
	(-4.47)		(-4.52)	(-2.71)	(-3.78)	(-3.05)
TTFvol5d		0.028***	0.021***	0.035***	0.015**	0.025***
		(5.36)	(3.93)	(3.58)	(2.25)	(3.22)
TTFlag1dRet		0	0.002	0	0.004	0.007
		(0.05)	(0.28)	(-0.01)	(0.37)	(0.62)
TTFlag5dRet		-0.005	0.001	-0.009	0.004	0.004
		(-1.43)	(0.16)	(-1.18)	(0.92)	(0.78)
Constant	0.021***	0.019***	0.015***	0.011***	0.024***	0.029***
	(12.40)	(14.20)	(9.80)	(6.55)	(26.23)	(12.83)
Observations	110 596	102 232	102 232	40 004	62 228	18 768
R-squared	0.286	0.271	0.291	0.301	0.226	0.24

(a) Analysis of 5-day Future Market Volatility in Relation with Oil and Gas Prices

Variables	(1) mscivol10d	(2) mscivol10d	(3) mscivol10d	(4) mscivol10d	(5) mscivol10d	(6) mscivol10d
				Before 2013	***After 2013***	***After 2020***
Lag1DRet	-0.025	-0.030	-0.026	-0.026	-0.015	-0.030
	(-0.89)	(-0.93)	(-0.89)	(-0.68)	(0.40)	(-0.36)
Lag5DRet	-0.098***	-0.106***	-0.098***	-0.070***	-0.120***	-0.147***
	(-6.20)	(-6.17)	(-5.96)	(-2.99)	(-5.79)	(-4.07)
APlag1dRet	0.031	0.019	0.032	0.054	0.022	0.045
	(0.50)	(0.26)	(0.49)	(0.56)	(0.39)	(0.38)
APlag5dRet	0.000	-0.019	0.006	-0.019	0.019	-0.009
	(0.00)	(-0.55)	(0.17)	(-0.37)	(0.59)	(-0.14)
USlag1dRet	0.006	-0.014	0.005	0.026	0.002	0.009
	(0.09)	(-0.19)	(0.07)	(0.27)	(0.02)	(0.06)
USlag5dRet	-0.088**	-0.116***	-0.092**	-0.093	-0.098**	-0.126
	(-2.52)	(-2.97)	(-2.50)	(-1.70)	(-2.17)	(-1.71)
Brentvol5d	0.161***		0.167***	0.410***	0.089***	0.113***
	(8.51)		(8.24)	(9.97)	(5.00)	(4.77)
Brentlag1dRet	-0.024		-0.027	-0.061	-0.018	-0.037
	(-1.10)		(-1.12)	(-1.17)	(-0.80)	(-0.93)
Brentlag5dRet	-0.042***		-0.043***	-0.065**	-0.027**	-0.033*
	(-3.73)		(-3.56)	(-2.60)	(-2.42)	(-1.84)
TTFvol5d		0.025***	0.016**	0.030**	0.008	0.019*
		(3.60)	(2.18)	(2.33)	(0.92)	(1.94)
TTFlag1dRet		0.004	0.007	0.004	0.007	0.011
		(0.30)	(0.56)	(0.19)	(0.52)	(0.60)
TTFlag5dRet		-0.011*	-0.003	-0.012	-0.001	-0.005
		(-1.78)	(-0.45)	(-1.17)	(-0.13)	(-0.52)
Constant	0.037***	0.034***	0.028***	0.018***	0.042***	0.058***
	(14.57)	(15.92)	(11.71)	(7.25)	(28.16)	(15.24)
Observations	110 596	102 232	102 232	40 004	62 228	18 768
R-squared	0.327	0.311	0.329	0.346	0.266	0.252

(b) Analysis of 10-day Future Market Volatility in Relation with Oil and Gas Prices

Variables	(1) mscivol20d	(2) mscivol20d	(3) mscivol20d	(4) mscivol20d	(5) mscivol20d	(6) mscivol20d
				Before 2013	***After 2013***	***After 2020***
Lag1DRet	-0.007	-0.007	-0.006	-0.009	0.003	-0.007
	(-0.17)	(-0.16)	(-0.15)	(-0.13)	(0.07)	(-0.08)
Lag5DRet	-0.093***	-0.099***	-0.096***	-0.140***	-0.053*	-0.065
	(-4.23)	(-4.24)	(-4.20)	(-3.86)	(-1.89)	(-1.56)
APlag1dRet	0.021	0.017	0.024	0.036	0.035	0.060
	(0.25)	(0.19)	(0.27)	(0.26)	(0.52)	(0.41)
APlag5dRet	-0.082*	-0.102**	-0.090*	-0.067	-0.121**	-0.204**
	(-1.85)	(-2.09)	(-1.86)	(-0.89)	(-2.78)	(-2.37)
USlag1dRet	-0.014	-0.018	-0.012	-0.001	-0.000	0.000
	(-0.16)	(-0.20)	(-0.13)	(-0.00)	(-0.00)	(0.00)
USlag5dRet	-0.020	-0.028	-0.018	-0.022	-0.016	-0.062
	(-0.41)	(-0.55)	(-0.35)	(-0.26)	(-0.26)	(-0.60)
Brentvol5d	0.112***		0.121***	0.426***	0.027	0.019
	(5.08)		(5.18)	(6.98)	(1.51)	(0.76)
Brentlag1dRet	-0.006		-0.006	-0.029	-0.006	-0.034
	(-0.21)		(-0.19)	(-0.35)	(-0.27)	(-0.82)
Brentlag5dRet	-0.012		-0.012	-0.014	-0.002	0.020
		(-0.87)	(-0.79)	(-0.36)	(-0.15)	(0.97)
TTFvol5d		-0.018**	-0.025**	-0.024	-0.028***	-0.035***
		(-2.08)	(-2.73)	(-1.22)	(-2.94)	(-2.98)
TTFlag1dRet		-0.002	-0.000	0.003	-0.002	-0.002
		(-0.13)	(-0.01)	(0.08)	(-0.17)	(-0.14)
TTFlag5dRet		-0.008	-0.004	0.015	-0.009	-0.018*
		(-1.24)	(-0.59)	(0.92)	(-1.22)	(-1.82)
Constant	0.045***	0.046***	0.041***	0.029***	0.054***	0.088***
	(14.93)	(15.75)	(13.27)	(7.94)	(29.95)	(13.94)
Observations	110 596	102 232	102 232	40 004	62 228	18 768
R-squared	0.291	0.285	0.290	0.303	0.221	0.169

(c) Analysis of 20-day Future Market Volatility in Relation with Oil and Gas Prices

*Note: The dependent variable is the future 5-day MSCI index return volatility (10-day and 20-day in Panels V.4b, and V.4c, respectively) in Panel V.4a in Models 1A-3A for the full sample, with model 3A specification replicated in Models 3B through 3D with various subsamples. The explanatory variables are defined in Table V.1. The sample is from March 24, 2003, to December 31, 2012, in Models 1A through 3B, from January 1, 2013, to December 31, 2019, in Models 3C, and from January 1, 2020, to December 31, 2022, in Models 3D. The cross-sectional coverage is the same as in Tables V.1 and V.2, 24 EEA countries. The coefficient estimates with the corresponding robust t-statistics (in parentheses) are reported from panel regression, with time and country fixed effects, with clustered standard errors at time and country dimensions. ***, **, and *, indicate the statistical significance at the 1 percent, 5 percent, and 10 percent levels.*

In Table V.5, we consider market development and test the impact of energy price volatility in conjunction with market development, using the local domestic currency trend as a proxy. Depreciating currencies (relative to EUR) tend to indicate economic weakness or uncertainty, making such countries more likely to be "hit harder" by energy price shocks. We use the 5-day change in the domestic currency exchange rate and interact it with the 5-day gas price volatility and oil price volatility measures. Our findings show that in countries with depreciating local currencies, crude oil price volatility and natural gas price volatility are associated with a larger market volatility impact. Moreover, the subsample analyses in Models 3B through 3D highlight that market volatility sensitivity is increasing over time, especially in vulnerable countries with weak domestic currencies.

Let's consider a country where the currency value declined by 5% in the last 5 days. The direct effect of the currency devaluation is about -0.005 ($= 0.102 \cdot 0.05$), indicating a 0.5% decline in the market volatility. For illustration, assuming again 10% increase in oil and gas prices and volatility. Based on Model 3A results, the country equity index volatility increases with 10% oil and gas price volatility by 1.07% and 0.21% respectively. Looking at the interaction variable with currency devaluation, the effect of oil price volatility and gas price volatility are magnified and outweighs the volatility reduction effect from the currency devaluation, noted above. Interpreting the oil price volatility and currency devaluation interaction, we estimate 0.852% ($= 0.05 \cdot 0.1 \cdot 1.704$) increase in volatility while from the TTF price volatility and currency devaluation interaction, we estimate 0.292% ($= 0.05 \cdot 0.1 \cdot 0.584$), with a combined effect of 1.144%.

Table V.5
MSCI Country Index Volatility Regression Analysis with Oil and Gas Price Volatility and FX

Variables	(Model 1A) mscivol5d	(Model 2A) mscivol5d	(Model 3A) mscivol5d	(Model 3B) mscivol5d	(Model 3C) mscivol5d	(Model 3D) mscivol5d
				Before 2013	***After 2013***	***After 2020***
Lag1DRet	-0.031	-0.034	-0.033*	-0.04	-0.013	-0.015
	(-1.62)	(-1.66)	(-1.73)	(-1.39)	(-0.60)	(-0.34)
Lag5DRet	-0.067***	-0.071***	-0.065***	-0.053***	-0.070***	-0.060**
	(-5.37)	(-5.28)	(-5.09)	(-3.22)	(-4.11)	(-2.75)
APlag1Ret	0.007	-0.004	0.005	0.009	0.004	-0.003
	(0.19)	(-0.10)	(0.11)	-0.15	(0.12)	(-0.05)
AP5dLagRet	-0.002	-0.02	-0.002	-0.022	0.021	0.014
	(-0.12)	(-0.86)	(-0.08)	(-0.69)	(0.93)	(0.32)
USlag1dRet	0.005	-0.01	0.003	-0.004	0.014	0.02
	(0.12)	(-0.23)	(0.06)	(-0.06)	(0.26)	(0.25)
USlag5dRet	-0.050**	-0.069**	-0.049**	-0.068*	-0.041	-0.074*
	(-2.32)	(-2.78)	(-2.18)	(-1.85)	(-1.61)	(-1.83)
Brentvol5d	0.105***		0.107***	0.206***	0.077***	0.100***
	(8.17)		(7.89)	(7.63)	(5.36)	(5.1)
FXlag5d·Brentvol	2.033***		1.704***	0.126	2.574***	2.555***
	(3.96)		(3.9)	(0.11)	(4.64)	(4.21)
FXlag1dsret	-0.03	-0.036	-0.039	0.001	-0.081*	-0.165**
	(-0.51)	(-0.59)	(-0.63)	(0.01)	(-1.94)	(-2.23)
FXlag5dsret	-0.069*	0.007	-0.102**	0.067	-0.168***	-0.269***
	(-1.86)	(0.21)	(-2.43)	(1.01)	(-2.99)	(-3.27)
LogFXprice	-0.003	-0.002	-0.003	0.006	0.004	0.046*
	(-0.81)	(-0.68)	(-0.95)	(0.51)	(0.76)	(1.72)
Brentlag1dret	-0.015		-0.016	-0.03	-0.012	-0.026
	(-0.93)		(-0.90)	(-0.86)	(-0.58)	(-0.74)
Brentlag5dret	-0.031***		-0.035***	-0.043**	-0.029***	-0.038***
	(-4.35)		(-4.44)	(-2.71)	(-3.64)	(-2.92)
TTFvol5d		0.027***	0.021***	0.036***	0.014**	0.024***
		(5.34)	(3.91)	(3.61)	(2.19)	(3.12)
FXlag5d×TTFvol		0.727***	0.584**	-0.640*	0.723***	0.865***
		(2.95)	(2.43)	(-1.79)	(2.89)	(3.32)
TTFlag1dret		0	0.002	0	0.004	0.007
		(0.06)	(0.29)	(-0.01)	(0.39)	(0.66)
TTFlag5dret		-0.006	0	-0.009	0.003	0.003
		(-1.57)	(0.04)	(-1.19)	(0.74)	(0.62)
Constant	0.023***	0.021***	0.018***	0.007	0.021***	-0.012
	(8.58)	(7.29)	(6.44)	(0.76)	(4.22)	(-0.51)
Observations	110 596	102 232	102 232	40 004	62 228	18 768
R-squared	0.286	0.271	0.291	0.301	0.229	0.246

*Note: The dependent variable is the future 5-day MSCI index return volatility in Models 1A-3A for the full sample, with model 3A specification replicated in Models 3B through 3D with subsamples, as in Table V.4. The explanatory variables are defined in Table V.1. In addition, we include exchange rate measure, $LogFXprice$, and lagged 1-day and 5-sday exchange rate changes and interaction variables of the lagged 5-day exchange rate changes with the oil and natural gas price volatility measures. The sample is from March 24, 2003, to December 31, 2012, in Models 1 A through 3B, from January 1, 2013, to December 31, 2019, in Models 3 C, and from January 1, 2020, to December 31, 2022, in Models 3D. The coefficient estimates with the corresponding robust t-statistics (in parentheses) are reported from panel regression, with time and country fixed effects, with clustered standard errors at time and country dimensions. ***, **, and *, indicate the statistical significance at the 1 percent, 5 percent, and 10 percent levels.*

With Tables V.3 - V.5, we show that while increases in crude oil and natural gas prices tend to reduce market volatility, oil and gas price volatility have a spillover effect and a significant positive relationship with equity market volatility. We find that the uncertainty in natural gas prices, rather than their level, is the driving force behind equity market volatility and this potential volatility transmission is more relevant in countries with currencies weakening relative to the Euro. These findings have important policy implications, particularly for countries vulnerable to energy price shocks.

In the next sub-section, we take a closer look at "our" network participants, the 24 European Economies in the EEA, and examine their equity markets in conjunction with energy shocks in a closed network setting, with the D-Y spillover index method.

V.4 Application of the Diebold-Yilmaz Spillover Index for European Markets

In Section V.4.1, we briefly discuss our application of Diebold-Yilmaz Spillover index method for a closed network analysis of all EEA countries MSCI indices. Where in the closed network in addition to the domestic country equity indices, we also include oil and natural gas prices, and aggregate equity market proxies for the US and Asia. In Section V.4.2, we present network analysis results of spillovers for 8 sub-periods from January 2004 to December 2022.

For the network analysis, we adopt the generalized version of the D-Y spillover index (Diebold and Yilmaz (2012)), based on a VAR method (Sims (1980)) with a major focus on the calculation of the Forecast Error Variance Decomposition (FEVD). The FEVDs are invariant to the ordering of the variables, which avoid the ordering of the variables in the VAR model. Given the goal is to assess the magnitude of the volatility spillovers rather than identifying the causal effects of structural shocks, this appears to be the preferred choice in the present context (Diebold and Yilmaz (2023)).

V.4.1 Application of the Diebold-Yilmaz Spillover Index for European Markets

Under the generalized VAR framework, we consider a covariance-stationary VAR (p) model with N-variable i.e., $Y_t = \sum_{t=1}^{p} \psi_i Y_{t-i} + e_t$, where $e_t \sim i.i.d(0, \Sigma)$ is a $N \times 1$ vector of residuals. The moving average representation of the VAR model takes the form of $Y_t = \sum_{j=0}^{\infty} \psi_i A_j e_{t-j}$ where A_j is an $N \times N$ is a coefficient matrix. A_j follows recursive pattern as $A_j = \psi_1 A_{j-1} + \psi_2 A_{j-2} + ... + \psi_p A_{j-p}$, A_0 is an identity matrix and $A_j = 0$ for $j < 0$. Diebold and Yilmaz (2012) apply a generalized VAR framework to calculate the H-step-ahead generalized forecast error decompositions as follows:

$$\phi_{ij}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h' \Sigma e_i)} \tag{V.4}$$

where σ_{ii} is the i-th element on the principal diagonal of Σ. Since the sum of each row of $\phi_{ij}(H)$ is not equal to 1, each element of the matrix is normalized as follows:

$$\bar{\phi}_{ij}(H) = \frac{\phi_{ij}(H)}{\sum_{j=1}^{N} \phi_{ij}(H)} \tag{V.5}$$

so that the decomposition including shocks in each market equals to unity, i.e., $\sum_{j=1}^{N} \bar{\phi}_{ij}(H) = 1$ and total decomposition of all variables sums to N, i.e., $\sum_{ij=1}^{N} \bar{\phi}_{ij}(H) = N$ The total spillover (TS) index is computed as follows:

$$TS(H) = \frac{\sum_{ij=1, i \neq j}^{N} \bar{\phi}_{ij}(H)}{N} \cdot 100 \tag{V.6}$$

The directional spillover measure at the asset level, capturing volatility spillover received by asset i, from the market with j assets, is defined as follows:

$$DS_{i \leftarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \bar{\phi}_{ij}(H)}{N} \cdot 100 \tag{V.7}$$

and similarly,

$$DS_{i \rightarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \bar{\phi}_{ji}(H)}{N} \cdot 100 \tag{V.8}$$

Last, the net spillovers (NS) from one node to another for a set of variables are calculated by subtracting Eq. V.7 from V.8 as follows:

$$NS_i(H) = DS_{i \rightarrow j}(H) - DS_{i \leftarrow j}(H) \tag{V.9}$$

We use the H step variation in the absolute changes in log prices as suggested by Forsberg and Ghysels (2007) to proxy for realized volatility.[26] We calculate the price change in asset iV_{it} at time t as $V_{it} = |ln(P_{it}) - ln(P_{(it-1)})|$.

While we focus on examining, the volatility transmission of domestic equity indices across Europe in relation with energy prices, we do acknowledge that equity indices are likely to react to earlier information from the US and Asian markets, and therefore, we also include MSCI aggregate US and Asian Pacific indices in our closed network analysis as and regressions, to mitigate omitted variable bias. Table V.6 presents key volatility spillover results of our equity index universe, for the year 2004. This year is of particular interest because on May 1st, 2004, the European Union welcomed 10 new countries.

[26] Our choice of volatility measures is motivated by Forsberg and Ghysels (2007), who show that absolute returns are good volatility predictors, as they have good population performance, low sampling errors and are robust to jumps.

Unfortunately, a number of the new extension EU countries have limited data coverage in the beginning of the sample because on only Hungarian and the Polish MSCI indices are available from 2004. In addition, there were no observations for the natural gas (i.e., TTF) which started trading in 2005.

Diebold and Yılmaz (2014), in their seminal paper, investigating the interconnectedness of the financial system, report a total spillover index of 78.3%, which is comparable to our 78.8% in 2004, implying a very strong interconnectedness in the network. A network participant is either a net volatility transmitter (positive values in Net row) or receiver (negative values in Net row), based on the difference between emitted and absorbed volatilities. According to the net spillover indices, the US equity market return is the largest volatility receiver (-56.5%). Similarly, the Asian aggregate index (i.e., APAC in the graph) is a volatility receiver, while Norway is a volatility transmitter. Brent has the strongest net positive effect (118.2%), suggesting that its volatility heavily impacts the domestic equity markets.

Table V.6

Volatility spillover summary table for MSCI equity indices of our sample EEA countries, US equity index, APAC equity index, and Brent one month ahead future prices during the period of 1/1/2004 and 12/31/2004

	AUT	BEL	DEU	DNK	FIN	FRA	GBR	NLD	SWE	ESP	GRC	IRL	ITA	PRT	HUN	POL	NOR	USA	APAC	Brent	From
AUT	18.0	4.1	4.9	4.2	4.8	3.9	3.0	4.0	7.2	4.7	4.0	1.9	3.1	2.3	5.7	2.7	7.7	1.4	2.5	10	82
BEL	4.6	9.8	8.0	4.0	7.3	6.6	4.1	6.0	8.5	6.5	3.4	2.0	4.4	3.7	3.4	2.2	5.7	1.4	1.2	7.3	90.2
DEU	3.9	5.6	12.3	3.5	7.4	7.6	3.6	7.4	10.5	6.8	3.2	1.6	4.8	2.6	3.2	1.8	5.2	1.4	1.3	6.4	87.7
DNK	5.6	4.6	5.1	10.9	5.7	4.2	3.4	4.4	7.5	5.3	4.7	2.4	2.9	4.2	4.5	2.2	6.0	2.0	1.0	13.6	89.1
FIN	2.0	2.6	3.2	1.6	56.7	2.5	2.5	2.5	5.1	2.2	1.3	1.2	1.5	1.8	3.2	1.4	2.7	0.9	0.4	4.7	43.3
FRA	4.1	5.9	9.8	3.5	7.9	9.5	3.8	7.6	9.6	6.9	3.2	1.3	4.8	2.6	3.3	1.6	5.4	1.4	1.0	6.9	90.5
GBR	3.7	5.0	6.6	3.4	9.7	5.4	10.4	5.6	7.1	5.3	2.9	2.1	3.7	3.0	5.2	2.8	8.5	1.7	1.3	6.8	89.6
NLD	4.1	5.6	9.9	3.7	8.0	7.9	4.1	9.8	8.7	6.6	3.4	1.5	4.7	2.7	3.1	1.3	6.0	1.6	1.2	6.2	90.2
SWE	4.3	4.6	7.5	3.5	7.9	5.3	2.6	4.6	22.5	4.4	3.2	2.0	3.3	3.2	2.9	2.1	5.5	1.5	1.9	7.5	77.5
ESP	4.6	5.7	8.3	4.0	6.0	6.4	3.9	5.9	8.1	12.4	4.0	1.7	4.7	3.2	3.6	1.9	6.0	1.8	1.3	6.7	87.6
GRC	4.2	3.5	3.9	4.0	4.8	3.0	3.1	3.2	5.6	5.0	23.3	2.6	2.4	2.9	5.9	3.0	8.1	2.2	1.4	8.0	76.7
IRL	3.5	3.5	4.1	3.2	6.6	2.3	3.3	2.9	8.7	3.1	4.6	17.1	2.1	4.2	5.9	3.2	8.1	2.1	2.6	8.8	82.9
ITA	4.3	5.5	8.6	3.6	5.5	6.6	4.1	6.2	8.1	7.4	3.2	1.5	8.6	3.3	4.0	2.7	6.7	1.5	1.1	7.6	91.4
PRT	3.3	5.1	3.7	4.9	8.1	3.1	2.8	3.3	8.2	4.2	4.1	3.1	2.8	16.1	4.5	3.1	5.3	1.8	1.2	11.7	83.9
HUN	4.7	2.0	2.4	2.6	5.4	1.9	2.2	2.1	5.2	2.5	3.4	1.4	1.5	1.9	36.1	3.7	7.4	1.5	2.9	9.3	63.9
POL	2.9	2.1	2.4	2.5	3.6	1.7	2.0	1.7	6.6	2.8	3.9	2.1	1.4	2.2	6.2	32.8	8.1	2.2	2.4	10.1	67.2
NOR	4.1	3.0	3.6	3.3	5.2	3.0	4.3	3.6	6.6	3.8	3.6	2.5	2.7	2.5	4.2	4.1	28.3	2.1	1.9	7.8	71.7
USA	4.4	3.2	4.3	4.1	7.1	3.0	3.4	4.1	8.2	3.8	3.7	2.0	2.2	2.7	4.5	1.7	8.2	15.5	1.3	12.8	84.5
APAC	4.7	2.7	3.8	2.2	3.4	1.8	1.6	2.5	8.5	2.8	2.2	2.3	1.3	1.8	8.7	3.6	9.2	1.7	24.1	11.1	75.9
BRENT	1.8	0.9	0.9	1.0	2.5	0.8	0.7	0.8	2.1	0.6	1.8	1.0	0.5	1.2	3.5	1.3	2.6	0.8	0.7	74.8	25.2
To	74.8	75.0	100.9	62.6	116.9	77.0	58.5	78.1	140.0	84.5	63.7	36.1	54.8	51.9	85.4	46.3	122.4	30.9	28.5	163.1	77.6
Net	-7.3	-15.2	13.2	-26.4	73.6	-13.5	-31.2	-12.1	62.5	-3.1	-13.0	-46.8	-36.7	-32	21.4	-20.9	50.7	-53.6	-47.3	137.8	

V.4.2 Network representation of the Diebold-Yilmaz Spillover Index

Using the connectedness table, it is also possible to construct a matrix containing the pairwise net directional connectedness of all pairs. Fig. V.1 provides a visual representation of these relations in an informative network graph. An arrow from variable y_i to variable y_j denotes a positive net directional connectedness (in other words, variable y_i explains more of variable y_j than the reverse). The assets are grouped and color-coded as follows:

- Red: Core EU countries
- Blue: PIIGS countries
- Green: Countries joined the EU after 2004
- Purple: Ex-EU countries and regions
- Grey: Brent crude oil benchmark (Brent)[27]

[27] TTF is represented with orange, however, it started trading in 2005 thus not represented in the 2004 plot.

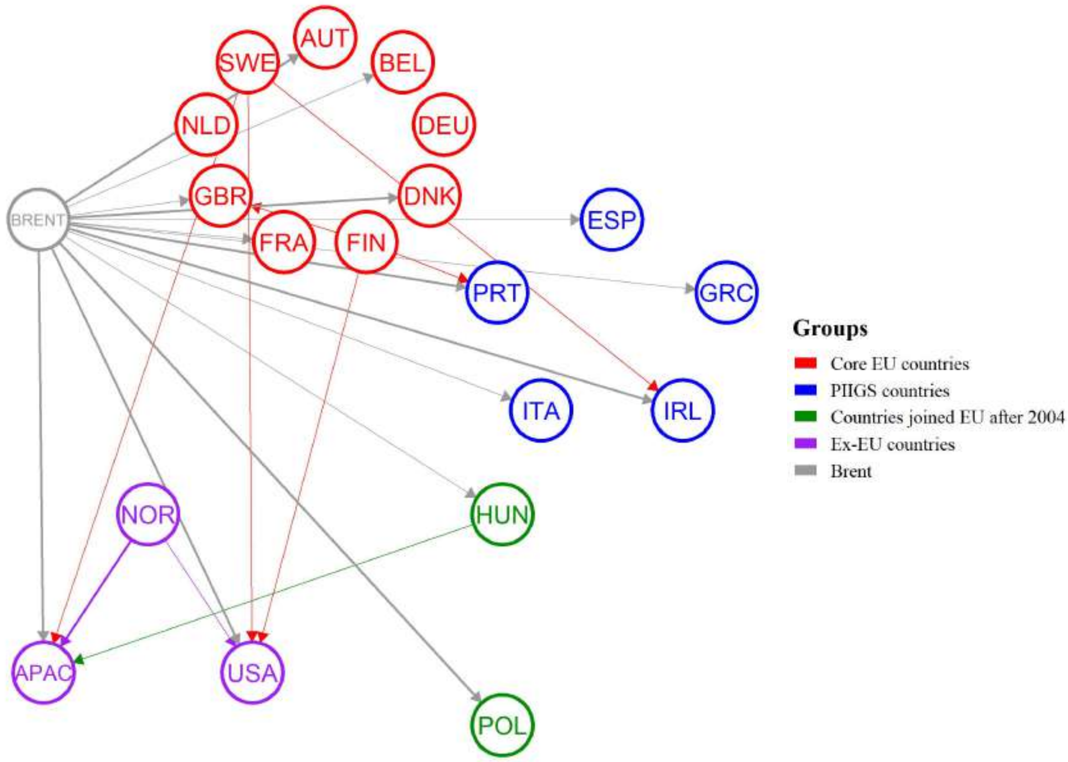


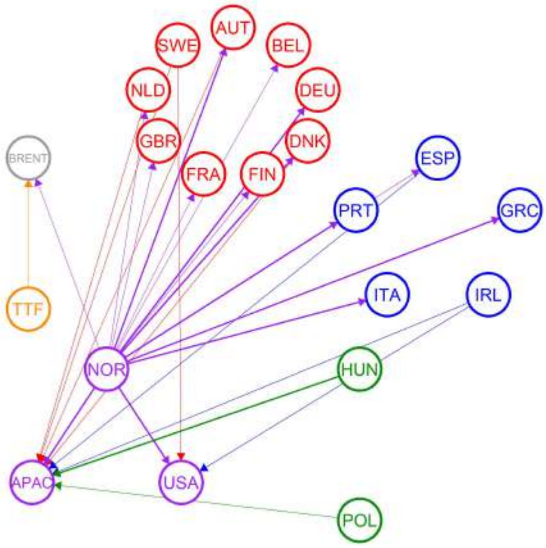
Fig. V.1. Static volatility interconnectedness network during the period of 1/1/2004 and 12/31/2004

Note:An arrow between two nodes indicates the direction of the spillover, and the color of the arrow indicates the group of countries or the asset from which it originates from. Thinner lines represent the strongest 5% of connections, while thicker lines show the uppermost 1% of connections. For the figure, we use Lag = 3 and H = 10 model inputs. The figure is prepared using the Diebold and Yılmaz (2014) spillover index method.

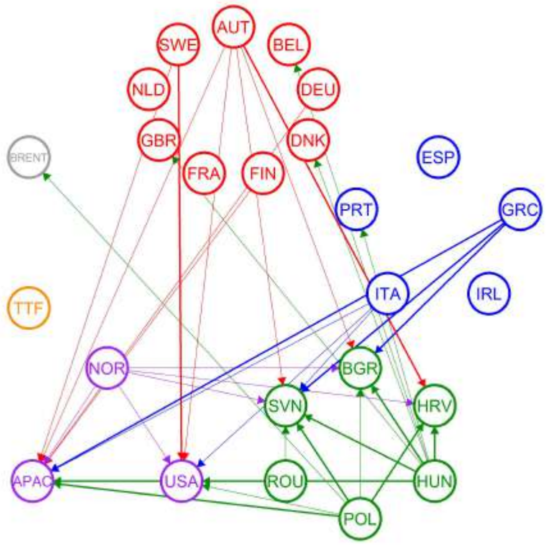
The colors of the arrows indicate the group of the transmitter participant. Only those edges in the uppermost 5% considering the magnitude of the net spillover, are shown. Thicker arrows represent connections in the top 1%, which are the strongest pairwise spillover connections. In Figure V.1, the grey-colored arrows dominate, which indicate that Brent is the primary volatility transmitter in the system in 2004. Out of the total 23 arrows, 14 are from this asset accounting for 61% of all edges. There are a few underlying reasons behind the high spillover ratio of Brent.

Bildirici and Bakirtas (2014) point out that demand for oil increased dramatically for rapidly developing countries such as China and India, which led to a rise in oil prices globally. Since 2003, the production of the Russian Yukos, a main Integrated Oil and Gas company, has been inconsistent because of legal challenges. This led to concerns about a potential supply shortage (and indeed Yukos went bankrupt in 2006) (Hanson (2005)). In addition, geopolitical tensions, and armed conflicts, such as the Iraq War and terrorist attacks in the Middle East, also had an impact on the Brent benchmark price (Choi and Hammoudeh (2010)).

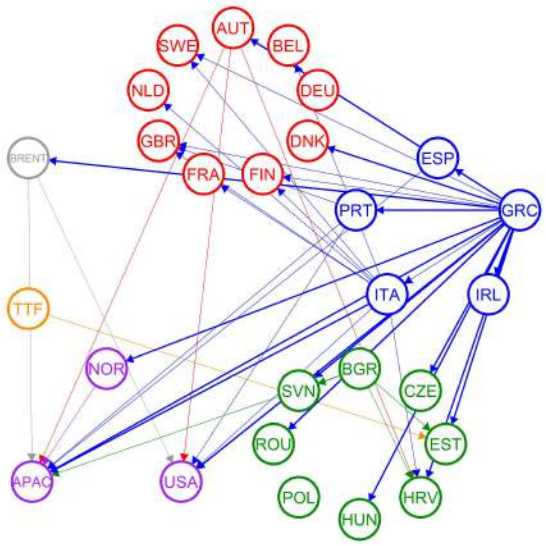
In the next section, we partition our estimation time frame into seven additional subsets, depicted in Figure. V.2. We progressively introduce new network elements as data becomes accessible. Specifically, in the period 2005-2008 (refer to Table C.3), we integrate TTF, and in the period 2009-2012 (refer to Table C.4), we incorporate more countries, particularly CEEC and the Baltics, thus expanding our network, particularly the non-core EU group in the model (refer to Tables C.5 and C.6). To gain a better understanding of specific disturbances such as the onset of the Covid-19 pandemic in 2020 (refer to Table C.7), the recovery in Europe in 2021 (refer to Table C.8), and the commencement of the Russo-Ukrainian conflict in 2022 (refer to Table C.9), we examine the years 2020, 2021, and 2022, one by one.



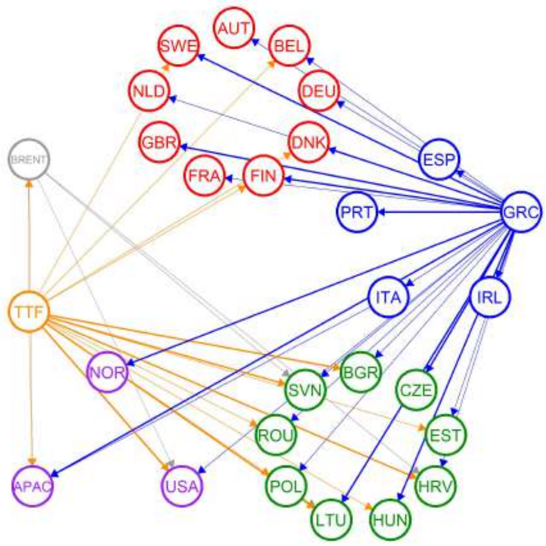
(a) 2005 - 2008



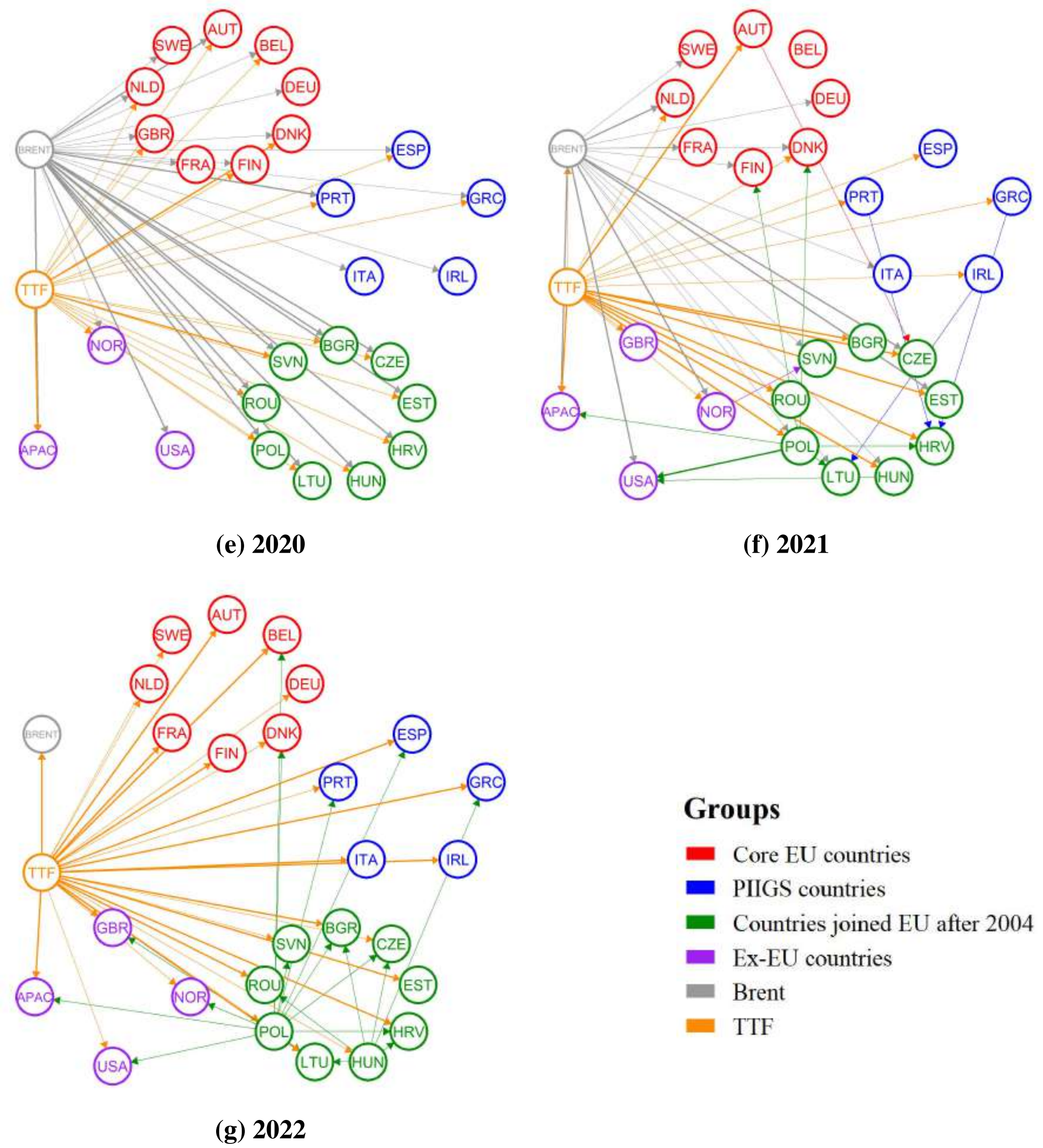
(b) 2009 - 2012



(c) 2013 - 2015



(d) 2016 - 2019



(e) 2020 **(f) 2021**

(g) 2022

Fig. V.2. Static volatility interconnectedness network during various periods

Note: An arrow between two nodes indicates the direction of the spillover, and the color of the arrow indicates the industry sector of the asset from which it originates from. Thinner lines represent the strongest 5% of connections, while thicker lines show the uppermost 1% of connections. For the figure, we use Lag=3 and H=10 model inputs. The figure is prepared using the Diebold and Yılmaz (2014) spillover index method.

Several studies (Liow (2015), Balli et al. (2015), Gamba-Santamaria et al. (2017)) find that the total volatility spillover increases during crisis periods. Our GFC and ESDC subperiods (2005 - 2008 and 2009 - 2012) show a total spillover increase of 85.47% and 85.65%, which is consistent with the earlier studies. Between 2005 and 2008 (Fig V.2a), Norway was the main volatility emitter, accounting for 57% of the total possible arrows. Park and Ratti (2008) highlight that the volatility of Norwegian stocks is particularly sensitive to negative and positive oil price shocks. Between July 2008 and December 2008, Brent price fell from 146 USD/Bbl to 36 USD/Bbl which greatly affected the volatility of the Norwegian price index.

Although Norway remained an important volatility emitter (13%), its dominance declined during 2009-2012, as Hungary (26%) and Poland (18%) emerged as major transmitters (Fig V.2b). A reason for the new volatility source from CEE countries is the lower stock market resilience against GFC shocks in CEEC compared to the eurozone economies as suggested by Mihaljek (2010). Austria (12.8%) is also a major volatility emitter during this period, likely due to the changes in political leadership and concerns over corruption, creating a climate of uncertainty and unpredictability.

Fernández-Rodríguez et al. (2015) and Mensi et al. (2018) report increased volatility spillover not just during the time of the GFC but also during the ESDC which affected Portugal, Italy, Ireland, Greece, and Spain (PIIGS). These countries were economically weaker and more vulnerable to financial instability than other countries in the Eurozone. Among the PIIGS countries, Greece was the closest to default, but it was bailed out. Although the European Sovereign Debt Crisis happened from 2009 to 2013, its effect reached the stock market later and hit Greece the most. From 2013 to 2015, Greece was the largest volatility emitter, accounting for 44% of the outgoing edges.

In June 2015, the Greek Government imposed capital controls which restricted the amount of money that could be withdrawn from banks and led to a significant decrease in liquidity and an increase in uncertainty in the financial markets (NPR (2015), Kosmidou et al. (2020)). Additionally, in January 2015, the far-leftist Syriza party won the election in Greece. The actions of the new government, which included renegotiating Greece's debt and opposing austerity measures, created uncertainty and concern among investors, further fueling volatility in the stock market (BBC (2015)). Italy faced similar political uncertainty during 2013 - 2015 when it could not form a strong government (Chiaramonte et al. (2018)). It was the second largest volatility transmitter during this time, accounting for 21% of the connections (Fig V.2c).

In the 2016 - 2019 period (Fig V.2d), Greece remained the most dominant volatility transmitter (54%), with TTF prices also in second place. One of the main reasons for the TTF price volatility was the oversupply of natural gas in the global market, particularly in the USA, putting downward pressure on prices. From 2016 to 2019, US natural gas production increased by 13% due to the shale gas revolution (EIA (2022), Middleton et al. (2017)). The expansion of the liquified natural gas (LNG) trade also contributed to the oversupply of natural gas worldwide, as LNG trade increased by 35% during this period (BP (2022)). Furthermore, tensions between Russia and Ukraine, two major natural gas producers, had led to supply disruption and price volatility (Zhiznin and Timokhov (2019)). It is noteworthy, that TTF mainly provides volatility towards the NEW countries which are heavily reliant on natural gas imports from Russia and are therefore more vulnerable to fluctuations in gas prices.

The rapid spread of Covid-19 had greatly increased uncertainty in both the financial and commodity markets, especially the energy market (Lin and Su (2021), Zhang et al. (2020)). Fig V.2e shows that all the arrows originate from Brent (57%) and TTF (43%). In the first half of the year, the pandemic led to a decrease in demand for oil and gas due to lockdowns and reduced economic activity. This decrease in demand caused a surplus in the market, which led to lower prices. In response to the decrease in demand, producers reduced their production levels, which ameliorated the oversupply (ACER (2022), Reuters (2022a)). Both Brent and TTF have a U-shaped price graph. As economies began to reopen and activities started to pick up, the production cuts led to a tightening of the market and higher prices. Besides these common factors, the price war between Saudi Arabia and Russia over oil production levels led to a significant increase in oil supply and further contributed to the oversupply and lower prices (Iglesias and Rivera-Alonso (2022)). In reaction, OPEC+ decided to cut production in May 2020 which helped stabilize the market and support higher prices in the second half of 2020 (Enerdata (2020)).

In 2021, as seen in Fig V.2f, the main sources of volatility transmission were still TTF (39%) and Brent (35%). Natural gas demand was driven by cold weather conditions which swept across Europe, in early 2021, leading to a surge in demand for natural gas for heating purposes. This increase in demand led to a supply shortage and contributed to higher prices and volatility (IEA (2021)). The global LNG market continued to experience imbalances in supply and demand, which affected TTF prices. The Covid-19 pandemic disrupted the LNG market with production and delivery delays, leading to supply shortages (Chai et al. (2021)). Furthermore, there were concerns about the possible disruptions of natural gas supplies from Russia, a large part of which were transported through Ukraine to Europe (Reuters (2022c)). The pandemic had less of an impact on Brent prices in 2021 compared to 2020, but it continued to affect the market. Variants of the virus and vaccination rollouts in different regions caused uncertainty in the demand for oil, which affected prices (CNBC (2022b)). In April 2021, OPEC+ decided to gradually increase production in response to the improving market conditions, which put downward pressure on prices. However, in July 2021, OPEC+ decided to maintain current production levels, which supported prices (Reuters (2021)).

In 2022, the unexpected Russian invasion of Ukraine created much uncertainty about unrestricted access to fossil commodities, especially to natural gas. The war in the first few months of 2022 raised concerns about the safety of Europe's gas supply and the unpredictability of gas prices. In the first quarter of 2022, the EU spent a projected €78 billion on natural gas imports, €27 billions of which came from Russia. The EU's net gas imports increased by 10% over this time, while imports of liquefied natural gas increased by 72% year on year (European Commission (2020), European Commission (2022)).

At their peak in August 2022, European gas prices topped 345 euros/MWh because (1)

Russia weaponized its natural gas exports in response to punitive EU sanctions, and (2) sky-high temperatures over the summer, drove up demand. Following that, however, unseasonably warm weather through winter in much of northwest Europe reduced demand for heating and allowed the continent to replenish its gas inventory. By the end of 2022, TTF price reverted to pre-war levels (CNBC (2022a)). This extreme hike and drop within a year made TTF the main volatility transmitter (59%) in 2022 (Fig V.2g). Besides TTF, Hungary (28%) and Poland (13%) are net volatility emitters. Silva et al. (2023) point out that from the European countries, Hungary and Poland have the largest trade exposure with countries at war (3.6% and 3.2% respectively). Our results are in line with Yousaf et al. (2022) and Silva et al. (2023) who claim that the equity markets of Hungary and Poland are the most sensitive to the Russia-Ukraine war.

V.5 Conclusion

In this study, we investigate the spillover effects of energy prices. Specifically, we examine the volatility spillover of crude oil and natural gas prices, on equity markets in 24 European Economic Area (EEA) countries to contribute to ongoing policy debates about Europe's energy stability. Our sample period from March 24, 2003, to December 31, 2022, covering about 20 years, includes several political and economic crises across Europe and globally.

In panel regression analyses, we examine oil and gas prices' influence on equity market returns and equity market volatility. Our results show that oil and gas prices have a weak impact on the equity markets in the sample countries. On the other hand, we do find that price volatility of crude oil and natural gas are major contributors to volatility in the equity markets, particularly in countries with relatively underdeveloped exchanges or weak domestic currencies. We also employ the D-Y spillover index method to perform network analysis for the 20-year sample period, with 5 shorter subsample analysis to provide focused analysis of specific crisis events.

We find significant differences in the sources of volatility across the subperiods, with the primary sources of volatility initially stemming from economic or political uncertainty. We also identify countries or groups of countries, such as Greece during the sovereign debt crisis, Central and Eastern European countries (CEEC) after the 2004 EU extension, and Norway during the 2008 oil rout, as key sources of volatility in the European equity markets. Interestingly, oil and gas price shocks have become direct primary volatility providers since 2019, with increasing volatility risk arising from natural gas, a green-labeled energy source, despite the ongoing efforts of diversification.

Overall, our study provides several unique contributions. First, we are the first to deploy the D-Y spillover index in the EEA context, providing insights into the interconnectedness of European economies in response to economic, political, and energy shocks. Second, we include natural gas (TTF) in addition to oil in our network model, acknowledging Europe's increasing gas dependency. Lastly, we provide a comprehensive panel regression analysis of crude oil and natural gas price shocks to equity markets before focusing on a closed network model, addressing potential omitted variable biases and allowing for external factors.

Our findings have policy implications for managing the risks associated with energy price volatility in the European equity markets. Our results suggest that policymakers should consider the potential impact of energy shocks on countries with relatively underdeveloped exchanges or weak domestic currencies. Additionally, our study highlights the need for diversification across different energy mixes to mitigate the risks associated with energy price volatility, particularly in light of Europe's increasing gas dependency. Finally, our study underscores the importance of currency risk management for energy import dependent small economies in general. While our analysis highlighted the vulnerability of CEEC countries especially during recent years, our results can also partially explain the severity of the economic crisis of Sri Lanka and the subsequent country default in 2022 (IMF (2019b)), where the weak domestic currency was a major impediment to energy stability because of the high cost of USD denominated oil imports.

CHAPTER

VI

DISCUSSION OF FUTURE RESEARCH OPPORTUNITIES ON CLIMATE RISK IMPICATIONS FOR PORTFOLIO MANAGEMENT

My research (the second and the third papers in the thesis) has been providing one of the first insights about climate risk, and the importance of climate risk resilience at the firm and country level in Europe. One of many potential future research topics, an extension of my work, is the management of the risk of energy reliance in firms of different sectors, especially given the mounting ESG pressure from climate advocates and policymakers.

With heightened concerns about climate change and sustainability, stakeholders closely scrutinize firms' energy consumption practices. Energy reliance exposes firms to various risks, including supply chain disruptions, regulatory uncertainties, reputational harm, and, in conclusion, volatile prices. To address these risks, firms must implement strategies encompassing energy efficiency measures, diversification of energy sources, investment in renewables, and transparent reporting. Integrating ESG considerations into systemic risk management is crucial for aligning energy strategies with sustainability goals.

There is a need for more advanced models for climate risk assessment at the firm, country, region, and global levels, boiling down environmental and biodiversity violations into net present value (or expected loss). There are various ways to approach climate risk and resilience at the firm level at the most straightforward level: (1) with hedging, (2) forward-looking with proactively discounting costs from future sustainability policy violations. The second approach is inherently difficult and expensive, and companies worldwide face pushback from investors and even from state governments to refocus on shareholder value maximization (Reuters (2023)).

My work is closely related to the first approach and can be extended to formal optimization decisions, specifically minimizing climate risk with the constraint of maintaining long-run returns to ensure investor retention. Consistent with the modern portfolio theory (MPT) proposed by Markowitz (1952) and the Capital Asset Pricing Model (CAPM) proposed by Treynor (1961) and further developed by Lintner (1975), Mossin (1966) and Sharpe (1964). While in MPT the investors' objective function is maximizing return given the risk (total risk), in the CAPM the idiosyncratic firm risks are neglected and only the systematic risk or market risk is considered. CAPM is the most regarded equilibrium asset pricing model in finance where the expected return of an asset (a specific asset) is the expected risk-free rate of return + risk compensation, where risk compensation is a function of the asset's exposure to systematic risk. The formalized concept is:

$$E(R_{i,t}) - Rf_t = \beta_i(MRP_t), \tag{VI.1}$$

where the left side of the formula is the excess return on the asset, and the right side is the beta of the asset, the exposure to systematic risk, proxied by the market risk, and MRP is the market risk premium. While in the theoretical model the "Market" contains all traded and non-traded assets because of the limitation on information access, we use the S&P500 portfolio as the market portfolio and calculate the MRP as the historical average annual excess return (i.e., the return on the market portfolio minus the annualized yield on the 10-year US Treasury) generally. Beta is calculated as the last 3 or 5-year historical asset i return covariance with the market return divided by the market portfolio return variance.

In CAPM, some of the key assumptions that all investors have homogeneous expectations, they are rational, and that all firm-specific risks can be diversified away; therefore investors should receive return compensation only for non-diversifiable market risk. Using this logic the investors' risk preference would determine their market exposure. The often overlooked issues are: market risk cannot be measured because we have only an incomplete market risk proxy; and thus empirically testing CAPM is rather problematic (see the critic in Roll (1977) for details, and in the later work of Roll and Ross (1994)). Also, the risk compensation in empirical tests tends to be too low, suggesting that perhaps we do not have the right risk measure, or we overlooked a risk measure such as climate risk.

With the advancement of information technology and access to data Eugene Fama (later received Nobel prize for his work on asset pricing) and Kenneth French in a series of papers explored cross-sectional return patterns in US stocks. To improve upon ex-post return explanation (which was rather limited with the CAPM model), Fama and French proposed a 3-factor model Fama and French (1992)), which in addition to the market risk factors (similar to CAPM), includes two additional factors: the size factor (SMB, Small

Minus Big), and the value factor (HML, High Minus Low). The size factor accounts for the observed outperformance of small-cap stocks over large-cap stocks, while the value factor captures the tendency of stocks with high book-to-market ratios to outperform those with low ratios.

$$PortfRet_t - Rf_t = \beta_p(MRP_t) + s_p(SMB_t) + h_p(HML_t) + e_{pt} \tag{VI.2}$$

The authors claimed that with these 3 factors they are able to explain 96% variation in diversified stock portfolios. Unlike the CAPM, which is an equilibrium model based on theoretical assumptions about investor behavior and market conditions, the Fama and French models are empirical models derived from observed market data. The factors are also only applicable to diversified portfolios and not relevant to understand individual stock return expectations, only at best factor related surprises. More importantly, while Fama and French factors are often referred to as risk factors, they are rather stylized factors, results of one of the first machine learning exercise analyzing 50+ years of stock return data from the US.

In 2015 Fama and French (Fama and French (2015)) expanded their original model and introduced an additional two new factors, still ignoring the Momentum Factor (Carhart (1997)) and Liquidity factor (Pástor and Stambaugh (2003)) which were shown to significantly improve the 3-factor models. The momentum factor created as a difference of returns on portfolio of stocks performing well in the last period and portfolio of stocks performing badly, so called winner minus loser portfolio. The liquidity factor aims to capture the illiquidity premium popularized by Amihud (2002), that stocks with higher liquidity (i.e., those that are easier to buy and sell without affecting the price) tend to have lower returns than less liquid stocks. Liquidity is a critical consideration for investors because it affects the cost of trading and the risk associated with holding an asset, especially during periods of market stress when liquidity can dry up.

The Fama and French (2015) updated 5-factor asset pricing model suggested the inclusion of new profitability (RMW, Robust Minus Weak) and investment (CMA, Conservative Minus Aggressive) factors. The profitability factor captures the tendency of firms with high operating profitability to outperform those with low profitability. The investment factor reflects that firms with conservative investment policies tend to outperform those with aggressive investment policies. This expansion aimed to address additional anomalies that were not explained by the original 3-factor model, providing a more comprehensive framework for understanding stock returns.

Empirical asset pricing studies or anomaly studies tend to put significant emphasis on liquidity and more importantly on momentum and various versions of the Fama and French Factor models used, most frequently the original 3 factors with Momentum factor (Carhart (1997)) or with including a liquidity factor, see Eq. VI.3 and VI.4 respectively.

$$PortfRet_t - Rf_t = \beta_p(MRP_t) + s_p(SMB_t) + h_p(HML_t) + u_p(UMD_t) + e_{pt} \quad \text{(VI.3)}$$

$$\begin{aligned} PortfRet_t - Rf_t &= \beta_p(MRP_t) + s_p(SMB_t) \\ &+ h_p(HML_t) + u_p(UMD_t) + l_p(liq_t) + e_{pt} \end{aligned} \quad \text{(VI.4)}$$

Professional asset managers and academics tend to embrace the newer and newer models, and keep adding factors. Skočir and Lončarski (2018) recently published an eight factor asset pricing model extending on the 5-factor Fama and French model with the above noted momentum and liquidity factors and a newly introduced default risk factors. With machine learning, the opportunities for new factor discoveries are limitless. Each factor brings additional explanatory power, but also introduces complexity and the potential for overfitting. As the field of asset pricing continues to evolve, researchers and practitioners must balance the trade-off between model complexity and explanatory power, ensuring that models remain robust and applicable across different market conditions and time periods. The Fama and French models, while foundational and highly influential, are part of an ongoing dialogue in finance aimed at improving our understanding of what drives asset returns.

Despite their empirical success, both the 3-factor and 5-factor models are not without criticism. Some argue that the factors may be capturing behavioral biases or other market inefficiencies rather than true risk factors. Additionally, the models' reliance on historical data means they may be less and less relevant in the future with the 4th industrial-technological revolution and the emergence of climate risk, and the need to reevaluate energy and IT dependence. Thus, perhaps it is time to go back to the drawing board and revisit CAPM, or the market risk, and perhaps consider creating a more representative market portfolio (instead of overreliance on the US-dominated S&P500 portfolio) and introduce a climate risk measure.

In future work, leveraging on the empirical work from my thesis, I want to formalize new investment objective functions for individuals and asset managers, to aid sustainable investment and self-reliance of citizens by creating and managing portfolios which are climate-reliant. Recent theoretical works are also considering reevaluating asset pricing theories where some section of the market, the so-called green investors, may be considered irrational in the traditional sense or perhaps more forward-looking. And other important consideration is the integration of climate risk measures into existing asset pricing models. The inclusion of climate risk factors aims to account for the financial impact of climate change on asset returns.

Tentatively, we could consider a climate risk factor in addition to the market factor, with time-varying correlation and importance. Again, we could try to go back to the equilibrium setting and consider the decomposition of global market risk into an observable market risk (proxied by equity portfolio) and a portfolio of non-traded assets that capture the climate risk component:

$$PortfRet_t - Rf_t = \beta_p(MRP_t) + k_i(ClimateRisk) \tag{VI.5}$$

One of the major shortcomings in risk management globally is assuming fixed (time-independent) correlation of asset classes, which resulted in the 2008 Global Financial Crisis. A realistic setting, or model, would consider market risk in conjunction with climate risk, where each of these risks would likely magnify the other under adverse scenarios, thus it could be valuable to incorporate dynamic correlation structures in risk management models. Recognizing that correlations between asset classes can change over time, especially during periods of market stress, is crucial for accurately assessing risk. This dynamic approach would better capture the co-movements of assets under different market conditions, providing a more realistic measure of portfolio risk.

A revision of a factor model or the CAPM could provide valuable insights into expected returns amid changing investor preferences. However, effective risk management requires a deeper understanding of the risk implications associated with climate change and sustainability. Current models, such as the Fama-French 3, 5, or 7-factor models, fail to address these concerns adequately.

Returning to the basics of CAPM is crucial because, as an equilibrium model, CAPM offers insights into both expected returns and asset or portfolio volatility. According to CAPM, portfolio variance can be derived from systematic risk exposure and market portfolio variance. Thus, if we can construct a market portfolio that accurately captures climate risk exposure, we can return to using CAPM.

However, the complexity arises from investors' exposure to both market and climate risks. The critical challenge lies in identifying the appropriate market and climate risk portfolios. My forthcoming research aims to explore various measures of climate risk and develop a climate risk portfolio or factor that can be integrated into a market factor.

From my point of view, the expected return is not the key importance, I am keen on understanding the connection between climate risk and market risk and their mutual implications on portfolio risk management. There are already approaches to try to adopt a new market portfolios, for example, MSCI has already developed a climate resilience market portfolio (MSCI (2024)), which could perhaps allow the creation of orthogonalized market risk and climate risk measures.

According to the CAPM, the expected return of a portfolio is composed of the beta-weighted expected return on the market portfolio, an epsilon, and an alpha. This framework also implies that the portfolio variance can be expressed as:

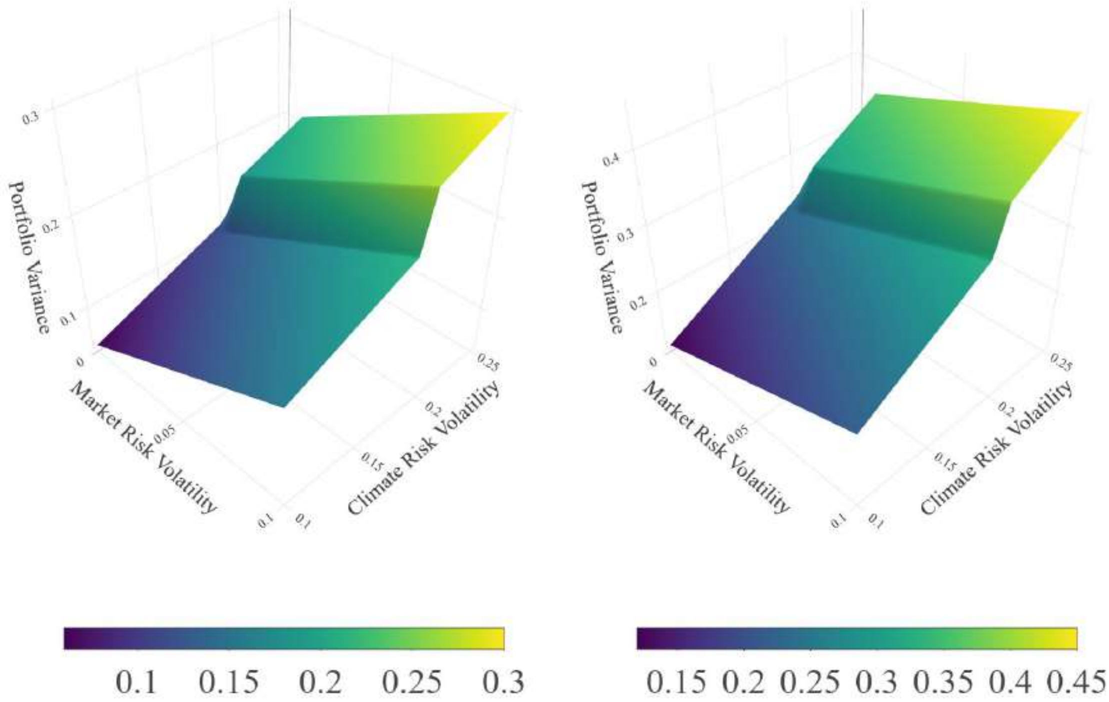
$$\sigma_p^2 = \beta_p^2 \sigma_M^2 + \sigma^2(e_p) \tag{VI.6}$$

where σ_p is the portfolio volatility, β_p is the measurement portfolio's volatility relative to the entire market, σ_M is the market portfolio volatility, while portfolio's idiosyncratic risk is denoted by $\sigma^2(e_p)$. Prior research (e.g. Fu (2009), Goyal and Santa-Clara (2003)) indicates that idiosyncratic volatility possesses return predictability, suggesting a systematic risk component within idiosyncratic volatility. Consequently, in a simplified model, we can separate the portfolio's idiosyncratic risk into climate risk and residual portfolio risk. The climate risk component is expected to depend on the portfolio composition, exposure to nontradable energy and climate risk natural resources and exposure to certain geographic regions.

Fig. VI.1 provides schematic plots for the portfolio variance depending on market risk volatility and climate risk volatility. In this scenario, the portfolio variance is calculated as:

$$\sigma_p^2 = \begin{cases} \beta_p^2 \sigma_M^2 + \sigma_c^2, & \text{if } \sigma_M^2 \text{ is smaller than } 20\%, \\ \beta_p^2 \sigma_M^2 + \sigma_c^2 + 5\%, & \text{if } \sigma_M^2 \text{ is equal or larger than } 20\% \end{cases} \tag{VI.7}$$

where, as previously, σ_p is the volatility of the portfolio, β_p measures the portfolio's volatility relative to the overall market, σ_M is the volatility of the market, while σ_c is the climate volatility.



(a) β**= 0.6** **(b)** β**= 1.2**

Fig. VI.1. Portfolio variance depending on market risk volatility and climate risk volatility

When market risk exceeds a certain point, (20% in this model), the resulting jump in portfolio variance can be attributed to several interconnected financial factors. Market perception and sentiment play a significant role; as climate risk becomes more prominent, investors may perceive it as an immediate threat, leading to increased uncertainty and volatility. Regulatory changes also come into play, as higher climate risks might trigger stricter policies aimed at mitigating climate impacts. Such regulations can increase operational costs, reduce profitability, or even threaten the viability of businesses in high-risk sectors like energy and manufacturing. Sectoral shifts occur as capital moves away from vulnerable industries towards more resilient or sustainable ones, creating volatility from sudden, widespread reallocation. Supply chain disruptions become more frequent and severe with significant climate risks, leading to volatile earnings as companies grapple with damaged infrastructure, disrupted transportation, and production schedules. Additionally, the costs of insuring assets and managing risks rise with increased climate risk, affecting profitability and cash flows and contributing to greater stock price variability. Transition risks are also critical; the shift to a low-carbon economy requires significant changes in technology, policy, and consumer behavior, creating financial instability for companies slow to adapt and high upfront costs for proactive ones. These dynamics collectively amplify market volatility, reflecting higher portfolio variance. Understanding these factors enables investors and risk managers to develop strategies to mitigate such risks, such as diversifying portfolios to include climate-resilient assets and engaging in active risk management practices to hedge against climate-related uncertainties.

In future work, I aim to formally measure climate risk with a climate risk beta, where I examine firms' sensitivity to climate risk exposure. By establishing a climate risk beta, I can quantify how much a firm's value is influenced by climate-related factors, providing a valuable tool for investors to assess potential risks. Climate risk factors may be more readily available now using for example carbon credit information or return spread on within industry portfolio stocks with minimum external energy reliance versus highly external energy-reliant firms, adopting external finance theory into the energy market context. Moreover, understanding the implications of climate risk on various asset classes, such as bonds, real estate, and commodities, is essential. Each asset class may react differently to climate-related events and policy changes. Research should focus on how climate risk can affect the returns and volatilities of these asset classes, thereby enhancing portfolio diversification strategies.

Additionally, I aim to also connect to the exploding ESG rating literature and test the climate risk relevance of various European rating agencies. Specifically, I intend to examine whether a reduction in climate risk, proxied by improvements in ESG ratings, can effectively mitigate climate risks in climate-sensitive industries in Europe. This approach could offer a robust framework for integrating climate risk into traditional financial models, thus bridging the gap between environmental sustainability and financial performance. Another area of extension could be the development of sector-specific guidelines for managing climate risk. Different industries face unique challenges and opportunities related to climate change; therefore, tailored strategies are essential. For example, the energy sector might focus more on transitioning to renewable sources, while the manufacturing sector could emphasize improving energy efficiency and reducing emissions.

By conducting detailed case studies and empirical analyses across various sectors, my research can provide actionable insights and practical recommendations for firms to enhance their climate resilience. This sectoral approach would also help policymakers design targeted regulations that support sustainable practices without stifling innovation and growth. Furthermore, investigating the role of corporate governance in driving effective climate risk management could provide additional insights. Strong governance frameworks may be critical in ensuring that firms adhere to climate risk mitigation strategies and integrate climate considerations into their decision-making processes. Additionally, assessing the impact of corporate social responsibility (CSR) initiatives on climate risk management could reveal how proactive CSR strategies influence firm performance and investor perceptions. This examination can highlight the importance of CSR in enhancing a firm's climate resilience and attractiveness to investors.

Lastly, examining how different jurisdictions and regulatory frameworks impact climate risk management practices is crucial. The effectiveness of climate risk measures can vary significantly across countries due to differences in regulations, market structures, and economic conditions. Future research should consider these factors to provide a comprehensive understanding of climate risk management in a global context. In particular, analyzing how international climate agreements and local regulations influence corporate behavior can offer insights into the effectiveness of policy interventions. Such analysis can inform recommendations for policymakers on designing more impactful climate policies and encourage international collaboration on climate risk management. Moreover, understanding the challenges and opportunities faced by firms operating in diverse regulatory environments can help in developing best practices for global climate risk management. This approach can ensure that firms are well-equipped to navigate the complexities of varying regulations and successfully manage their climate risks across different regions.

CHAPTER

VII

SUMMARY, REFLECTION AND CONCLUSION

In summary, systemic risk, typically associated with system breakdowns resulting from global events or extreme incidents, remains a complex and elusive phenomenon in financial markets. It manifests through simultaneous declines in the prices of most or all entities in the system during large-scale collapses. Heightened systemic risk and potential global crises are exacerbated because of the interconnectedness of modern businesses and financial institutions. While there are numerous approaches suggested by BIS, IMF and national policymakers to strengthen the financial system and the resilience to crisis triggers, preparedness seems to be lacking in terms of addressing the unexpected such as the 2015–2016 stock market selloff, the Covid-19 pandemic, and energy crisis due to the start of Russia's war on Ukraine.

Overall, today, we still have numerous open questions related to systemic risk, the sources of systemic risks, and their relation with systematic risk. While with the first source of systemic risk, identified during the Global Financial Crisis, we have made some headways to identify the sources as key financial institutions, systemically important financial Institutions (SIFIs), and we still have no clear understanding of the source of systemic risks, and therefore, we are still in search for the right measurements. Various approaches have been used to measure systemic risk, including the widely known CBOE Volatility Index (VIX), which gauges market risk and fear. However, debates persist about the accuracy of VIX, its forward-looking nature, and its impact on realized market volatility. This ongoing uncertainty underscores the need for developing more sophisticated and reliable tools for assessing systemic risk. Enhanced understanding and measurement of these risks are crucial for better preparation and mitigation strategies in future crises. More recently, with the emergence of new source of systemic risk, arising from climate risk, or energy instability, financial professional, researchers and regulators face new challenges. These challenges also open up new opportunities, revisiting well-accepted asset pricing theories where the ex post profit maximization in conjunction with risk management was rather well defined under specific financial constraints. Today, with the emergence of environmental-conscious and sustainability investors, impact investing and climate resilience call for setting new guidelines and objective functions for investors and portfolio managers globally.

In my research, I familiarized the reader with systemic risk definition, provided a thorough discussion of the economics, financial and social implications of unmanaged systemic risk and presented three case studies (journal articles) with in-depth insights into the different facets of systemic risk. Specifically, I focused on network approach in assessing systemic risk within closed networks, to introduce the intricate and interconnected nature of modern financial systems. Throughout this dissertation, I have presented both the theoretical and empirical aspects of systemic risk, including its vague definition, various models on a high level and two methodological frameworks (Toda and Yamamoto (1995); Diebold and Yilmaz (2012)) in detail. By analyzing historical events, such as the global financial crisis of 2008, the European Sovereign Debt Crisis, the Covid-19 pandemic, and the Russian-Ukranian war, I have provided insights into the potential consequences of systemic risk and the need for effective risk management strategies.

This thesis contributes to the existing literature in ten points:

1. Chapter III employs the Toda and Yamamoto (1995) causality test to analyze a comprehensive network of sovereign yield curves over an extended time frame.

2. Chapter III analyzes a large dataset of sovereign yield curves from 12 countries over 23 years, using the Level, Slope, and Curvature factors as modeled by Diebold and Li (2006).

3. Chapter III offers unique insights by delving into the intricate structure of the sovereign yield curves network, revealing the following: (1) global crises result in denser networks compared to local crises; (2) US latent factors play a pivotal role in the network, although their influence varies over time; (3) the cointegrated relationship between Canada and the US leads to Canada's co-driving role within the network during crisis periods.

4. Chapter III extends previous research on sovereign yield curve studies by examining the dynamics of key participants' dominance in the network and linking these

dynamics to monetary policy decisions.

5. Chapter IV provides the first comprehensive analysis of volatility transmission dynamics across all major European oil and natural gas companies, encompassing over 90% of the European energy sector's total market capitalization over nearly 20 years.

6. Chapter IV adopts a full network approach, offering a broader view of volatility transmission across all major European energy companies.

7. Chapter IV differentiates Upstream, Downstream, Midstream, and Integrated Oil and Gas (IOG) segments along the production line to pinpoint the mechanisms behind idiosyncratic volatility spillovers in European energy companies.

8. Chapter V applies the Diebold and Yilmaz (2012) spillover index in the context of the European Economic Area (EEA) to understand how European economies are interconnected and respond to economic, political, and energy shocks.

9. Chapter V includes natural gas (i.e., TTF) in addition to oil in the network model, given Europe's increasing gas dependency.

10. Chapter V goes beyond existing applications of the Diebold and Yılmaz Index by offering a comprehensive panel regression analysis on the effects of crude oil and natural gas price shocks on equity markets.

One key finding of this research is that systemic risk is not confined to individual institutions or sectors; it encompasses the entire financial system. As a tiny slice of the topic, I have introduced two fields, the sovereign bond market and the energy market. Failures or disruptions in any system can quickly spread and have far-reaching consequences, affecting the stability of economies and the well-being of individuals. As such, the importance of identifying, monitoring, and mitigating systemic risk cannot be overstated. Another crucial aspect highlighted in this thesis is the role of interconnectedness and complexity in amplifying systemic risk. The increasing interdependencies among financial institutions, markets, and instruments have created a web of relationships that can transmit shocks and vulnerabilities across borders and sectors. Therefore, a holistic approach to risk management is essential, which considers the interconnections and dependencies within the system. Furthermore, the advancement of technology and the increasing reliance on complex financial instruments pose new challenges for systemic risk management. The rapid growth of digitalization, fintech, and cryptocurrencies has introduced novel sources of risk that require continuous monitoring and adaptation of regulatory frameworks. Ultimately, tackling systemic risk requires a multi-faceted and collaborative effort involving regulators, financial institutions, policymakers, and other stakeholders.

Enhancing transparency, promoting information sharing, and fostering international co-operation are crucial steps toward creating a resilient and robust financial system. In this thesis work, with a collection of articles, I have provided new insights about various facets of systemic risk in Europe and in a global context. With the last two articles, I have been emphasizing the evolving market features, whether the manifestation of the climate risk demands continuous vigilance and increasing proactive measures. I believe that with better understanding the complexities and interconnectedness of the financial system, stakeholders and policymakers could work together to build a more resilient and stable global economy.

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A Supplementary material for Chapter III

A.1 Explanatory Tables

Table A.1
Summary table of the network-related literature

Article	Method	Data	Level of the analysis	Crisis periods	Crisis comparison	Analysis of the crisis	Identifying key Participants	Key Participants during crises	Dynamics of key participants	Drivers behind the key participants
Antonakakis and Vergos (2013)	VAR based D-Y	10YYSGY	node	E	N	D	-	-	-	-
Gómez-Puig and Sosvilla-Rivero (2013)	Granger	10YYSGY	node	E	N	D	-	-	-	-
Gómez-Puig and Sosvilla-Rivero (2016)	Granger	10YYSGY	node	G, E	N	D	-	-	-	-
Claeys and Vašíček (2014)	FAVAR based D-Y	10YYSGY	node	G, E	N	D	-	-	-	-
Fernández-Rodríguez et al. (2015)	VAR based D-Y	10YYSGY	node	E	N	S, D	-	-	-	-
Fernández-Rodríguez et al. (2016)	VAR based D-Y	10YYSGY	node	E	N	S, D	-	-	-	-
Reboredo and Ugolini (2015)	CoVAR	10YY	node	E	N	D	-	-	-	-
Bernal et al. (2016)	CoVAR	10YYSGY	node	-	-	-	-	-	-	-
De Santis and Zimic (2018)	SVAR based D-Y	10YY	node	E	N	S, D	Y	Y	-	-
Chatziantoniou and Gabauer (2021)	TPT-VAR	10YY	node	E	N	D	-	-	-	-
Hamill et al. (2021)	VAR based D-Y	BI	node	G, E	N	S	Y	Y	-	-
Benlagha and Hemrit (2022)	VAR based D-Y	2YY, 30YY	node	-	-	-	-	-	-	-
Berardi and Plazzi (2022)	VAR based D-Y	YCC	node	-	-	-	-	-	-	-
Sowmya et al. (2016)	VAR based D-Y	D-LYCF	factor	G, E	N	D	-	-	-	-
Umar et al. (2021c)	VAR based D-Y	D-LYCF	factor	G, E, C	N	D	-	-	-	-
Cavaca and Meurer (2021)	VECM based D-Y	D-LYCF	factor	-	-	-	-	-	-	-
Gabauer et al. (2022)	TVP-VAR	D-LYCF	factor	G	N	D	-	-	-	-
Umar et al. (2022)	VAR based D-Y	D-LYCF	factor	-	-	-	-	-	-	-

Note: The following abbreviations are used in the table: ***10YYSGY****: 10-year yield spreads over the corresponding German yield;* ***BI****: Bond indices;* ***2YY****: 2-year yields;* ***10YY****: 10-year yields;* ***30YY****: 30-year yields;* ***YCC****: Yield curve components,* ***D-LYCF****: Diebold-Li yield curve factors;* ***E****: European Sovereign Debt Crisis;* ***G****: Global Financial Crisis;* ***C****: Covid-19 Pandemic;* ***N****: No;* ***Y****: Yes;* ***S****: Static model;* ***D****: Dynamic model*

Table A.2
Country yield series and corresponding Bloomberg tickers

Yield series	Ticker
AUD Australian Sovereign	F127
CAD Canada Sovereign	F101
CHF Swiss Sovereign	F256
EUR German Sovereign	F910
EUR Spain Sovereign	F902
EUR France Sovereign	F915
GBP United Kingdom	F110
EUR Italy Sovereign	F905
JPY Japan Sovereign	F105
KRW Korean Sovereign	F054
EUR Netherlands Sovereign	F920
USD USA Sovereign	F082

Table A.3
Start and end dates of crisis periods

Dotcom Bubble	Start date	03/10/2000
	Event	NASDAQ Composite stock market index peaked at 5,048.62
	End date	12/02/2001
	Event	Enron declares bankruptcy
Global Financial Crisis	Start date	09/15/2008
	Event	Bankruptcy of Lehman Brothers
	End date	07/21/2010
	Event	Dodd-Frank Act being enacted
European Debt Crisis	Start date	11/21/2010
	Event	Ireland requests for IMF - EU bailout
	End date	07/21/2010
	Event	Ireland manages to regain complete lending access to financial markets
Covid-19 Pandemic	Start date	01/20/2020
	Event	WHO declares the coronavirus outbreak a Public Health Emergency of International Concern
	End date	12/31/2021
	Event	End of our study period

Table A.4
Descriptive statistics of country yield curve nodes

Node	Average	St. dev	Minimum	Maximum	ρ(1)	ρ(10)
Australia						
1 year	3.65	1.94	-0.05	7.39	0.999	0.994
5 years	4.02	1.90	0.24	7.30	0.999	0.994
10 years	4.36	1.74	0.61	7.43	0.999	0.993
30 years	4.78	1.46	1.17	7.67	0.999	0.099
Canada						
1 year	2.21	1.67	0.12	6.43	0.999	0.994
5 years	2.87	1.68	0.28	6.70	0.999	0.994
10 years	3.38	1.62	0.45	6.78	0.999	0.994
30 years	3.64	1.42	0.71	6.25	0.999	0.994
Switzerland						
1 year	0.54	1.28	-1.09	3.83	0.999	0.994
5 years	1.04	1.41	-1.11	3.97	1.000	0.996
10 years	1.55	1.43	-0.97	4.20	1.000	0.995
30 years	2.07	1.56	-0.70	4.95	1.000	0.994
Germany						
1 year	1.37	1.87	-0.99	5.24	1.000	0.996
5 years	1.93	1.97	-1.01	5.39	0.999	0.996
10 years	2.52	1.92	-0.87	5.75	1.000	0.996
30 years	3.16	1.88	-0.47	6.48	1.000	0.994
Spain						
1 year	1.80	1.77	-0.80	6.44	1.000	0.990
5 years	2.75	1.85	-0.45	7.65	0.999	0.992
10 years	3.54	1.80	-0.01	7.67	0.999	0.992
30 years	4.37	1.57	0.85	7.85	0.999	0.990
France						
1 year	1.42	1.84	-0.87	5.30	0.999	0.996
5 years	2.11	1.88	-0.78	5.40	0.999	0.995
10 years	2.82	1.84	-0.44	5.92	1.000	0.995
30 years	3.57	1.66	0.24	6.51	1.000	0.993
Great Britain						
1 year	2.32	2.25	-0.17	6.62	1.000	0.995
5 years	2.84	1.97	-0.11	6.52	0.999	0.995
10 years	3.25	1.67	0.11	5.92	1.000	0.994
30 years	3.47	1.26	0.53	5.06	1.000	0.991
Italy						
1 year	1.88	1.70	-0.59	8.17	0.999	0.989
5 years	2.93	1.65	-0.10	7.76	0.999	0.989
10 years	3.76	1.52	0.49	7.35	0.999	0.990
30 years	4.59	1.32	1.50	7.37	0.999	0.988
Japan						
1 year	0.08	0.24	-0.35	0.84	0.999	0.989
5 years	0.43	0.48	-0.39	1.72	0.999	0.987
10 years	0.97	0.70	-0.28	2.58	0.999	0.991
30 years	1.84	0.81	0.04	3.31	0.999	0.990
South Korea						
1 year	3.18	2.28	0.35	13.51	0.999	0.978
5 years	4.30	2.22	0.79	14.34	0.999	0.976
10 years	5.05	2.11	1.44	15.12	0.996	0.972
30 years	6.06	3.01	1.71	18.56	0.996	0.976
The Netherlands						
1 year	1.41	1.87	-0.94	5.31	0.995	0.996
5 years	2.07	1.95	-0.85	5.52	0.996	0.996
10 years	2.71	1.92	-0.63	5.91	1.000	0.995
30 years	3.21	1.87	-0.39	7.56	1.000	0.994
USA						
1 year	1.95	1.94	0.04	7.07	1.000	0.996
5 years	2.79	1.63	0.20	6.95	0.999	0.993
10 years	3.46	1.44	0.50	6.92	0.999	0.991
30 years	4.10	1.23	1.08	6.67	0.999	0.988

Note: $\rho(t)$ denotes sample autocorrelation at displacement t.

Table A.5
Results of unit-root tests

Country	AUS		CAN		CHE		DEU		ESP		FRA	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	-3.84	0.02**	-3.52	0.04**	-3.16	0.10*	-3.06	0.13	-1.63	0.74	-2.94	0.18
Slope	-2.81	0.24	-2.06	0.55	-2.91	0.19	-2.37	0.42	-2.12	0.53	-2.21	0.49
Curvature	-4.08	0.01***	-3.01	0.15	-3.26	0.08*	-3.05	0.13	-3.80	0.02**	-2.97	0.17
Country	GBR		ITA		JPN		KOR		NLD		USA	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	-2.25	0.47	-1.91	0.61	-3.91	0.01***	-5.61	0.01***	-3.06	0.13	-4.71	0.01***
Slope	-1.84	0.64	-2.70	0.28	-4.98	0.01***	-2.88	0.20	-2.20	0.49	-2.06	0.55
Curvature	-1.84	0.65	-4.16	0.01***	-3.49	0.04**	-3.19	0.09*	-3.38	0.06*	-2.06	0.55

(a) ADF test results

Country	AUS		CAN		CHE		DEU		ESP		FRA	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	42.25	0.01	47.24	0.01	47.59	0.01	47.03	0.01	26.92	0.01	44.16	0.01
Slope	2.58	0.01	5.55	0.01	18.27	0.01	6.84	0.01	5.38	0.01	4.24	0.01
Curvature	25.23	0.01	9.07	0.01	2.50	0.01	4.45	0.01	13.02	0.01	9.08	0.01
Country	GBR		ITA		JPN		KOR		NLD		USA	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	37.28	0.01	27.33	0.01	40.71	0.01	40.11	0.01	46.48	0.01	43.70	0.01
Slope	12.42	0.01	7.46	0.01	42.11	0.01	8.49	0.01	5.97	0.01	4.04	0.01
Curvature	24.43	0.01	10.23	0.01	22.73	0.01	6.71	0.01	4.04	0.01	6.11	0.01

(b) KPSS test results

Country	AUS		CAN		CHE		DEU		ESP		FRA	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	-17.73	0.01***	-17.65	0.01***	-17.95	0.01***	-18.79	0.01***	-18.26	0.01***	-17.29	0.01***
Slope	-16.75	0.01***	-15.80	0.01***	-17.44	0.01***	-17.42	0.01***	-17.68	0.01***	-16.12	0.01***
Curvature	-4.10	0.01***	-17.59	0.01***	-17.68	0.01***	-18.45	0.01***	-18.55	0.01***	-18.34	0.01***
Country	GBR		ITA		JPN		KOR		NLD		USA	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	-18.08	0.01***	-18.30	0.01***	-17.39	0.01***	-5.22	0.01***	-18.56	0.01***	-4.70	0.01***
Slope	-16.09	0.01***	-15.68	0.01***	-4.93	0.01***	-16.82	0.01***	-16.75	0.01***	-16.42	0.01***
Curvature	-17.91	0.01***	-4.14	0.01***	-18.07	0.01***	-19.20	0.01***	-18.86	0.01***	-18.83	0.01***

(c) ADF(1) test results

Country	AUS		CAN		CHE		DEU		ESP		FRA	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	0.06	0.1***	0.05	0.1***	0.03	0.1***	0.08	0.1***	0.12	0.1***	0.09	0.1***
Slope	0.04	0.1***	0.18	0.1***	0.03	0.1***	0.08	0.1***	0.09	0.1***	0.09	0.1***
Curvature	0.03	0.1***	0.05	0.1***	0.06	0.1***	0.04	0.1***	0.03	0.1***	0.03	0.1***
Country	GBR		ITA		JPN		KOR		NLD		USA	
	value	P	value	P	value	P	value	P	value	P	value	P
Level	0.09	0.1***	0.11	0.1***	0.15	0.1***	0.21	0.1***	0.09	0.1***	0.05	0.1 ***
Slope	0.32	0.1***	0.10	0.1***	0.09	0.1***	0.04	0.1***	0.09	0.1***	0.15	0.1***
Curvature	0.10	0.1***	0.02	0.1***	0.12	0.1***	0.02	0.1***	0.03	0.1***	0.06	0.1 ***

(d) KPSS(1) test results

*Notes: Rejection of null hypothesis at 1%, 5%, and 10% levels are denoted by ***, **, and * respectively.*

The null hypothesis (H_0) of the ADF test says, the time series has a unit root, so it is non-stationary. This implies that the series follows a random walk or a trend. As per the alternative hypothesis (H_a), the series does not have unit root, meaning it is stationary. Therefore the series is mean-reverting and has a constant variance over time. On the contrary, the H_0 of the KPSS says, that the time series is stationary around a deterministic trend, while H_a claims that the time series has a unit root, meaning it is non-stationary.

Table A.6

Average connection count by types and grouped by countries during the six subperiods - 750 days long window size

	Whole Period	DCB	CALM1	GFC	ESDC	CALM2	C19
Australia							
Level	1.3	0.7	1.2	1.6	1.1	1.7	0.9
Slope	1.2	0.1	0.5	3.6	1.4	1.2	0.8
Curvature	1.1	1.2	1.1	1.5	0.4	1.0	2.0
Cross Connections	8.1	5.0	6.3	11.2	9.1	8.8	8.0
All connections	11.8	6.9	9.0	18.0	12.0	12.8	11.7
Canada							
Level	0.7	0.9	0.7	0.4 0.4	0.5	1.8	
Slope	1.1	2.4	1.2	2.0	0.9	0.8	1.0
Curvature	1.2	1.2	1.3	1.9	1.2	1.0	0.9
Cross Connections	6.8	4.8	6.7	10.7	8.6	5.6	5.6
All connections	9.8	9.4	10	15.1	11.0	7.8	9.3
Switzerland							
Level	0.8	0.6	0.6	2.8	0.6	0.3	1.7
Slope	0.9	0.2	0.9	2.2	1.0	0.4	1.5
Curvature	1.3	1.1	0.8	1.7	1.3	1.3	3.1
Cross Connections	7.4	2.4	5.0	15.1	6.8	6.6	11.8
All connections	10.5	4.4	7.2	21.8	9.8	8.7	18.1
Germany							
Level	0.8	0.2	0.4	2.3	0.9	0.4	1.8
Slope	1.0	1.2	0.8	2.5	1.9	0.6	1.0
Curvature	0.7	0.1	0.6	2.0	0.4	0.5	0.7
Cross Connections	5.8	1.9	4.4	17.1	7.4	3.4	6.8
All connections	8.3	3.4	6.1	24.0	10.7	4.8	10.3
Spain							
Level	0.8	0.6	0.2	2.3	1.7	0.5	1.3
Slope	0.9	0.9	0.5	1.8	1.6	0.9	1.4
Curvature	1.1	0.4	0.5	1.9	1.1	0.9	3.3
Cross Connections	5.8	3.5	2.8	11.3	8.2	5.1	10.5
All connections	8.6	5.5	4.0	17.4	12.5	7.4	16.4
France							
Level	0.8	0.3	0.4	1.9	1.0	0.6	1.3
Slope	0.9	1.0	0.7	1.2	1.8	0.8	1.2
Curvature	1.0	0.9	0.8	1.1	1.2	0.9	1.5
Cross Connections	5.8	4.2	3.6	8.3	8.8	5.5	8.5
All connections	8.5	6.5	5.5	12.4	12.8	7.8	12.5
Great Britain							
Level	0.5	0	0.3	1.0	0.7	0.5	0.4
Slope	0.8	0.4	0.4	2.4	1.4	0.5	1.0
Curvature	0.9	0.7	1.0	1.3	0.7	0.8	1.0
Cross Connections	4.7	3.9	3.9	8.6	5.9	3.9	5.4
All connections	6.9	4.9	5.5	13.4	8.7	5.8	7.8
Italy							
Level	0.7	0.3	0.3	2.4	1.3	0.5	0.6
Slope	0.9	1.3	0.6	1.6	1.6	1	0.5
Curvature	0.9	0.4	0.9	1.5	0.9	0.7	0.8
Cross Connections	6.9	2.6	3.3	12.0	12.6	7.2	7.8
All connections	9.4	4.6	5.0	17.5	16.4	9.4	9.7
Japan							
Level	0.7	0.2	0.4	0.9	0.6	1.0	1.4
Slope	0.7	1.2	0.8	0.6	0.7	0.7	0.4
Curvature	0.5	0.4	0.3	0.9	0.6	0.5	1.2
Cross Connections	4.9	3.9	4.0	3.8	4.4	5.3	7.6
All connections	6.9	5.7	5.4	6.2	6.3	7.5	10.6
South Korea							
Level	0.8	1.7	0.6	1.3	0.8	0.6	1.9
Slope	1.0	1.9	0.6	2.3	1.3	0.6	1.9
Curvature	1.3	0.4	0.7	3.5	0.8	1.1	2.5
Cross Connections	6.7	6.7	4.6	16.7	7.1	4.8	10.1
All connections	9.8	10.8	6.4	23.9	10.1	7.1	16.4
The Netherlands							
Level	0.6	0.0	0.4	1.6	0.5	0.4	1.2
Slope	0.7	0.1	0.5	1.6	1.1	0.5	1.0
Curvature	1.0	0.3	0.6	1.3	1.8	0.8	1.2
Cross Connections	4.5	2.2	3.0	9.0	5.5	3.8	6.8
All connections	6.8	2.6	4.4	13.4	8.9	5.6	10.2
USA							
Level	1.3	1.5	1.1	3.5	0.9	1	1.2
Slope	1.0	2.0	1.1	1.7	1.9	0.6	0.7
Curvature	1.6	3.4	1.6	3.4	0.6	1.2	1.6
Cross Connections	6.7	6.0	6.2	15.6	5.6	4.5	8.9
All connections	10.6	12.9	10.0	24.1	9.0	7.2	12.4

Table A.7
Net connections through different subperiods, aggregated by countries

DCB		CALM1		GFC		ESDC		CALM2		C19	
County	Net	County	Net	County	Net	County	Net	County	Net	County	Net
KOR	32	**USA**	**48**	**USA**	**37**	**USA**	**41**	**USA**	**42**	**USA**	**45**
USA	**19**	CAN	24	CAN	22	KOR	16	CAN	38	CAN	43
CAN	18	KOR	24	FRA	8	ITA	12	DEU	11	ITA	26
FRA	7	CHE	5	DEU	7	NLD	8	ITA	11	DEU	2
GBR	4	DEU	4	KOR	5	CAN	6	NLD	10	FRA	1
ITA	1	FRA	3	NLD	-1	FRA	6	FRA	8	**JPN**	**0**
JPN	**0**	ITA	3	ESP	-2	DEU	3	ESP	7	ESP	-1
ESP	-2	NLD	2	GBR	-2	GBR	2	KOR	-1	GBR	-11
DEU	-5	ESP	-2	ITA	-3	ESP	-1	CHE	-2	NLD	-13
CHE	-19	GBR	-4	AUS	-16	CHE	-4	GBR	-4	CHE	-19
AUS	-24	**JPN**	**-49**	CHE	-20	**JPN**	**-40**	**JPN**	**-48**	KOR	-31
NLD	-31	AUS	-58	**JPN**	**-35**	AUS	-49	AUS	-72	AUS	-42

A.2 Robostness Checks

A.2.1 Comparing Granger causality and Toda-Yamamoto causality

In the network-related literature (CoVaR, D-Y), it is common to corroborate the results with a Granger causality model. Zhang (2017), Malik and Umar (2019) and Umar et al. (2021d) compare their Diebold-Yilmaz total spillover index to a Granger causality-based network connectedness. Comparing connection numbers is convenient for us because the T-Y model is a modified Granger causality test. We run the two models with the same parameters (the confidence level is 1%, the lag selection is based on AIC and the window size is 750). The sum of connections for the two models for each day is shown in Fig. A.1.

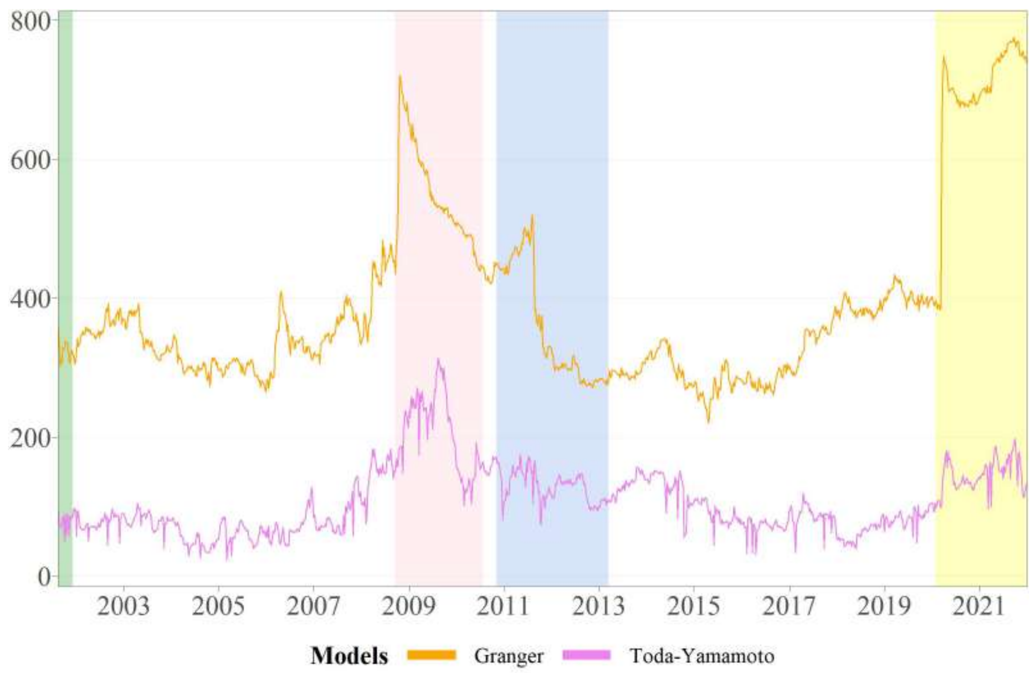


Fig. A.1. Summarized connection numbers during the study period, estimated by dynamic Toda-Yamamoto model and dynamic Granger causality model

Notes: Window size of 750 days and a lag determined by the AIC. The green area denotes the Dotcom Bubble, the red-shaded shows the Global Financial Crisis, the blue field represents the European Sovereign Debt Crisis, and the yellow covers the Covid-19 period. The orange line indicates the number of significant connections resulting from the Granger causality model, while the violet one represents the number of significant connections resulting from the T-Y causality model.

When evidence of a cointegrating relation is shown, the Granger representation theorem (Granger (1969), Granger (1988)) suggests causation at least in one direction. We demonstrate how strongly cointegrated our time series are; thus, many spurious connections are to be expected when applying the Granger causality method. By using the T-Y causality test we obtain approximately one-quarter of the connections resulting from the Granger approach.

A.2.2 Explanatory tables and plots for the robustness checks

Table A.8
Average total connection count by types during the sub-periods

	Whole period	DCB	CALM1	GFC	ESDC	CALM2	C19
L+S+C	24.0	31.3	19.7	39.3	19.8	23.1	27.7
Cross connections	55.9	57.5	47.0	84.7	55.0	52.0	72.6
All connections	79.9	88.7	66.7	124.0	74.7	75.1	100.4

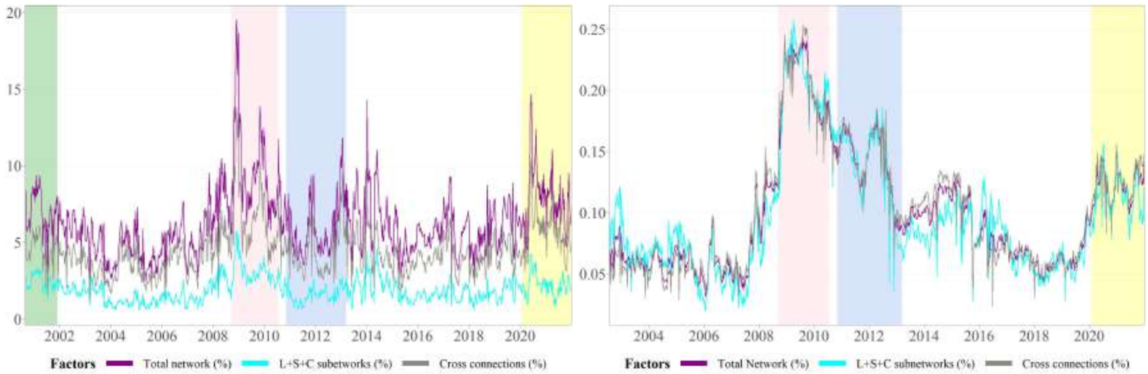
(a) Average total connection count by types during the six sub-periods - 500 days long window size

	Whole period	DCB	CALM1	GFC	ESDC	CALM2	C19
L+S+C	32.4	34.2	24.3	67.4	35.1	25.9	44.9
Cross connections	75.5	43.4	54.3	139.7	93.1	65.9	100.3
All connections	108.0	77.6	78.6	207.1	128.2	91.8	145.3

(b) Average total connection count by types during the six sub-periods - 750 days long window size

	Whole period	CALM1	GFC	ESDC	CALM2	C19
L+S+C	38.6	26.3	81.4	53.5	30.0	45.0
Cross connections	88.1	56.9	178.4	123.5	72.3	107.6
All connections	126.8	83.1	259.7	177.0	102.4	152.6

(c) Average total connection count by types during the five sub-periods - 1000 days long window size



(a) 500 days long rolling window **(b) 1000 days long rolling window**

Fig. A.2. Summarized connection ratios during the study period, estimated by dynamic Toda-Yamamoto model

Notes: Window sizes of 500 and 1000 days, lag determined by the AIC. The green area denotes the Dotcom Bubble, the red-shaded shows the Global Financial Crisis, the blue field represents the European Sovereign Debt Crisis, and the yellow covers the Covid-19 period. The purple line indicates the ratio of total significant connections, the cyan represents the summarized edges in the three subnetworks, and the gray line is the time series of the cross-connection ratios, compared to the maximum number of possible edges.

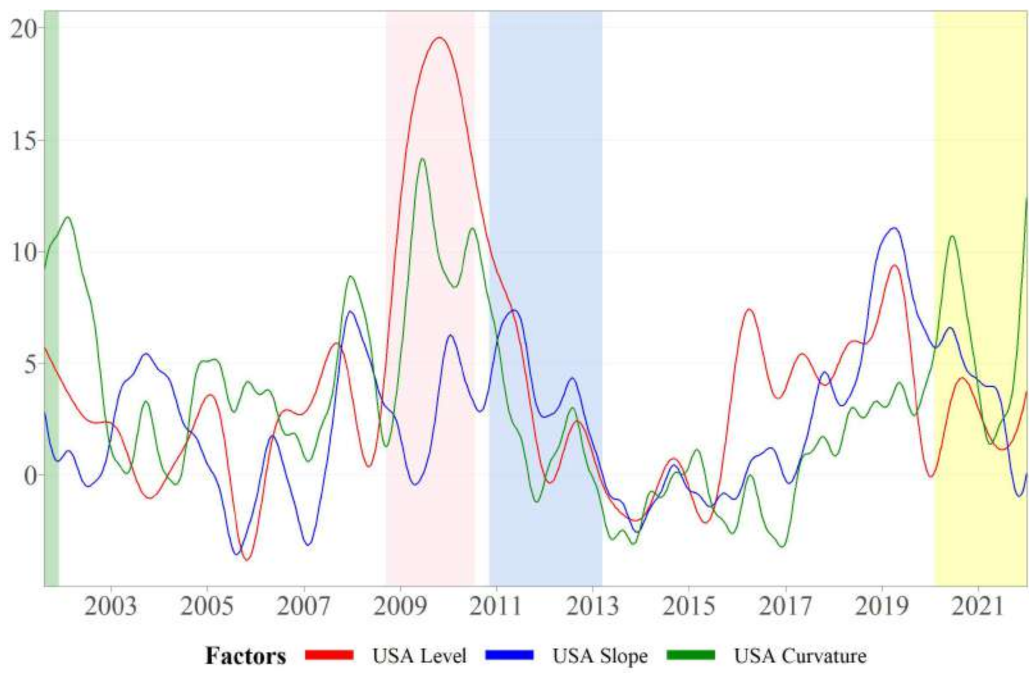


Fig. A.3. Time series of USA Level Slope and Curvature factor net connections, estimated by dynamic Toda-Yamamoto model

Notes: Window size of 750 days and a lag determined by the AIC, smoothed by cubic spline method. The green area denotes the Dotcom Bubble, the red-shaded shows the Global Financial Crisis, the blue field represents the European Sovereign Debt Crisis, and the yellow one covers the Covid-19 period. The red line indicates the number of significant net Level connections, the blue line represents the number of significant net Slope connections and the green line stands for the number of significant net Curvature connections.

B Supplementary material for Chapter IV

B.1 Realized volatilities

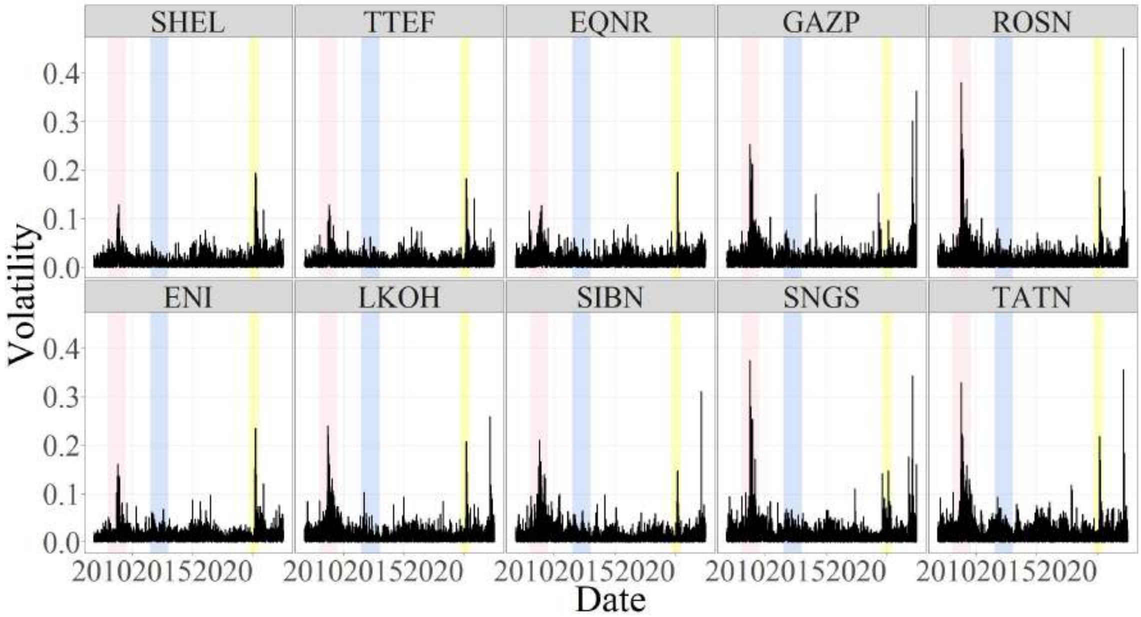


Fig. B.1. Realized volatilities of the firms within Integrated Oil and Gas sector

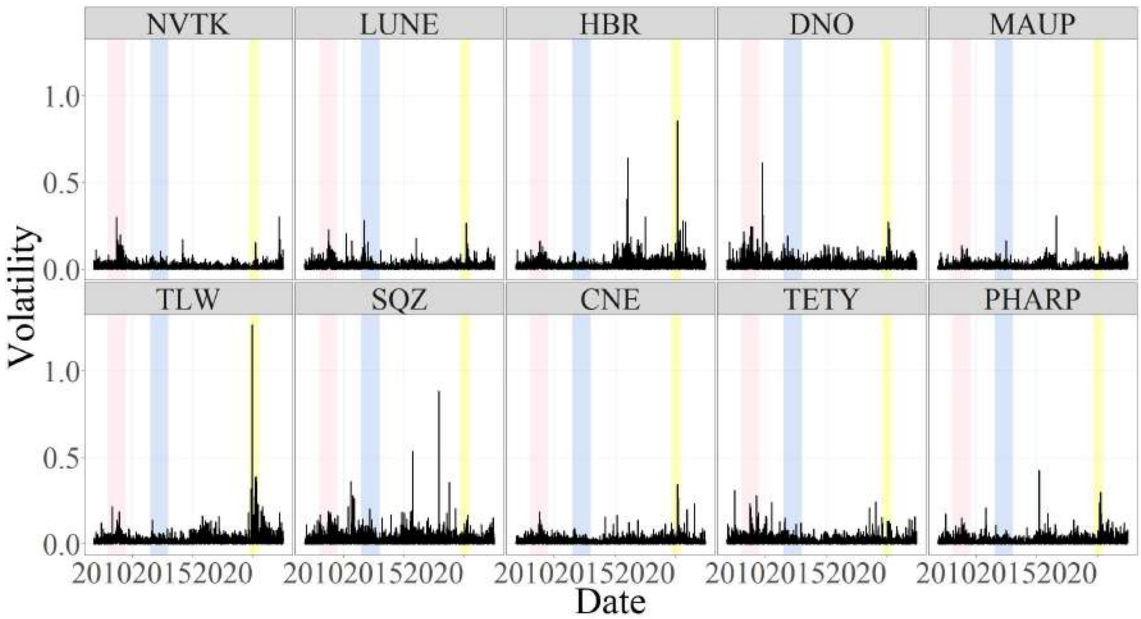


Fig. B.2. Realized volatilities of the firms within the upstream sector

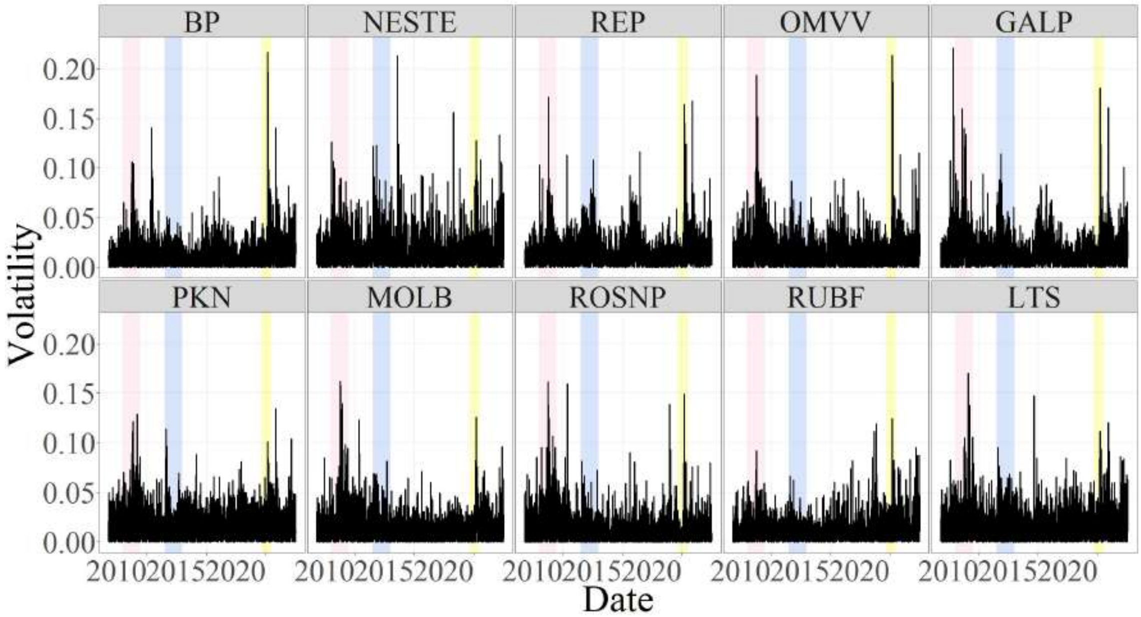


Fig. B.3. Realized volatilities of the firms within the downstream sector

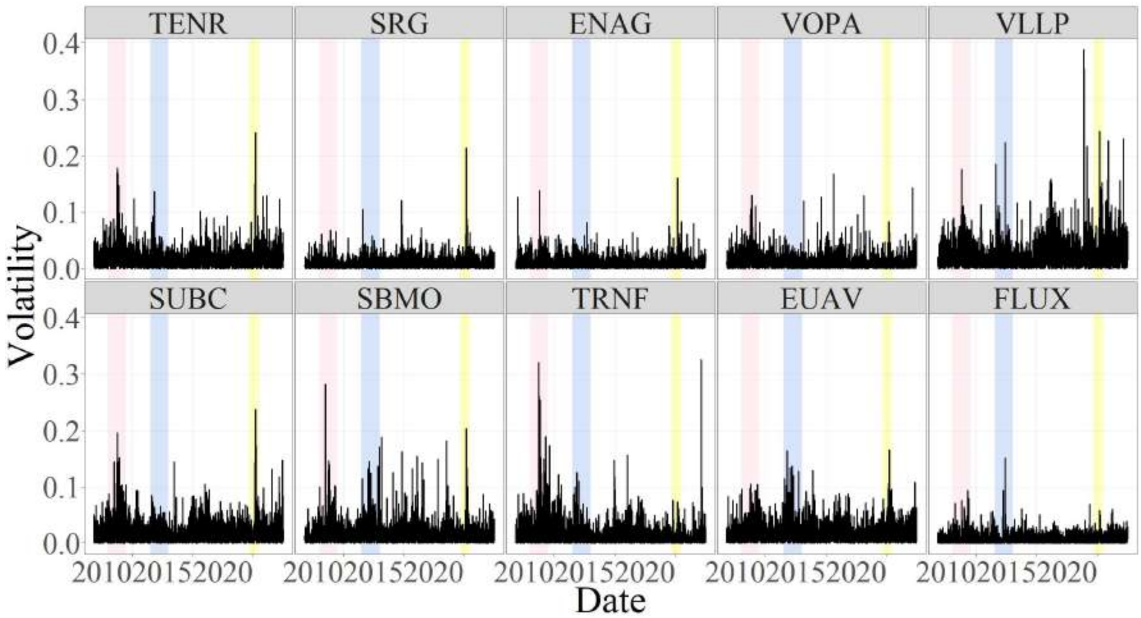


Fig. B.4. Realized volatilities of the firms within midstream sector

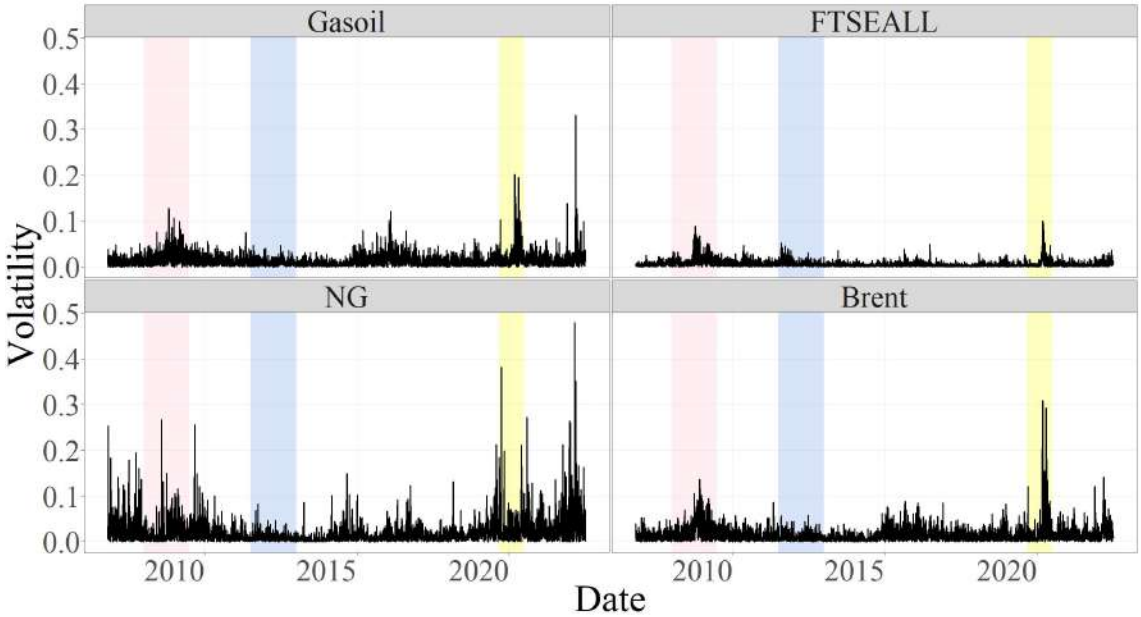


Fig. B.5. Realized volatilities of Gasoil, FTSEALL, Natural Gas and Brent

B.2 Volatility sillover

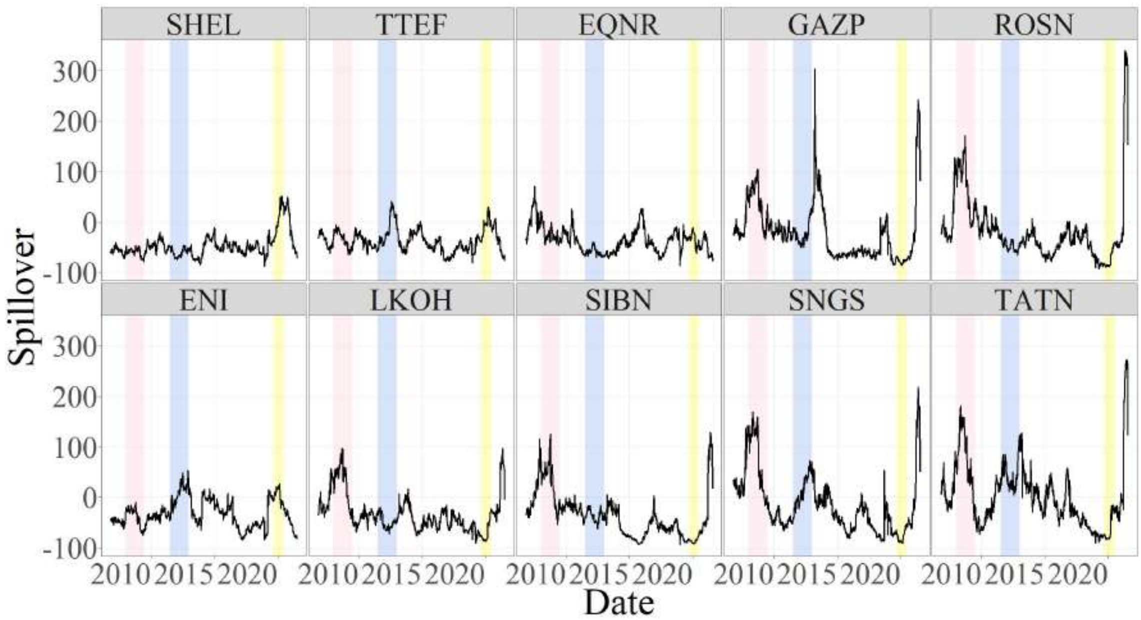


Fig. B.6. Net Spillover of the firms within the Integrated Oil and Gas sector

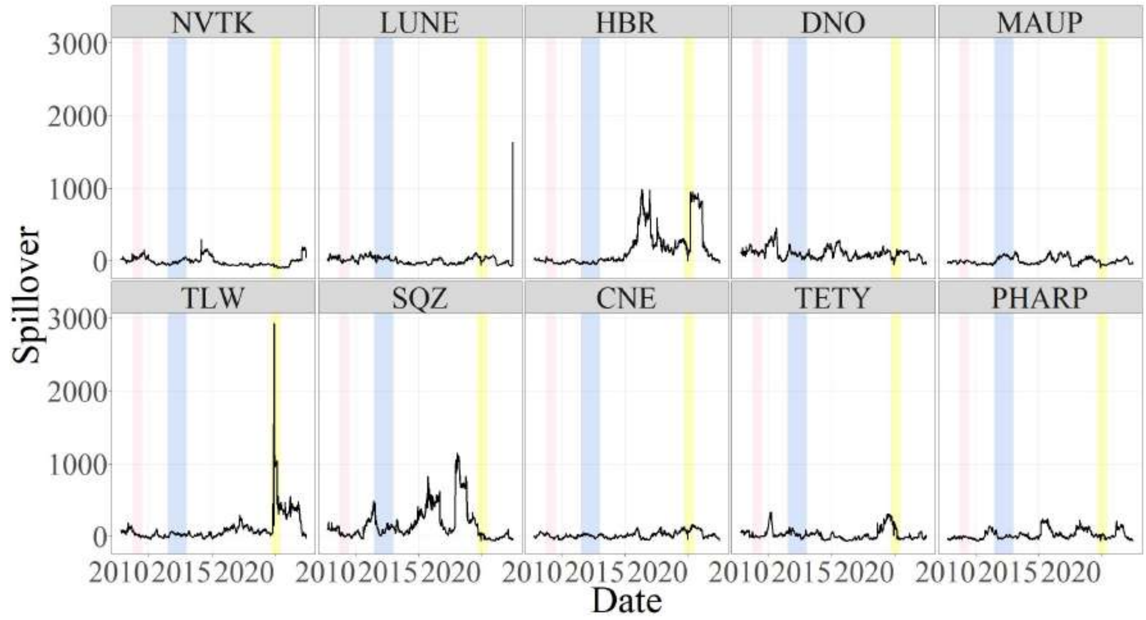


Fig. B.7. Net Spillover of the firms within the upstream sector

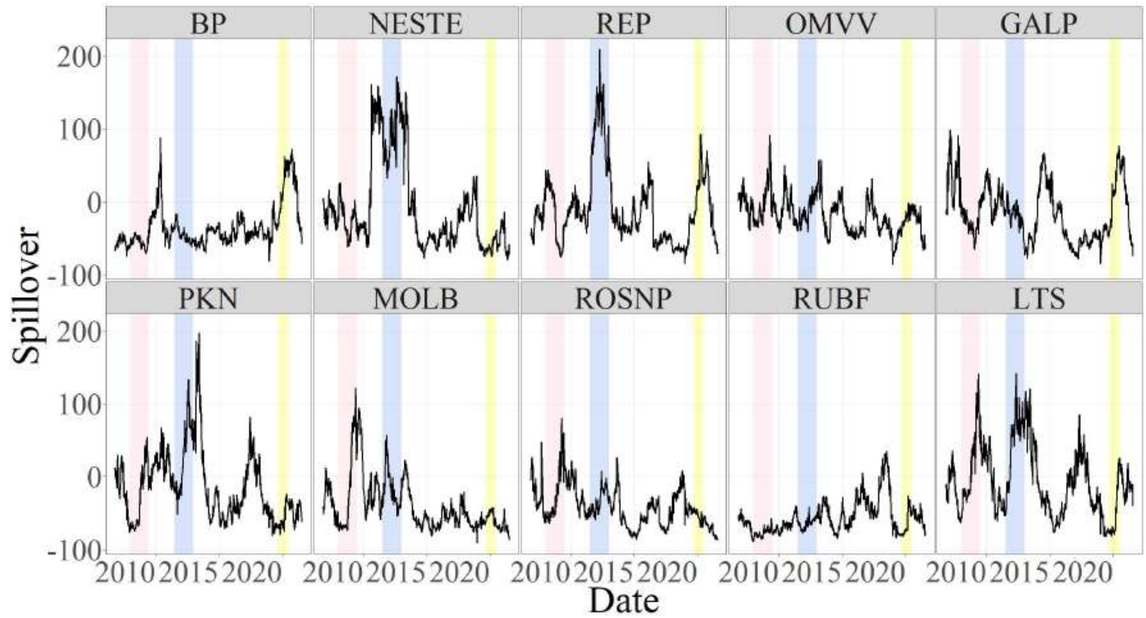


Fig. B.8. Net Spillover of the firms within the downstream sector

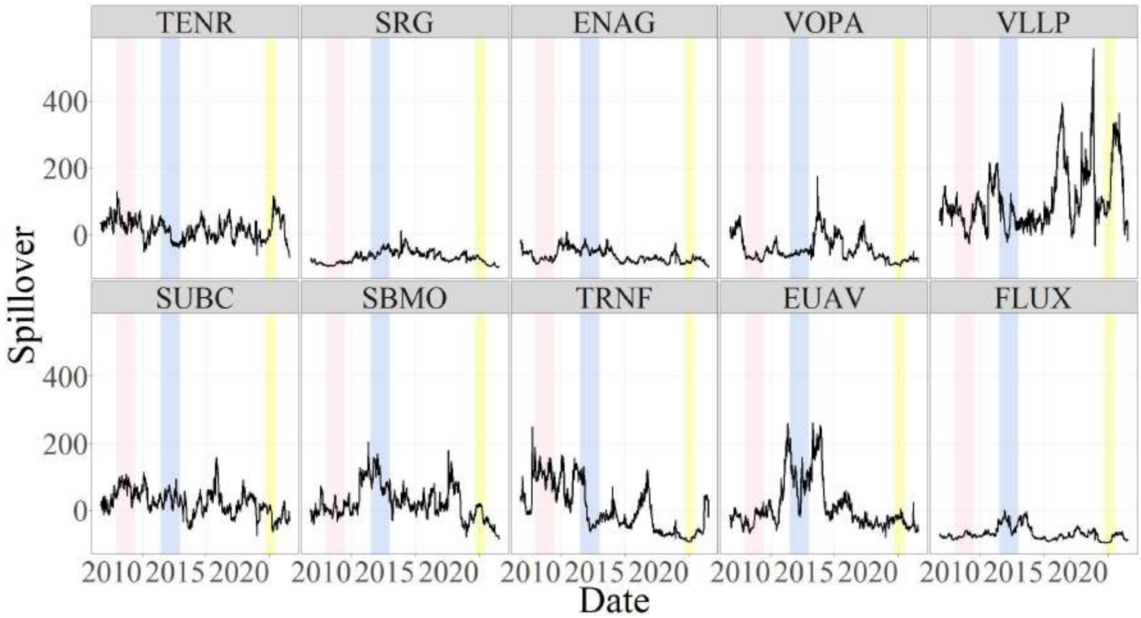


Fig. B.9. Net Spillover of the firms within the midstream sector

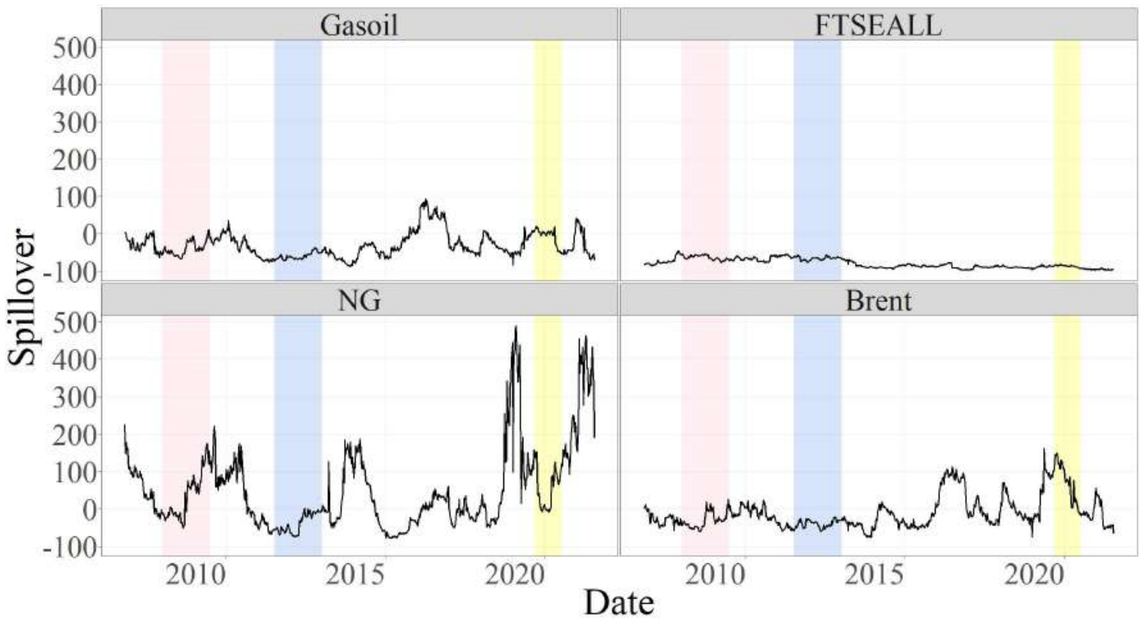


Fig. B.10. Net Spillover of Gasoil, FTSEALL, Natural Gas and Brent

Table B.1

Volatility spillover index of the corporations and external assets

	SHEL	TTEF	EQNR	GAZP	ROSN	ENI	LKOH	SIBN	SNGS	TATN	NVTK	LUNE	HBR	DNO	TLW	MAUP	SQZ	CNE	TETY	PHARP	BP	NESTE	REP	OMVV	GALP	PKN	MOLB	ROSNP	RUBF	LTS	TENR	SRG	ENAG	VOPA	VLLP	SUBC	SBMO	TRNF	EUAV	FLUX	Gasoil	FTSEALL	NG	Brent	From
SHEL	7.1	3.5	2.4	0.7	0.9	3.3	0.9	0.7	0.8	1.1	0.9	4.3	9.3	4.6	6.9	2.6	1.1	3.4	2	2.4	4.6	1.1	3.6	2.5	2.9	0.8	0.8	0.7	0.7	0.9	3.9	0.5	0.5	0.6	4.4	3.6	2.6	0.5	1.2	0.1	1.6	0.6	0.6	2.2	92.9
TTEF	3.3	6.5	2.4	1.1	1.5	4.2	1.3	1	1.3	1.8	1.4	3.5	7.3	4.8	5.6	2.5	1.1	3.1	1.9	2	3.5	1.3	4.3	2.9	3	1	1	0.8	0.7	1	4.1	0.6	0.7	0.6	4.3	3.5	2.8	0.9	1.2	0.1	1.1	0.7	0.5	1.7	93.5
EQNR	2.3	2.2	9.2	1.2	1.6	2.1	1.1	1	1.4	1.8	1.5	4.4	7.5	5.9	4.8	2.8	1.7	2.7	2.4	1.5	2.3	1.2	2.6	2.3	2.6	1	0.8	0.7	0.6	0.9	3.6	0.4	0.4	0.8	4.6	5.7	2.8	1.2	1.5	0.1	1.5	0.5	0.8	2	90.8
GAZP	0.5	0.7	1	19.1	9.7	0.7	6.7	4.5	7.1	7.8	6.1	1.9	1.3	2.6	0.9	1.1	0.8	1	1.5	0.6	0.6	0.8	0.9	1.5	1.1	0.8	0.7	0.9	0.3	0.8	1.8	0.1	0.2	0.5	1.8	2	1.4	5.5	1.1	0.1	0.3	0.4	0.6	0.4	80.9
ROSN	0.6	0.8	1.2	8.1	18.4	0.8	6.9	4.6	7.7	8.5	6.2	1.3	2.1	2.5	1.2	1	0.7	1.4	1.4	0.7	0.7	0.6	0.9	1.5	1	0.6	0.6	0.8	0.3	0.7	1.6	0.2	0.2	0.4	1.9	2.1	1.2	5.9	0.9	0.1	0.4	0.4	0.4	0.7	81.6
ENI	3	3.9	2.2	1.1	1.4	8.1	1	0.8	1.1	1.7	1.2	3.2	8.3	4.5	5.3	2.7	1.2	3.1	1.9	2	3	1.3	4.3	2.7	3	1	0.8	0.7	0.7	1	4.6	0.8	0.7	0.6	4.5	3.3	3	0.9	1.4	0.1	1.1	0.7	0.5	1.8	91.9
LKOH	0.8	0.9	1.2	7.3	9.2	0.9	13.7	4.5	7.4	8	5.7	2	2.5	3.2	1.8	1.2	0.8	1.6	1.4	0.7	0.9	0.7	1	1.7	1.2	0.6	0.7	0.9	0.4	0.7	1.9	0.2	0.3	0.5	2.1	2.1	1.4	4.8	0.9	0.1	0.6	0.5	0.4	1	86.3
SIBN	0.6	0.7	1.2	6.9	8.2	0.8	5.8	16.4	6.6	7.4	5.5	2.7	1.9	2.8	1.1	1.1	0.8	1.4	1.4	0.7	0.7	0.7	0.8	1.7	1.1	0.8	0.9	1.3	0.3	1	1.9	0.2	0.3	0.6	1.6	2.3	1.4	5	1.1	0.1	0.5	0.5	0.5	0.9	83.6
SNGS	0.5	0.7	0.9	6.2	8.4	0.7	5.8	3.9	21	7.4	5.5	7.3	1.2	2.5	1.5	0.9	1	1.2	1.2	0.8	0.6	0.7	0.8	1.2	1	0.6	0.6	0.7	0.3	0.7	1.5	0.2	0.3	0.4	1.3	1.7	1.2	5	0.9	0.1	0.3	0.4	0.5	0.5	79
TATN	0.7	0.9	1.2	5.9	7.7	1	5.8	3.8	6.6	20.8	5.8	1.7	2.2	3.3	1.6	1.1	1.1	1.1	1.6	0.8	0.7	0.7	1	1.7	1.2	0.8	0.8	0.9	0.3	0.7	2	0.2	0.3	0.5	1.9	2.4	1.4	4.9	1	0.1	0.4	0.4	0.5	0.9	79.2
NVTK	0.6	0.7	1	6.3	7.6	0.7	5.2	3.7	6.4	7.4	22.2	1.4	1.8	2.6	1.2	1.1	0.9	1.3	1.5	0.8	0.6	0.8	1	1.9	1.2	1	0.7	0.8	0.4	0.9	1.8	0.2	0.3	0.5	1.9	2.2	1.4	4.5	1.2	0.1	0.4	0.4	0.7	0.7	77.8
LUNE	0.1	0.1	0.1	0.1	0	0.1	0	0	0	0	0.1	97.3	0.2	0.2	0.1	0.1	0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0	0	0	0.1	0.1	0	0	0	0.1	0.1	0.1	0	0.1	0	0	0	0.1	0	2.7
HBR	1.3	1.1	1.4	0.2	0.4	1.4	0.4	0.2	0.2	0.4	0.2	1.5	47.6	3.6	8.4	1.6	1	2.9	1	2.1	1.4	0.4	1.4	1	1.4	0.5	0.4	0.3	0.4	0.6	2	0.4	0.3	0.2	4.2	2.1	1.4	0.2	0.8	0.1	1.2	0.2	0.5	2.1	52.4
DNO	1	1.1	1.7	0.9	1.1	1.2	0.8	0.7	1.1	1.1	1	2.8	5.4	41.5	4	1.7	1.8	2.2	2.1	1.2	1.1	0.8	1.5	1.2	1.7	0.8	0.6	0.5	0.3	0.9	2.2	0.3	0.3	0.5	2.6	2.9	1.8	1.1	1.3	0.1	1	0.4	0.6	1.4	58.5
TLW	1.1	1	1	0.2	0.3	1	0.3	0.2	0.3	0.3	0.2	1.5	9.5	3.2	54.7	1.4	0.8	1.9	0.9	1.6	1.2	0.5	1.3	0.8	1.1	0.4	0.3	0.2	0.3	0.5	1.6	0.3	0.2	0.2	2.8	1.7	1.1	0.2	0.6	0.1	1.1	0.2	0.5	1.7	45.3
MAUP	1.7	1.6	1.9	1	1	1.8	0.8	0.6	0.9	1	0.9	2.7	7.1	4.3	5.1	20.9	2.3	2.1	2	2.1	1.9	1.3	2.9	1.6	2.5	1.3	0.6	0.6	0.6	1.2	3.2	0.4	0.4	0.7	6.2	3.2	2.7	0.8	1.9	0.1	1.4	0.5	1.1	1.6	79.2
SQZ	0.4	0.3	0.5	0.5	0.4	0.3	0.3	0.2	0.5	0.6	0.6	0.5	1.7	1.5	1.4	0.7	74	0.7	0.9	0.9	0.5	0.6	0.6	0.5	0.7	0.7	0.3	0.1	0.2	0.7	0.8	0.2	0.2	0.4	1.3	1	0.8	0.6	0.8	0.1	0.4	0.1	0.9	0.4	26
CNE	1.7	1.6	1.7	0.9	1.4	1.7	1	0.7	1.1	1.2	1	2.3	10.9	5.2	6.9	2	1.5	21.2	2	2.2	1.8	1	2	1.6	2	0.8	0.8	0.7	0.4	0.9	3	0.5	0.4	0.5	3.9	2.9	2.5	0.8	1.4	0.1	1.1	0.5	0.8	1.9	78.8
TETY	1.1	1	1.4	1	1	1	0.7	0.7	1	1.3	1.2	2.8	3.1	4.7	2.8	1.8	2.4	1.9	40	1.3	1.1	1.1	1.4	1.5	1.7	1.3	0.7	0.6	0.5	1.3	2.2	0.4	0.3	0.7	2.3	2.3	1.7	1.5	1.6	0.1	1	0.3	1.4	1.1	60.1
PHARP	1.6	1.4	1.1	0.4	0.7	1.4	0.6	0.5	0.7	0.7	0.7	2.5	9.5	4.2	7.2	1.9	2	2.8	1.3	30.8	1.7	0.7	1.7	1.3	1.7	1	0.7	0.5	0.6	1	2.4	0.6	0.4	0.4	3.3	2.1	1.7	0.5	1.1	0.1	1.5	0.4	0.9	2.1	69.2
BP	4.3	3.4	2.4	0.8	1.1	3.1	1	0.8	1	1.2	1.1	3.2	8.9	3.9	6.7	2.6	1.6	3.4	2	2.3	9.7	1	3.7	2.4	3	0.8	0.8	0.7	0.7	1	3.7	0.5	0.5	0.5	4.4	3.3	2.4	0.6	1.1	0.1	1.4	0.6	0.8	1.9	90.3
NESTE	1.3	1.5	1.5	1.4	1.5	1.5	1	0.9	1.4	1.7	1.7	7.3	3.7	3.9	3.4	2.1	2.1	2.2	2.2	1.6	1.5	20.5	2.3	2.1	2.1	1.6	0.8	0.6	0.7	1.7	3	0.7	0.6	0.8	4.1	2.7	2.5	1.1	2.2	0.2	0.9	0.6	1.5	1.2	79.5
REP	2.8	3.4	2.2	0.8	1	3.7	0.8	0.5	0.8	1.2	1.1	2	7.4	4	5.6	3.3	1.6	2.6	1.7	2.1	3	1.3	12	2.5	3.4	1.2	0.8	0.6	0.7	1.3	4	0.6	0.8	0.6	5.3	3.3	3.1	0.6	1.6	0.1	1.4	0.7	0.8	1.7	88
OMVV	2	2.3	1.9	1.5	1.8	2.3	1.6	1.3	1.5	2.2	2	2.6	6.3	4.4	5.2	2.3	1.1	2.6	2.2	1.8	2	1.5	2.9	14	2.6	1.3	1.2	1	0.8	1.4	3.7	0.5	0.6	0.7	4.3	3.5	2.3	1.3	1.4	0.1	1.2	0.7	0.8	1.7	86
GALP	2	2.2	2.2	1	1.2	2.4	0.9	0.7	1.1	1.4	1.2	3.9	6.6	4.6	5.1	2.8	2.1	2.6	1.9	1.9	2.2	1.4	3.4	2.4	13.4	1.3	0.9	0.8	0.7	1.3	4.2	0.5	0.6	0.7	4.6	3.4	3.2	1.2	1.6	0.1	1.2	0.6	1	1.6	86.6
PKN	1.1	1.2	1.3	1.6	1.5	1.2	1	1.1	1.6	1.9	1.8	3	3.8	4.3	2.5	2.1	3	1.7	3.1	1.8	1.2	1.6	2	2	2.1	18.9	1.4	0.9	0.8	5.7	3.1	0.5	0.6	0.9	4.3	2.7	1.9	1.5	2	0.2	1.2	0.5	2.1	1.3	81.1
MOLB	1.1	1.3	1.6	2.2	2.5	1.3	1.6	1.9	2.2	2.3	2.5	2	3.6	5.2	2.7	2	2.8	2.1	3.2	1.5	1.3	1.4	2.1	2.5	2.2	2.1	16	1.9	0.7	1.8	3.4	0.5	0.7	1	3.1	3	2.2	2.4	2.2	0.2	1	0.8	1.1	1.3	84
ROSNP	1	1	1.6	2.7	2.5	1.2	1.9	1.8	2.1	2	2.1	2.4	3.9	5.3	1.9	2.1	1.3	2.2	2.6	1.4	1.3	1.1	1.8	2.2	1.8	1.4	1.6	21.5	0.7	1.4	3.4	0.3	0.5	0.9	2.9	3	2.4	2.8	2.1	0.2	0.9	0.7	1.2	1.2	78.6
RUBF	1.6	1.8	1.8	0.9	1.2	1.8	1	0.8	1.1	1.2	1.4	5.3	7.7	4.1	5.3	2.3	2.1	2.7	2.3	2.4	1.8	1.5	2.4	2.3	2.3	1.5	0.9	0.8	12.4	1.8	2.9	0.9	0.9	0.9	4.6	2.8	2.3	0.9	1.9	0.3	1.8	0.7	1.2	1.8	87.6
LTS	1	1.2	1.1	1.2	1.2	1.2	0.8	1.2	1.3	1.6	1.5	2.8	4.2	3.8	3.4	1.5	2.9	2	2.5	1.8	1.2	1.7	2	1.9	1.9	5.9	1	0.7	0.7	23.5	2.5	0.7	0.7	0.8	4.1	2.5	1.7	1.2	2	0.2	1.1	0.4	2.3	1.3	76.5
TENR	2	2.1	2	1.3	1.2	2.6	0.9	0.8	1.1	1.4	1	3.6	7	4.3	4.9	2.7	1.6	2.7	2	1.9	2.1	1.4	2.9	2.2	3	1.2	0.7	1	0.5	1.1	14.4	0.4	0.5	0.7	7	3.8	3	1	1.7	0.1	1.2	0.6	1	1.6	85.6
SRG	1.5	1.8	1.7	0.6	0.9	3.1	0.7	0.5	0.9	1.2	0.9	3.5	12.2	4.5	5.5	1.7	2.3	3.5	1.9	2.6	1.7	1.8	2.6	1.8	2.1	1.4	0.8	0.5	1.2	1.9	2.6	10.2	1.8	0.7	3.9	2.2	2.9	0.7	2.1	0.3	1.4	0.5	1.5	2.3	89.8
ENAG	1.4	1.8	1.6	1.4	1.6	2.4	1.1	1	1.7	1.5	1.6	3.5	7.6	4.3	3.9	1.9	2.7	3	2.4	1.9	1.7	1.5	3.2	1.9	2.7	1.4	1	1.1	1	2.1	3.5	1.6	10.3	1	4	2.5	3.1	1.5	2.2	0.2	1	0.8	1.2	1.5	89.7
VOPA	1.3	1.4	1.8	1.6	1.6	1.6	1.2	1.3	1.6	2.1	1.6	4.7	4.4	4.6	2.9	2.8	2.7	2.1	3	1.6	1.3	1.5	2.2	1.7	2.1	1.5	0.9	0.8	0.8	1.6	3.2	0.5	0.7	15.6	4	3.7	2.8	1.8	2.4	0.2	1.4	0.7	1.2	1.7	84.4
VLLP	1.1	1.2	1.5	0.8	0.8	1.4	0.5	0.4	0.7	0.9	0.8	1.7	7.4	3.4	5	2.9	1.6	1.8	1.2	1.5	1.2	0.9	2.2	1.3	1.8	1.1	0.5	0.4	0.5	1.1	3.8	0.3	0.3	0.5	36.4	2.9	2.1	0.6	1.4	0.1	0.9	0.3	1.7	1.1	63.6
SUBC	1.6	1.8	2.9	1.3	1.6	1.6	1.2	0.9	1.3	1.9	1.4	3.3	5.8	5.3	4.8	2.5	1.5	2.4	1.9	1.5	1.6	1.2	2.1	2.2	2.2	1.2	1	0.9	0.5	1	3.7	0.4	0.5	0.9	4.9	19.5	2.9	1.4	1.4	0.1	1.2	0.6	0.9	1.8	80.5
SBMO	1.5	1.8	1.8	1.1	1.3	1.9	0.9	0.8	1.4	1.5	1.2	3.1	5.2	4.1	3.7	2.4	2	2.9	1.8	1.6	1.5	1.4	2.6	1.6	2.7	1.2	0.7	0.7	0.5	1	3.6	0.5	0.6	0.9	4.2	4.1	23.7	1.1	2	0.2	0.7	0.5	0.9	1.2	76.3
TRNF	0.4	0.5	1	5.8	7.3	0.6	4.4	3.3	5.8	6.4	4.7	1.4	1.2	2.6	1	0.9	1.2	0.9	2.3	0.6	0.5	0.7	0.8	1.2	1.1	0.7	0.6	1	0.2	0.8	1.7	0.1	0.2	0.5	1.3	2.1	1.1	30.2	1.2	0	0.3	0.4	0.6	0.5	69.8
EUAV	1.1	1	1.5	1.3	1.1	1.2	0.7	0.7	1.2	1.4	1.5	2	4.1	4	2.9	2.4	3.4	2	2.4	1.3	1.2	1.9	2.3	1.6	1.9	1.6	0.9	0.6	0.6	1.9	2.6	0.6	0.6	1	3.8	2.5	2.6	1.3	28.6	0.1	0.9	0.5	2.2	1.3	71.4
FLUX	1	1	1.3	1	1.1	1.1	0.8	1	1.5	1.3	1.4	2.2	5	4.2	3.7	2.1	4.6	2.5	2.8	2	1.5	1.5	2.2	1.7	2	2.1	1	1	0.6	2.4	2.3	0.9	0.9	1	4	2.1	3	1.2	2.4	18	1.3	0.4	3.8	1.3	82
Gasoil	1.8	1.1	1.8	0.6	0.7	1.3	0.6	0.5	0.7	0.8	0.7	2.3	7.9	4.3	5.5	2.5	1.6	1.5	2	1.9	1.8	0.9	1.9	1.5	1.9	1.1	0.7	0.6	0.7	1	2.6	0.3	0.3	0.9	4	2.8	1.6	1	1.2	0.1	19	0.5	1.5	12.4	81
FTSEALL	1.9	2.5	1.8	1.9	2.3	2.7	1.8	1.6	2.1	2.3	2.2	3.8	5.6	5.2	4	2.6	1.4	3.3	2.1	2	2	1.8	3.3	2.5	2.6	1.2	1.4	1.3	0.8	1.2	4.3	0.6	0.9	1	4.1	4	2.9	1.5	2	0.1	1.6	3.1	0.5	2.4	96.9
NG	0.5	0.4	0.8	0.8	0.6	0.5	0.4	0.4	0.9	0.9	0.9	2.5	2.7	3.4	1.9	1.5	2.1	1.2	1.8	1.1	0.7	1	1	0.8	1	1.2	0.4	0.3	0.4	1.3	1.4	0.3	0.3	0.5	2.7	1.4	1.1	1	1.2	0.2	1	0.2	54.8	1.1	45.2
Brent	1.9	1.4	2	0.6	0.7	1.6	0.8	0.5	0.8	0.9	0.8	2.6	10	4.7	5.7	2.2	1.5	2.1	1.6	2	1.8	0.8	1.9	1.5	1.9	0.8	0.7	0.7	0.6	0.8	2.7	0.4	0.4	0.7	3.8	3.2	2	0.8	1.2	0.1	9.4	0.5	1.2	17.9	82.1
To	59.8	62.8	66.3	84.2	100.6	68.2	72.8	56.9	88	100.7	82.6	124.7	234.9	168.2	164.7	83.2	73.5	91.6	81	66.5	64.8	46.6	87.6	74.7	82	50.5	33.3	31.3	23.8	52.9	117.7	19	20.9	27.5	150.2	116.4	89.2	72.8	62.5	5.3	51.3	20.8	43.6	70.1	**76**
Net	-33.1	-30.7	-24.5	3.3	19	-23.7	-13.5	-26.7	9	21.5	4.8	122.1	182.5	109.7	119.5	4.1	47.6	12.8	21	-2.7	-25.5	-32.8	-0.4	-11.3	-4.6	-30.6	-50.7	-47.3	-63.9	-23.6	32	-70.8	-68.8	-56.9	86.6	35.9	12.9	3.1	-8.9	-76.7	-29.7	-76.1	-1.7	-12	

B.3 Robustness Tests

B.3.1 GICS Classification

Table B.2

Summary of the sample firms by industry segments of Upstream, Midstream, Downstream and IOG, based on the GICS industry classification

Ticker	Company Name	Exchange	Industry group	Capitalization
Integrated Oil and Gas				
SHEL	Shell	UK	Integrated Oil and Gas	205 631
TTEF	TotalEnergies	France	Integrated Oil and Gas	141 241
EQNR	Equinor	Norway	Integrated Oil and Gas	113 235
GAZP	Gazprom	Russia	Integrated Oil and Gas	103 229
BP	BP	Russia	Integrated Oil and Gas	97 670
ROSN	Rosneft	Russia	Integrated Oil and Gas	58 363
ENI	Eni	Italy	Integrated Oil and Gas	50 832
NVTK	Novatek	Russia	Integrated Oil and Gas	40 117
Sum				**759 486**
Upstream				
TATN	Tatneft	Russia	Oil & Gas Exploration and Production	40 117
HBR	Harbour Energy	UK	Oil & Gas Exploration and Production	4 106
DNO	DNO	Norway	Oil & Gas Exploration and Production	1 680
MAUP	Maurel and Prom	France	Oil & Gas Exploration and Production	1 002
TLW	Tullow Oil	UK	Oil & Gas Exploration and Production	901
SQZ	Serica	UK	Oil & Gas Exploration and Production	801
CNE	Capricorn Energy	UK	Oil & Gas Exploration and Production	743
Sum				**21 935**
Midstream				
VOPA	Vopak	Netherlands	Oil & Gas Transportation Services	3 306
TRNF	Transneft	Russia	Oil & Gas Transportation Services	2 723
EUAV	Euronav	Belgium	Oil & Gas Transportation Services	2 691
TRMDa	Torm	Denmark	Oil & Gas Transportation Services	1 105
EXMR	Exmar	Belgium	Oil & Gas Transportation Services	558
FLUX	Fluxys Belgium	Belgium	Oil & Gas Transportation Services	359
CCORb	Concordia	Sweden	Oil & Gas Transportation Services	25
Sum				**10 767**
Downstream				
NESTE	Neste	Finland	Oil & Gas Refining and Marketing	32 991
PKN	PKN Orlen	Poland	Oil & Gas Refining and Marketing	6 723
VBKG	Verbio VB	Germany	Oil & Gas Refining and Marketing	2 935
MORr	Motor Oil Hellas	Greece	Oil & Gas Refining and Marketing	1 972
HEPr	HELLENiQ	Greece	Oil & Gas Refining and Marketing	1 895
CE2G	CorpEnergies	Germany	Oil & Gas Refining and Marketing	1 101
ESSF	Esso Societe	France	Oil & Gas Refining and Marketing	784
Sum				**48 401**

Note: Market capitalization is expressed in million €.

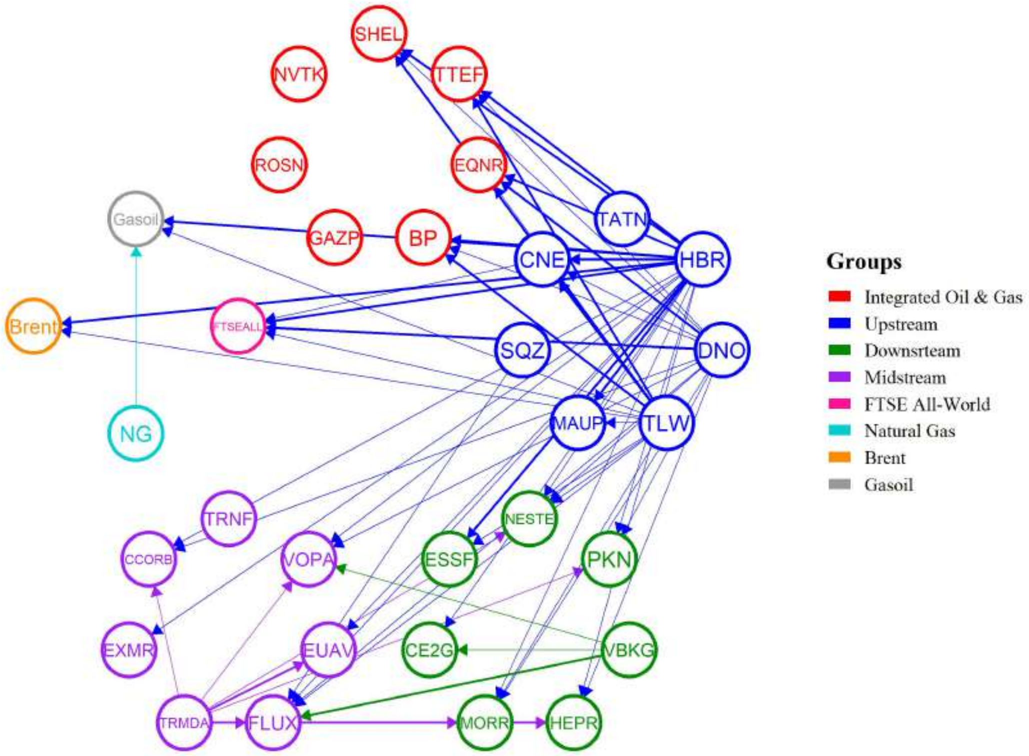
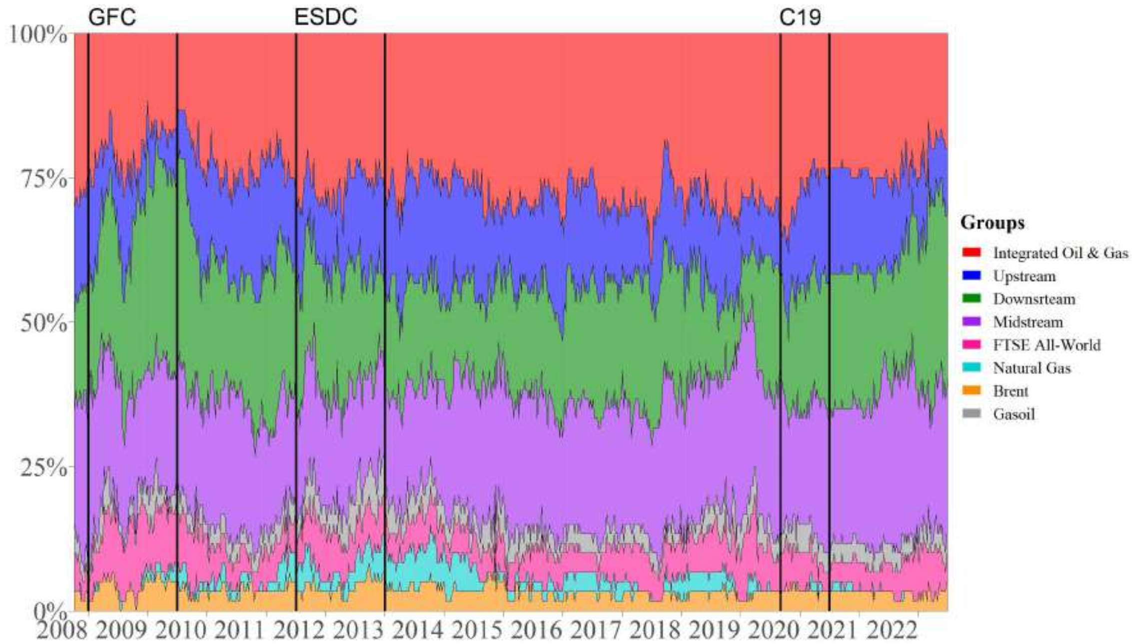
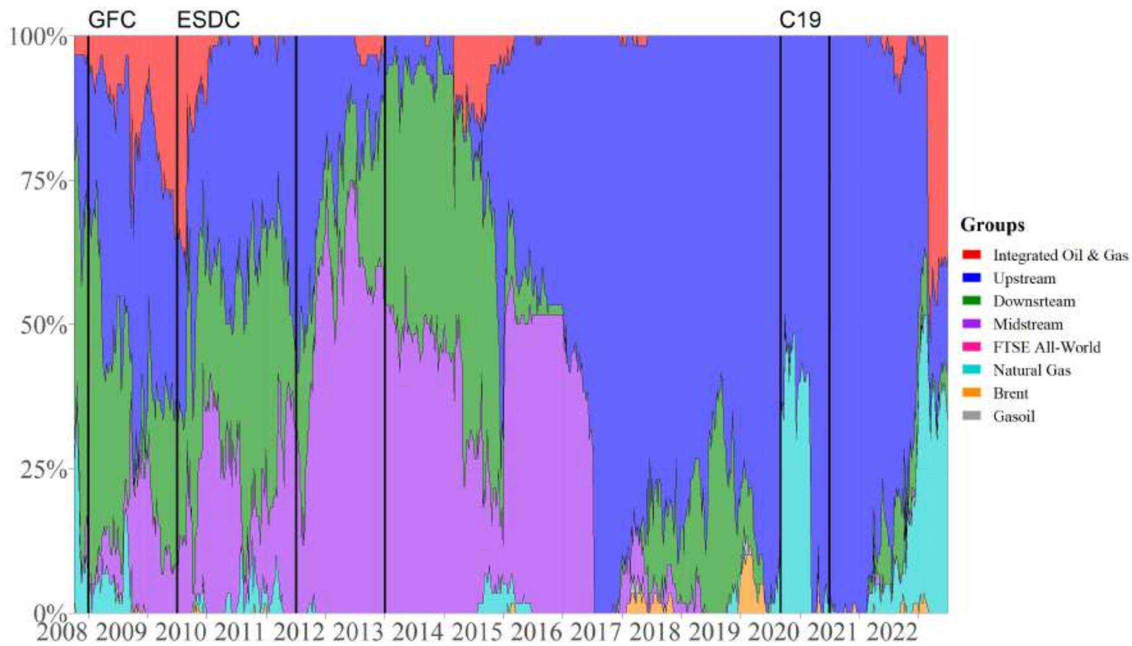


Fig. B.11. Static, full-sample volatility interconnectedness network [According to GICS classification]

Note: An arrow between two nodes indicates the direction of the spillover, and the color of the arrow indicates the industry segment of the asset that originates from. Thinner lines represent the strongest 5% of connections, while thicker lines show the uppermost 1% of connections. For the figure, we use Lag=3 and H=10 model inputs.



(a) Distribution of imported volatility from the various energy sectors and commodities, over times



(b) Distribution of emitted volatility from the various energy sectors and commodities, over time

Fig. B.12. Distribution of imported and emitted volatility over time

Note: Panel (a) displays the distribution of imported volatility over time, while Panel (b) shows the distribution of emitted volatility over time. For both figures, in the model input, we use Lag=3 and H=10, with a window size of 250 days and we display the strongest 5% of edges. [According to GICS classification]

B.3.2 Conditional Volatility

The volatility of each asset is calculated based on the variance equation of a GARCH(1,1) model. The variance equation models the conditional variance (σ^2) of the series as a function of past squared residuals and past conditional variances:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{B.1}$$

where σ_t^2 is the conditional variance of the series at time t, ω is the constant term, $\alpha\epsilon_{t-1}^2$ is the ARCH term, representing the effect of past squared residuals (ϵ_{t-1}^2) on the currenct conditional variance. Finally $\beta\sigma_{t-1}^2$ is the GARCH term, representing the effect of past conditional variances (σ_{t-1}^2) on the current conditional varaince.

The GARCH(1,1) model is widely used for asset volatility assumption due to its simplicity, flexibility, and ability to capture volatility clustering. It effectively models the persistence of volatility using few parameters, ensuring mean reversion and adaptability to various financial data. The model's ease of implementation and support for heavy-tailed residuals make it a robust choice for forecasting asset volatility across different asset classes.

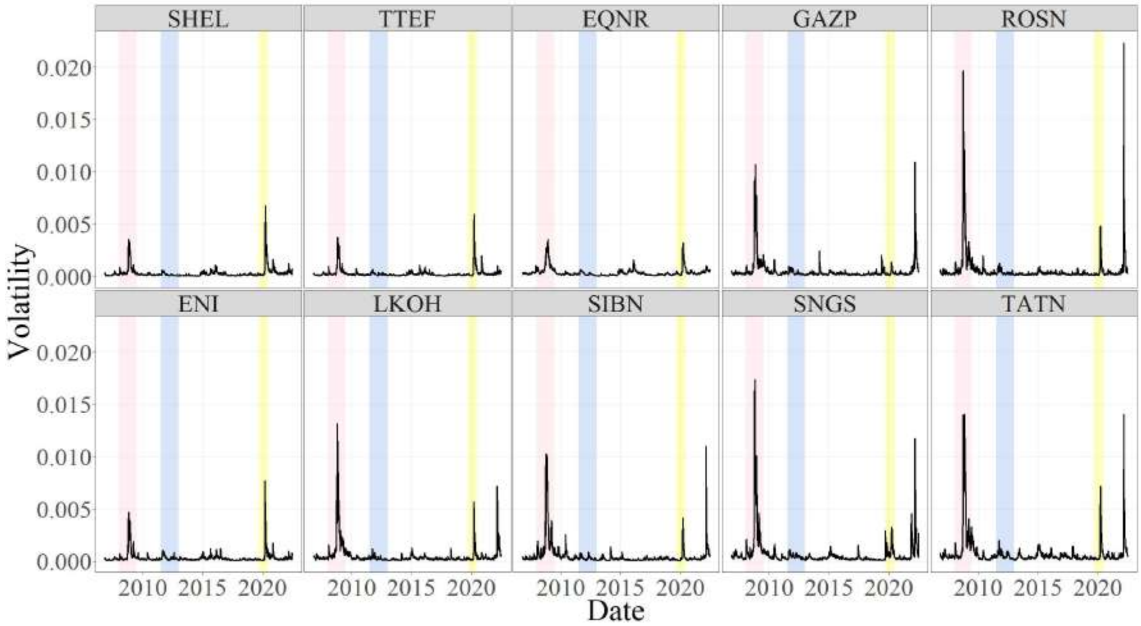


Fig. B.13. Realized volatilities of the firms within Integrated Oil and Gas sector

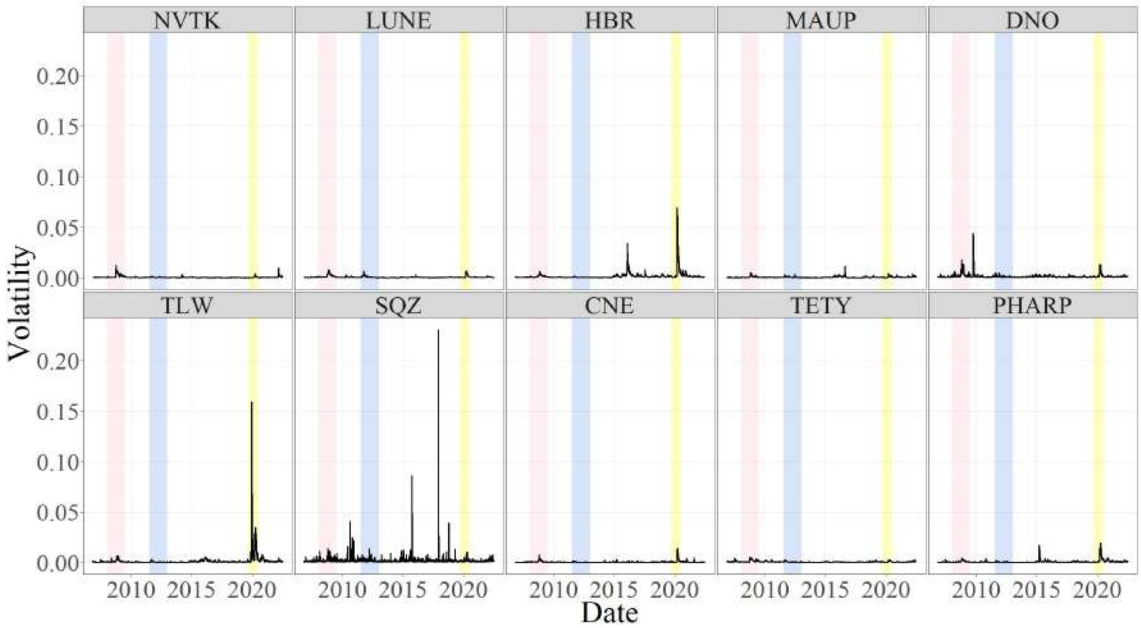


Fig. B.14. Conditional volatilities of the firms within the upstream sector

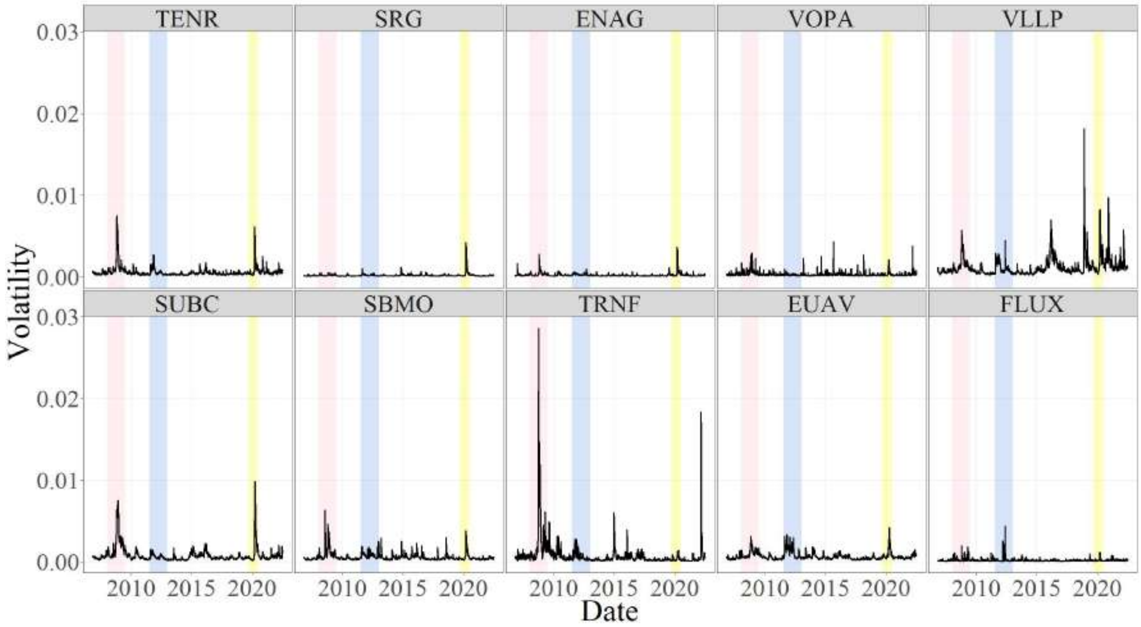


Fig. B.15. Conditional volatilities of the firms within the downstream sector

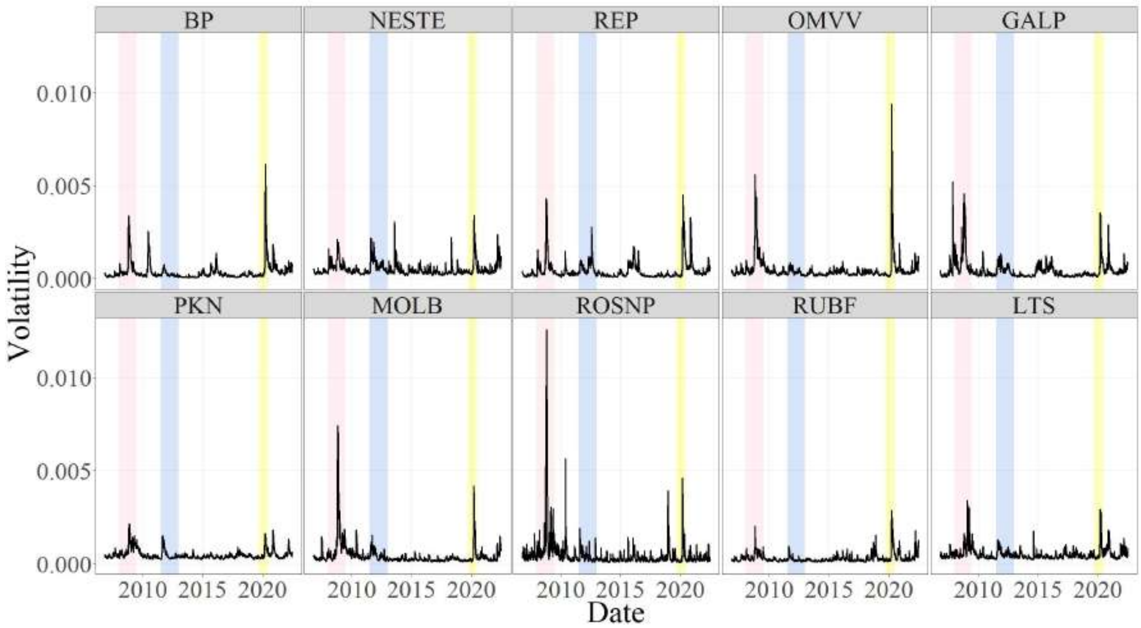


Fig. B.16. Conditional volatilities of the firms within midstream sector

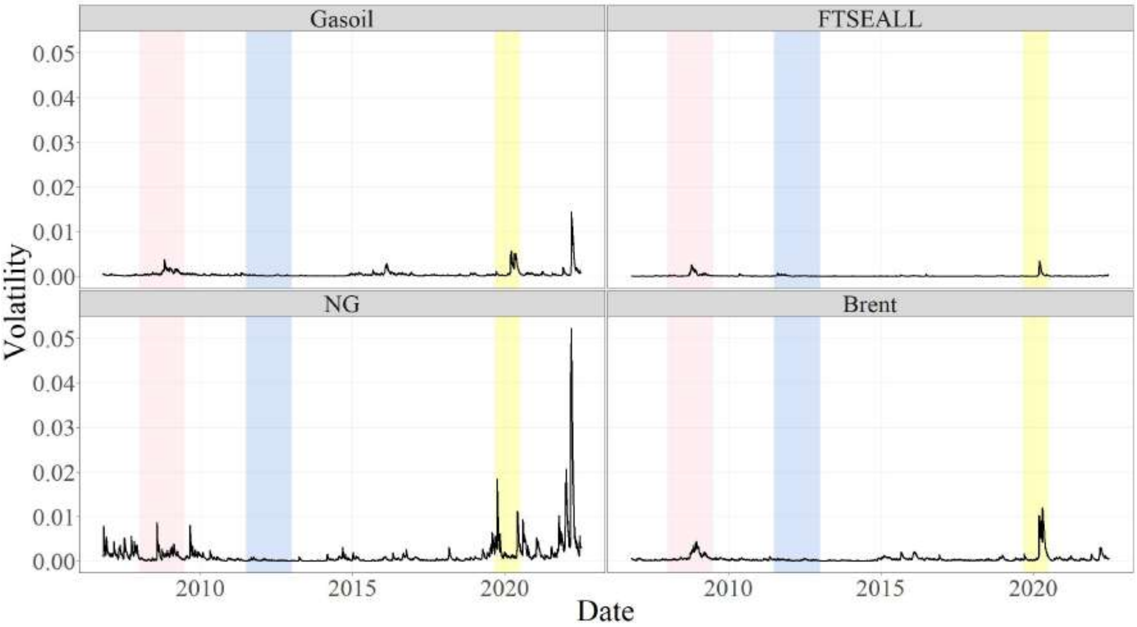


Fig. B.17. Conditional volatilities of Gasoil, FTSEALL, Natural Gas and Brent

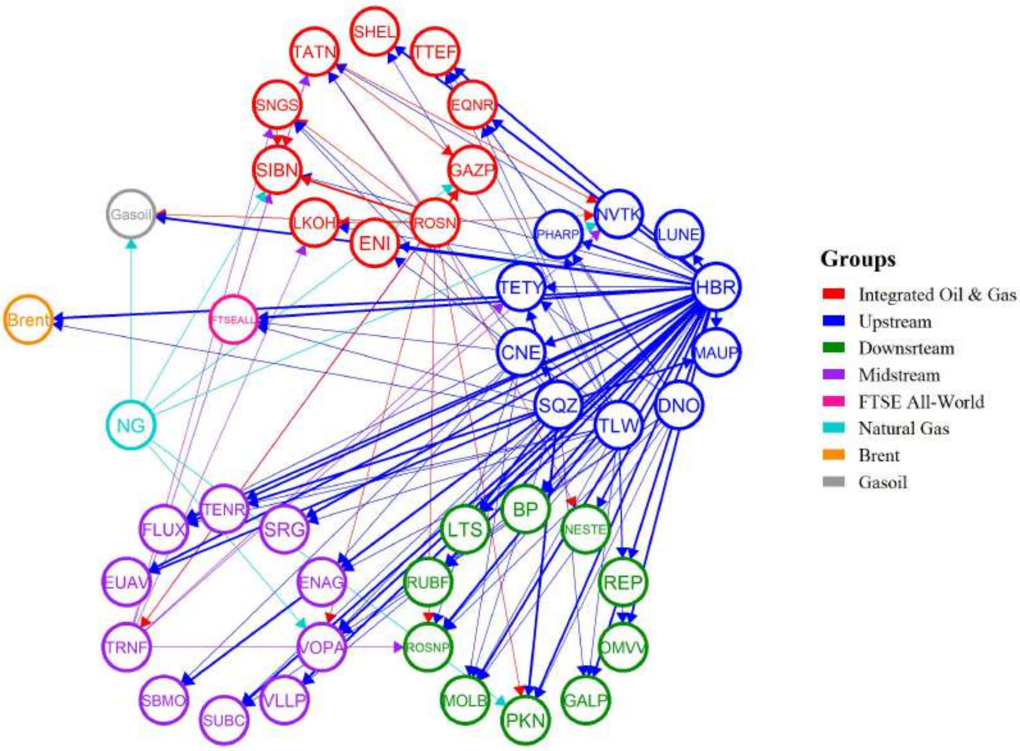
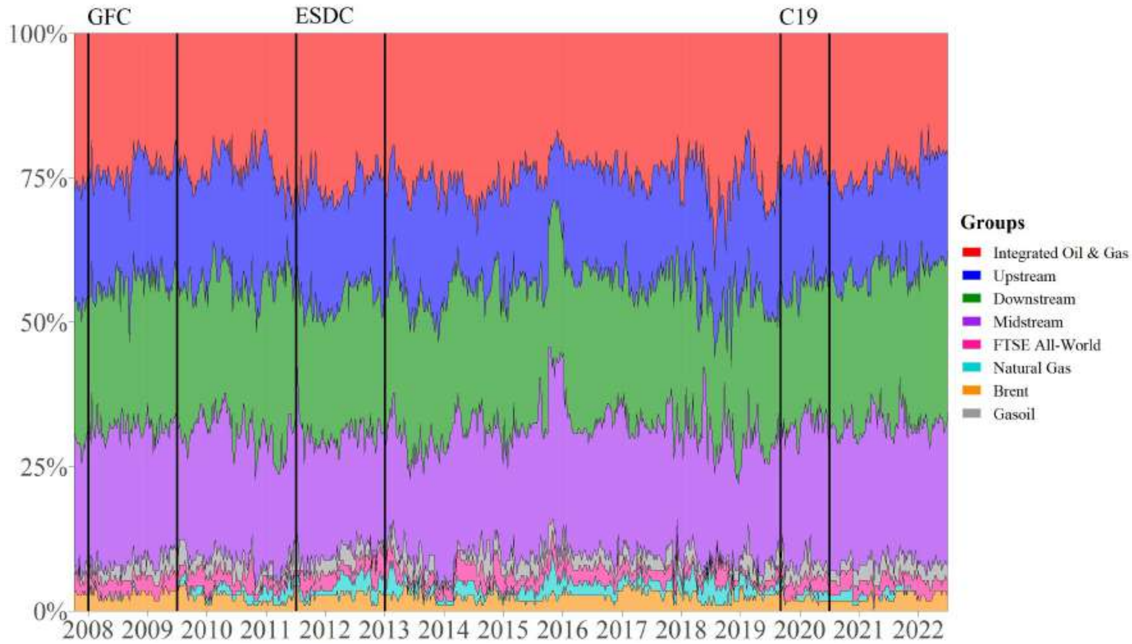
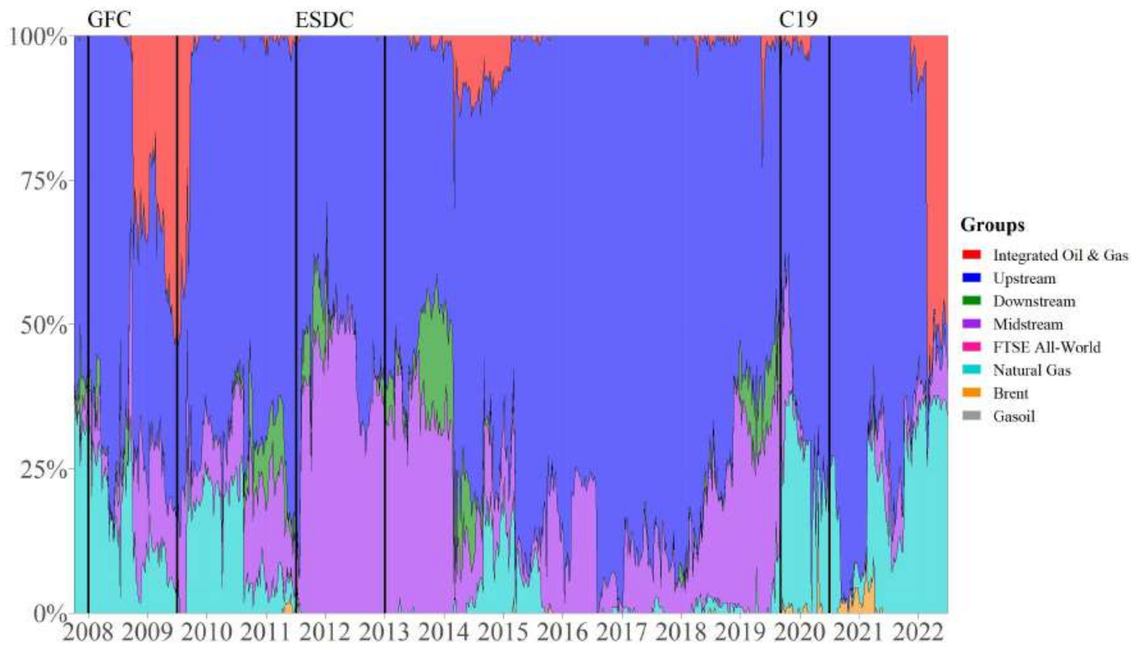


Fig. B.18. Static, full-sample volatility interconnectedness network, based on conditional volatilities

Note: An arrow between two nodes indicates the direction of the spillover, and the color of the arrow indicates the industry segment of the asset that originates from. Thinner lines represent the strongest 5% of connections, while thicker lines show the uppermost 1% of connections. For the figure, we use Lag=3 and H=10 model inputs.



(a) Distribution of imported volatility from the various energy sectors and commodities, over times



(b) Distribution of emitted volatility from the various energy sectors and commodities, over time

Fig. B.19. Distribution of imported and emitted volatility over time, based on conditional volatilites

Note: Panel (a) displays the distribution of imported volatility over time, while Panel (b) shows the distribution of emitted volatility over time. For both figures, in the model input, we use Lag=3 and H=10, with a window size of 250 days and we display the strongest 5% of edges.

C Supplementary material for Chapter V

C.1 The two-way fixed effect panel regression model

The conventional two-way fixed effect panel regression (Allison (2009); Angrist and Pischke (2009); Baltagi and Baltagi (2008); Wooldridge (2010)) is well-known and often used in economic and social science research. It is called ”two-way” because it includes fixed effects for two different dimensions: one for the cross-sectional dimension and one for the time dimension. The specification of a two-way fixed effect panel regression model is as follows:

$$Y_{it} = \alpha + \beta X_{it} + \gamma_i + \lambda_t + \epsilon_{it} \tag{C.1}$$

where Y_{it} is the dependent variable for entity i at time t. X_{it} is a vector of independent variables for entity i at time t. α is the intercept term and β is a vector of coefficients for the independent variables. γ_i is fixed effect for the cross-sectional dimension. λ_t is the fixed effect for the time dimension. ϵ_{it} is the error term, which captures any remaining variation not explained by the independent variables and fixed effects. The fixed effects γ_i and λ_t control for unobserved factors that vary across entities and time periods, respectively, allowing you to focus on the relationship between the independent variables and the dependent variable while accounting for these potential confounding factors.

The standard assumptions of ordinary least squares (OLS) regression, such as independent and identically distributed (iid) errors and homoskedasticity, often do not hold in panel regression, particularly in finance research. Petersen (2008) extensively discussed various fixed effect models and the treatment of standard errors in his seminal paper. Fixed effects (FE) models are favored in finance studies as they absorb non-invariant firm and time dimensions, thereby addressing the issue of omitted variable bias (OVB) due to the lack of confounders.

Petersen (2008) also delves into the handling of standard errors in fixed effect models. He introduced two-way fixed effect and time and cross-section standard error clustering solutions. However, despite their effectiveness in addressing certain issues, these methods can be computationally inefficient for large datasets.

Given the computational challenges associated with the conventional $xtreg$ panel regression model, especially when dealing with large dimensions typical in finance studies, researchers often seek more computationally efficient approaches. In finance studies, it's common to encounter datasets with thousands of cross-sections and tens of thousands of time series observations. Correia et al. (2016) introduce a feasible estimator that overcomes these challenges by leveraging the properties of within-group variation in the data. By exploiting the structure of the fixed effects, the proposed estimator provides consistent estimates of the model parameters without requiring the full enumeration of fixed effects.

C.2 Explanatory Tables

Table C.1
Countries’ energy dependence from Eurostat

	2005	2007	2009	2011	2013	2015	2017	2019	2021
European Union	29 441 984	28 904 772	27 982 895	28 570 736	28 877 544	27 517 445	26 789 746	25 859 096	25 020 138
Belgium	579 188	602 174	604 422	635 369	599 887	431 246	608 210	635 731	727 241
Bulgaria	445 601	415 730	406 303	512 485	446 676	503 770	491 010	489 470	507 772
Czechia	1 391 402	1 423 187	1 322 336	1 355 677	1 269 171	1 195 468	1 145 589	1 113 694	1 020 576
Denmark	1 312 269	1 136 416	1 004 452	864 758	702 705	676 515	654 635	522 975	400 756
Germany	5 768 694	5 800 693	5 399 614	5 239 374	5 189 841	5 046 999	4 838 166	4 407 692	4 310 906
Estonia	169 148	197 369	158 913	212 502	226 300	204 724	248 355	213 034	184 532
Ireland	71 190	59 407	60 017	72 111	97 476	82 200	204 428	174 056	127 004
Greece	434 493	427 049	424 130	405 246	392 122	357 121	313 613	266 661	217 419
Spain	1 256 081	1 261 678	1 277 587	1 345 647	1 459 332	1 428 453	1 421 929	1 451 635	1 518 628
France	5 685 445	5 590 974	5 433 094	5 759 308	5 802 396	5 895 199	5 503 485	5 615 633	5 476 689
Croatia	199 489	205 592	207 561	193 371	186 630	184 822	176 876	163 298	165 593
Italy	1 264 753	1 303 627	1 323 951	1 336 320	1 539 344	1 511 354	1 535 160	1 545 339	1 535 543
Cyprus	2 136	3 076	3 785	4 243	4 799	5 483	6 058	8 724	9 955
Latvia	77 913	75 437	87 813	86 883	89 743	97 900	108 322	118 412	113 546
Lithuania	173 570	170 056	184 601	66 101	70 305	77 865	86 994	85 456	93 606
Luxembourg	4 464	4 931	4 657	4 745	5 541	6 304	7 673	9 842	13 119
Hungary	454 536	449 230	483 891	487 116	473 017	464 929	466 816	451 619	445 976
Malta	22	33	39	267	394	657	1 279	1 515	1 876
Netherlands	2 614 558	2 521 135	2 633 830	2 779 749	2 920 374	2 018 864	1 734 147	1 385 831	1 114 326
Austria	414 002	458 506	490 043	479 044	518 914	511 965	529 022	519 843	525 929
Poland	3 262 611	3 003 429	2 800 783	2 838 897	2 961 677	2 836 955	2 686 474	2 601 790	2 516 569
Portugal	151 341	194 253	206 226	231 592	240 845	247 354	244 496	274 324	291 051
Romania	1 168 617	1 160 468	1 180 135	1 151 073	1 080 553	1 104 248	1 067 236	1 027 018	961 808
Slovenia	156 193	155 108	151 836	156 730	147 183	138 887	148 671	141 578	137 403
Slovakia	269 699	242 599	243 256	258 309	268 480	267 711	266 691	290 563	291 065
Finland	698 852	675 947	680 272	701 872	740 518	720 680	763 482	793 360	816 450
Sweden	1 415 718	1 366 665	1 209 348	1 391 947	1 443 322	1 499 772	1 530 929	1 550 003	1 494 801
Iceland	99 832	161 307	198 086	217 676	221 156	206 326	205 999	223 022	217 400
Norway	9 694 217	9 003 668	9 087 873	8 385 555	8 218 518	8 693 198	9 006 763	8 193 266	8 974 852
Bosnia and Herzegovina						182 853	193 599	226 292	218 680
Montenegro	24 824	22 204	23 001	30 192	31 875	29 536	26 127	30 796	31 357
Moldova				23 292	25 098	27 488	32 211	27 949	31 885
North Macedonia	68 328	64 974	67 310	73 512	59 653	53 205	48 820	48 554	36 712
Albania	47 390	43 962	52 358	62 098	85 161	86 809	68 761	72 698	76 319
Serbia	428 554	438 821	426 877	467 619	476 060	450 606	439 428	427 846	426 489
Türkiye	991 342	1 149 739	1 239 077	1 290 186	1 218 006	1 317 145	1 526 771	1 889 653	1 934 628
Ukraine	3 304 612	3 440 055	3 230 319	3 437 633	3 515 399	2 695 985	2 465 619	2 526 927	
Kosovo	58 512	59 704	77 253	75 159	75 047	75 536	75 066	77 419	81 079
Georgia					59 824	55 201	55 837	45 726	52 236

(a) Primary energy production of the Europe Area countries, expressed in Terajoules

	2005	2007	2009	2011	2013	2015	2017	2019	2021
European Union	67 147 546	66 851 646	62 749 054	63 350 375	61 920 891	60 631 978	62 417 175	61 055 997	59 522 315
Belgium	2 482 289	2 412 352	2 371 597	2 371 864	2 364 939	2 247 483	2 362 538	2 348 224	2 377 861
Bulgaria	840 747	852 038	735 663	803 867	715 325	782 138	792 802	788 972	807 862
Czechia	1 906 457	1 945 516	1 793 745	1 826 187	1 818 996	1 760 635	1 819 704	1 797 660	1 790 561
Denmark	829 881	869 964	813 720	793 139	764 818	722 786	748 134	727 251	712 150
Germany	14 506 226	14 212 470	13 461 498	13 429 731	13 848 764	13 317 913	13 481 140	12 901 432	12 388 065
Estonia	230 073	266 898	185 739	241 593	246 477	203 114	247 563	205 835	192 909
Ireland	647 557	674 495	636 029	580 866	561 914	596 333	613 112	627 489	598 829
Greece	1 300 382	1 304 425	1 270 250	1 152 931	1 007 712	1 008 531	1 021 350	986 165	900 603
Spain	6 048 639	6 149 541	5 453 044	5 422 192	5 055 083	5 146 110	5 462 007	5 310 128	4 965 936
France	11 604 059	11 332 443	10 951 285	11 073 581	11 134 624	10 887 503	10 700 436	10 526 034	10 125 030
Croatia	411 391	425 302	400 415	387 723	358 206	356 065	371 865	367 983	364 016
Italy	7 931 685	7 854 749	7 225 238	7 167 457	6 631 521	6 520 088	6 678 476	6 507 655	6 433 486
Cyprus	106 699	115 784	119 180	113 611	92 256	96 295	107 748	109 949	100 879
Latvia	192 134	204 558	188 817	183 261	186 981	183 357	190 545	194 589	191 773
Lithuania	376 094	402 094	366 332	307 570	293 771	300 794	322 124	326 661	332 769
Luxembourg	201 050	194 037	182 904	191 322	181 710	174 934	181 305	190 323	176 950
Hungary	1 193 668	1 155 422	1 081 884	1 091 190	1 001 479	1 055 209	1 116 052	1 118 105	1 146 393
Malta	39 173	40 138	37 447	39 210	36 916	31 730	34 537	37 735	33 451
Netherlands	3 504 432	3 464 444	3 372 272	3 372 831	3 311 915	3 202 985	3 316 418	3 187 813	3 112 889
Austria	1 439 387	1 427 621	1 366 251	1 415 987	1 428 422	1 411 862	1 457 266	1 455 532	1 428 591
Poland	3 876 204	4 067 978	3 946 302	4 256 511	4 123 883	4 013 819	4 405 581	4 441 020	4 588 530
Portugal	1 148 770	1 096 857	1 054 216	995 194	937 709	987 621	1 031 756	1 000 880	902 003
Romania	1 619 718	1 666 553	1 456 660	1 496 838	1 334 244	1 334 457	1 404 026	1 390 235	1 435 953
Slovenia	316 649	318 451	295 733	303 244	283 985	272 121	288 982	281 530	274 023
Slovakia	782 887	743 416	698 785	719 935	701 563	680 977	722 131	712 758	744 951
Finland	1 458 823	1 566 532	1 407 366	1 483 552	1 407 657	1 367 522	1 434 183	1 432 282	1 411 602
Sweden	2 152 472	2 087 569	1 876 683	2 128 988	2 090 019	1 969 596	2 105 393	2 081 757	1 984 251
Iceland	141 239	205 801	244 426	248 583	253 979	243 813	249 661	265 301	253 273
Norway	1 241 963	1 179 839	1 280 972	1 193 982	1 334 407	1 106 604	1 287 241	1 231 664	1 244 150
United Kingdom	9 831 792	9 368 150	8 543 324	8 281 389	8 315 314	7 999 863	7 807 237	7 646 247	
Bosnia and Herzegovina						258 873	282 796	302 718	308 738
Montenegro	43 571	47 891	40 383	47 468	41 657	42 658	43 422	46 567	45 757
Moldova				108 244	107 189	108 956	119 344	118 900	125 973
North Macedonia	122 375	129 803	117 955	130 727	116 504	111 414	115 693	119 824	112 142
Albania	94 232	86 103	90 907	94 007	99 030	92 034	99 456	98 589	96 200
Serbia	671 871	695 062	637 666	683 501	625 526	620 006	659 356	645 496	679 868
Türkiye	3 570 350	4 246 387	4 175 121	4 724 478	4 773 447	5 541 699	6 298 842	6 285 362	6 773 154
Ukraine	5 912 973	5 849 682	4 809 161	5 311 525	4 872 732	3 898 453	3 758 402	3 753 109	
Kosovo	81 630	85 790	102 943	106 377	96 814	105 691	107 541	111 742	120 914
Georgia					177 860	199 358	208 989	217 916	225 472

(b) Gross inland energy consumption of the Europe Area countries, expressed in Terajoules

Note: Source: https://ec.europa.eu/eurostat/databrowser/view/nrg_bal_c/default/table?lang=en, *[Accessed March 15, 2023]*

Table C.3
Volatility spillover summary table for MSCI equity indices of our sample EEA countries, US equity index, APAC equity index, and Brent and TTF one month ahead future prices during the period of 1/1/2005 and 12/31/2008

	AUT	BEL	DEU	DNK	FIN	FRA	GBR	NLD	SWE	ESP	GRC	IRL	ITA	PRT	HUN	POL	NOR	USA	APAC	Brent	TTF	From
AUT	10.7	3.7	4.5	5.3	4.0	5.0	5.3	4.9	6.1	5.0	3.9	5.8	4.2	3.2	5.3	4.9	10.8	2.4	1.0	3.0	1.1	89.3
BEL	5.0	14.8	3.9	4.4	4.4	4.8	4.7	6.7	5.3	4.7	4.0	6.5	3.9	3.2	4.2	4.2	8.1	1.8	1.2	2.5	1.9	85.2
DEU	4.9	3.2	7.7	4.8	5.1	6.3	5.5	5.4	6.8	5.9	3.8	4.8	5.1	2.9	5.6	5.5	9.2	1.9	1.0	3.1	1.4	92.3
DNK	5.6	3.8	4.4	8.8	4.5	5.2	5.1	4.9	6.3	4.9	4.3	5.9	4.3	3.4	5.4	5.4	10.7	1.6	1.2	3.0	1.3	91.2
FIN	4.7	4.4	5.0	4.6	10.5	5.6	5.1	5.2	7.1	5.0	3.8	5.4	4.4	2.9	5.1	5.2	8.9	1.5	1.1	3.0	1.7	89.5
FRA	5.4	3.9	5.8	5.0	5.2	6.9	5.7	5.8	7.0	5.9	3.7	5.5	5.2	3.1	5.2	4.8	9.3	1.7	1.0	2.7	1.2	93.1
GBR	5.8	3.8	5.3	5.1	4.9	6.0	7.4	5.6	6.5	5.6	3.8	6.0	4.8	3.2	5.3	4.9	9.3	1.8	1.0	2.7	1.2	92.6
NLD	5.2	5.6	5.1	4.8	4.9	6.0	5.5	7.7	6.7	5.6	3.4	6.1	4.8	3.1	5.0	4.4	9.2	1.7	1.0	2.7	1.4	92.3
SWE	4.9	3.7	4.9	4.9	5.5	5.6	5.2	5.2	10.8	5.2	3.6	5.7	4.5	2.9	4.9	5.0	9.9	1.7	1.0	3.2	1.7	89.2
ESP	5.3	3.6	5.6	4.9	4.9	6.1	5.6	5.4	6.7	7.8	4.2	5.9	5.1	3.4	5.2	4.9	8.9	1.7	1.1	2.6	1.4	92.2
GRC	5.1	4.3	4.2	5.1	4.3	4.6	4.6	4.4	5.4	4.9	11	6.1	3.9	3.6	5.6	6.0	8.7	1.5	1.5	3.5	1.7	89.0
IRL	5.0	4.3	3.5	4.6	4.4	4.5	4.7	4.6	5.8	4.6	4.0	17.4	3.6	3.3	4.3	4.3	8.8	1.8	1.1	3.1	2.4	82.6
ITA	5.4	3.7	5.7	5.1	4.8	6.2	5.5	5.6	6.7	6.0	3.9	5.4	6.6	3.4	5.4	4.7	9.1	1.8	1.0	3.0	1.1	93.4
PRT	5.7	4.1	4.4	5.4	4.4	5.2	5.1	5.0	5.8	5.6	4.5	6.8	4.8	7.4	5.1	4.7	8.6	1.5	1.2	3.1	1.7	92.6
HUN	5.5	2.7	4.2	4.5	3.3	4.2	4.3	4.4	4.7	4.1	3.4	4.5	3.6	2.8	19.5	7.2	9.2	1.8	1.2	3.3	1.8	80.5
POL	4.6	3.4	4.2	4.5	4.1	4.2	4.3	4.1	5.0	4.1	4.2	4.4	3.5	2.6	8.5	15.7	8.7	1.5	1.3	4.2	3.1	84.3
NOR	5.4	3.5	4.2	5.2	4.2	4.7	4.6	4.5	6.2	4.2	3.6	5.2	3.8	2.6	5.5	5.2	19.0	1.8	1.1	3.7	2.0	81.0
USA	5.8	4.0	4.9	4.5	3.3	4.6	5.1	5.1	5.5	4.4	3.5	5.7	4.0	2.2	4.7	4.0	11.2	9.6	0.9	4.9	2.2	90.4
APAC	4.9	4.3	4.3	5.1	4.0	4.6	4.8	5.0	5.1	5.2	4.2	5.8	3.8	2.9	6.1	5.7	9.7	2.7	5.2	4.3	2.4	94.8
Brent	3.5	3.1	3.1	3.3	3.1	3.2	3.4	3.8	4.9	3.1	2.8	4.1	3.1	2.3	4.5	4.8	8.5	1.9	0.9	27.2	5.5	72.8
TTF	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.3	0.5	0.3	0.3	0.4	0.2	0.2	0.7	0.8	0.8	0.1	0.2	1.5	91.5	8.5
To	97.8	73.7	87.6	91.2	83.6	96.7	94.3	95.7	114	94.4	72.8	106	80.5	57.2	101.5	96.5	177.5	34.1	20.8	62.9	38.1	84.6
Net	8.5	-11.5	-4.7	0	-5.9	3.6	1.6	3.4	24.8	2.1	-16.2	23.4	-12.9	-35.4	21.1	12.3	96.5	-56.3	-74	-9.9	29.6	

Table C.4
Volatility spillover of MSCI equity indices of our sample EEA countries, US equity index, and APAC equity index, as well as Brent and TTF one month ahead future prices during the period of 1/1/2009 and 12/31/2012

	AUT	BEL	DEU	DNK	FIN	FRA	GBR	NLD	SWE	ESP	GRC	IRL	ITA	PRT	BGR	HRV	HUN	POL	ROU	SVN	NOR	USA	APAC	Brent	TTF	From
AUT	12.3	3.1	5.0	2.6	4.7	5.1	2.5	4.0	5.8	5.7	5.2	3.6	6.4	3.1	0.6	0.6	7.9	6.8	3.6	0.8	6.0	0.9	0.5	1.8	1.9	87.7
BEL	6.5	5.8	5.4	2.8	4.9	6.0	2.9	4.8	5.8	6.4	5.2	4.1	6.7	3.5	0.6	0.7	7.5	6.5	2.7	0.7	5.7	1.0	0.4	1.8	1.7	94.2
DEU	6.5	3.4	7.4	2.7	5.5	6.7	3.1	4.9	6.7	6.1	4.7	3.8	7.4	3.0	0.6	0.4	7.0	6.6	2.3	0.6	5.9	1.3	0.5	1.9	1.0	92.6
DNK	6.4	3.1	5.0	7.6	5.2	5.0	2.6	4.1	6.7	4.7	6.0	3.9	5.7	3.0	0.8	0.6	6.9	6.7	3.1	0.8	6.6	1.0	0.5	2.2	1.8	92.4
FIN	6.3	3.1	5.6	2.9	10	5.7	2.6	4.2	6.7	5.7	4.9	3.7	7.0	3.2	0.7	0.5	7.1	6.7	2.4	0.8	5.7	1.1	0.5	1.8	1.3	90.0
FRA	6.5	3.7	6.4	2.6	5.5	7.2	3.0	4.9	6.3	7.0	4.9	4.0	7.9	3.4	0.6	0.4	6.9	6.2	2.3	0.6	5.7	1.2	0.4	1.7	1.0	92.8
GBR	6.1	3.4	5.9	2.7	5.0	5.9	5.2	4.5	7.0	5.4	4.7	4.2	6.6	2.8	0.6	0.4	6.8	6.7	2.7	0.6	7.0	1.3	0.6	2.5	1.5	94.8
NLD	6.5	3.7	6.1	2.8	5.2	6.4	3.0	6.0	6.4	6.3	5.1	3.9	7.4	3.4	0.6	0.4	7.1	6.4	2.3	0.7	6.0	1.2	0.4	1.8	1.2	94.0
SWE	6.5	3.0	5.6	3.0	5.6	5.5	3.1	4.3	11.3	5.0	4.1	3.7	6.1	2.7	0.5	0.4	6.8	7.1	2.9	0.7	7.0	1.3	0.5	2.1	1.4	88.7
ESP	6.5	3.5	5.3	2.2	4.8	6.2	2.4	4.3	5.0	12.0	5.8	3.9	8.8	4.1	0.6	0.4	7.2	5.8	2.4	0.7	4.4	1.0	0.3	1.5	1.1	88.0
GRC	4.5	2.1	3.2	2.3	3.0	3.2	1.5	2.8	3.3	4.1	36.8	2.8	4.1	2.8	1.0	0.3	5.4	5.0	3.0	0.8	3.5	0.6	0.5	1.3	2.3	63.2
IRL	6.0	3.1	4.7	3.0	4.4	5.1	2.8	3.9	5.5	5.4	5.4	13.3	5.7	2.9	0.6	0.4	6.3	6.2	2.6	0.6	6.0	1.1	0.5	2.2	2.4	86.7
ITA	6.7	3.3	5.8	2.4	5.4	6.4	2.7	4.6	5.7	8.0	4.9	3.8	10.5	3.8	0.6	0.5	7.1	6.0	2.1	0.7	5.4	1.2	0.4	1.6	0.8	89.5
PRT	6.5	3.5	4.8	2.6	5.0	5.5	2.3	4.2	5.2	7.6	6.9	3.7	7.5	7.3	0.7	0.6	7.4	6.1	2.9	0.8	5.0	0.9	0.3	1.4	1.4	92.8
BGR	5.4	2.1	3.4	2.7	3.9	3.0	1.5	2.6	4.6	3.8	8.2	2.5	4.6	2.3	15.7	2.0	6.4	5.9	4.2	1.4	5.0	1.1	1.0	3.7	3.2	84.3
HRW	6.1	2.3	2.6	2.0	2.7	2.5	1.4	2.2	3.7	3.0	3.9	2.0	3.3	1.9	1.3	24.1	6.5	9.5	3.8	1.2	5.0	0.7	0.7	2.9	4.7	75.9
HUN	6.5	2.8	4.3	2.4	4.1	4.4	2.2	3.6	4.9	5.1	4.6	3.4	5.5	2.8	0.7	0.6	19.4	8.1	3.3	0.8	5.3	0.9	0.5	2.0	2.1	80.6
POL	6.5	2.8	4.8	2.4	4.7	4.7	2.5	3.7	6.1	4.9	4.8	3.5	5.5	2.8	0.6	0.7	9.4	14.4	3.1	0.7	6.1	0.9	0.5	1.9	2.2	85.6
ROU	6.2	2.2	2.9	2.4	3.1	2.9	1.8	2.4	4.4	3.3	5.8	2.7	3.5	2.2	0.8	0.6	6.3	5.7	26.5	1.2	5.6	1.0	0.7	2.8	3.3	73.5
SVN	6.1	2.7	3.9	3.1	4.5	3.8	1.8	3.2	4.8	4.1	8.4	3.3	5.0	2.7	1.6	1.3	6.9	6.3	5.5	8.4	5.2	1.1	0.8	2.7	2.8	91.6
NOR	6.8	3.0	5.2	2.9	4.9	5.1	3.2	4.1	7.0	4.5	4.3	3.9	5.9	2.7	0.6	0.6	7.1	6.9	3.1	0.7	11.9	1.1	0.5	2.3	1.8	88.1
USA	5.8	2.7	5.5	2.6	5.0	5.1	3.1	4.2	6.8	4.8	4.5	4.1	6.4	2.4	0.7	0.7	5.7	6.0	3.6	0.6	6.0	7.2	0.8	3.9	2.1	92.8
APAC	5.9	2.5	5.0	2.7	4.8	4.1	2.4	3.5	5.5	4.2	7.8	3.7	5.4	2.5	1.3	0.8	6.8	7.3	4.2	0.9	5.7	1.9	4.7	3.6	2.9	95.3
Brent	5.0	2.1	3.6	2.5	3.4	3.1	2.5	2.8	4.2	3.1	4.6	2.8	4.1	1.7	0.8	1.0	5.9	6.6	4.3	0.8	6.1	1.6	0.9	22.6	4.1	77.4
TTF	3.0	1.1	1.6	1.2	1.3	1.3	1.0	1.4	2.8	1.3	4.5	2.2	1.2	0.8	0.5	0.6	4.7	5.5	1.8	0.5	3.3	0.4	0.5	1.9	55.6	44.4
To	144.8	68.2	111.5	61.2	106.4	112.6	57.4	89.1	130.6	119.3	129.2	83.1	137.5	66.3	17.9	15.5	162.6	156.5	74.2	18.4	133.2	25.7	12.9	53.1	49.7	85.5
Net	57.1	-26.1	18.9	-31.2	16.4	19.8	-37.4	-5.0	41.9	31.3	66	-3.6	48	-26.5	-66.4	-60.4	82	71	0.7	-73.2	45.1	-67.1	-82.4	-24.3	5.3	

Table C.5
Volatility spillover of MSCI equity indices of our sample EEA countries, US equity index, and APAC equity index, as well as Brent and TTF one month ahead future prices during the period of 1/1/2013 and 12/31/2015

	AUT	BEL	DEU	DNK	FIN	FRA	GBR	NLD	SWE	ESP	GRC	IRL	ITA	PRT	BGR	CZE	EST	HRV	HUN	POL	ROU	SVN	NOR	USA	APAC	Brent	TTF	From
AUT	16.8	3.6	4.9	2.1	4.2	4.8	2	3.5	3.4	5.5	6.1	3.3	7.6	5.5	2.8	2.2	1.3	1.1	3.6	4	1.3	1.5	3.2	1	0.7	2.4	1.9	83.2
BEL	5.2	10.6	6.1	2.4	4.4	6.5	3.2	5.4	4	6.6	3.5	3.9	7.2	5.2	3.2	2	1.2	0.8	3.4	3.5	1.3	1.4	3.5	0.9	0.7	2.1	1.5	89.4
DEU	6	5.2	10.1	2.4	4.7	7.3	3.2	5.9	4.4	6.2	3.8	4.1	8.2	4.9	2.4	1.6	1.1	0.8	3.3	4	1.2	1.3	3.1	0.9	0.6	1.7	1.8	89.9
DNK	4.6	3.6	4.3	15.5	4	3.7	2.3	3.7	4.4	4.1	8.1	3.6	4.7	4.1	3.7	2.3	1.4	0.9	3.4	4.1	1.5	1.5	3.4	0.9	0.9	2.9	2.4	84.6
FIN	6.3	4.4	5.5	2.7	10.8	5.5	3	4.6	4.5	5.6	5.3	3.8	7.5	5.2	2.9	1.7	1.3	0.8	2.7	3.7	1.5	1.7	3.4	1	0.8	2.2	1.8	89.2
FRA	5.7	5.4	7.2	2.1	4.7	8.9	3.4	5.9	4.3	7.5	3.7	4.1	9.4	5.3	2.5	1.4	1.1	0.7	3	3.5	1.1	1.2	3.1	0.9	0.6	1.7	1.7	91.1
GBR	4.5	4.9	5.9	2.2	4.5	6.3	8.5	5.6	4.5	5.5	4.5	4.1	7	5.4	2.5	1.4	1.1	0.7	2.3	3.7	1	1.2	4.9	1.7	0.9	3.4	1.8	91.6
NLD	5.3	5.6	7.2	2.5	4.9	7.3	3.6	8.5	4.5	6.6	3.7	4	8.4	5.1	2.4	1.2	1.1	0.7	3	3.5	1.2	1.5	3.4	1	0.6	1.7	1.7	91.5
SWE	5.4	4.3	5.7	3.2	4.8	5.8	3.3	4.8	10.9	5.3	4.4	3.1	6.8	4.3	2.8	2	1.3	0.8	3.1	4.7	1.4	1.4	4.6	1	0.9	2.2	1.8	89.1
ESP	5.7	4.7	5.2	1.9	4	6.3	2.4	4.4	3.3	13.3	4.4	3.7	10.9	6	2.8	1.6	1.6	0.8	3.3	3.4	1	1.4	2.8	0.9	0.6	1.8	1.9	86.7
GRC	1.1	0.7	0.6	0.6	0.6	0.5	0.2	0.3	0.3	0.8	79.8	0.9	1.1	1	1.6	0.7	0.8	0.4	0.6	0.8	0.5	0.5	1.1	0.4	0.2	2.6	1.4	20.2
IRL	4.8	4.1	4.6	2.4	3.5	4.8	2.5	3.7	2.6	5.2	7.7	16.6	6.1	5.1	3.4	1.8	1.2	1.1	3.5	2.5	1.3	1.4	2.9	0.9	0.8	2.6	3.1	83.4
ITA	6	3.9	5.4	1.8	4	6	2.3	4.3	3.4	8.1	4.9	3.5	17.1	6	2.8	1.5	1.4	0.8	3.4	3.1	1.2	1.5	2.6	0.8	0.5	1.3	2.4	82.9
PRT	5.1	3.4	3.8	1.9	3.1	4	2.1	3.2	2.3	5.5	7.6	3.5	7	19.9	3.1	1.7	1.5	1.1	3	3.1	1.3	1.6	3.7	0.8	0.7	2.6	3.6	80.1
BGR	3.6	2.6	1.7	2.1	1.9	1.8	0.8	1.3	1.5	2.9	4.4	2.5	3.1	2.6	41.8	1.8	1.5	1.7	4	2.2	2.6	3.5	1.9	0.6	0.8	2	2.9	58.2
CZE	4.5	2.9	2.7	2.2	2.3	2.6	1.3	1.8	2.6	3.4	9.3	2.7	4	3.1	4.2	19.4	2.3	1.2	5	6.8	2	2	3.6	0.8	1.3	2.7	3.4	80.6
EST	3.2	2.7	2.6	2	2.1	2.3	1	1.7	1.9	3.3	10.1	2.2	3.8	3.3	5	2.8	23.3	2.1	2.9	3.1	2.4	2.5	2.5	0.8	0.8	4.5	5.1	76.7
HRV	4.8	2.7	2.5	2.3	2.1	2.5	1	1.8	1.9	3	9.9	3.7	4.6	3.8	5.4	2.9	3.3	17.6	3.6	3.5	3.1	3	2.8	0.9	1	2.6	3.8	82.4
HUN	4.8	2.9	3.1	2	2.3	2.9	1.1	2.3	2.3	3.6	6.5	3.3	4.8	3.3	3.2	2.7	1.7	1.4	27.5	5.6	1.9	1.8	2.3	0.6	0.8	2.1	3.3	72.5
POL	4.7	3.2	4	2.3	3.2	3.7	2.1	2.9	3.8	3.9	3.7	2.5	4.7	3.2	3	3.7	1.2	1	5.6	23.9	2.3	1.7	3.1	0.7	0.9	2.6	2.3	76.2
ROU	4.1	3.4	2.8	2.1	2.9	2.5	1.3	2.4	2.2	2.7	6.8	3	3.7	2.8	5.8	2.9	2.3	2.2	4.7	4.7	18.8	4.7	2.8	0.8	0.9	2.8	4.1	81.2
SVN	4.1	2.9	2.2	2	2.6	2.2	1.1	1.9	1.9	3.1	6.4	3.5	4.3	3	7	2.1	2.5	2	4	3.6	4.2	22.8	2.4	0.9	0.8	2.8	3.9	77.2
NOR	4.2	3.3	3.6	2	3.2	3.7	3	3.2	3.9	3.8	8.5	2.8	4.8	5.5	3.1	2.1	1.6	1	2.1	3.2	1.1	1.4	19.4	1.2	0.8	5.2	2.2	80.6
USA	4.5	3.6	4.2	2	3.7	4.1	3.7	3.9	3.2	3.8	8.6	3.5	5.3	5.2	3.3	1.5	1.4	1.1	2.1	3.1	1.5	2	4.3	10.4	1.7	5.6	2.7	89.6
APAC	4.2	3.8	3.8	2.5	3.4	3.8	3.2	3.3	3.9	4.1	6.3	3.6	5.3	4.7	4.2	2.3	2	1.1	3.3	3.8	2.1	1.9	5	3.1	9.3	3.8	2.1	90.7
Brent	1.9	1.4	1.4	0.9	1.1	1.3	1.3	1.5	1.1	1.5	13.9	1.1	1.6	2.3	2	1.2	1.5	0.9	1.2	1.6	0.9	1	3.5	1.5	0.5	47.7	4.4	52.3
TTF	0.9	0.6	0.7	0.7	0.6	0.5	0.2	0.4	0.4	0.4	3.3	0.6	0.8	1.4	2	0.6	0.9	1	1.4	0.9	1.3	1.1	0.6	0.2	0.2	2.2	76	24
To	115.1	89.8	101.7	53.3	82.9	102.7	54.4	83.8	76.4	111.6	165.1	80.4	142.8	107.1	87.2	49.5	39.7	28.2	81.5	89.7	42.2	45.3	80.3	25.3	19.7	70.3	69.4	77.6
Net	31.9	0.4	11.7	-31.2	-6.2	11.5	-37.2	-7.7	-12.7	24.9	144.9	-2.9	59.9	27	29.1	-31.1	-37	-54.2	8.9	13.5	-39	-31.9	-0.4	-64.3	-71.1	18	45.4	

Table C.6

Volatility spillover of MSCI equity indices of our sample EEA countries, US equity index, and APAC equity index, as well as Brent and TTF one month ahead future prices during the period of 1/1/2016 and 12/31/2019

	AUT	BEL	DEU	DNK	FIN	FRA	GBR	NLD	SWE	ESP	GRC	IRL	ITA	PRT	BGR	CZE	EST	HRV	HUN	LTU	POL	ROU	SVN	NOR	USA	APAC	Brent	TTF	From
AUT	15.9	2.6	4	2	2.2	3.9	3.3	2.5	2.9	6.2	12.3	3.2	7.4	3.2	1.6	1.4	0.5	0.8	3	0.8	5.1	1.8	1	3.6	1	0.6	3.1	4.1	84.1
BEL	4.6	11.5	4.5	2.6	2.4	4.9	3.3	3.7	3.2	5.8	10.1	4.2	6.8	3.2	1.6	1.4	0.6	0.8	2.5	0.9	4.3	1.8	0.9	3.6	1.2	0.7	3	6.1	88.5
DEU	5.2	3.4	8.1	2.5	3	6.1	4.3	4.3	4.4	6.8	10.7	4.3	8.1	3.4	0.8	1.1	0.4	0.7	2.5	0.7	4.7	1.1	0.7	3.9	1.2	0.6	2.5	4.4	91.9
DNK	3.5	2.8	3.5	13.4	1.9	3.5	2.7	2.7	2.5	4.4	14	3.5	5.5	3	1.5	2	0.5	1.1	3	0.8	4.4	1.4	1.2	4.2	0.9	0.8	4.5	7	86.6
FIN	5.1	2.9	4.7	2.7	9.9	4.4	3.2	3.3	4.8	4.9	11.3	4.2	6.3	3.2	1.3	1.5	0.6	1	2.5	0.9	4.8	1.4	1	4.2	1.3	0.6	3.1	5.1	90.2
FRA	5	3.6	5.9	2.3	2.7	7.5	4.7	4.4	4	7.5	10.8	4.6	8.7	3.9	0.9	1.1	0.3	0.6	2.4	0.6	4.6	1.3	0.6	4.1	1.1	0.6	2.3	3.9	92.5
GBR	4.9	2.6	4.8	2.1	1.9	5.4	9	3.7	3.6	7.4	13.9	4.5	8.2	3.7	0.8	1.2	0.4	0.7	2.6	0.5	4.6	1.2	0.6	4.4	1.1	0.7	2.7	2.9	91
NLD	4.4	3.7	5.8	2.6	2.7	6.1	4.6	6.4	3.8	7	11.4	4.3	7.7	3.5	0.9	1.2	0.4	0.6	2.4	0.7	4.3	1.5	0.8	3.8	1.4	0.6	2.8	4.8	93.6
SWE	4.8	2.8	5.1	2.5	3.6	4.9	3.9	3.3	9.2	5.2	11.2	4.4	6.8	3.2	0.9	1.3	0.4	0.8	2.5	0.7	4.9	1.3	0.7	5.1	1.3	0.6	3.1	5.9	90.8
ESP	5.2	2.8	4.5	2	1.5	5.1	4.2	3.5	2.5	12.7	14	3.7	10.4	3.8	1	1.4	0.4	0.8	2.9	0.5	4.6	1.4	0.8	3.6	0.8	0.6	2.7	2.7	87.4
GRC	2.7	1.2	1.9	1.8	0.6	2	2.1	1.5	1.2	4.2	51.2	1.8	5.2	1.9	0.9	1.4	0.3	0.7	2.2	0.5	3.9	1	0.7	2.6	0.4	0.6	3.1	2.4	48.8
IRL	4.2	3	4.3	2.6	2.3	4.6	4.2	3.2	3.5	5.9	14.6	11.8	7.1	2.8	1	1.2	0.5	0.7	2.5	0.7	4.5	1.4	0.9	3.3	1.1	0.5	2.9	4.8	88.3
ITA	5.2	2.6	4.5	2	1.6	4.8	3.7	3.1	2.7	8.7	14.5	3.5	16.8	3.6	0.9	1.2	0.3	0.7	2.4	0.5	4.3	1.2	0.8	3.3	0.9	0.5	3.4	2.7	83.2
PRT	4.1	2.6	3.7	2.4	1.8	4.2	3.5	2.8	2.5	6.4	13	2.9	7	12.4	1.2	1.4	0.6	0.9	2.9	0.6	5.3	1.3	1.2	4.5	0.9	0.8	4.3	4.9	87.6
BGR	2.7	1.7	1.5	2.4	0.9	1.2	0.8	0.9	0.9	1.9	9	1.6	2.7	2.4	30.6	2	1.9	1.8	2.6	1.2	4.8	1.8	2.4	1.8	0.9	0.7	5.2	11.7	69.4
CZE	3.5	2	2.2	2.4	1.4	2.2	2	1.6	1.4	4.3	17.2	2.2	5.6	3.2	2.7	13	1.2	1.4	4	1.4	6.1	2.2	1.6	3.4	0.8	0.9	5.7	4.6	87
EST	2.2	1.7	1.6	2.7	1.1	1.3	1.2	1.3	0.8	2.3	9.4	2	2.4	2	2.8	1.8	32	2.1	3.2	2	5.6	2	3.2	2.2	1	0.7	4.3	5.5	68
HRV	3	1.8	1.9	2.4	1.4	1.6	1.5	1.2	1.2	2.8	9.7	1.6	3.5	2.9	4.9	1.9	3	15.6	3.7	1.6	5.3	2.5	3	2.3	0.8	0.7	6.6	11.9	84.4
HUN	3.8	1.8	2.6	2.1	1.2	2.4	2.2	1.8	1.9	4.2	12.8	2.1	4.6	3.1	1.7	2.3	1	1.2	20.7	0.9	7.6	2.3	1.4	2.9	0.9	0.8	3.3	6.3	79.3
LTU	3.4	2.3	2	2.8	1.7	1.9	1.4	1.5	1.8	2.8	10.6	2.1	3.6	3	3.4	2.6	2.7	1.7	3.9	13.8	5.8	2	2.8	2.9	1.5	1	5	10.1	86.2
POL	4	2.2	3.1	2	1.7	3	2.5	2.1	2.6	4.4	11.4	2.8	4.6	3.2	1.6	2	1	1	5	1	21.2	1.7	1.4	3.5	0.8	0.9	3.2	6.3	78.8
ROU	2.8	1.7	1.3	1.9	0.8	1.6	0.9	1.1	0.6	2.7	7.4	1.4	3.2	2.4	1.6	1.2	1	1.3	2.4	1.2	3.8	42.6	1.5	1.8	1	0.5	4.1	6.3	57.4
SVN	2	1.5	1.5	2.8	1.1	1.3	0.9	1	0.6	2.4	8.4	1.7	3	3.2	3.4	1.7	2.1	1.7	4	1.5	5.2	1.7	23.7	2.3	0.6	0.7	6.8	13.3	76.4
NOR	4.1	2.5	3.8	2.7	2.4	4	3.5	2.6	4	5.2	13.4	3.2	6.1	3.8	1.3	1.5	0.4	0.7	2.5	0.7	5	1.7	0.8	13.2	1	0.9	4.8	4.3	86.8
USA	3	2.6	3.6	2	1.7	3.5	2.6	3.3	2.8	4	6.5	3.3	5.7	2.2	1.3	0.8	0.5	0.6	1.7	1.1	3.8	3.1	0.9	2.4	16	0.9	6.3	14.1	84
APAC	3.2	2.5	3	2.5	1.2	3	2.6	2.4	1.9	3.9	13.6	2.1	5.4	3.4	2.2	1.7	0.6	1	2.6	1.2	5.2	1.8	1.8	4.2	3	9.2	6.8	7.9	90.8
Brent	1.3	1.1	1.2	1.7	0.7	1.1	0.8	0.9	0.9	1.8	7.5	1.1	2.9	1.6	1.2	0.9	0.3	0.5	0.7	0.5	2.2	1.6	1.1	2	0.8	0.8	53.9	9.2	46.1
TTF	0.3	0.3	0.2	0.5	0.2	0.2	0.1	0.2	0.2	0.2	1.2	0.4	0.3	0.3	0.5	0.1	0.1	0.2	0.5	0.2	0.6	0.4	0.4	0.3	0.2	0.1	2	89.8	10.2
To	98	62.1	86.4	60.7	45.8	88.1	70.6	63.9	63	123.1	300	76.6	148.5	78.9	43.7	39.4	21.9	25.8	73.1	23.7	125.2	44	34.3	86	27.7	18.3	107.5	172.9	78.9
Net	13.9	-26.4	-5.4	-25.9	-44.3	-4.4	-20.5	-29.8	-27.8	35.7	251.3	-11.7	65.4	-8.8	-25.7	-47.6	-46.2	-58.6	-6.2	-62.5	46.4	-13.4	-42	-0.9	-56.3	-72.5	61.4	162.7	

Table C.7

Volatility spillover of MSCI equity indices of our sample EEA countries, US equity index, and APAC equity index, as well as Brent and TTF one month ahead future prices during the period of 1/1/2020 and 12/31/2020

	AUT	BEL	DEU	DNK	FIN	FRA	GBR	NLD	SWE	ESP	GRC	IRL	ITA	PRT	BGR	CZE	EST	HRV	HUN	LTU	POL	ROU	SVN	NOR	USA	APAC	Brent	TTF	From
AUT	7.6	5.1	4.4	0.9	2.6	4.7	3.4	2.3	3.6	4.6	3.7	2.4	6	2.7	2.6	1.9	0.5	0.8	4	1.1	3.6	1.9	1.4	4.8	1.9	0.4	13.1	8.1	92.4
BEL	5.4	7.9	4.7	1.2	2.7	4.9	3.9	2.5	4.1	4.4	4.1	2.6	6	2.5	2.2	1.5	0.6	0.8	3.8	1.2	4.1	2	1.1	5.1	1.9	0.5	11.7	7	92.1
DEU	4.9	5.1	6.3	1.2	3	5.3	3.9	3	4.6	4.6	3.2	3	6.7	3.2	1.9	1.9	0.4	0.7	4.4	1	4.3	2.1	1.2	4.9	1.9	0.4	11.1	6.1	93.7
DNK	2.3	4	4.4	4.4	2.4	4	2.9	3	3.9	3.2	4.3	2.5	5	3.6	1.6	1.4	0.3	0.7	3.6	1.1	5.5	2.1	1.6	4.4	1.6	0.5	9.6	16.2	95.6
FIN	4.7	4.8	5	1.3	4.4	4.7	3.7	2.8	4.6	4.3	4.5	3	5.8	3	2.2	1.6	0.3	0.7	4.3	1.2	4.4	2.2	1.3	5.4	2.3	0.4	11.1	6	95.6
FRA	5.3	5.4	5.4	1.3	2.9	5.9	4.1	2.8	4.5	5	3.7	2.8	6.8	3.1	1.9	1.9	0.4	0.7	4.3	0.9	4.2	2.1	1.2	5.1	1.9	0.4	10.7	5.4	94.1
GBR	4.7	5.2	5	1.2	2.8	5.1	5.5	2.8	4.3	4.8	4.1	2.9	6.4	3.1	2	1.9	0.4	0.6	4.1	0.8	4.1	2.4	1.1	5	2	0.5	10.7	6.3	94.5
NLD	4	4.7	5.3	1.5	3	4.7	3.8	4	4.4	3.9	3.7	3	6.3	3.6	2.2	1.7	0.3	0.7	4.1	1	4.1	2.1	1.3	4.9	2.1	0.5	11.2	7.9	96
SWE	4.6	5.2	5.3	1.3	3.2	5.1	4	2.9	5.6	4.3	3.1	3.1	6.3	3.1	1.9	1.5	0.3	0.8	4.3	1	4.2	2.1	1.2	5.6	2	0.5	11.8	5.9	94.4
ESP	5.2	4.8	4.8	1.2	2.7	5	3.9	2.5	3.8	6.2	4.3	2.3	6.8	3.2	2.3	1.9	0.3	0.7	3.8	0.9	4.4	2.1	1.2	4.7	2	0.4	11.9	6.7	93.8
GRC	3.2	4	3.4	1.4	2.3	3.4	3	2.2	2.3	3.9	14.5	1.9	4.7	2.9	2.6	1.9	0.5	0.7	3.4	0.8	5	2.2	1.4	4.9	2.6	0.5	14.2	6.2	85.6
IRL	4.6	4.9	5	1.2	3	4.7	3.8	2.8	4.2	3.9	4.7	4.9	6	3	2.4	1.7	0.5	0.8	4.3	1.1	4.1	2.3	1.5	5	2.4	0.5	11.2	5.5	95.1
ITA	4.6	4.8	5	1.2	2.6	5	3.8	2.8	4.1	4.9	3.5	2.6	8.1	3.5	2.5	1.7	0.3	0.8	3.6	0.9	4.1	2	1.3	4.9	1.9	0.4	13.5	5.8	92
PRT	3.2	3.8	4.7	1.6	2.5	4.3	3.4	3	3.8	3.9	4.1	2.6	6.6	6.5	2.8	1.5	0.4	0.8	3.6	1	4.6	1.9	1.4	4.9	1.9	0.5	13.4	7.5	93.5
BGR	2.8	3	2.7	0.8	1.9	2.7	2.2	2.2	2.2	2.6	5	1.9	4.8	3.3	10.2	1.2	0.5	1.1	3	1.3	3.2	1.9	1.9	4.1	2.6	0.6	24.3	6.3	89.8
CZE	4.2	3.6	4.2	1.1	2.3	3.9	3	2.4	2.9	4	5.5	2.4	5.6	3.1	2.9	4	0.5	1	4.3	1.2	4.3	2.6	1.8	4.4	2.1	0.5	14.2	8.2	96
EST	2.9	3.5	2.9	1.3	1.8	3	2.2	1.9	2.2	2.9	5.5	1.8	4.6	3.1	4.4	1.4	3.8	1	3.4	1.5	3.9	2.5	2	4.1	2.3	0.6	19.2	10.5	96.2
HRV	3.4	3.5	3.4	1.3	1.9	3.3	2.3	2.3	2.8	3.2	5.1	2	5.6	3.7	4.7	1.5	0.6	2.1	3.5	1.4	4.7	1.8	2	4.5	2.2	0.5	18.4	8.4	97.9
HUN	3.9	4.1	4.3	1.2	2.4	4	3.2	2.5	3.4	3.6	4.4	2.4	5.5	3	3	1.9	0.4	0.8	8.5	0.9	5.2	2.6	1.4	4.7	2.2	0.4	13.7	6.6	91.5
LTU	3.6	3.9	3.5	1	2.4	3.2	2.1	2.1	2.9	3.1	4.4	2.3	5.2	3.2	4.2	1.6	1.2	1.4	3.8	5.1	4.6	2.3	2.2	4.3	2.4	0.6	17.6	5.9	94.9
POL	3.4	4	4.4	1.6	2.5	3.9	3.3	2.5	3.4	4	5	2.6	5.5	3.4	2.2	1.7	0.4	0.8	4.5	1.1	8.8	2.4	1.4	4.6	1.8	0.5	13.6	6.6	91.2
ROU	3.5	4.3	4.1	1.2	2.4	4.1	3.5	2.3	3.3	3.8	4.5	2.5	5.3	2.9	2.5	2.1	0.6	0.8	4.8	1.3	4.7	5.7	1.7	4.7	2	0.6	13.6	7.4	94.3
SVN	3	2.8	3.5	1.3	1.9	2.9	2.2	2.1	2.3	2.7	5.1	2.1	4.7	3.1	3.4	1.5	0.6	1	3.2	1.3	3.8	2.4	4.7	3.9	2.1	0.5	19.2	12.7	95.3
NOR	4.5	5.1	4.7	1.3	2.9	4.6	3.7	2.7	4.3	4.1	4.2	2.4	6	3.1	2.1	1.7	0.4	0.7	4	1	4.3	2.1	1.2	7.1	2.1	0.5	11.9	7.1	92.9
USA	3.2	4.5	4.1	1.2	2.3	3.8	3.4	2.7	3.1	3.5	6	2.5	5.7	3.4	3.4	1.2	0.6	0.8	4	1	4	2	1.6	5.3	5.1	0.6	17	4.2	95
APAC	3.4	4.1	3.8	1.3	2.1	3.7	2.9	2.4	3.3	3	4.1	2.2	5.3	3	3.3	1.4	0.5	0.9	3.7	1.2	4	2.1	1.6	5.1	2.5	1.8	15	12.4	98.2
Brent	2.2	2.7	2.4	0.8	1.6	2.6	2.4	1.6	2.2	2.1	3.3	1.8	3.6	1.9	2.8	1	0.2	0.4	2.4	0.5	2.1	1.7	1.2	3.7	2.2	0.4	45.9	4.7	54.2
TTF	0.8	0.7	1.4	0.5	0.7	1	0.6	0.8	1	0.8	0.4	0.6	1.1	0.7	0.5	0.5	0.1	0.2	0.5	0.3	0.6	0.4	0.3	0.8	0.2	0.1	2.5	81.9	18.1
To	101.5	111.6	111.6	32.3	64.4	107.4	84.5	65.7	91.5	98.9	113.3	64.3	147.8	81.1	70.6	42.7	12	20.9	100.6	28.2	110.1	56.4	38.5	123.8	54.8	12.6	365.3	201.3	89.8
Net	9.1	19.4	17.9	-63.3	-31.1	13.3	-10	-30.3	-3	5.1	27.7	-30.8	55.9	-12.3	-19.2	-53.3	-84.2	-77	9.1	-66.7	18.9	-37.9	-56.8	30.9	-40.2	-85.6	311.1	183.2	

Table C.8

Volatility spillover of MSCI equity indices of our sample EEA countries, US equity index, and APAC equity index, as well as Brent and TTF one month ahead future prices during the period of 1/1/2021 and 12/31/2021

	AUT	BEL	DEU	DNK	FIN	FRA	GBR	NLD	SWE	ESP	GRC	IRL	ITA	PRT	BGR	CZE	EST	HRV	HUN	LTU	POL	ROU	SVN	NOR	USA	APAC	Brent	TTF	From
AUT	16.7	3.1	1.6	1.5	1.9	2.7	1.2	3	5.3	4.3	3.6	4.3	3.2	0.2	1.9	0.3	0.4	3.1	0.9	4.2	1.1	0.3	4.4	5.6	0.5	0.5	5.7	18.6	83.4
BEL	6.6	10.6	3.7	1.8	2.7	4.4	2.3	4.7	5.9	5.8	4.1	5.5	4.4	0.4	1	0.6	0.5	4	1.1	5.3	1.2	0.7	5.3	5.4	0.8	1	5.7	4.7	89.4
DEU	4.3	3.7	8.2	2.2	4.3	5.1	5.4	6.8	4.6	3.5	4.1	6.6	2.8	0.4	1	0.6	0.6	4.5	0.9	5.9	0.6	0.4	5	4.9	1	0.6	7.8	4.3	91.8
DNK	4.7	2.6	3.1	20.1	3.2	2.2	5.2	4.5	3.2	4.4	2.7	2.9	3.6	0.5	0.9	0.8	0.4	4	0.8	7.8	1.2	0.7	2.4	3.3	1.5	0.7	7.5	5.3	79.9
FIN	5.4	3.1	4.3	2.8	10.5	3.8	4.2	6.9	3.9	3.8	3.2	5.3	4.6	0.6	1.4	0.7	0.7	4.4	1.6	6.7	1	1	4	5.2	1.3	0.9	6	2.7	89.5
FRA	6.7	4.4	5.5	1.5	4.1	7.5	3.5	5.9	6.4	4.1	3.8	7.3	3.2	0.6	1.4	0.7	0.4	4	1	5.4	0.7	0.6	5.4	5.7	1.1	0.6	7.5	1.4	92.6
GBR	4.4	2.4	4.8	3.8	4.3	3.2	15.4	6.4	3.5	3.8	2.7	3.9	3.3	0.6	1.1	1.1	0.5	4.3	0.8	5.1	0.5	0.7	3.6	4.1	1.7	0.8	8.5	4.8	84.6
NLD	5.3	3.1	4.7	2.1	4.3	3.8	4.4	13	3.4	3.6	3.8	4.7	3.8	0.6	1.1	0.8	0.4	4.6	1	5.3	1	1	4.5	6.3	0.8	0.8	7.8	4	87
SWE	9.1	4.4	3.5	1.2	2.6	4.8	2.2	3.4	11.6	5	3.8	6.8	3.9	0.6	1.6	0.8	0.5	4	0.8	4.6	0.8	0.6	5.3	5.1	0.9	0.5	6.8	5	88.4
ESP	6.4	3.8	2.4	2.2	2.1	2.8	3.2	3.5	5.1	18	2.5	4.7	4.2	0.3	1.7	0.5	0.5	5.7	0.7	4	1.9	0.8	4	4.6	0.9	0.8	6.2	6.8	82
GRC	6.2	3.4	3.3	2.1	2.9	2.7	2.7	5.3	3.9	4.1	14.8	5	5.2	0.7	1.6	0.8	0.6	3.2	1.2	5.1	0.9	0.8	5.2	5.5	0.9	0.8	6.1	5.3	85.2
IRL	6.8	3.9	5	1.1	3.5	5.2	2.5	5.1	6.4	4.4	4.5	11.6	2.6	0.4	1.2	0.8	0.4	3.2	0.8	4.5	0.9	0.3	5.4	5.9	0.7	0.5	7.8	4.8	88.4
ITA	4.6	3.4	2.1	2.3	3.1	2.2	2	3.7	4.2	6	4.1	3.2	24.2	1	1.4	1.1	0.9	2.4	1.8	4.8	1.4	0.8	4	4.3	0.6	1	4.3	5.2	75.8
PRT	3.1	0.9	0.6	1.8	0.8	0.9	1.3	2.2	1	4.1	2.7	1.2	3	45.8	0.8	1.2	0.4	1.5	1.7	2.7	1.6	1.4	1	1.8	0.6	0.3	3.6	12.1	54.2
BGR	6.6	1.4	1.5	2.2	2	1.6	2.1	2.5	2.6	4.5	3.3	2.5	3.1	1.5	17.1	0.6	0.5	5.4	1	3.7	1.3	0.7	1.8	4.2	0.8	0.9	8.4	16.6	82.9
CZE	1	0.6	0.7	0.4	0.4	1	0.9	2.8	1	2.2	0.5	1	1.5	1.3	0.6	37.3	0.4	1.5	2.2	2.1	1.2	0.3	0.7	2.3	0.1	2	21.3	12.8	62.7
EST	4.3	2.3	1.5	2.4	3.1	1	1.3	2.6	2.5	6.3	3.6	2.9	6.9	1	1.4	1.3	7.1	4.6	1.7	5.2	2	0.6	2	2.6	0.6	0.8	4.7	23.7	92.9
HRV	5.8	1.6	2	2.1	1.7	1.7	2.3	2.5	3.6	6	2.5	2.8	2.9	0.9	1.8	0.4	0.8	23.2	0.9	4.5	1.5	0.4	2.4	3	0.8	0.6	8.5	12.9	76.8
HUN	3.2	2.2	2	1	3.5	2.4	1	4	1.7	4.9	6.3	3.2	4.1	2	0.9	5.2	0.9	2.4	21.7	7	1.7	0.9	2.6	4	0.2	0.7	6.3	4	78.3
LTU	5.2	2.5	2.7	1.9	2.1	2.1	1.5	3.2	3.1	3.5	3	3.3	2.2	0.3	0.8	1.1	0.4	3.5	0.8	19.9	1.6	0.9	3.7	3.8	0.5	0.6	9.1	17.1	80.1
POL	3	1.4	0.8	1.8	1.3	0.8	1.1	2.4	1.3	4.4	2.1	1.8	2.7	2.5	0.8	1.1	0.5	2.9	1.2	3.3	11.4	1.8	1.9	3.1	0.3	0.6	5.3	38.6	88.7
ROU	3.3	1.4	1.2	2.4	3.4	1.4	1.5	4.5	1.8	5	3.1	1.9	5.1	1.5	1.7	2.6	0.9	3.8	2.9	5.3	3.5	20.7	3.9	5.9	0.5	1.1	6.3	3.8	79.3
SVN	7.3	3.7	3.9	1.8	3.2	4	2.8	5.2	5.1	4	4.9	5.6	4	0.5	1.3	0.4	0.4	2.8	0.8	5.8	0.8	0.8	9.9	7.6	0.9	0.8	6.4	5.7	90.1
NOR	6.4	2.8	2.5	1.1	2.3	2.8	1.6	4.7	3.6	4.1	2.7	4.1	3.2	0.6	1.5	0.6	0.4	3.4	1.2	4.7	1.4	0.9	5.4	18.9	0.8	1.2	10.9	6.5	81.1
USA	5	3	3.4	3.1	3.5	3	4.5	4.3	5	5	3.2	3.3	3.3	1.8	1.3	0.6	0.4	6.5	0.6	7.7	0.6	0.8	4.3	4.5	7.8	1.5	9.1	3.1	92.2
APAC	5.1	2.9	2.5	2.1	2.5	2.4	3.4	4.3	4.4	3.9	3.7	3.4	2.9	1.7	1.1	1.1	0.4	3.5	0.6	5.9	0.9	1.1	4.6	4.9	2.3	7.4	10.9	10.1	92.6
Brent	3.2	1.2	1.6	1.2	0.9	1.5	1.2	1.9	2.5	2.5	1.6	2.4	1.6	0.5	0.8	0.7	0.2	3.6	0.4	3.2	0.9	0.1	2.1	3.7	0.6	1.4	53.4	5.3	46.6
TTF	0.7	0.2	0.1	0.5	0.1	0.1	0.2	0.1	0.2	0.2	0.5	0.2	0.1	0.2	0.3	0.1	0	0.5	0.2	0.4	0.2	0.1	0.2	0.3	0.1	0	0.3	94	6.1
To	133.3	69.6	70.8	50	69.5	69.7	65	106.3	95.2	113.3	86	99.7	91.5	22.9	32.2	26.5	13.1	97.2	29.2	130	32.2	19.2	95.1	117.6	21.6	21.9	198.6	245.2	79.4
Net	49.9	-19.8	-21	-30	-20	-22.9	-19.6	19.2	6.8	31.3	0.8	11.3	15.7	-31.3	-50.7	-36.2	-79.8	20.4	-49.1	50	-56.4	-60.1	5	36.6	-70.6	-70.7	152	239.1	

Table C.9

Volatility spillover of MSCI equity indices of our sample EEA countries, US equity index, and APAC equity index, as well as Brent and TTF one month ahead future prices during the period of 1/1/2022 and 12/31/2022

	AUT	BEL	DEU	DNK	FIN	FRA	GBR	NLD	SWE	ESP	GRC	IRL	ITA	PRT	BGR	CZE	EST	HRV	HUN	LTU	POL	ROU	SVN	NOR	USA	APAC	Brent	TTF	From
AUT	10.9	2	3.6	0.7	2.7	3	3	3.6	2.4	2.4	3.1	4.1	0.9	0.9	2.3	0.6	0.7	8.7	1.9	8.9	1.1	2.2	1.9	1.6	0.7	0.2	0.9	25.3	89.1
BEL	6.3	3.9	4.7	1.5	3.2	3.9	4.8	4.9	3.2	2.4	4.3	5	1	0.8	2.5	0.9	0.6	6.1	1.5	8.7	0.9	1.4	2.5	1.2	1.6	0.2	0.5	21.7	96.1
DEU	6.6	2.6	6.2	1.1	3.1	4.5	5.8	5.5	3.4	2.3	5.1	5.6	0.9	0.8	1.9	0.9	0.6	6.5	1.4	8.7	1.2	1.6	2.4	1.3	1.3	0.1	0.5	18.2	93.8
DNK	3.5	2.7	3.6	14.5	3.2	3.6	6.2	7.2	2.5	1.5	5.5	3.9	1.6	1.6	1.4	0.5	0.8	3.4	1	7.3	0.8	0.6	2.1	3.3	3.6	0.6	1.1	12.5	85.5
FIN	6.4	2.3	4.2	1.3	5.2	3.4	4.1	5.8	2.8	2.2	4.1	4.5	1	0.7	2.4	0.8	0.8	6.5	1.4	8.7	1	1.6	2.3	2.1	1.2	0.3	0.5	22.5	94.8
FRA	6.1	2.5	5.2	1.3	2.9	4.9	5.5	4.9	3.3	2.3	4.8	5.4	0.9	0.8	1.8	0.8	0.7	7.3	1.4	8.4	1.1	1.6	2.5	1.2	1.3	0.2	0.5	20.4	95.1
GBR	5.3	2.8	5.9	1.8	3.2	4.8	10.6	6.7	3	2.2	5.7	5.3	1.1	0.9	1.9	1	0.7	6.9	1.3	7.7	0.9	1.2	2.4	1.3	2.6	0.3	0.5	12.1	89.4
NLD	5.4	2.6	5.3	2.2	4	4.1	6.6	9.9	2.9	2.3	5.6	4.9	0.8	1	1.6	0.8	0.7	4.9	1.3	9	0.9	1.1	2.4	2.2	2.2	0.3	0.5	14.5	90.1
SWE	6.3	2.6	4.8	1.1	2.9	4	4.1	4.4	5.1	2.4	4.4	5.8	1	0.8	2.2	0.7	0.7	7.1	1.5	9.2	1.2	1.6	2.9	1.8	1.3	0.2	0.4	19.8	94.9
ESP	6	1.7	2.9	0.7	2.4	2.5	2.9	3.4	2.3	8.5	3	3.4	0.6	1.2	2.5	0.9	0.7	8.9	1.7	8.5	1	2.1	1.7	1.8	0.9	0.3	0.9	26.7	91.5
GRC	5.6	2.2	4.7	1.7	2.9	4	5.6	5.5	3	2.3	8.3	4.5	0.6	0.9	1.5	0.7	0.8	8	1.5	8.3	0.9	1.4	2.3	1.5	1.8	0.2	0.6	18.8	91.7
IRL	6.7	2.5	5.1	1	3	4.2	4.6	4.6	3.7	2.2	4.3	7.2	0.9	0.7	2.2	0.8	0.6	6.1	1.4	8.6	1	1.5	2.7	1.6	1.1	0.1	0.4	21.3	92.8
ITA	5.8	2.4	3.7	2.5	3.4	3.1	3.8	4.5	3.2	1.5	3.2	4.5	8.1	1.4	2.3	0.6	1.3	4.9	1.7	7.4	1.5	1.5	3.2	3.6	3.1	0.3	0.7	17	91.9
PRT	4.7	1	2.3	1.2	1.7	1.9	2.9	3.9	1.5	2.4	3	2.4	0.7	7.6	1.9	1.2	0.9	7.2	2.2	9	1	2.1	1.2	1.4	1.4	0.3	1.5	31.8	92.4
BGR	4.9	1.8	2.8	0.7	3.2	2.1	2.8	3.2	2.1	1.5	2.5	3.1	0.5	0.8	17.4	0.9	1.1	9.3	1.7	10.5	1.6	2.4	1.9	1.4	1.1	0.3	1.9	16.4	82.7
CZE	4.6	1.3	2.5	0.7	3	1.9	2.3	3.4	1.6	1.9	2	2.4	1	1.2	2.5	7.1	0.7	6.5	2.2	6.6	1.3	2.6	1	0.9	1	0.3	1.1	36.5	92.9
EST	4.2	1.1	2.7	0.9	2.4	2.6	2.5	3.2	2	1.5	2.8	3	0.7	1.4	2.7	0.4	4.6	8.6	1.8	8.8	2.2	1.8	2	1.9	2.4	0.4	0.5	30.9	95.4
HRV	6.7	1.3	2.5	0.4	2.1	2.1	2.4	2.7	1.7	2.6	2.7	2.4	0.6	1	2.9	0.5	0.9	24.5	2.4	10.2	1	2.8	1.2	1	0.8	0.2	0.6	20	75.5
HUN	5.7	1.4	2.7	0.7	2.1	2.1	2.5	3.3	1.9	2.4	3.2	3	0.6	1.2	2.5	1	0.8	10.5	3.8	9.4	1.1	2.9	1.9	1.1	0.8	0.2	0.5	30.9	96.2
LTU	5.7	1.8	3.6	0.9	2.7	3	3.2	4.3	2.6	2.7	3.9	3.8	0.6	1	2.7	0.6	0.8	8.5	1.8	16.9	1.2	2.2	2.2	1.8	0.9	0.3	0.7	19.8	83.1
POL	4.9	1.1	2.5	0.5	2.2	1.9	1.9	2.8	1.9	1.5	1.9	2.4	0.6	0.9	2	1	1	8.6	1.6	7	7.5	2.5	1	0.7	1.2	0.2	0.5	38.4	92.5
ROU	7.5	1.4	3	0.6	2.8	2.3	2.8	4	1.8	2.7	3	2.8	0.8	1.2	3.1	0.6	0.8	7.7	2.3	11.2	1.6	11.4	1.9	1.5	1.5	0.6	1.1	18	88.7
SVN	6.3	2.4	4.3	1.1	3.2	4	4.2	4.5	3.8	2.4	4.6	5.5	1.3	0.6	2.3	0.6	0.9	4.4	1.8	9.3	0.7	1.7	5.4	3.5	1.6	0.2	0.4	19.2	94.6
NOR	5.7	1.2	2.6	2	3.8	2.2	2.1	4.5	2.8	2.4	2.7	4.4	1.8	0.8	2.8	0.5	1.1	2.6	1.3	8.1	0.5	1.1	4.3	20	1.8	0.6	1.7	14.7	80.1
USA	3.2	1.9	4	1.7	2.2	3.3	7.1	5.8	2.5	0.6	4.1	3.9	0.8	1.3	2.1	0.4	1.3	5.6	1.2	7.5	1.6	0.9	2.3	2.5	18.7	0.5	1.4	11.9	81.3
APAC	4	1.3	3.3	1.1	2.8	2.7	5.1	4.5	2	1.4	3	2.9	1.1	1.6	2.3	0.6	1.3	5.5	1.4	6.9	2.4	2.5	1.6	2.4	6.2	3.8	1.9	24.4	96.2
Brent	3.6	0.5	1.2	0.3	1.5	1.1	1.2	2	0.8	1.3	0.9	1.5	0.3	0.9	3.1	0.7	0.8	4.9	1	4.3	1.4	1.6	0.6	1.7	1	0.2	17.8	43.9	82.2
TTF	1.7	0.4	0.7	0.3	0.8	0.7	0.7	1.2	0.6	0.6	0.7	0.9	0.3	0.3	0.5	0.2	0.3	2.3	0.7	3.3	0.5	1	0.5	0.3	0.4	0.1	0.2	80.2	19.8
To	143.3	48.7	94.4	29.9	73.3	78.8	100.6	114.2	65	53.6	94	101.3	22.7	26.6	59.7	19.1	22.3	177.6	42.2	221.7	31.3	47.3	54.5	46.4	44.8	7.7	21.8	607.5	87.5
Net	54.2	-47.4	0.6	-55.5	-21.5	-16.3	11.1	24.1	-29.9	-37.9	2.2	8.5	-69.2	-65.8	-22.9	-73.8	-73.1	102.2	-54.1	138.6	-61.2	-41.3	-40.1	-33.6	-36.5	-88.4	-60.4	587.7	0

Table C.10

Volatility spillover of MSCI equity indices of our sample EEA countries, US equity index, and APAC equity index, as well as Brent and TTF one month ahead future prices during the period of 1/1/2022 and 12/31/2022

	SHEL	TTEF	EQNR	GAZP	ROSN	ENI	LKOH	SIBN	SNGS	TATN	NVTK	LUNE	HBR	DNO	TLW	MAUP	SQZ	CNE	TETY	PHARP	BP	NESTE	REP	OMVV	GALP	PKN	MOLB	ROSNP	RUBF	LTS	TENR	SRG	ENAG	VOPA	VLLP	SUBC	SBMO	TRNF	EUAV	FLUX	Gasoil	FTSEALL	NG	Brent	From
SHEL	7	3.4	2.4	0.8	1	3.2	1	0.8	0.9	1.2	0.9	4.3	9.2	4.4	2.5	7	1.2	3.4	2	2.4	4.5	1	3.5	2.4	2.8	0.8	0.8	0.7	0.7	0.9	3.8	0.4	0.5	0.5	4.4	3.5	2.7	0.6	1.2	0.1	1.5	0.6	1.3	2.1	93.1
TTEF	3.2	6.4	2.3	1.2	1.6	4.2	1.4	1	1.3	1.8	1.5	3.5	7.3	4.7	2.5	5.7	1.2	3.1	1.9	2	3.4	1.2	4.3	2.9	2.9	1	1	0.8	0.7	1	4.1	0.6	0.7	0.6	4.3	3.5	2.9	0.9	1.2	0.1	1.1	0.7	0.8	1.7	93.6
EQNR	2.2	2.1	9	1.3	1.7	2	1.2	1	1.5	1.9	1.5	4.4	7.4	5.8	2.7	4.9	1.7	2.7	2.4	1.5	2.3	1.2	2.6	2.3	2.6	1	0.8	0.8	0.6	0.9	3.6	0.4	0.4	0.7	4.5	5.6	2.9	1.3	1.5	0.1	1.4	0.5	1.4	2	91
GAZP	0.5	0.7	1	18.7	9.5	0.8	6.5	4.4	7	7.7	6	1.9	1.3	2.6	1.1	1	0.9	1	1.6	0.6	0.6	0.8	0.9	1.5	1.1	0.8	0.7	0.9	0.3	0.9	1.8	0.1	0.3	0.5	2	2.1	1.4	5.4	1.2	0.1	0.3	0.4	0.7	0.5	81.3
ROSN	0.6	0.8	1.2	8	18.1	0.8	6.8	4.5	7.6	8.4	6.1	1.3	2.2	2.5	1	1.3	0.8	1.4	1.5	0.8	0.7	0.7	0.9	1.5	1	0.6	0.7	0.8	0.3	0.7	1.7	0.2	0.2	0.4	2	2.1	1.2	5.8	0.9	0.1	0.4	0.4	0.6	0.7	82
ENI	2.9	3.8	2.2	1.1	1.4	8	1	0.8	1.1	1.8	1.2	3.2	8.3	4.4	2.6	5.4	1.2	3.1	1.9	2	3	1.3	4.3	2.7	3	1	0.8	0.8	0.7	1	4.5	0.8	0.7	0.6	4.5	3.3	3	0.9	1.5	0.1	1.1	0.7	0.5	1.8	92.1
LKOH	0.8	0.9	1.2	7.2	9	0.9	13.4	4.4	7.3	7.9	5.6	2	2.5	3.2	1.2	1.9	0.9	1.6	1.4	0.8	0.9	0.7	1	1.7	1.3	0.7	0.7	0.9	0.4	0.7	1.9	0.2	0.3	0.5	2.3	2.2	1.4	4.7	1	0.1	0.6	0.5	0.5	1	86.6
SIBN	0.6	0.7	1.2	6.8	8	0.8	5.7	16	6.5	7.2	5.4	2.6	1.9	2.8	1.1	1.2	0.8	1.4	1.4	0.8	0.7	0.7	0.9	1.7	1.1	0.8	1	1.3	0.3	1	1.9	0.2	0.3	0.6	1.8	2.3	1.5	4.9	1.2	0.1	0.5	0.5	0.8	0.9	84
SNGS	0.5	0.7	1	6.1	8.2	0.7	5.7	3.9	20.6	7.2	5.5	7.1	1.3	2.5	0.9	1.7	1.1	1.2	1.3	0.8	0.6	0.7	0.9	1.2	1	0.6	0.6	0.8	0.3	0.8	1.5	0.2	0.3	0.4	1.5	1.7	1.3	5	1	0.1	0.3	0.4	0.6	0.5	79.4
TATN	0.7	0.9	1.2	5.8	7.6	1	5.6	3.8	6.5	20.3	5.7	1.7	2.2	3.3	1.1	1.7	1.2	1.1	1.7	0.8	0.7	0.7	1	1.8	1.2	0.8	0.8	0.9	0.3	0.8	2	0.2	0.3	0.5	2.1	2.4	1.4	4.8	1.1	0.1	0.5	0.4	0.4	1	79.7
NVTK	0.6	0.7	1	6.2	7.4	0.7	5.1	3.7	6.3	7.2	21.6	1.4	1.8	2.6	1.1	1.3	1	1.4	1.5	0.8	0.7	0.8	1.1	1.9	1.2	1	0.7	0.8	0.4	1	1.8	0.2	0.3	0.5	2.1	2.2	1.5	4.5	1.3	0.1	0.5	0.4	0.9	0.8	78.4
LUNE	0.1	0.1	0.1	0.1	0	0.1	0	0	0	0.1	0.1	97.3	0.2	0.2	0.1	0.2	0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0	0	0	0.1	0.1	0	0	0	0.1	0.1	0.1	0	0.1	0	0	0	0.1	0	2.7
HBR	1.3	1.1	1.4	0.2	0.4	1.3	0.4	0.2	0.3	0.4	0.2	1.5	47.2	3.5	1.6	8.5	1.1	2.9	1	2.1	1.4	0.4	1.4	1	1.4	0.5	0.4	0.4	0.4	0.6	2	0.4	0.3	0.2	4.2	2.1	1.4	0.2	0.8	0.1	1.2	0.2	0.5	2.1	52.8
DNO	1	1.1	1.7	0.9	1.1	1.2	0.9	0.8	1.1	1.2	1.1	2.8	5.3	40.7	1.7	4	1.9	2.2	2.2	1.2	1.1	0.8	1.5	1.2	1.7	0.8	0.6	0.6	0.3	0.9	2.2	0.3	0.3	0.5	2.8	2.9	1.8	1.1	1.4	0.1	1	0.4	0.6	1.4	59.3
MAUP	1.7	1.5	1.8	1	1.1	1.7	0.8	0.6	1	1.1	1	2.7	7	4.2	20.4	5.2	2.5	2.1	2	2.1	1.8	1.3	2.8	1.6	2.4	1.3	0.6	0.6	0.6	1.1	3.1	0.4	0.4	0.7	6.2	3.2	2.7	0.9	1.9	0.1	1.3	0.5	1.6	1.5	79.6
TLW	1.1	1	0.9	0.2	0.4	1	0.3	0.2	0.3	0.4	0.3	1.5	9.4	3.1	1.3	54.4	0.9	1.9	0.9	1.7	1.2	0.5	1.3	0.8	1.1	0.4	0.3	0.2	0.3	0.5	1.6	0.3	0.2	0.2	2.8	1.7	1.1	0.3	0.7	0.1	1	0.2	0.5	1.6	45.6
SQZ	0.4	0.3	0.5	0.5	0.5	0.4	0.3	0.3	0.6	0.7	0.7	0.5	1.7	1.5	0.7	1.6	72.9	0.8	1	0.9	0.5	0.6	0.7	0.5	0.7	0.7	0.3	0.2	0.2	0.7	0.9	0.2	0.2	0.4	1.4	1.1	0.9	0.6	0.8	0.1	0.4	0.1	0.6	0.4	27.1
CNE	1.7	1.6	1.7	1	1.4	1.7	1	0.8	1.1	1.3	1.1	2.2	10.7	5.1	2	6.9	1.7	20.8	2	2.2	1.8	1	2	1.6	2	0.8	0.8	0.7	0.4	0.9	3	0.5	0.5	0.5	4	2.9	2.5	0.8	1.5	0.1	1.1	0.5	0.5	1.9	79.2
TETY	1	0.9	1.4	1	1.1	1	0.8	0.7	1	1.4	1.3	2.7	3.1	4.6	1.8	3	2.6	1.9	39	1.3	1.1	1.1	1.4	1.5	1.7	1.3	0.7	0.6	0.5	1.3	2.2	0.3	0.3	0.7	2.4	2.3	1.7	1.6	1.7	0.1	0.9	0.3	1.4	1.1	61
PHARP	1.6	1.4	1.1	0.5	0.8	1.4	0.6	0.5	0.7	0.8	0.8	2.4	9.4	4.1	1.8	7.4	2.1	2.8	1.3	30.1	1.6	0.7	1.7	1.3	1.6	1	0.7	0.5	0.6	1	2.4	0.6	0.4	0.4	3.3	2.1	1.7	0.5	1.1	0.1	1.4	0.4	1.2	2.1	69.9
BP	4.2	3.3	2.4	0.8	1.1	3.1	1.1	0.8	1.1	1.3	1.1	3.2	8.7	3.8	2.5	6.8	1.6	3.3	2	2.3	9.4	1	3.6	2.3	2.9	0.8	0.8	0.7	0.7	0.9	3.7	0.5	0.5	0.5	4.3	3.3	2.5	0.6	1.2	0.1	1.3	0.5	1.6	1.8	90.6
NESTE	1.2	1.4	1.5	1.5	1.6	1.5	1.1	1	1.5	1.9	1.8	7.1	3.7	3.7	2	3.6	2.3	2.2	2.3	1.6	1.4	19.9	2.3	2.1	2.1	1.6	0.8	0.6	0.7	1.6	2.9	0.7	0.6	0.8	4.2	2.7	2.5	1.2	2.3	0.2	0.9	0.6	1.8	1.1	80.1
REP	2.7	3.3	2.1	0.9	1.1	3.6	0.9	0.5	0.9	1.3	1.1	2	7.3	3.9	3.2	5.7	1.7	2.6	1.8	2.1	3	1.3	11.8	2.4	3.4	1.2	0.8	0.6	0.6	1.3	4	0.6	0.8	0.6	5.3	3.3	3.1	0.7	1.7	0.1	1.3	0.7	0.9	1.7	88.2
OMVV	1.9	2.3	1.9	1.5	1.9	2.3	1.6	1.3	1.6	2.2	2	2.5	6.2	4.2	2.3	5.3	1.2	2.6	2.2	1.8	2	1.5	2.9	13.7	2.6	1.3	1.2	1	0.8	1.4	3.7	0.5	0.6	0.7	4.4	3.5	2.3	1.3	1.5	0.2	1.2	0.7	1	1.7	86.3
GALP	2	2.2	2.2	1.1	1.3	2.3	1	0.7	1.2	1.5	1.3	3.9	6.5	4.4	2.7	5.2	2.2	2.6	1.9	1.9	2.2	1.4	3.3	2.3	13.1	1.3	0.9	0.8	0.7	1.3	4.2	0.5	0.6	0.7	4.6	3.4	3.3	1.3	1.7	0.1	1.2	0.6	1.2	1.5	86.9
PKN	1	1.2	1.3	1.7	1.6	1.2	1.1	1.2	1.8	2.1	1.9	2.9	3.7	4	2	2.8	3.2	1.7	3.2	1.8	1.2	1.6	2	2	2	18.1	1.4	1	0.7	5.5	3	0.5	0.6	0.8	4.3	2.7	2	1.7	2.1	0.2	1.1	0.5	2.3	1.2	81.9
MOLB	1.1	1.3	1.6	2.2	2.5	1.3	1.6	1.9	2.2	2.3	2.5	1.9	3.6	5	1.9	2.9	2.9	2.1	3.3	1.5	1.3	1.4	2.1	2.5	2.2	2.1	15.3	1.9	0.7	1.8	3.4	0.5	0.7	1	3.3	3	2.3	2.4	2.3	0.2	1	0.8	0.7	1.3	84.7
ROSNP	1	1	1.6	2.7	2.5	1.2	1.9	1.8	2.1	2	2.1	2.3	3.9	5.2	2.1	2	1.5	2.2	2.7	1.4	1.4	1.1	1.9	2.2	1.9	1.4	1.5	20.5	0.7	1.5	3.4	0.3	0.5	1	3.2	3.1	2.5	2.8	2.3	0.3	0.9	0.7	0.6	1.2	79.5
RUBF	1.6	1.7	1.7	1	1.3	1.8	1.1	0.8	1.2	1.3	1.5	5.2	7.5	3.9	2.2	5.5	2.2	2.7	2.3	2.3	1.7	1.4	2.4	2.2	2.3	1.5	0.9	0.8	12	1.7	2.9	0.9	0.9	0.8	4.5	2.8	2.4	1	2	0.3	1.6	0.6	2.2	1.7	88
LTS	1	1.1	1.1	1.3	1.3	1.2	0.9	1.3	1.4	1.8	1.6	2.7	4.1	3.6	1.4	3.7	3.1	2	2.5	1.8	1.2	1.7	2	1.9	1.9	5.7	1	0.8	0.7	22.6	2.5	0.7	0.7	0.7	4.2	2.5	1.8	1.3	2.1	0.3	1	0.4	2.6	1.3	77.5
TENR	1.9	2.1	1.9	1.3	1.3	2.5	0.9	0.8	1.2	1.5	1.1	3.6	6.9	4.1	2.7	5	1.7	2.7	2	2	2.1	1.4	2.9	2.2	2.9	1.2	0.7	1	0.5	1.1	14.1	0.4	0.5	0.7	7	3.8	3	1	1.8	0.1	1.2	0.6	1	1.6	85.9
SRG	1.4	1.8	1.7	0.7	1	3	0.7	0.5	1	1.3	1	3.4	11.9	4.4	1.7	5.7	2.4	3.5	1.9	2.6	1.7	1.8	2.6	1.8	2.1	1.4	0.8	0.6	1.1	1.9	2.6	9.8	1.8	0.7	4	2.2	3	0.8	2.2	0.3	1.3	0.5	1.4	2.2	90.2
ENAG	1.4	1.8	1.5	1.4	1.6	2.3	1.2	1	1.8	1.6	1.6	3.3	7.4	4.2	1.9	4.1	2.9	3	2.4	1.9	1.6	1.6	3.1	1.9	2.7	1.5	1	1.1	1	2.1	3.5	1.5	9.9	0.9	4.2	2.6	3.1	1.5	2.3	0.2	1	0.8	1.1	1.5	90.1
VOPA	1.2	1.4	1.8	1.7	1.7	1.5	1.3	1.3	1.7	2.3	1.7	4.6	4.3	4.4	2.7	3.1	2.8	2.1	3	1.6	1.2	1.5	2.1	1.7	2.1	1.5	0.9	0.9	0.8	1.5	3.2	0.5	0.7	15.2	3.9	3.7	2.9	1.9	2.4	0.2	1.3	0.7	1.9	1.6	84.8
VLLP	1.1	1.1	1.5	0.9	1	1.4	0.6	0.4	0.8	1.1	0.8	1.6	7.3	3.2	2.8	5.3	1.7	1.8	1.3	1.5	1.2	0.9	2.2	1.3	1.8	1.1	0.5	0.5	0.5	1.1	3.7	0.3	0.3	0.5	35.6	2.9	2.2	0.6	1.5	0.2	0.9	0.3	1.9	1.1	64.4
SUBC	1.5	1.7	2.8	1.3	1.7	1.6	1.2	1	1.4	2	1.4	3.2	5.7	5.2	2.4	4.9	1.6	2.4	1.9	1.5	1.6	1.2	2.1	2.2	2.2	1.2	1	0.9	0.5	1.1	3.7	0.4	0.5	0.8	5	19.1	3	1.5	1.5	0.1	1.1	0.6	0.9	1.8	80.9
SBMO	1.5	1.7	1.8	1.2	1.3	1.9	1	0.8	1.4	1.5	1.3	3	5.2	4	2.4	3.8	2.1	2.9	1.9	1.7	1.5	1.4	2.6	1.7	2.7	1.2	0.7	0.7	0.5	1	3.6	0.5	0.6	0.9	4.4	4.2	23.2	1.2	2.1	0.2	0.7	0.5	0.5	1.2	76.8
TRNF	0.4	0.5	1	5.7	7.1	0.6	4.3	3.3	5.7	6.3	4.7	1.4	1.2	2.7	0.9	1.1	1.3	0.9	2.4	0.7	0.5	0.7	0.8	1.3	1.2	0.8	0.6	1.1	0.3	0.9	1.7	0.2	0.2	0.5	1.5	2.2	1.2	29.4	1.3	0	0.4	0.4	0.4	0.5	70.6
EUAV	1.1	1	1.4	1.3	1.2	1.2	0.8	0.8	1.3	1.6	1.6	1.9	4	3.8	2.3	3.2	3.7	2	2.5	1.3	1.2	1.9	2.3	1.6	1.9	1.6	1	0.6	0.6	1.9	2.6	0.6	0.6	1	4.1	2.6	2.7	1.4	27.8	0.2	0.9	0.5	1.4	1.3	72.2
FLUX	1	0.9	1.3	1.1	1.3	1.1	1	1.1	1.7	1.4	1.6	2.1	5	3.9	2	4.2	5	2.5	2.9	2	1.4	1.5	2.2	1.7	2	2.1	1	1.1	0.6	2.3	2.3	0.8	0.9	1	4.3	2.2	3.1	1.3	2.6	16.9	1.2	0.4	2.6	1.3	83.1
Gasoil	1.6	1	1.7	0.7	0.8	1.2	0.7	0.5	0.8	0.9	0.8	2.3	7.7	4	2.2	5.6	1.6	1.5	1.9	1.8	1.6	0.8	1.8	1.4	1.7	1	0.7	0.6	0.6	0.9	2.5	0.3	0.3	0.8	3.7	2.7	1.6	1.1	1.2	0.1	17.8	0.5	5.2	11.9	82.2
FTSEALL	1.9	2.4	1.8	1.9	2.3	2.6	1.8	1.6	2.1	2.3	2.2	3.7	5.6	5.2	2.5	4.1	1.4	3.3	2.2	2.1	2	1.8	3.3	2.5	2.6	1.3	1.4	1.3	0.8	1.3	4.3	0.6	0.9	1	4.2	4	2.9	1.5	2	0.1	1.6	3.1	0.4	2.4	96.9
NG	1.8	1.3	1.9	0.7	0.8	1.6	0.9	0.6	0.9	1.1	0.9	2.6	9.8	4.5	2.1	5.9	1.6	2.1	1.6	2	1.8	0.8	1.8	1.4	1.8	0.8	0.7	0.7	0.5	0.8	2.6	0.4	0.4	0.6	3.8	3.2	2.1	0.9	1.3	0.1	9	0.5	2	17.5	24.9
Brent	1.8	1.3	2	0.6	0.7	1.6	0.8	0.5	0.8	0.9	0.8	2.6	10	4.7	2.2	5.7	1.5	2.1	1.6	2	1.8	0.8	1.9	1.5	1.9	0.8	0.7	0.7	0.6	0.8	2.7	0.4	0.4	0.7	3.8	3.2	2	0.8	1.2	0.1	9.4	0.5	1.2	17.9	82.5
To	58.4	61.1	65.3	85	102.7	66.9	74.4	57.9	89.8	103.3	84.5	121.2	230.2	160.8	80	170.4	76.6	90.9	81.8	66.4	63.3	46.6	86.7	73.9	81.2	49.7	33.5	32.6	23.2	52.3	116.6	18.5	20.9	26.8	152.6	116.4	90.8	74.5	64.8	5.7	49.4	20.6	50.9	68.4	76.1
Net	-34.7	-32.5	-25.6	3.6	20.7	-25.2	-12.2	-26.2	10.4	23.6	6.1	118.5	177.4	101.5	0.4	124.8	49.5	11.7	208	-3.4	-27.3	-33.5	-1.5	-12.4	-5.7	-32.2	-51.2	-46.9	-64.7	-25.2	30.7	-71.7	-69.2	-58	88.2	35.5	14	3.9	-7.4	-77.4	-32.8	-7631	26	-14.1	