Thesis booklet

Investigating Systemic Risk With Co-occurrence Networks

Studies from the fields of sovereign bond and energy markets

Kotró Balázs Bence

Supervisor: Huszár Zsuzsa Réka Ph.D.

1. Motivation

The objective of this thesis is to provide education on the various aspects of systemic risk that originate from multiple sources, such as the financial sector and the energy market, as well as other potential sources that may not yet be identified.

Systemic risk, a crucial concept within finance and economics, refers to the potential for disturbances or shocks to cascade across interconnected financial institutions and markets. This can result in widespread disruptions and possibly severe consequences for the entire financial system and economy. As implied by the term, systemic risk threatens the stability of the financial system and, by extension, the broader economy, particularly in concentrated markets. It is distinct from the more commonly understood systematic risk, which pertains to market-wide factors such as interest rates and economic cycles. While systematic risk is relatively predictable and can be quantitatively measured, systemic risk is often elusive and challenging to assess.

The concept of systemic risk was first introduced in the banking sector due to the significant impact that banking issues can have on the broader financial system. Initially, the term "systemic risk" described threats to the overall stability of the financial system, including the potential for widespread failures and disruptions. The phrase “too big to fail” emerged during the Global Financial Crisis (GFC), conveying the notion that certain banks are so large and integral to the economy's functioning that their failure could have severe systemic consequences.

Even if systemic risk originates within the banking sector, where interconnected institutions and markets can amplify disturbances or shocks, this kind of risk extends beyond this realm, affecting other markets such as the sovereign debt markets and energy sector, for example. The aim of this thesis is to broaden the terminology of systemic risk by these aspects.

Chapter III. of this dissertation is dealing with systemic risk on the sovereign bond market. The Global Financial Crisis heightened concerns about the fragility of debt markets. In Europe, these worries were compounded by the European Sovereign Debt Crisis (ESDC) and the potential systemic risk that could arise from a sovereign default and its impact on other European debt markets. Consequently, it is not surprising that most papers related to systemic risk focus on this region during that era. Since the perception of systemic risk is often tied to how financial distress in an asset or institution affects other assets or the entire financial system, it is closely related to the spread of failures from one asset, institution, or market to another. Many studies on systemic risk in sovereign bond markets apply this concept of systemic risk, considering the repercussions of a possible sovereign debt default in one country on other sovereign bond markets (Reboredo and Ugolini, (2015)).

In Chapters IV. and V. energy market related systemic risk is discussed. The energy market holds a critical position in the economic system, and recent years have seen increased volatility in energy prices, bringing high risk and significant uncertainty (Ji and Zhang, (2019)). Such fluctuations substantially impact the real economy and pose an indirect threat to the stability of the financial system, potentially creating systemic risks for global financial markets. In studies on the energy market, systemic risk is primarily associated with the transmission of price and volatility shocks within the financial system (Lautier and Raynaud, (2012)). Since the GFC, there has been a growing focus on cross-market risk contagion within the energy system, particularly during turbulent periods. Key areas of attention include risk spillovers across different energy markets, risk spillovers into various commodities markets, and risk spillovers into distinct stock markets.

Financial networks are valuable for quantifying systemic risk as they map interconnected financial institutions and markets. Such networks are complex systems composed of numerous institutions and assets interconnected in various ways. Despite differences in the nature of the financial network, all models underscore how financial interdependencies contribute to systemic risks. By employing a formal model of financial networks, the sources of systemic risk can be measured, predicted, and monitored.

In many cases, financial entities are not always directly connected through flows of money, shareholdings, or financial exposures but rather through indirect co-occurrences such as commonality, similarity, or correlation (Bardoscia et al., (2021)). A common example of a co-occurrence network is one where nodes represent financial entities characterized by empirical time series data, such as stocks traded in a financial market. The connections between these nodes are weighted based on measured correlation (Tumminello et al., (2005); Kremer et al., (2019)) or causality (Billio et al., 2012) between the respective time series.

2. Used Methodologies

2.1. The Diebold-Li yield curve decomposition method

Nelson and Siegel, (1987) propose a flexible and parsimonious framework based on exponential components, which effectively captures a range of common yield curve shapes such as forward sloping, inverse, and humped curves. This framework allows for clear interpretation of the estimated factors. Diebold and Li, (2006) (D-L) expanded upon the Nelson-Siegel (N-S) approach by enabling dynamic changes in the latent factors. A key aspect of this model is that the factors can be understood as Level, Slope, and Curvature, as demonstrated by Diebold et al., (2006). Building on the N-S and D-L models, these components are assumed to encompass most of the information in the term structure of the yield curve. The D-L model is versatile and widely applicable across various markets. The observed yield curve can be described with the following equation:

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

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.

2.2. The Toda-Yamamoto causality method

The Toda and Yamamoto (1995) model (T-Y hereafter) is a key tool for researchers studying complex causal relationships in economic data. This model extends the traditional Granger causality test to accommodate non-stationary time series data, offering valuable insights into dynamic interdependencies between economic variables. As T-Y highlight, the classic Granger causality test (Granger, (1969)) based on a VAR model for cointegrated time series can produce spurious connections (Dolado and Lütkepohl, (1996); Zapata and Rambaldi, (1997); Pittis, (1999)). The T-Y model addresses this issue by introducing a modified Wald test (MWald) that imposes restrictions on the parameters of the VAR(p) model. TheT-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($p + d^{max}$) is described by the below equations:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \delta_{1i} Y_{t-i} + \sum_{j=p+1}^{d^{max}} \alpha_{1j} Y_{t-j} + \sum_{j=1}^{p} \theta_{1i} X_{t-j} + \sum_{j=p+1}^{d^{max}} \beta_{1j} X_{t-j} + \omega_{1t}$$
$$X_t = \alpha_1 + \sum_{i=1}^{p} \delta_{2i} Y_{t-i} + \sum_{j=p+1}^{d^{max}} \alpha_{2j} Y_{t-j} + \sum_{j=1}^{p} \theta_{2i} X_{t-j} + \sum_{j=p+1}^{d^{max}} \beta_{2j} X_{t-j} + \omega_{2t}$$

where α, δ,θ ,β are model parameters, p is the optimal lag for the original VAR model, ω_{1t} and ω_{2t} are the error terms of the VAR model and d^{max} is the maximum integration order.

2.3. The Diebold-Yilmaz spillover method

The spillover index 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 Diebold-Yilmaz (D-Y) model relies on a VAR method (Sims, (1980)) with a strong emphasis on calculating the Forecast Error Variance Decomposition (FEVD). The model employs a generalized VAR framework (e.g., Koop et al., (1996)) that maintains the FEVDs' invariance to the ordering of variables, thus circumventing the need to order variables within the VAR model. This approach is particularly advantageous given the goal of evaluating the extent of volatility spillovers rather than pinpointing the causal impacts of structural shocks, making it a preferred choice in the current context (Diebold and Yilmaz, (2023)).

Under the generalized VAR framework, we consider a covariance-stationary VAR (p) model with N-variable i.e., $Y_t = \psi_i Y_{t-i} + e_t$, 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 $N \times N$ coefficient matrix. A_j follows recursive pattern as $A_j = \psi_1 A_{j-1} + \psi_2 A_{j-2} + \cdots + \psi_p A_{j-p}$. 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:

$$\Phi_{ij}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e'_i A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e'_i A'_h \Sigma e_i)}$$

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

$$\widetilde{\Phi}_{ij}(H) = \frac{\Phi_{ij}(H)}{\sum_{j=1}^{N} \Phi_{ij}(H)}$$

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

$$TS(H) = \frac{\sum_{ij=1, i \neq j}^{N} \widetilde{\Phi}_{ij}(H)}{N} \cdot 100$$

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

$$DS_{i\leftarrow j}(H) = \frac{\sum_{j=1,i\neq j}^{N} \widetilde{\Phi}_{ij}(H)}{N} \cdot 100$$

and

$$DS_{i\rightarrow j}(H) = \frac{\sum_{j=1,i\neq j}^{N} \widetilde{\Phi}_{ji}(H)}{N} \cdot 100$$

Finally, the net spillovers from one variable to another for a set of variables are calculated by taking the difference the upper two equations

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

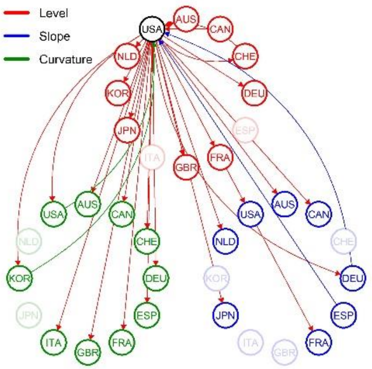
3. Main contributions

3.1. The impact of crisis periods and monetary decisions of the Fed and the ECB on the sovereign yield curve network

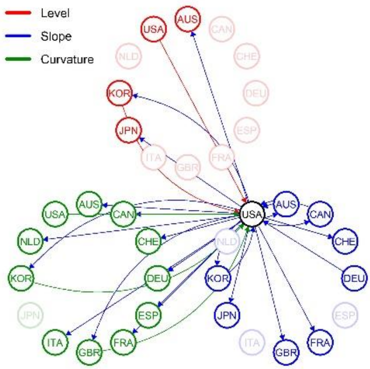
This paper offers four main contributions to existing literature. First, it is the first study to employ the Toda-Yamamoto, (1995) causality test to analyze a comprehensive network of sovereign yield curves over an extended time frame. While the Time-Varying Parameter Vector Autoregression (TVP-VAR) model has been recently suggested for network analysis (Rossi, (2005); Rossi and Wang, (2019)), the choice of the Toda-Yamamoto model is motivated by its simplicity and flexibility, which avoids complexities associated with TVP-VAR in cointegrated series.

The T-Y causality test can be applied regardless of whether the series are $I(0)$, $I(1)$, or $I(2)$, or whether they are cointegrated in any order. This approach eliminates biases from unit root and cointegration tests by avoiding the need to pre-test the system's cointegrating properties. This paper provides evidence of several cointegrated time-series yield curve pairs using the Engle-Granger (Engle and Granger, (1987)) and Johansen (Johansen, (1988)) tests.

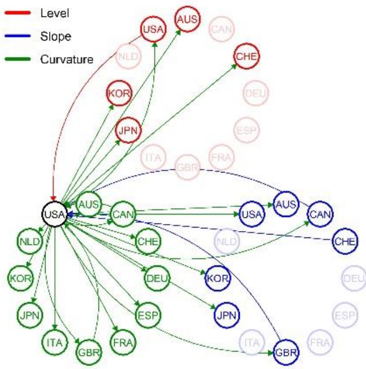
Second, this paper analyzes a large dataset of sovereign yield curves from 12 countries over 23 years, using the Level, Slope, and Curvature factors as modeled by Diebold and Li, (2006). It explores the interconnections among these sovereign yield curve factors and reveals significant linkages between the Level, Slope, and Curvature sub-networks. The study identifies the US factors as dominant key participants in the sovereign yield curve network across all sub-periods, with some temporal variations. These findings build upon other recent research on yield curve papers, which focused on spillover effects among Level, Slope, and Curvature factor networks but did not identify the primary nodes within the system.



USA Level



USA Slope

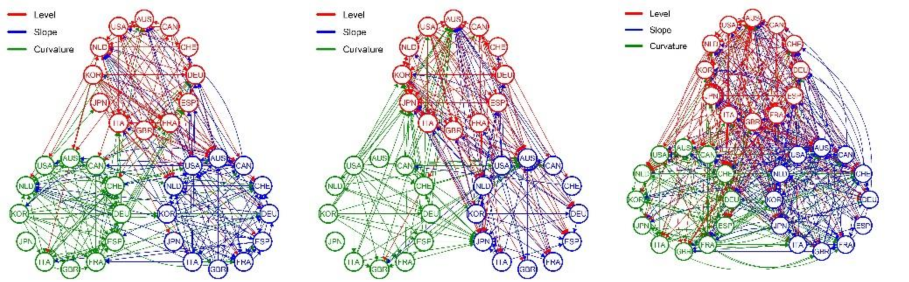


USA Curvature

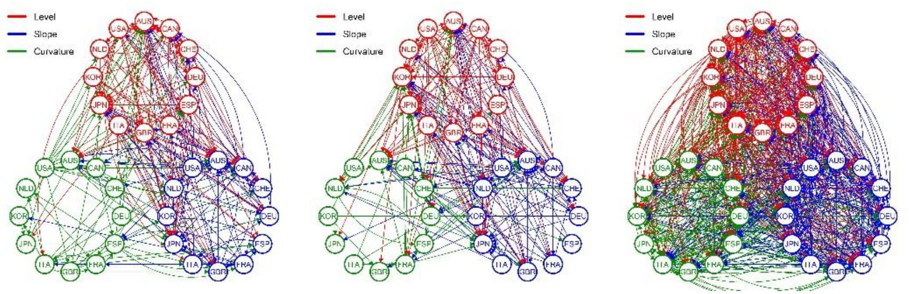
Role of the USA nodes in the system, estimated by static Toda-Yamamoto model

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 $70 = (2\ (12 + 12 + 11))$. *Cross-connection ratios are 67.7% for Level, 62.1% for Slope and 38.0% for Curvature.*

Third, this study offers unique insights by delving into the intricate structure of the 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.



Dotcom bubble **Calm period 1** **Global financial crisis**

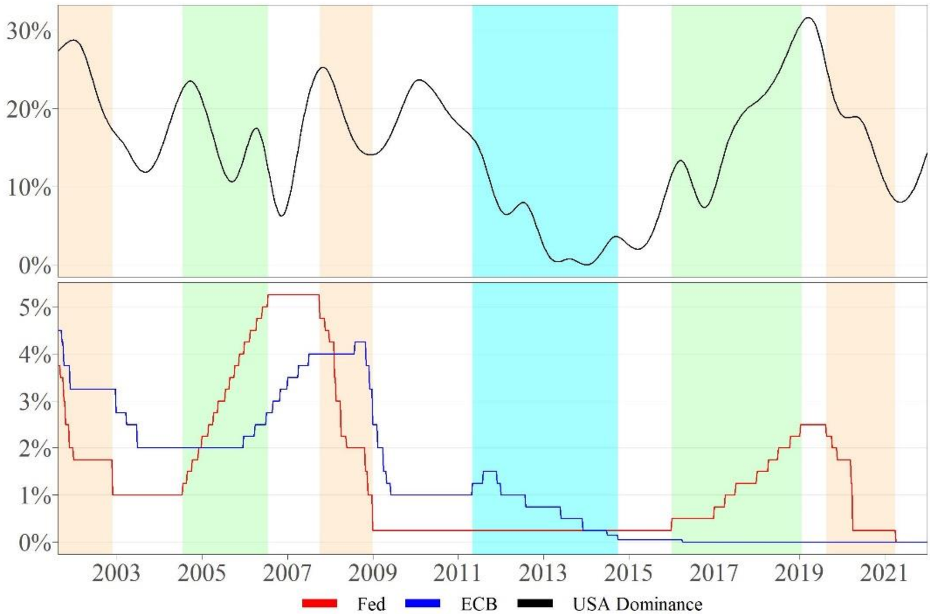


European s. d. crisis **Calm period 1** **Covid-19 Pandemic**

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: 206, in GFC:414, in ESDC: 234, in CALM2: 225, in C19: 763.

Lastly, this paper adds to the body of literature on the spillover effect of monetary policy decisions, offering valuable insights for discussions on monetary policy. This study 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. Through an analysis of the influence of easing and tightening decisions by the Federal Reserve (Fed) and the European Central Bank (ECB) on key participants in the sovereign yield curve network, the research finds that the dominance of US factors peaks when the Fed leads a rate hike cycle and diminishes when the ECB leads an interest rate cycle.



Dynamic dominance of US factors, estimated by dynamic Toda-Yamamoto model

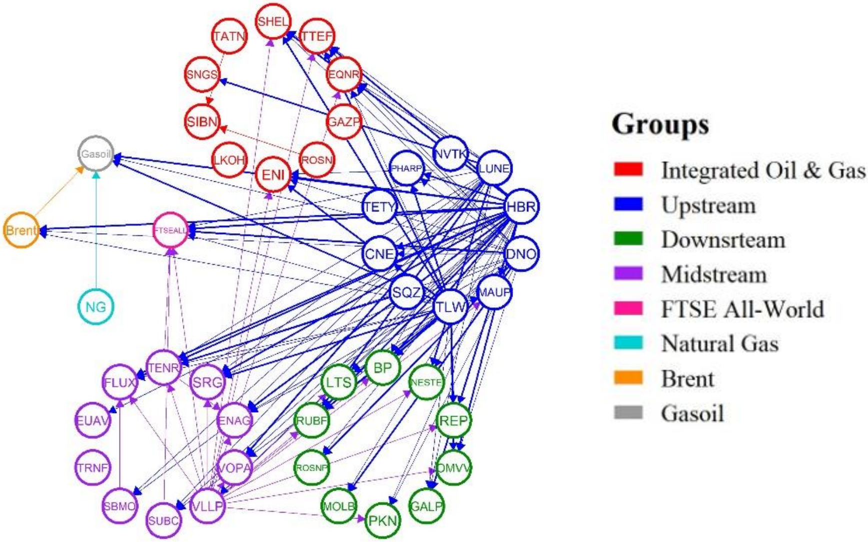
Notes: Window size of 750 days and a lag determined by the AIC, smoothed by cubic spline method. The orange areas denote the Fed interest rate cut, the green-shaded parts show Fed interest rate hikes and the cyan field represents the period when ECB leads the interest rate cycle. The red line stands 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.

3.2. Dynamic volatility transfer in the European oil and gas industry

This paper contributes to literature in three significant ways. First, it 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 (from 2003 to 2022). Previous research has concentrated on a limited number of major oil companies (e.g., Antonakakis et al., (2018)) and shorter time frames. The study covers three key exogenous shock periods: the 2008 Global Financial Crisis (GFC), the European sovereign debt crisis (ESDC), and the COVID-19 pandemic (C19).

Second, this study adopts a full network approach, offering a broader view of volatility transmission across all major European energy companies. While prior research has focused on individual companies during both normal and stress periods, this paper includes all major participants in the European energy network to identify the most significant net connections (i.e., edges in the network). This approach provides crucial insights into the system's vulnerable points.

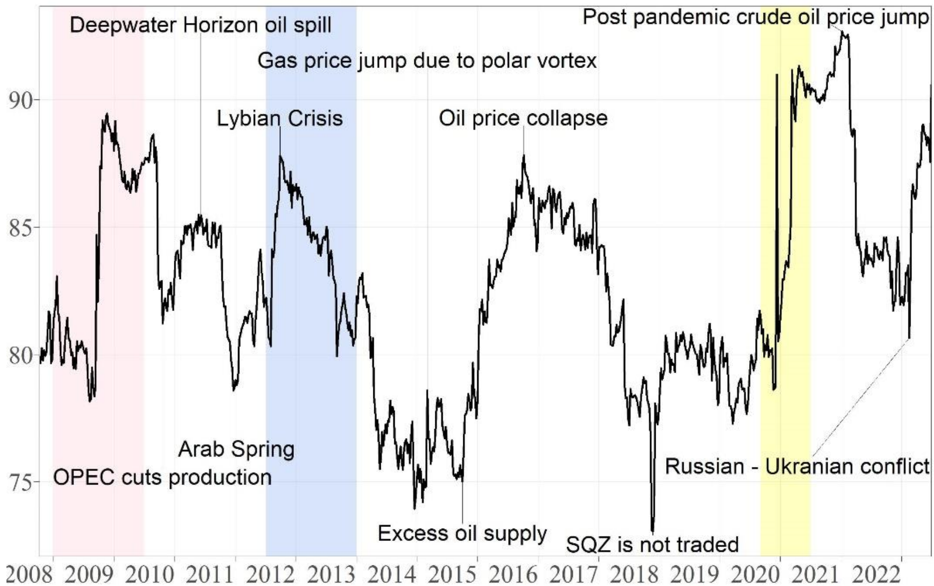
Third, this study differentiates Upstream, Downstream, Midstream, and Integrated Oil and Gas (IOG) segments along the production line to pinpoint the mechanisms behind idiosyncratic volatility spillovers in European energy companies.



Static, full-sample volatility interconnectedness network

Notes: 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, Lag=3 and H=10 model inputs are used.

By identifying system fragility points during stressful periods, the analysis highlights the energy market's vulnerability to external factors such as weather, political decisions, wars, and pandemics. For instance, Russia's war on Ukraine has negatively impacted publicly traded European energy companies, particularly those in the IOG segment. Since the war began in February 2022, the IOG segment has emerged as a major transmitter of volatility, a concerning shift given its prior role in receiving and absorbing volatility and supporting system stability.

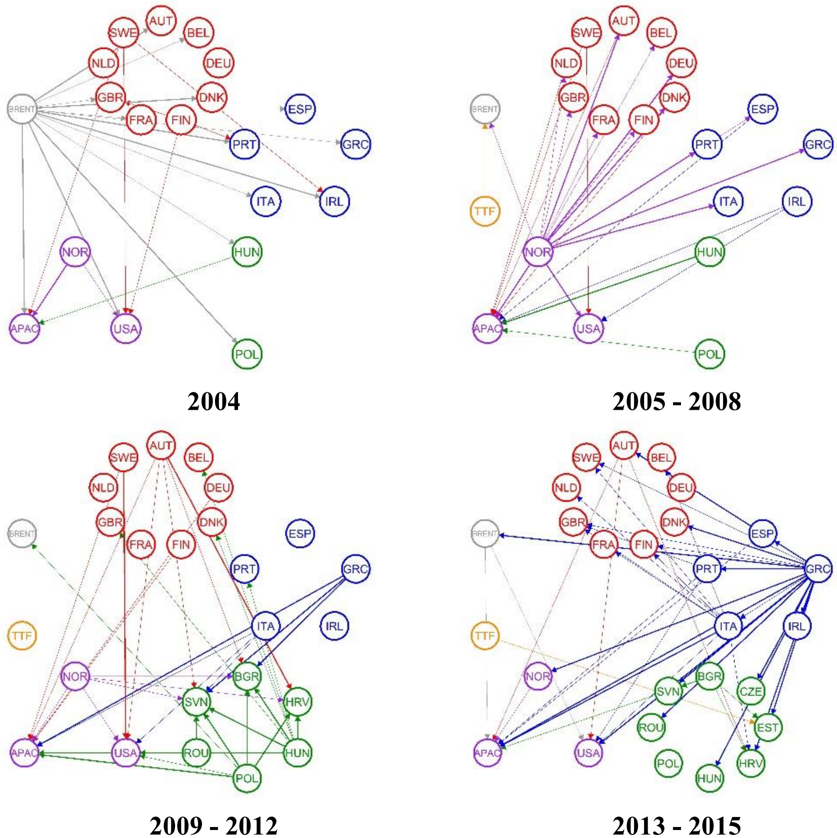


Total volatility spillover over the observation horizon

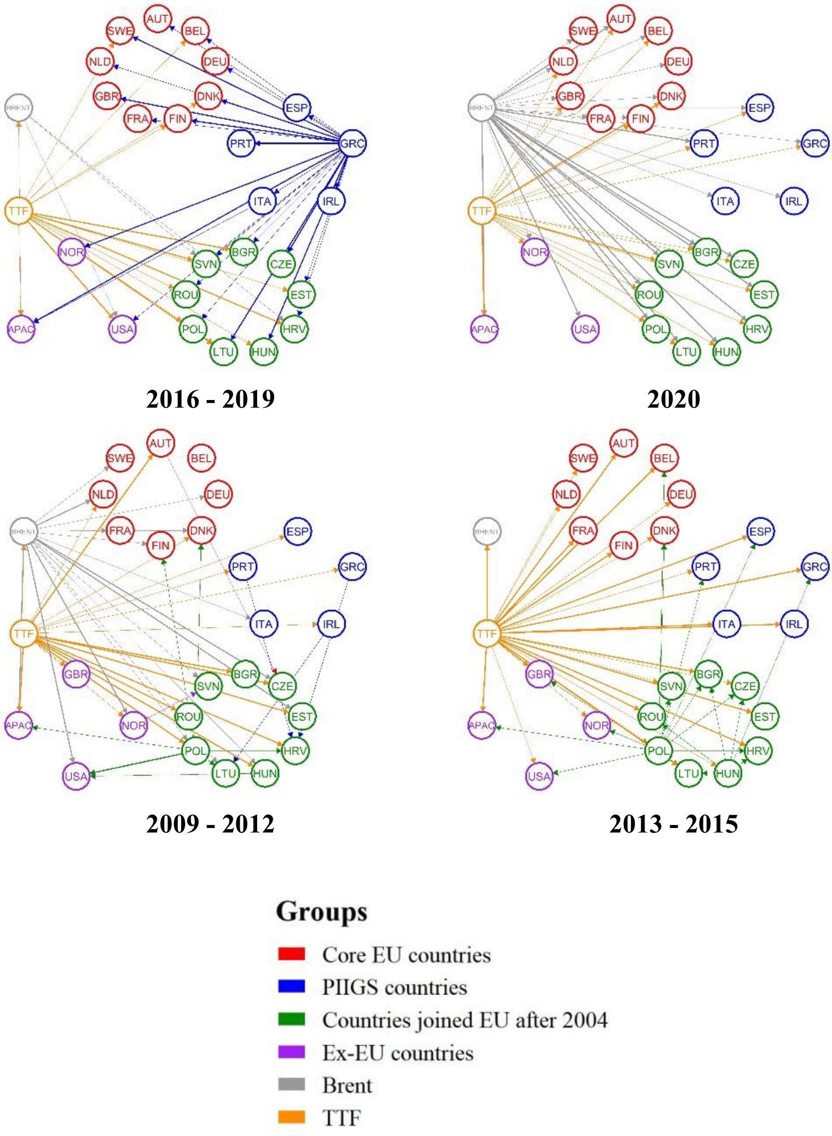
Notes: The total volatility (100%) is indicated on the left axis. The shaded areas represent various crises periods, namely the GFC: January 1, 2008 - July 1, 2009 (pink area), the ESDC: July 1, 2011 - January 1, 2013 (blue area), and the C19: September 1, 2019 - July 1, 2020 (yellow area). In creating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

3.3. European equity markets volatility spillover: Destabilizing energy risk is the new normal

This study examines the spillover effects of oil and natural gas prices on equity indices, offering a broader perspective on the energy commodity market and various aspects of energy risk. It makes three unique contributions. First, it is the first to apply the Diebold and Yılmaz, (2014) 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.



Static volatility interconnectedness network during various periods



Static volatility interconnectedness network during various periods (continued)

Notes: 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 Yilmaz (2014) Spillover index method.

Second, in addition to oil, natural gas (i.e., TTF) is included in the network model, in view of Europe's increasing gas dependency.

Finally, this study 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. This approach provides a more complete view by incorporating additional, unidentified external factors in the model with fixed effects. In the panel regression analysis, the equity market performances of the sample countries are evaluated using MSCI index daily returns. The results indicate that crude oil and natural gas prices systematically influence equity markets and contribute significantly to MSCI index volatility. Notably, countries with relatively underdeveloped exchanges or weaker domestic currencies exhibit greater sensitivity to energy shocks.

4. Main references

- Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., De Gracia, F.P., 2018. Oil volatility, oil and gas firms and portfolio diversification. Energy Economics 70, 499–515.
- Bardoscia, M., Barucca, P., Battiston, S., Caccioli, F., Cimini, G., Garlaschelli, D., Saracco, F., Squartini, T., Caldarelli, G., 2021. The physics of financial networks. Nature Reviews Physics 3, 490–507.
- Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics 104, 535–559.
- Dolado, J.J., Lutkepohl, H., 1996. Making Wald tests work for cointegrated VAR systems. Econometric reviews 15, 369–386.
- Engle, R.F., Granger, C.W., 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica: Journal of the Econometric Society, 251–276.
- Diebold, F.X., Li, C., 2006. Forecasting the term structure of government bond yields. Journal of Econometrics 130, 337–364.
- Diebold, F.X., Li, C., Yue, V.Z., 2008. Global yield curve dynamics and interactions: a dynamic Nelson–Siegel approach. Journal of Econometrics 146, 351–363.
- Diebold, F.X., Rudebusch, G.D., Aruoba, S.B., 2006. The macroeconomy and the yield curve: a dynamic latent factor approach. Journal of Econometrics 131, 309–338.

- Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal 119, 158–171.
- Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting 28, 57–66.
- Diebold, F.X., Yılmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics 182, 119–134.
- Diebold, F.X., Yilmaz, K., 2015. Trans-Atlantic equity volatility connectedness: US and European financial institutions, 2004–2014. Journal of Financial Econometrics 14, 81–127.
- Diebold, F.X., Yilmaz, K., 2023. On the past, present, and future of the Diebold–Yilmaz approach to dynamic network connectedness. Journal of Econometrics 234, 115–120.
- Granger, C.W., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica: Journal of the Econometric Society, 424–438.
- Ji, Q., Zhang, D., 2019. China's crude oil futures: Introduction and some stylized facts. Finance Research Letters 28, 376–380.
- Johansen, S., 1988. Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control 12, 231–254.
- Kremer, M., Becker, A.P., Vodenska, I., Stanley, H.E., Sch¨afer, R., 2019. Economic and political effects on currency clustering dynamics. Quantitative Finance 19, 705–716.

- Lautier, D., Raynaud, F., 2012. Systemic risk in energy derivative markets: a graph-theory analysis. The Energy Journal 33.
- Nelson, C.R., Siegel, A.F., 1987. Parsimonious modeling of yield curves. Journal of Business, 473–489.
- Pittis, N., 1999. Efficient estimation of cointegrating vectors and testing for causality in vector autoregressions. Journal of Economic Surveys 13, 1–35.
- Reboredo, J.C., Ugolini, A., 2015. Systemic risk in European sovereign debt markets: A CoVaR-copula approach. Journal of International Money and Finance 51, 214–244.
- Rossi, B., 2005. Optimal tests for nested model selection with underlying parameter instability. Econometric Theory 21, 962–990.
- Rossi, B., Wang, Y., 2019. Vector autoregressive-based granger causality test in the presence of instabilities. The Stata Journal 19, 883–899.
- Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with possibly integrated processes. Journal of Econometrics 66, 225–250.
- Tumminello, M., Aste, T., Di Matteo, T., Mantegna, R.N., 2005. A tool for filtering information in complex systems. Proceedings of the National Academy of Sciences 102, 10421–10426.
- Zapata, H.O., Rambaldi, A.N., 1997. Monte Carlo evidence on cointegration and causation. Oxford Bulletin of Economics and statistics 59, 285–298.

5. Own references

- Badics, M.C., Huszar, Z.R. and Kotro, B.B., 2023. The impact of crisis periods and monetary decisions of the Fed and the ECB on the sovereign yield curve network. Journal of International Financial Markets, Institutions and Money, p.101837.
- Huszár, Z.R., Kotró, B.B. and Tan, R.S., 2023. Dynamic volatility transfer in the European oil and gas industry. Energy Economics, 127, p.107052.
- Huszár, Z.R., Kotró, B.B. and Tan, R.S., 2023. European equity markets volatility spillover: Destabilizing energy risk is the new normal. Journal of Financial Research, 46, pp. S205-S271.