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An examination of the oil market at the outset of the Russia-Ukraine conflict

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Abstract

The study explores the drift in the connectedness of 28 global energy markets during the Russian-Ukraine war that instigated one of the largest energy disruptions in history. We reveal a significant positive relationship between the energy dependency on Russia and the change in the return shock transmission. Though some developed markets with diversified energy sources signpost resistance post-invasion, most neighboring countries with higher energy dependency are exposed to amplified connectivity and vulnerability to shock transmission.

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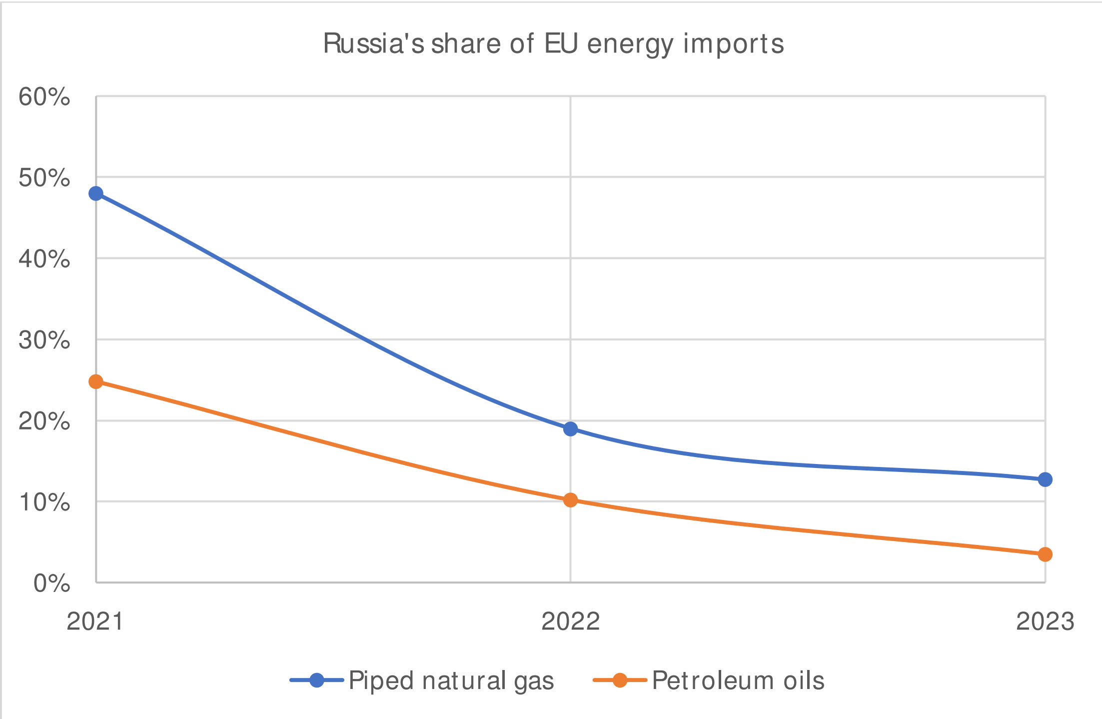
1 Introduction

The Russian-Ukraine conflict has presented a critical dilemma: Should the global community sacrifice Russian oil and gas to prevent a severe humanitarian crisis? While the US and UK have already imposed outright bans on Russian imports, the EU is considering reducing its reliance on Russian energy. However, given the deep economic integration between Europe and Russia, and Russia's position as a major global oil and gas exporter[1], any significant reduction in Russian energy exports could exacerbate an economic downturn (Goldthau and Boersma, 2014).



Source: Eurostat

The war has triggered one of history's most severe energy crises. Consequently, global financial markets are facing significant negative repercussions (Boungou and Yatie, 2022; Tosun and Eshraghi, 2022). This study highlights the interconnectedness of global energy markets, especially those reliant on Russia. We can identify systemically important energy hubs by uncovering emerging connections within these markets. Such insights are crucial for making informed investment decisions and developing effective policy responses.

To the best of our knowledge, this is the first empirical study to investigate the impact of the Ukraine-Russia war on global energy markets. Previous research has established war-related risks as a significant factor in predicting fluctuations in financial variables (Rigobon and Sack, 2005; Choudhry, 2010).

Our study contributes to the existing literature by demonstrating a strong positive relationship between a country's energy dependency on Russia and changes in its return shock. While mature markets with diversified energy sources have shown resilience in the post-invasion period, nations with higher energy

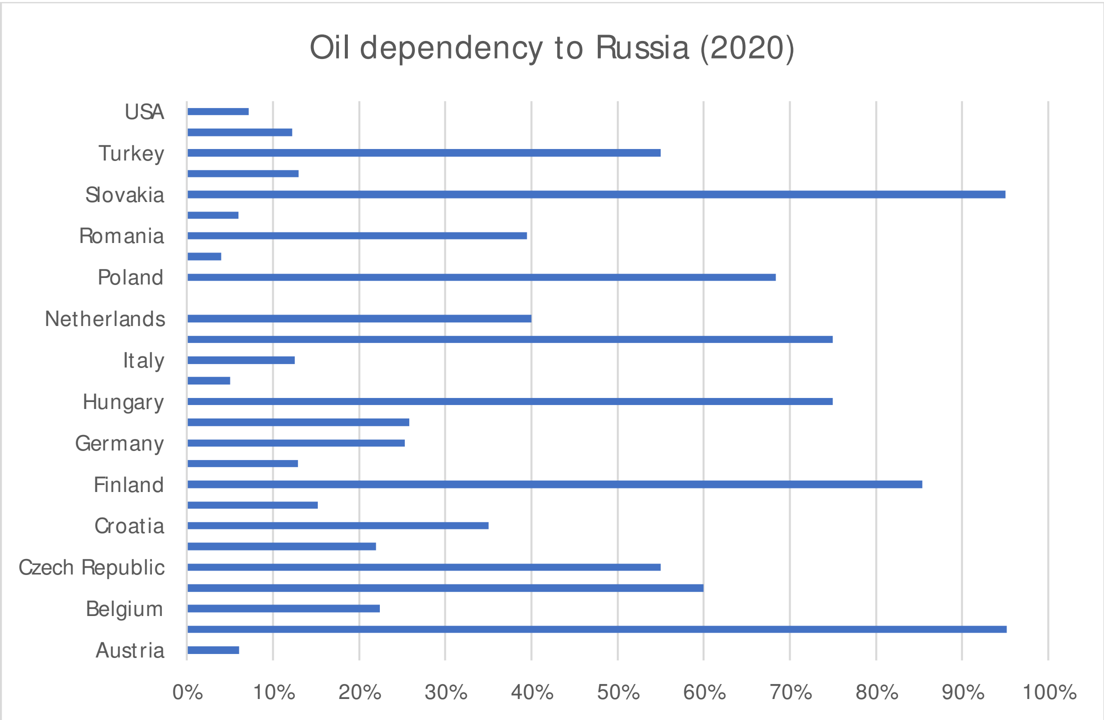
[1] European countries collectively buy the most Russian oil and gas for heat, electricity, gasoline, and other petroleum products. Unlike the US and China, which source from various suppliers, several Eastern European countries are nearly totally reliant on Russia.

dependency on Russia and relatively shallow market capitalization are more susceptible to amplified connectivity and vulnerability to shock transmission.

The rest of this article proceeds as follows. First, section 2 describes the data and empirical approaches. Then, section 3 presents the empirical findings and related insights. Lastly, section 4 concludes.

2 Data and methodology

We obtain daily index prices of the energy sector for 28 countries (Austria, Belarus, Belgium, Bulgaria, China, Croatia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, Turkey, UK, and the USA) for the period 01.01.2016--08.04.2022 from Refinitiv DataStream. The selected countries that import Russian oil, gas, and other petroleum products impact global development with their high degrees of commodity requirement[2]. Moreover, we collect the import composition of the countries concerning the countries from the OPEC database. The aim is to extract Russia's share of the total oil and gas imports of the 28 sampled countries.



Source: Statista

We compute return as natural logarithmic first difference of consecutive prices as: $r_{i,t} = \ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right)$. The descriptive statistics of the return series are available on request. Croatia has the least dispersion (0.010), and Belarus has the largest dispersion (0.076%). Most of the series is skewed to the left, but Finland, Ireland, Poland, and Portugal have right-tailed distributions. All the series are leptokurtic. However, the Jarque-Bera test statistics confirm normal distributions, and the standard augmented Dickey-Fuller and Phillips-Perron tests imply that the series is stationary at their levels.

[2]Read more: https://www.washingtonpost.com/business/2022/03/08/russia-oil-imports-ban/

For our empirical analysis, we rely on a contemporary connectedness technique that is built on Generalized Forecast Error Variance Decomposition (GFEVD) computed from a Time-varying Parameter Generalized Vector Autoregressive (TVP-VAR) means (Antonakakis et al., 2018). This technique overcomes the shortcomings related to rolling window analyses. The TVP-VAR (1) implied by the Bayesian Information Criterion (BIC) is presented as:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t;\ \ \varepsilon_t | F_{t-1} \sim N(0, S_t) \qquad \text{(i)}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + \nu_t;\ \ \nu_t | F_{t-1} \sim N(0, \Xi_t) \qquad \text{(ii)}$$

where Y_t and Y_{t-1} are $N \times 1$ dimensional endogenous variable vectors; ε_t is the $N \times 1$ dimensional disturbance term with an $N \times N$ dimensional time-varying variance-covariance matrix, S_t; β_t is the $N \times N$ dimensional VAR coefficient matrix; ν_t is an $N^2 \times 1$ disturbance vector with an $N^2 \times N^2$ dimensional time-varying variance-covariance matrix, Ξ_t; $vec(\beta_t)$ is the vectorization of β_t[3].

To compute the GFEVD, the TVP-VAR is transformed into Vector Moving Average (VMA) representation as:

$$Y_t = \sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j} \qquad \text{(iii)}$$

Where A_{jt} is an $N \times N$ dimensional matrix through the customary Wold Representation Theorem.

The scaled GFEVD normalizes the unscaled GFEVD, denoted as $\theta_{ij,t}^{g}(H)$, so that each row sums up to unity. As a result, $\theta_{ij,t}^{g}(H)$ represents the influence that variable j has on variable i in terms of its forecast error variance share, which is defined as the pairwise directional connectedness from $j\ to\ i$. This indicator is computed by

$$\theta_{ij,t}^{g}(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} \left(e_i' A_t S_t e_j\right)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} \left(e_i A_t S_t A_t' e_i\right)} \qquad \text{(iv)}$$

To ensure that each row sums up to unity, implying that selected variables explain 100% of variable *i*'s forecast error variance, we compute the scaled GFEVD ($\tilde{\theta}_{ij,t}^{g}(H)$) as:

$$\tilde{\theta}_{ij,t}^{g}(H) = \frac{\theta_{ij,t}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij,t}^{g}(H)} \qquad \text{(v)}$$

where, $\sum_{j=1}^{k} \theta_{ij,t}^{g}(H) = 1, \sum_{i,j=1}^{k} \tilde{\theta}_{ij,t}^{g}(H) = k$, and e_i is a vector with one on the i^{th} element and zero otherwise; $\tilde{\theta}_{\mathrm{ij,t}}^{\mathrm{g}}(\mathrm{H})$ represents a measure of the bidirectional connectedness from index j to index i at horizon H.

The GFEVD is utilized to compute various connectedness measures within the framework of Diebold and Yilmaz (2014) - the system-wide total connectedness across the sampled indexes under study (TCI_t) in Eq. (vi) (Figure 2), the total directional connectedness of index i to all indexes ($C_{j \leftarrow i,t}(H)$) in Eq. (vii) (Figure 3),

[3]Within this study, we look at the benchmark values for κ1 and κ2 driven by the Koop and Korobilis (2014) study, based on which κ1=0.99 and κ2=0.96. It must also be emphasized that though the computation methods are accessible, which allow the decay factors to fluctuate gradually, we maintain them consistent at fixed values as Koop and Korobilis (2013) also realized that the value added by time-varying decay elements relative to the forecasting performance was suspicious and augmented the computation concern of the Kalman filter algorithm substantially.

the total directional connectedness of all indexes to index $i(C_{i\leftarrow j,t}(H))$ in Eq. (viii) (Figure 4), the net total directional connectedness ($C_{i,t}(H)$) in Eq. (ix) (Figure A.1).

$$TCI_t = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij,t}^{g}(H)} \tag{vi}$$

$$C_{j\leftarrow i,t}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji,t}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji,t}^{g}(H)} \times 100$$

(vii)

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij,t}^{g}(H)} \times 100$$

(viii)

$$C_{i,t}(H) = C_{j\leftarrow i,t}(H) - C_{i\leftarrow j,t}(H) \tag{ix}$$

3 Empirical findings

In this study, our main interest is to present the nature of the shift in the connectedness network of 28 energy markets by the Russian-Ukraine war, creating one of the largest energy disruptions in history. Therefore, we use the contemporary network diagram to exhibit our benchmark results instead of tabulating a giant matrix[4] (M x N = 28 X 28), as presented in Figure 1.

Before the invasion (as presented in Figure 1.1), France[5] is captured as the largest contributor to the return shock transmission, followed by Spain, the UK, Italy, and Norway, signifying their deep mature market status. These countries are also captured as the largest recipient of shocks from others. The highest bidirectional transference appears between France and the UK and between France and Italy. However, we notice significant variations during the invasion (as presented in Figure 1.2). Turkey is captured as the largest contributor to the return shock transmission, followed by Austria, Czechia, Greece, and Romania, though Spain, the UK, and Italy remain the largest recipients of shocks from others. The highest bidirectional transference develops between Sweden and Norway and between Denmark and Germany.

Before the invasion, the sampled Eastern European countries, particularly Belarus, Bulgaria, Croatia, Czechia, Hungary, Poland, and Romania, were net recipients of return shocks, but their position strikingly transformed into net transmitters except for Belarus and Croatia. Interestingly, the net position of the Western European countries, particularly Austria, Belgium, France, Germany, Ireland, Netherlands, and the UK, remain unchanged, reflecting their relatively mature market status. In the case of the two largest economies the USA and China, though both countries are somewhat isolated, only the USA changed the net position. The magnitude of the system-wide total connectedness index spiked from 59.23% before the invasion to 72.48% during the invasion.

Next, we move our attention to the dynamic system-wide total connectedness index over time, as presented in Figure 2. As highlighted, the impact of the COVID-19 pandemic subsided before it picked up at the onset of the invasion, which further intensified with the development of the invasion. This also signals

[4]Tabulated complete results of connectedness before and during Russian invasion of Ukraine are available on request.
[5]France is Europe's second-largest consumer of energy after Germany. However, it heavily relies on imports to meet most of its oil and gas consumption.

higher interdependence of the energy markets in the extreme market situation, consistent with existing studies.

At this point, it would be more insightful to see market-wise dynamic total return shocks transmission 'to others' (as presented in Figure 3) and 'from others' (as presented in Figure 4). In the case of 'to others', we see heterogeneity with noticeable shock transference from Bulgaria, Czechia, Greece, Hungary, Ireland, Lithuania, Netherlands, Romania, Slovakia, and Turkey in the course of the war. It is worth reporting nearly no impact from Belarus and the marginal impact from China and the USA. We are more interested in transmitting the collective shocks 'from others' to a specific market. We notice two patterns – mature markets with either no or marginal impacts (Austria, Italy, Norway, Portugal, UK, and to some extent, China, Denmark, Finland, France, Germany, Netherlands, Poland, Spain, Sweden, and the USA) alongside markets that are either neighbors to Russia or heavily dependent on Russian oil and gas (Belarus, Belgium, Bulgaria, Czechia, Croatia, Greece, Hungary, Lithuania, Malta, Romania, Slovakia, and Turkey (in consonance with Balli et al. 2022; Boungou and Yatie, 2022).

Probing further, we dive deep into the oil dependency on Russia. We first compute the % change in shock transmission from others to a specific country by taking the % change between 2021 and 2022 as one variable and the country's oil dependency on Russia as another variable. We then regress those before retaining the results into a scatter plot, as presented in Figure 5. The regression line signifies a positive relationship between the oil dependence on Russia and the % change in the transmission of the shocks resulting from the war. As explored before, some mature developed markets (France, Germany, as well as Norway, the USA, and China with no significant dependency on Russia) showed some resistance, but most countries, particularly Belarus, Bulgaria, Croatia, Finland, Lithuania, Slovakia, and Turkey, with higher dependency and relatively shallow market capitalizations, showed more amplified connectivity and vulnerability to global shocks transmission.

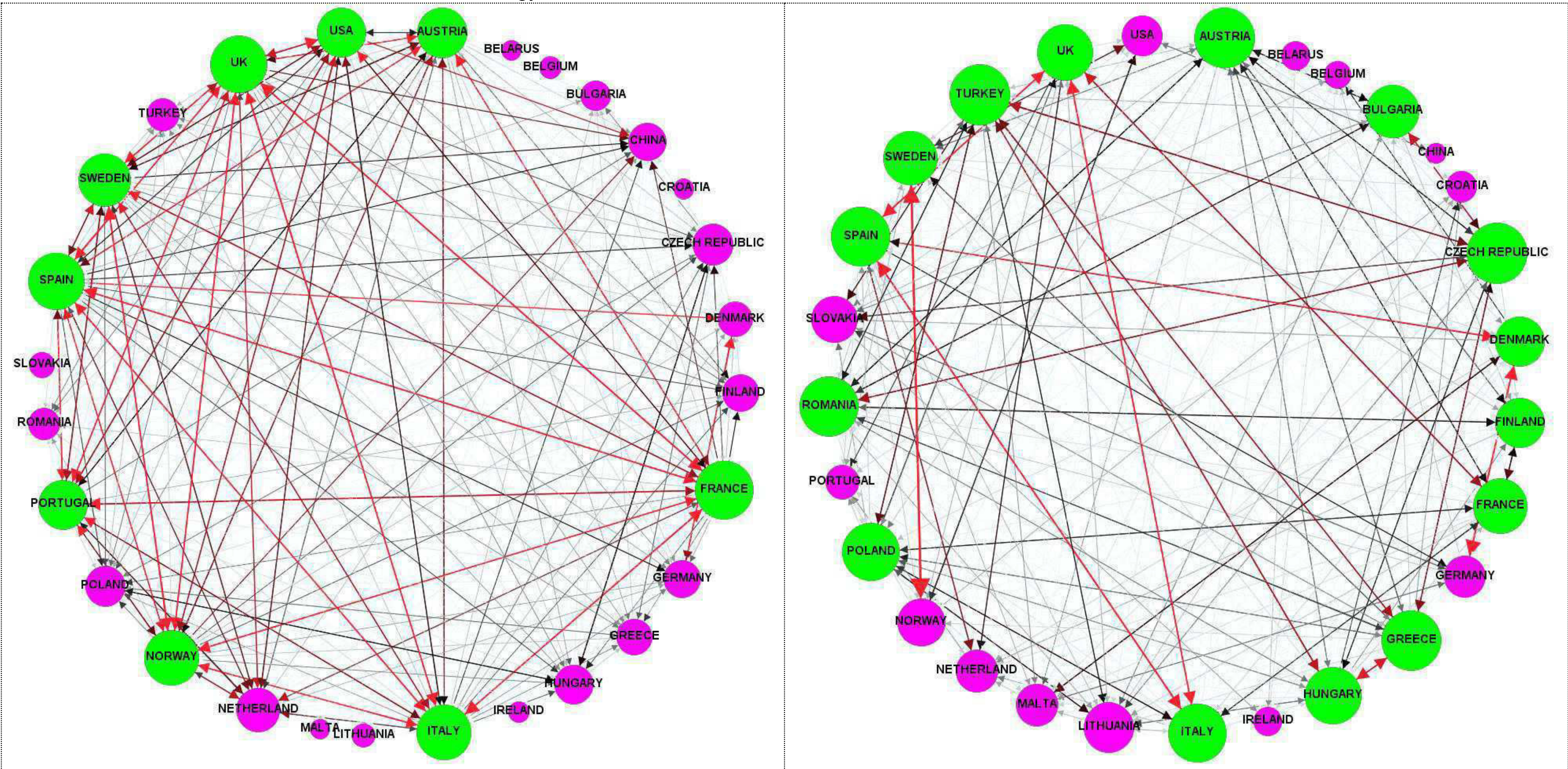
For a more comprehensive analysis, we have also calculated dynamic net return shock transmission, detailed in Appendix Table A1. These findings align with the results presented in Figures 3 and 4, further reinforcing the timely implications for cross-border investors, portfolio managers, and policymakers.

4 Conclusions

Leveraging daily return data spanning 1 January 2016 to 8 April 2022, this study examines the evolving network connectedness among 28 global energy markets during the Russian-Ukraine war. Our analysis reveals a strong positive correlation between a country's energy dependence on Russia and the subsequent increase in the transmission of return shocks. While mature, diversified markets demonstrated resilience post-invasion, countries with significant reliance on Russian energy sources experienced heightened connectivity and vulnerability to shock propagation. These findings carry significant implications for cross-border investors, portfolio managers, and policymakers in the energy sector, as the conflict is likely to exacerbate financial contagion risk in the short term.

To mitigate geopolitical risks, countries should prioritize energy diversification. This includes reducing reliance on single-source energy supplies through investments in renewables, diversifying import partners, and enhancing energy storage. Robust regulatory frameworks and international cooperation are crucial for a resilient global energy market. By taking these steps, policymakers can safeguard financial stability and reduce systemic risk.

Figure 1. Connectedness network in the sectoral energy markets

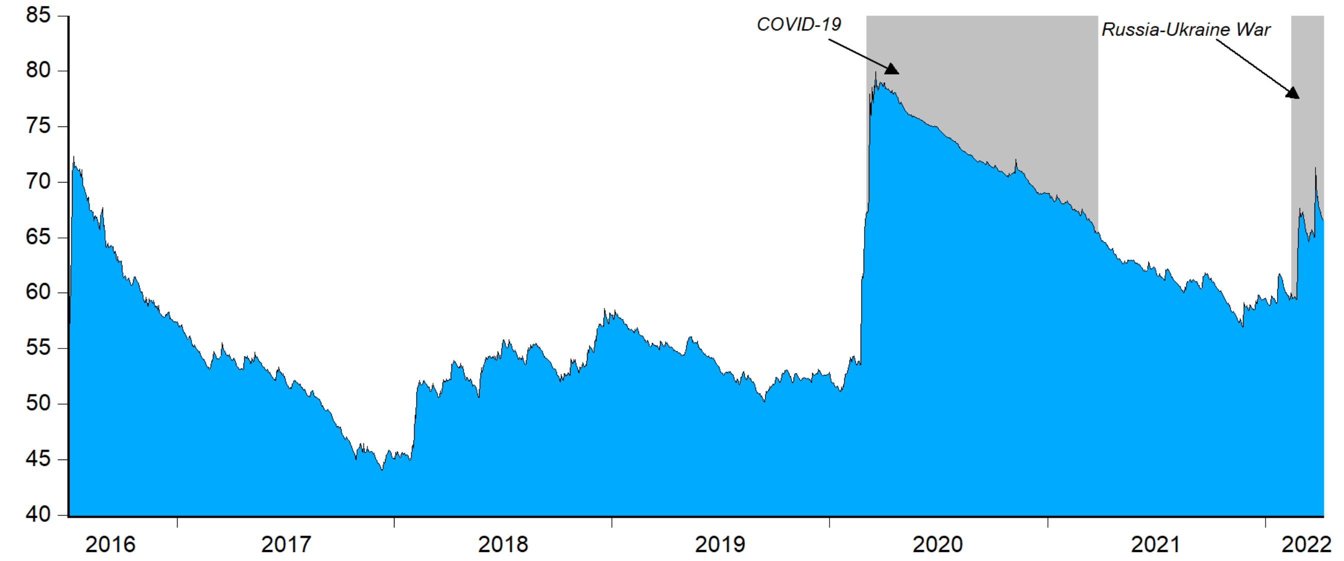


1. Before Russian invasion of Ukraine (system-wide total connectedness index: 59.23%)

2. During Russian invasion of Ukraine (system-wide total connectedness index: 72.48%)

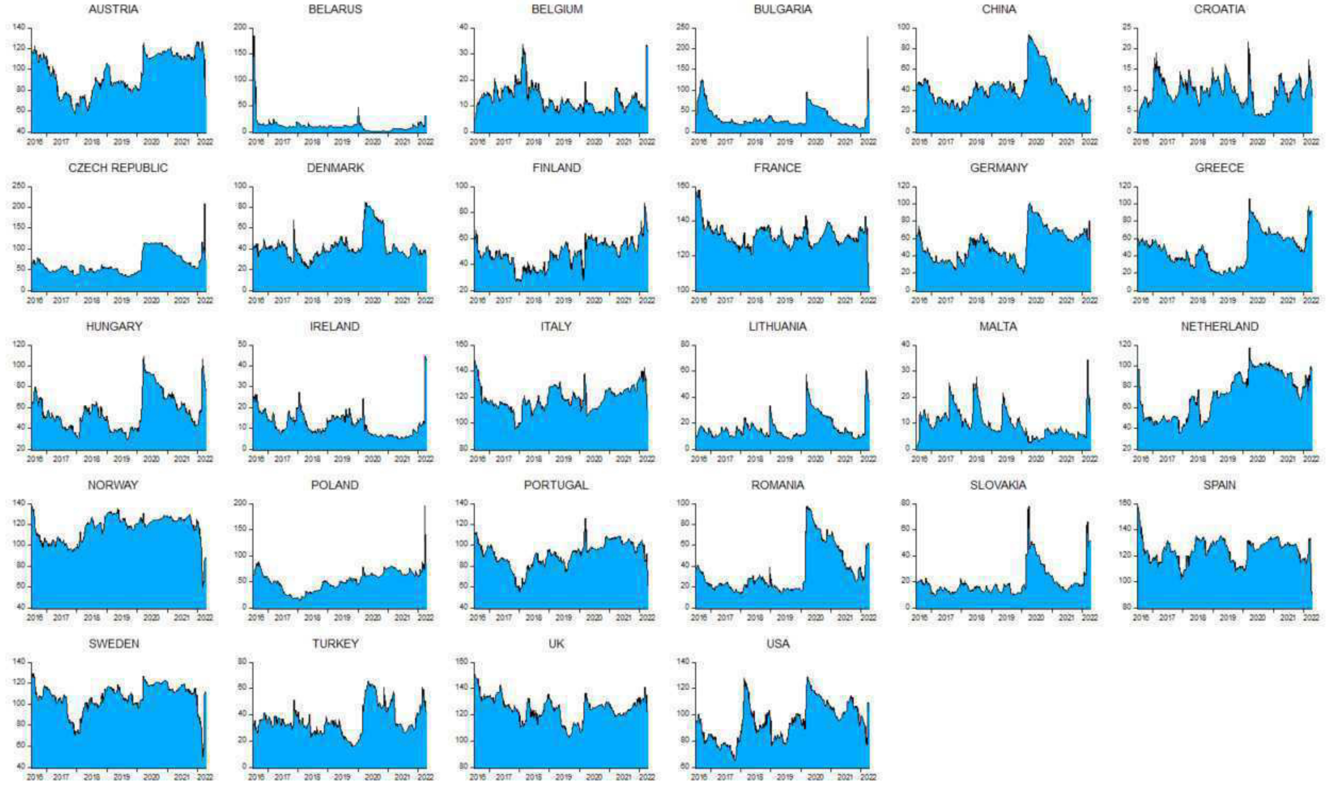
Notes: The network diagram is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD. Nodes size refers to the extent of connectivity, and colour refers to whether a market is a net transmitter (green) or recipient (pink) of return shocks. The finite directional layout algorithm sets the position of the nodes, with the number of vectors forming the route of the nodes. The width of the arrows signifies the strength of the multiple gradients, and the colour indicates the direction of the gradients from the strongest (ruby) to the weakest (black).

Figure 2. System-wide dynamic total connectedness index



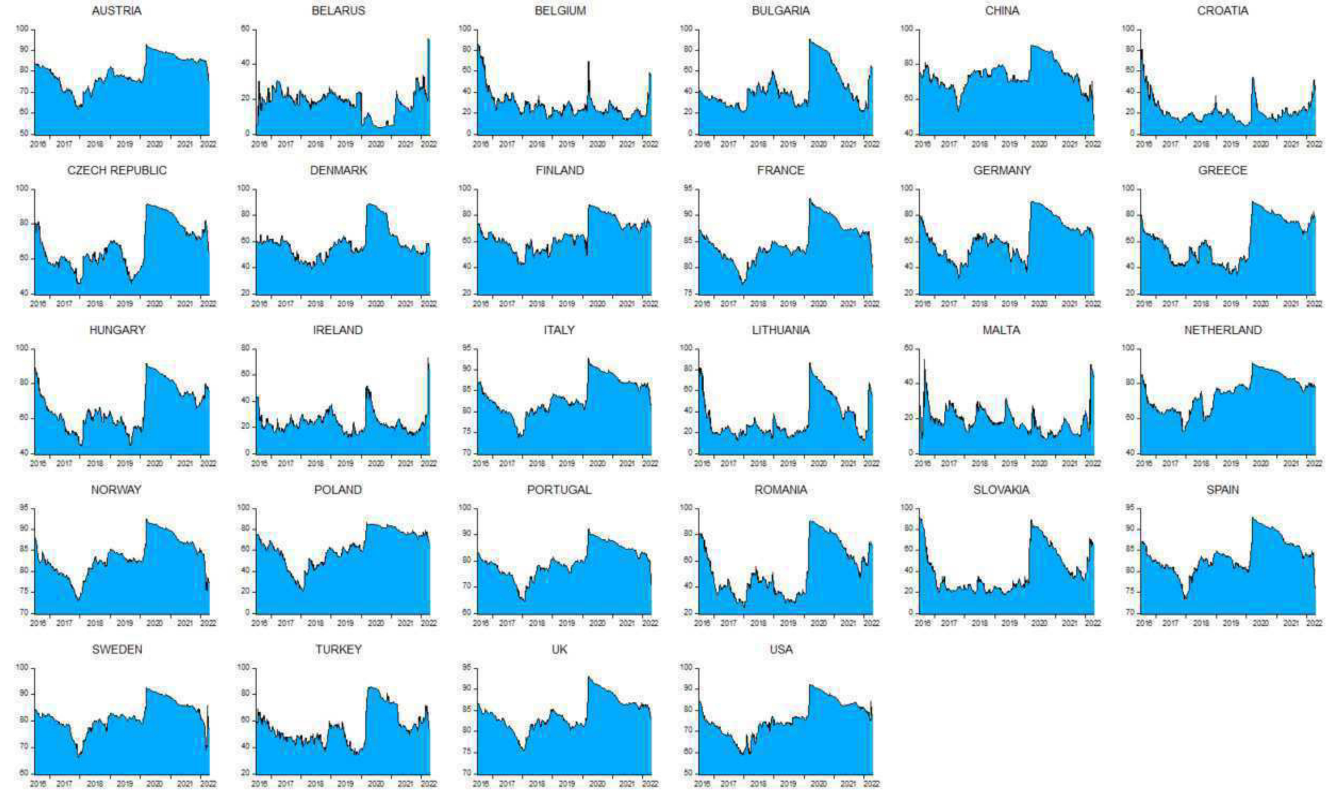
Notes: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.

Figure 3. Dynamic total return shocks to others



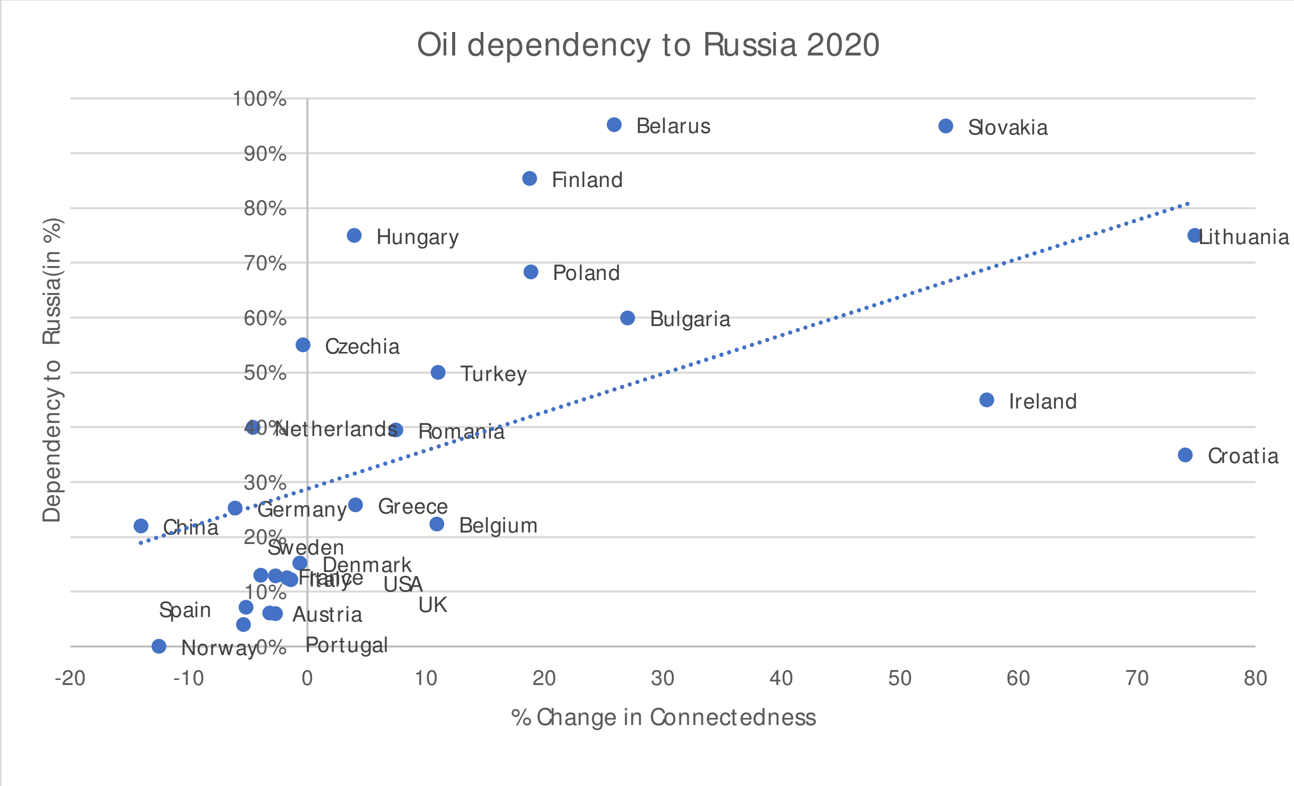
Notes: See Figure 2.

Figure 4. Dynamic total return shocks from others



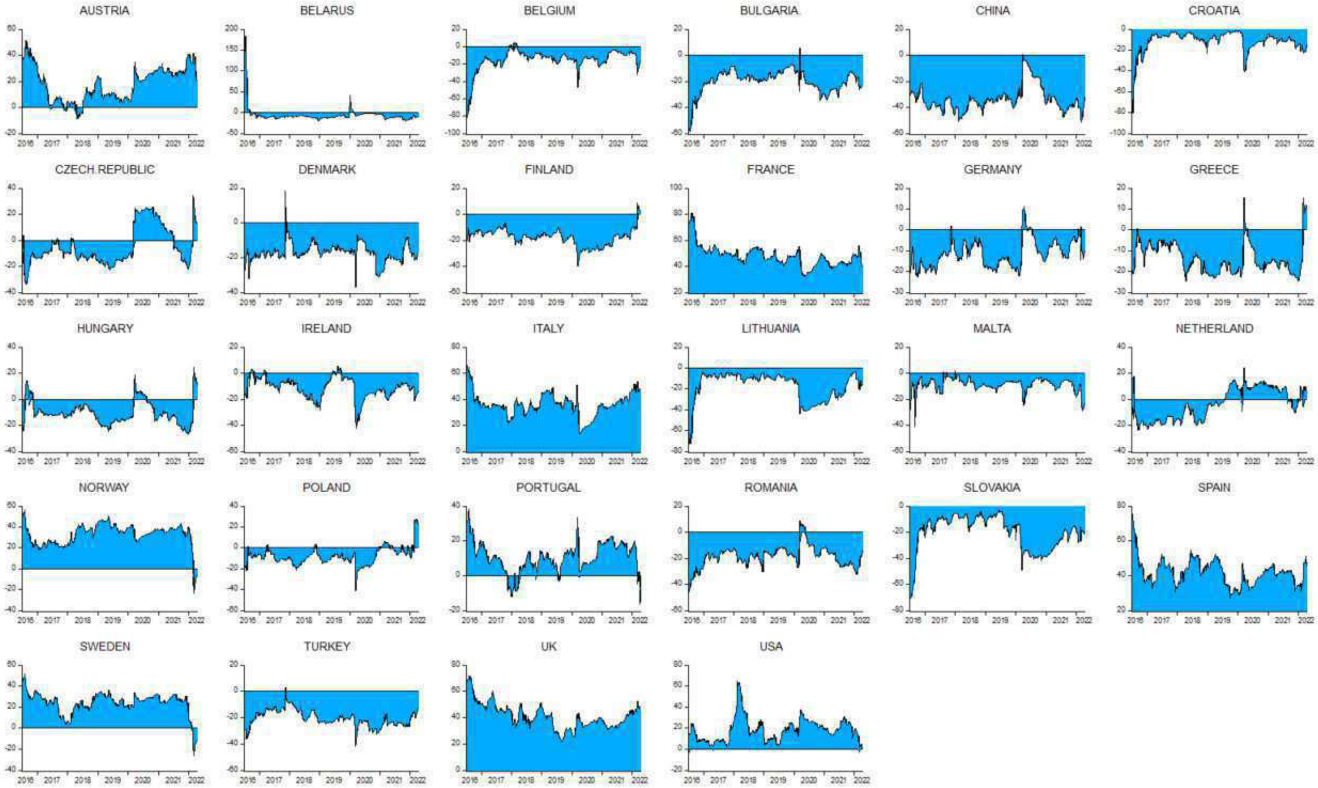
Notes: See Figure 2.

Figure 5. Scatter plot of oil dependence to Russia vs. % change in shock transmission (from others)



Notes: The blue dashed trend line refers to a positive relationship between the oil dependence on Russia and the % change in the transmission of the shock resulting from the war. Oil dependence on Russia is sourced from OPEC and T&E Eurostat.

Figure A1. Dynamic net return shock transmission



Notes: See Figure 2.

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