COLLEGIUM OF ECONOMIC ANALYSIS
WORKING PAPER SERIES

The role of uncertainty and sentiment for intraday volatility connectedness between oil and financial markets

Karol Szafranek and Michał Rubaszek and Gazi Salah Uddin

SGH KAE Working Papers Series Number: 2023/095 November 2023

The role of uncertainty and sentiment for intraday volatility connectedness between oil and financial markets

Karol Szafranek*[a], Michał Rubaszek[a], and Gazi Salah Uddin[b]

[a]*SGH Warsaw School of Economics, Collegium of Economic Analysis*
[b]*Linkoping University, Department of Management and Engineering, Sweden*

Abstract

We quantify intraday volatility connectedness between oil and key financial assets and assess how it is related to uncertainty and sentiment measures. For that purpose, we integrate the well-known spillover methodology with a TVP VAR model estimated on a unique, vast dataset of roughly 300 thousand 5 minute quotations for crude oil, the US dollar, S&P 500 index, gold and US treasury prices. This distinguishes our investigation from previous studies, which usually employ relatively short samples of daily or weekly data and focus on connectedness between two asset classes. We contribute to the literature across three margins. First, we document that market connectedness at intraday frequency presents new picture on markets co-movement compared to the estimates obtained using daily data. Second, we show that at 5 minute frequency volatility is mostly transmitted from the stock market and absorbed by the bond and dollar markets, with oil and gold markets being occasionally important for volatility transmission. Third, we present evidence that daily averages of intraday connectedness measures respond to changes in sentiment and market-specific uncertainty. Interestingly, our results contrast with earlier findings, as they show that connectedness among markets decreases in periods of high volatility owing to market-specific factors. Our study points to the importance of using high-frequency data in order to better understand market dynamics.

Keywords: volatility connectedness, uncertainty and sentiment, oil market, intraday data, TVP-VAR model.

JEL classification: C32, C58, D80, Q31

*Correspondence should be directed to `karol.szafranek@sgh.waw.pl`. Postal address: Al. Niepodlegglosci 162, 02-554 Warsaw, Poland. Karol Szafranek and Michał Rubaszek acknowledge the financial support from the National Science Centre (Poland) within grant No. 2021/43/D/HS4/00380. We would like to thank Joscha Beckmann, Robinson Kruse-Becher and other participants of *Workshop on Expectations and Sentiments for Energy Price Dynamics*, hosted in Berlin by FernUniversität Hagen in October 2023. The authors do not declare any conflict of interest.

1 Introduction

The importance of uncertainty and sentiment for both the economy and financial markets is already well recognized in the literature. The theoretical frameworks of Bernanke (1983) and Pastor and Verones (2012) imply that a spike in economic uncertainty should lead to a decline in economic activity and prices of risky assets. There is also a voluminous empirical literature gauging the reaction of the economy and financial markets to changes in sentiment, which has emerged and flourished in the last decade.

The increase in academic interest regarding the effects of uncertainty and sentiment shocks is related to the unfolding of critical events in recent times after a long period of relative macroeconomic and financial stability. These include the global financial crisis, the European sovereign debt crisis, the outbreak of the Covid-19 pandemic or the Russian full-scale invasion of Ukraine. Moreover, advances in machine learning coupled with rising computational power and the dissemination of dedicated software allowed researchers to easily examine, describe and interpret textual data by transforming it into a quantitative representation (see Algaba et al., 2020, for the survey on sentometrics). In economics, the spread of text processing methods has facilitated the development of news-based uncertainty and sentiment measures, such as the Economic Policy Uncertainty (EPU, Baker et al., 2016) or their Twitter-based (TEU) alternatives, the Geopolitical Risk Index (GPR, Caldara and Iacoviello, 2022) or the News Sentiment Index (NSI, Buckman et al., 2020). In this sense, the development in natural language processing made it possible to conduct econometric analyses on the link between uncertainty or sentiment and economic or financial variables (see Castelnuovo, 2023, for a comprehensive survey).

Given this progress, a large body of literature has concentrated on the causal link between both uncertainty or sentiment and commodity markets. For instance, Antonakakis et al. (2017) show that GPR shocks negatively affect oil prices and their volatility. Bilgin et al. (2018) report that gold prices increase after EPU shocks, thus confirming the role of this commodity as a safe haven in times of high risk aversion triggered by either economic or political uncertainty. Uddin et al. (2018) conclude that economic uncertainty shocks exert stronger effects on energy commodity prices than geopolitical shocks. Ozcelebi and Tokmakcioglu (2022) document that geopolitical risk affects negatively oil supply and prices. The empirical literature also investigates connectedness between both uncertainty or sentiment and commodity markets. For instance, Sharif et al. (2020) or Gao et al. (2021) focus on spillovers between EPU and oil prices, whereas Li et al. (2022) investigate links between GPR and oil. Finally, there are few recent studies, which undertake the research question similar to ours and examine the importance of uncertainty and sentiment in driving the connectedness between financial and commodity markets (Albulescu et al., 2019; Mensi et al., 2022a; Akyildirim et al., 2022; Gong and Xu, 2022a; Wu et al., 2023; Dai and Zhu, 2023). We will review these studies in detail in the next section.

Against this background, in this article we contribute to the scarce empirical literature identifying the drivers of spillovers across commodity and financial markets. We investigate whether uncertainty and sentiment drive connectedness between the crude oil market and the markets for most frequently traded, key financial assets, i.e., the US dollar, S&P 500, gold and US treasury bonds. For that purpose, we first employ the commonly used time-varying parameter vector autoregression model (TVP-VAR) á la Koop and Korobilis (2014) to estimate Diebold and Yilmaz (2012, 2014, henceforth DY) and Barunik and Krehlík (2018, henceforth BK) connectedness measures defined for the time and frequency domains, respectively. Second, we test if connectedness estimates obtained in the first stage of our analysis are related to various popular uncertainty and sentiment measures. We contribute to the literature along three margins.

First of all, we quantify volatility spillovers with the means of a unique database consisting of intraday data, while contemporaneous studies frequently rely on daily observations. Our approach allows us to discuss to what extent connectedness among oil and financial markets at intraday (high) frequency compares to connectedness estimates obtained using daily data. Specifically, in our model we account for almost 300 thousand of 5 minute observations spanning the period from January 2, 2018 to May 27, 2022. We show that measures of connectedness based on intraday data deliver new perspective on the joint dynamics of financial and commodity markets compared to their counterparts obtained using daily data.

Second, we present new evidence on intraday volatility connectedness of crude oil prices with the volatility on four most important financial markets, i.e., the US exchange rate, stocks, bonds and gold. This makes our study more comprehensive compared to most previous investigations, which frequently focus on connectedness between oil and one particular class of assets. We document that at intraday frequency the stock market transmits volatility, while the bond and exchange rate markets absorb it, with oil and gold markets being occasionally significant for the volatility flow.

Third, we enrich the literature by examining how volatility connectedness between crude oil and key financial assets is related to various uncertainty and sentiment proxies. We find, counter-intuitively, that increases in uncertainty measured with implied volatility lead to declines in total and directional spillovers. On the other hand, Twitter-based sentiment measure, that filters short communication circulating among market participants, is very important for the link between oil and other studied asset classes. In turn, newspaper-based uncertainty such as the economic policy uncertainty, news sentiment or geopolitical risk index do not affects connectedness among markets. Our intuition suggests that this outcome stems from the backward-looking nature of these proxies. Overall, our results shed new light compared to earlier studies based on daily data, which conclude that connectedness among markets increases in periods of high uncertainty and low economic sentiment.

The remainder of the article is structured as follows. Section 2 provides an in-depth discussion of the literature. In section 3 we characterize our unique dataset employed in the study. Section 4 outlines the methodology. The main results are reported in section 5. The last section delivers conclusions and policy implications.

2 Literature review

In this section, we review three strands of the literature to which we contribute in this paper. Subsection 2.1 describes studies focusing on the connectedness of crude oil with stocks, exchange rates, gold and bonds. Subsection 2.2 discusses articles aimed at identifying drivers of oil market connectedness, with a specific focus on uncertainty and sentiment variables. Finally, subsection 2.3 summarizes works that employ intraday data in oil market analyses.

2.1 The connectedness of crude oil and other markets.

The empirical literature examining the relationship among oil and key financial markets of our interest (stocks, exchange rates, gold and bonds) has exploded in the last decade. Thus, providing an exhaustive literature review here is infeasible. For that reason, we limit our discussion to the most important channels of transmission and the main results of selected studies that focus on the dynamic relationship between oil and other markets.

Oil and stocks. The reaction of stock prices to oil shocks is usually justified by changes in future cash flows and expected returns, whereas the response of oil to equity market shocks is related to the financialization of commodity markets. The empirical studies confirm the existence of strong ties between these markets. Awartani and Maghyereh (2013) indicate that oil prices transmit more to Gulf countries stock indices than they receive, both in terms of returns and volatility. Similar results for implied volatility and eleven major stock markets are presented by Maghyereh et al. (2016). On the contrary, Zhang (2017) explores the connectedness of returns from oil and six major stock markets to find that oil is net receiver of shocks and that, apart from the episodes of increased volatility, the contribution of oil shocks to the variance of equity market returns is limited. Several studies focus on individual stocks to deepen the understanding of the oil-equity relationship. Antonakakis et al. (2018) point to the existence of significant volatility spillovers among oil and stock prices of 25 largest global oil and gas corporations. Peng et al. (2018) document significant and asymmetric spillovers from crude oil to stock returns for 529 firms listed on the Shanghai stock exchange, emphasizing that transmission from oil price shocks to firm returns depends on the firm's characteristics. Ma et al. (2019) reports that US energy stocks are net transmitters to oil returns. Taking a long-term perspective, Benlagha et al. (2022) illustrate that the connectedness between oil, renewable energy and stock markets increases in times of pandemics. In a similar vein, Wang et al. (2023b) show that spillovers between returns from crude oil prices and eleven sector stock indices in China rises during extreme market events. In general, it can be concluded that there are significant bi-directional spillovers between oil and stock markets, with ambiguous results for net transmission.

Oil and exchange rates. The reaction of exchange rates to oil shocks is related to the wealth transfer from oil-importing towards oil-exporting countries. On top of this effect, the intensity of energy use in a given country also affects inflation and interest rate response to oil shocks, which indirectly transmits to exchange rate developments. In turn, shocks to the value of the US dollar affect nominal oil prices as they are expressed in USD terms. As regards empirical evidence, the influential study of Chen et al. (2010) show that commodity currencies contain predictive power in predicting commodity prices, whereas the reverse relationship is not significant. In the same vein, Beckmann and Czudaj (2013) document a time-varying causality from the US dollar effective rate to oil prices. On the contrary, Wang et al. (2023a) detect nonlinear effect of crude oil prices on the US dollar exchange rate, without evidence on reverse causality. The recent contributions of Smiech et al. (2021) and Dabrowski et al. (2022) indicate that shocks to oil prices and volatility affect exchange rates of oil-exporting countries, but the response is heterogeneous and depends on the specific characteristics of each country. As regards rare spillover analyses, Malik and Umar (2019) find that the connectedness of returns among oil and exchange rate markets is low and broadly balanced, both for major oil-exporters and importers. Albulescu et al. (2019) report that for returns oil rather transmits than receives shocks towards G10 currencies, whereas the spillover effect materializes predominantly for commodity currencies. Finally, most recently Obstfeld and Zhou (2023) corroborates the negative relation between the dollar and global commodity prices (including oil). In general, spillovers between oil and exchange rates are rather low, with oil playing mostly the role of net transmitter.

Oil and gold. Oil shocks exert an impact on gold prices as they lead to higher inflation and interest rates. Given that gold is used as a hedge against inflation but also as an investment alternative to fixed income financial assets, the total effect is ambiguous. Moreover, there is also a potential cause for long-run relationship as the prices of both commodities are expressed in USD terms. Indeed, Zhang and Wei (2010) and Narayan et al. (2010) point to the existence of a long-term equilibrium between prices of both assets. They also indicate that in the short run oil prices Granger cause gold prices, with no reverse link. As regards studies based on the connectedness framework, Rehman et al. (2018) show that gold returns are only weakly affected by oil market shocks in normal times, but the link becomes substantial during financial crisis. They also show that, on average, oil transmits and gold receives shocks in net terms. In turn, Cui and Maghyereh (2023) focus on numerous commodity futures to find that oil is the largest net transmitter of spillovers, both for returns and volatility, while gold is a mild receiver of shocks. The authors also demonstrate that the scale of connectedness among commodity markets was relatively high at the beginning of the Covid-19 pandemic and the Russian invasion of Ukraine. In general, the analyses of spillovers between oil and gold indicate that oil is net transmitter of shocks.

Oil and bonds. The reaction of fixed income securities to oil shocks is justified by the existence of the expected inflation component in nominal bond yields and monetary policy reaction to inflation triggered by energy price increases. Specifically, rising oil prices cause the expected inflation and policy rates to rise, which pushes up bond yields and lowers bond prices. However, higher oil prices also generate additional income for oil exporters, which usually translates into higher demand for financial instruments, including bonds. This channel cushions the scale of bond prices decline following an oil price shock. As regards the reverse causality, expansionary policy measures conducted by major central banks, through the effect on global economic activity and the demand for crude oil industry, lead to higher oil prices. The empirical evidence indicates that global oil market shocks represent a significant source of US bond prices variability, but the effect of bond market shocks on oil prices is negligible (Kang et al., 2014). Similarly, Gormus et al. (2018) show that oil price and volatility shocks affect high-yield US bond prices and that the relationship is unidirectional. Balcilar et al. (2020) confirm the transmission from oil shocks to US bonds by showing that oil price uncertainty helps in predicting US bonds returns and volatility, with the effect on the latter being stronger. In turn, Dai and Kang (2021) document that US bond yields have some explanatory power for oil returns. In a cross-country analysis, Demirer et al. (2020) report that oil shocks exert an effect on yields of 21 sovereign bond markets. Nazlioglu et al. (2020) analyze price and volatility causality between crude oil and 14 major bond markets to find that oil prices Granger cause bond prices in most cases, whereas the feedback from bonds to oil prices is weak and detected only for the largest economies in the sample, i.e., China and the US. Finally, several studies apply the connectedness framework to analyze the relationship between sovereign yields and oil prices. Umar et al. (2022) report that oil and US bond yields are the main transmitters of shocks, whereas bond yields in other investigated economies are net recipients of shocks. Similarly, Umar et al. (2023) document a sizable connectedness of oil price shocks with three fixed income asset classes, with oil found to be net transmitter of shocks. In general, the above studies point out that the oil market is the source of bond prices variability, whereas the reverse causality is weak.

Multiple assets. There are also rare contributions evaluating the interaction among oil and several asset classes using the connectedness framework. Awartani et al. (2016) point to a strong volatility spillover from oil to US equities, and moderate spillovers to the euro dollar exchange rate and precious metals. Husain et al. (2019) investigate the connectedness among oil, S&P 500 index and precious metals volatility to find that platinum is net contributor in the system, crude oil is net receiver, whereas gold and stocks are broadly neutral. Adekoya and Oliyide (2021) examine connectedness among five markets (oil, gold, stocks, bitcoin and exchange rates) and document that gold and USD are net receivers of shocks, whereas oil and stocks play the role of net transmitters.

Finally, Dai et al. (2022) focus on volatility spillovers among oil, gold and Chinese stocks. They show that there exists a high interdependence among all analyzed assets, especially during major crisis events. Moreover, they report that on average crude oil and gold are net receivers and stock markets are net transmitters of systemic shocks.

2.2 What drives connectedness of oil and financial markets?

We continue the literature review by discussing results of rare, recent studies that extend connectedness computation for the second stage of the analysis, which is aimed at identifying the main drivers of spillover indices. In the context of our investigation, we are especially interested whether uncertainty and sentiment are important determinants of links between markets. It is worthy to note that the methodology of this second stage analysis is very diverse across articles. Albulescu et al. (2019) use a battery of linear and nonlinear Granger-type causality tests to show that there is a significant causal relationship from the EPU index to the total spillover index (TSI) for oil and currency markets. Adekoya and Oliyide (2021) use causality-in-quantiles tests to indicate that the severity of the Covid-19 pandemic is a cause for the TSI for major global assets. Mensi et al. (2022a) apply quantile coherency analysis to find that neither EPU nor VIX are significant drivers of the TSI for precious metals and currency markets. Akyildirim et al. (2022) run quantile regression and show that connectedness among energy equity indices of oil-exporting and importing countries is significantly influenced by economic sentiment index extracted from newspapers or Twitter. In another investigation on connectedness across commodity and financial markets, Wu et al. (2023) apply regime-switching framework to identify EPU as an important driver of the interactions among these markets. In turn, using MIDAS framework, Gong and Xu (2022b) show that the dynamic connectedness among various commodity markets is dependent on the level of the GPR index. Finally, Dai and Zhu (2023) use predictive regression framework to document that credit spreads as well as VIX contain predictive content for the TSI for oil and Chinese stocks. Overall, the above studies provide robust evidence that both uncertainty and sentiment can affect connectedness across markets.

2.3 Intraday data within the connectedness framework.

The connectedness of the crude oil market with other asset classes is usually analyzed with data of relatively low frequency (i.e., daily, weekly or even monthly). Consequently, they do not measure intraday fluctuations of asset prices. Our intraday analysis sheds new light on the dependence among crude oil and other asset classes, especially during extreme market events. For that reason, in this subsection we describe rare studies that use intraday data in oil market analyses.

In several studies, intraday data are only used to calculate daily series for realized moments (e.g., volatility, skewness or kurtosis), which are then used in connectedness analysis (e.g., Luo and Ji, 2018; Zhang et al., 2021; Bouri et al., 2021; Iqbal et al., 2023; Dai and Zhu, 2023; Maghyereh and Abdoh, 2022; Naeem et al., 2023). These studies are not a focus of this review as they do not provide guidelines on intraday connectedness.

Our investigation is related to studies examining the relationship between oil and other asset classes at frequencies measured in minutes. For instance, Phan et al. (2016) employ 5 minute data from 2009-2012 and predictive regression framework to show that bid–ask spread, trading volume and price volatility of US equity markets improve volatility predictability for crude oil prices. Using DCC-GARCH, Corbet et al. (2020) analyze co-movements among oil and US energy stocks hourly returns during the outbreak of the Covid-19 pandemic. The authors document positive and meaningful spillovers from oil to stock prices. Using similar methodology but 15 minute data, Mensi et al. (2022b) examine volatility spillovers between oil, US stocks and gold around the Covid-19 pandemic. They show that conditional correlations between markets were higher during lockdowns. Okhrin et al. (2023) use 1 minute data to explore connectedness between oil prices, US equities, USD exchange rate and the VIX. Using cross-quantilograms and copula regression, the authors conclude that connectedness increases sharply during the Covid-19 pandemic and the Russian invasion of Ukraine.

According to our best knowledge there are only two studies that apply the connectedness framework on intraday data to investigate the interdependence of oil and other financial markets. In the first one, Farid et al. (2021) focus on the volatility connectedness across the US equity index and major commodities, including oil and gold. With the sample of 5 minute data spanning the period January 2019 - May 2020, the authors find that the outbreak of Covid-19 pandemic exerted a significant impact on volatility linkages. The authors also indicate that the S&P 500 index was net transmitter and crude oil net receiver of shocks throughout the sample. In the second study, Adekoya et al. (2022) examine how crude oil connects with bonds, bitcoin, the US dollar, gold, and stocks. In this case, the sample is based on 30 minute observations from January 2022 to March 2022. The authors indicate that the Russian invasion of Ukraine significantly increased returns connectedness between oil and other markets, with oil becoming net transmitter of spillovers.

Against this rich literature of market connectedness, our contribution is threefold. First, we employ a unique and vast dataset of intraday data as we make use of roughly 300 thousand observations of 5 minute frequency. Second, our analysis on volatility connectedness encompasses oil and four key, most heavily traded assets (i.e., the US dollar, S&P 500 index, gold and bonds). Third, we examine how various proxies of uncertainty and sentiment are related to intraday connectedness of oil with other markets and disentangle a set of its robust determinants.

3 Data

In the paper we account for two data sources. First, we retrieve intraday price data from FirstRateData.com, which serve for capturing market connectedness. Our unique dataset contains quotations for five assets ($i = 1, 2, ..., 5$), i.e., continuous futures for the WTI crude oil prices (OIL), effective exchange rate of the US dollar (USD), continuous futures for the S&P 500 index (SPX), continuous futures for gold prices (GOLD) and continuous futures for 10-Year Treasury Note (BONDS). The sample covers 1136 trading days over the period from 2 January 2018 to 27 May 2022, with the last observation limited by data availability. Nonetheless, our sample allows us to quantify market spillovers before the Covid-19 pandemic, throughout its outbreak and following the onset of the Russian full-scale invasion of Ukraine.

We start by discussing the characteristics of this intraday database. For the majority of working days the market for stocks, bonds, gold and oil opens at 6:00 p.m. and closes at 5:00 p.m. ET (Sunday to Friday). The exception is the US dollar, which is traded for 21 hours a day (from 8:00 p.m. to 5:00 p.m. ET) from Monday to Friday, while on Sunday evening the market for Monday's trade date opens earlier (at 6:00 p.m. ET). To facilitate our analysis, we adjust the time index of our database from ET (original dating in the FirstRateData.com database) to UTC so that all trades take place on working dates (from Monday to Friday).

The price data at our disposal are available at 5 minute frequency, which constitutes a sound balance between microstructure noise and accurate estimations (Farid et al., 2021). This means that for Mondays we gather up to 276 observations per day, whereas for the remaining days up to 252 observations per day are available.[1] Since missing data throughout the trading day may occur, we fill them with the last recorded price if the gap does not exceed 30 minutes.

Overall, our database consists of 289,273 observations for five variables. For the overwhelming majority of cases (i.e., 99.6%) the time distance, τ_t, between two adjacent observations t and $t-1$ amounts to 5 minutes. For 871 observations the time interval stands at 185 minutes, which is the equivalent of the 3 hour interval between trading days. In 210 cases the time difference is 2945 minutes, which corresponds to the weekend break.[2] The development in prices at all studied markets is illustrated in the left column of Figure 1.

[1] The variation in the number of observations within each day stems from several features of the database. First, as already pointed out, for Monday the market opens earlier than for the remaining trading days. Second, occasionally no trade can occur, resulting in missing observations. Third, in rare cases throughout the year (e.g., for days preceding the Independence Day, Thanksgiving holidays or Christmas) US markets close earlier than usually.

[2] Moreover, there are only 33 instances for which τ_t varies between 40 and 150 minutes, which points to a larger interval within a given day due to missing data we do not impute. Furthermore, for 55 observations the time gap is larger than 185 but smaller than 4625 minutes (after excluding the weekend break). This can be ascribed to various calendar effects throughout the year we mention in footnote 1.

Following the recent contributions of Antonakakis et al. (2018) and Corbet et al. (2020) to the literature focusing on modeling the connectedness of oil and equity markets, we define price volatility as the absolute return, $V_{it} = |p_{it} - p_{i,t-1}|$, where $p = \log P$. However, given that our analysis is based on intraday data, we make two additional adjustments. First, we compute the diurnal pattern of V_{it} with the truncated maximum likelihood method combined with smoothing based on five *cos* and *sin* functions. This allows us to eliminate deterministic component and construct detrended volatility V_{it}^*. Second, to account for the fact that τ_t does not always equal to five minutes, we adjust V_{it}^* by using the square root of time principle. The reason for this adjustment is motivated by the fact that the distribution of unadjusted absolute returns at market opening is significantly more dispersed than the distribution of subsequent returns as market participants may discount the information appearing between trading hours and change their exposure already starting from market pre-open. This overnight bias of unadjusted series would make it difficult to use them within the TVP-VAR framework. Ultimately, we define volatility as:

$$\tilde{V}_{it} = V_{it}^* \tau_t^{-\frac{1}{2}} \tag{1}$$

The development in $\tilde{V}_{it}$ is presented in the right column of Figure 1, whereas basic descriptive statistics are summarized in the upper panel of Table 1. The mean, standard deviation, skewness and kurtosis of crude oil volatility is much higher than that of the remaining assets. These results can be partly explained by the oil price development after the outburst of Covid-19 (see Figure 1). The table also shows that the US exchange rate and US bonds are less volatile than gold and stock prices. Finally, all the series are stationary, skewed and characterized by fat tails. As regards links between the series, the left panel of Table 2 illustrates that Pearson correlations among all the series are positive and range between 0.10 for OIL-BONDS pair to 0.30 for the SPX-BONDS pair.

In Tables 1 and 2 we also report descriptive statistics for daily series calculated using the last observation for each trading day. In this way our dataset could be compared to studies based on daily data, which we have reviewed in the previous section, with the stipulation that by using intraday data we fully control the moment of the observation applied to calculate daily returns.

Our second database serves the purpose of establishing whether uncertainty and sentiment drives intraday volatility connectedness of oil and key financial asset classes. To this end, we collect daily observations for various popular uncertainty and sentiment measures. We have decided to include both measures implied from prices of underlying financial assets as well as proxies based on quantitative representation of textual data. We note here that the distinction between sentiment and uncertainty is vague, but both these concepts relate to expectations of market participants that may impact the development of asset prices. Birru and Young (2022) provide an insightful discussion on various sentiment and uncertainty proxies, including the ones we use in this paper.

We start with the volatility index (VIX), which represents market expectations for the 30-day ahead S&P 500 volatility derived from options prices. We also extract daily implied volatilities for oil (OIV), gold (GIV) and bonds (BIV) from respective at-the-money options with 3-months ahead maturities. These measures are sourced from Bloomberg. Next, we include the Economic Policy Uncertainty (EPU) index for the US constructed by Baker et al. (2016). This index (sourced from FRED Economic Data of St. Louis) is a weighted average of three components: the frequency of major news on economic and policy related uncertainty in ten major US newspapers, a measure of expiring tax provisions and forecasters' disagreement about the economic outlook. We also consider the Twitter-based economic uncertainty index (TEU) of Baker et al. (2021) extracted by scraping English-language tweets (taken from the webpage maintained by Scott R. Baker, Nick Bloom and Steven J. Davis) and the News Sentiment Index (NSI) of Buckman et al. (2020), which approximates economic sentiment based on counting words related to economic activity in 16 major US newspapers (this measure is sourced from the webpage of Federal Reserve Bank of San Francisco). Finally, we take the Geopolitical Risk (GPR) index developed by Caldara and Iacoviello (2022), which aims to proxy geopolitical tensions by quantifying sentiment from a tally of newspaper articles reporting on threats to peace or actual hostilities. GPR is downloaded from the webpage of Matteo Iacoviello.

Figure 2 illustrates the development of the above eight uncertainty and sentiment indices normalized so that their increase indicates rising uncertainty or deteriorating sentiment. It shows a substantial increase in all indices except for GPR after the outburst of the Covid-19 pandemic. In turn, the GPR has not moved considerably in 2020, but spiked following the Russian full-scale invasion of Ukraine. Overall, there is visible co-movement between the investigated indices. However, Figure 2 also illustrates that the short-term dynamics of these indices is quite heterogeneous, with high amplitude changes for EPU, TEU and GPR and relatively smooth changes of VIX, OIV, GIV, BIV and NSI. This comovement is quantified in Table 3, which presents correlation coefficient for levels and first differences. Its upper panel shows high positive correlation among VIX, OIV, GIV, EPU, TEU and NSI, moderate correlation with BIV and almost no correlation with GPR. Following differencing, correlation for all pairs drops substantially, indicating that at daily frequency these indices deliver complementary information on market sentiment (see the bottom panel of Table 3).

4 Methodology

Our investigation comprises of two steps. First, we quantify the relationship among market volatilities at intraday frequency by estimating the TVP VAR model for the demeaned vector

$$y_t = [\tilde{V}_t^{OIL}, \tilde{V}_t^{USD}, \tilde{V}_t^{SPX}, \tilde{V}_t^{GOLD}, \tilde{V}_t^{BONDS}]'$$

and calculating two well-known connectedness measures: Diebold and Yilmaz (2012, 2014) in the time domain and Barunik and Krehlík (2018) in the frequency domain. Second, we utilize Bayesian model averaging to establish whether uncertainty or sentiment measures exert a robust impact on the market connectedness in the sample.

TVP VAR. The TVP VAR model á la Koop and Korobilis (2014) assumes that the data generating process for the vector y_t of size $m \times 1$ is:

$$y_t = \sum_{i=1}^{p} B_{i,t} y_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, Q_t). \tag{2}$$

All parameters are allowed to vary over time, including the autoregressive matrices, $B_{i,t}$, $i \in \{1, ...p\}$, and the variance-covariance matrix Q_t. All technical details of this method are provided in Appendix A. Here we only note that we have decided to use the TVP VAR rather than the rolling window VAR for several reasons as argued by Antonakakis et al. (2020). The chosen framework allows all coefficients to evolve over time and introduces heteroscedasticity in the variance-covariance matrix. Thus, it overcomes the issue of choosing arbitrarily the rolling window size in an *ad hoc* manner. It also does not lead to information loss or excessive persistence of estimated parameters. Finally, it can be quickly estimated by Kalman filter, thus without relying on commonly used, but computationally insentive likelihood-based estimation techniques (such as Bayesian methods based on Markov Chain Monte Carlo simulations).[3]

Diebold and Yilmaz (2012) connectedness methodology. To establish how intraday volatility is interconnected in the time domain, we use the Diebold and Yilmaz (2012, 2014) methodology. This well-known framework allows to quantify the fraction of the H-step-ahead error variance in forecasting variable k that is due to the shock in variable j. Since this decomposition is based on the KPPS generalized IRF method (Koop et al., 1996; Pesaran and Shin, 1998), it is insensitive to the ordering of variables and thus enables the researcher to measure both total and directional spillovers. Hence, it is a suitable tool to capture the connectedness and spillovers between the studied variables

[3] This feature of the model á la Koop and Korobilis (2014) is especially appealing as our sample is vast and providing tens of thousands draws for each time period would be infeasible.

and to establish which one transmits or receives signals from the remaining ones. Since the methodology by Diebold and Yilmaz (2012, 2014) is well known, we provide the technical description of this framework in Appendix B. In integrating the TVP VAR model á la Koop and Korobilis (2014) with the DY framework we follow the implementation by Antonakakis et al. (2020).

Barunik and Krehlík (2018) decomposition of market spillovers. To further investigate the volatility connectedness between analyzed markets we employ the Barunik and Krehlík (2018) methodology within our TVP VAR. The key appealing feature of this approach is that it allows us to decompose the connectedness measures obtained in the time domain and quantify the spillovers between variables arising from heterogeneous responses to shocks at different frequencies, which is especially informative for analyses based on intraday data. Thus, it helps to understand the drivers in the connectedness and spillover measures estimated in the time domain as it identifies the contribution of selected frequency components. The technical details of the BK framework are described in Appendix C.

Bayesian model averaging. Following the computation of market connectedness measures, we investigate how various uncertainty and sentiment proxies are linked to them. In this context, with no a priori guidance or theoretical underpinnings as well as high correlation among selected measures, the Bayesian model averaging (BMA) framework seems especially appealing.[4] It provides a robust inference by utilizing information from every possible empirical model that can be constructed from a predetermined set of explanatory variables. Information from the entire model space is averaged using Bayesian inference to derive posterior probabilities for all regressors and all considered models. Consequently, this method explicitly indicates robust regressors and addresses model uncertainty while mitigating the risk of data-mining and inferring from a potentially misspecified and subjectively chosen model. In this sense, BMA is a model selection method that allows us to isolate these indices, which exert a robust impact on market connectedness measures.

We consider a linear time series model as follows:

$$z_d = \alpha_0 + X_d \beta + \xi_d \tag{3}$$

where z_d is the dependent variable and $d = 1, \ldots, D$ denote days. In the paper, for our dependent variable we take the total spillover index as well as directional spillovers to and from the oil market. In turn, X_d denotes the vector of size K collecting the lagged

[4] BMA technique as a variable selection method is frequently used to model macroeconomic dynamics and relationships at financial markets (e.g., Sala-i-Martin et al., 2004; Eicher et al., 2011; Moral-Benito, 2016; Szafranek et al., 2020).

dependent variable and eight uncertainty measures, which are potentially related to z_d.[5] The strength of this relation is determined by the vector of paramaters β. The error term is denoted with ξ_d. Equation 3 can be incorporated into the BMA framework in a straightforward manner.

Note that in our case matrix X_d contains (only) nine potential explanatory variables, some bearing similar information. Since K is small, within BMA we can estimate a model for every subset $X_d^{(j)} \in X_d$ (there are 2^K of those), without relying on Markov Chain Monte Carlo Model Composition (MC^3) samplers.[6] We discuss shortly technical details related to the BMA approach in Appendix D.

In presenting the results, we compute unconditional moments of regression coefficients.[7] In interpreting estimation outcomes, our attention focuses on the posterior inclusion probability (PIP, informing on the robustness of a given regressor). Conforming to the scales proposed by Kass and Raftery (1995) and Eicher et al. (2011), a given variable can be described to have a weak (50-75% PIP), substantial (75-95%), and strong (above 95%) impact on the dependent variable. For an excellent discussion on the BMA and methods of estimation we refer to Raftery et al. (1997) or Hoeting et al. (1999).

Model assumptions. For the TVP VAR model we set the maximum lag to $p = 2$. Thus, we allow for a richer model dynamics while retaining parsimony and mitigating the computational burden related to using high lag orders.[8] As regards the Minnesota prior, we use the standard value of the overall tightness parameter at 0.1 and use random-walk assumption for autoregressive parameters.

For the DY and BK connectedness measures we need to establish the maximum horizon for the generalized IRFs. Following the common practice in the literature, we set H in time and frequency domains to 100 periods (i.e., $H = 100$). In our case this corresponds to slightly over 8 hours. In frequency decomposition, we differentiate between short-term (up to 1 hour) and long-term (above 1 hour) frequencies.

Finally, as regards the BMA framework, for model prior we take advantage of the uniform prior, while for the Zellner's g prior for the regression coefficient we use unit information prior.

[5] Since our independent variables are of daily frequency, we upscale our spillover measures to daily frequency by taking averages.

[6] For large K the computation burden of enumerating all models is prohibitively exhaustive and a version of Metropolis-Hastings algorithm is used instead.

[7] Thus, in calculating these moments we take into account results from all models, also those, where a particular coefficient is restricted to zero.

[8] The indication on the VAR lag order based on traditional information criteria for constant-parameter VAR are useless as for a large sample the penalty for the number of parameters is extremely low, hence they point to uncommonly high values of p

5 Results

The evolution in model parameters. We start by presenting the estimation results for the TVP VAR model by inspecting the evolution of model parameters over time. The left and middle column of Figure 3 present own lags autoregressive coefficients, whereas the right column refers to time-varying volatility. It can be seen that there is a considerable amount of time variation of all coefficients, which fluctuate around their long term values. This means that both the propagation of shocks and the strength of the impulse varies over time. This result stands at odds with studies based on data of lower frequency, in which autoregressive parameters are usually very stable (e.g., Primiceri, 2005; Cogley and Sargent, 2005; Koop and Korobilis, 2013; Lubik et al., 2016; Wiggins and Etienne, 2017; Anand and Paul, 2021; Szafranek and Rubaszek, 2023; Szafranek et al., 2023a).

Total Spillover Index (TSI). We continue by investigating the evolution of the TSI and its short- and long-term components obtained with the BK method. These results are presented in Figure 4 (Panel A), together with the values of the TSI calculated using daily observations. The figure clearly shows that the intraday TSI (after aggregation to daily observations) is hardly correlated with the daily TSI. The correlation coefficient is very low and amounts to merely 0.067. The intraday TSI is also visibly less persistent than its counterpart based on daily data. It can also be seen that at the 5 minute frequency markets can be either strongly connected or move independently: the minimum value of TSI amounts to 6.1 on April 1, 2021, and the peak of 58.0 was reached on November 28, 2019. Finally, Panel A of Figure 4 illustrates that the relative contribution of short- and longer-term frequencies is time dependent.

Panel B of Figure 4 shows the evolution of intraday connectedness around the onset of the Russian invasion of Ukraine. At 3:00 a.m. UTC Putin announced invasion, the first explosions in Mariupol were at 3:46 a.m.m and at 4:15 a.m. there were explosions in Kiev. These events are reflected as a sizable jump in TSI, which value increased from below 10 at 3:40 UTC to 46.8 at 4:05 UTC and 52.9 at 5:15 a.m. UTC. Following this initial shock, the intraday connectedness has slowly declined.

Individual market spillovers. In the next step we track which markets transmit and receive shocks. Figure 5 presents the evolution of gross spillovers calculated both with intraday and daily data. Once again, it can be seen that intraday connectedness measures deliver very different picture compared to those based on daily observations. The divergence is especially visible after the outbreak of the Covid-19 pandemic. The gross spillover estimates based on daily data suggest that throughout 2020 the equity market was a sizable source of shocks, which were received by bonds and the US dollar markets. As regards intraday results, the figure shows that the strength of gross spillovers has diminished since the outbreak of the Covid-19 pandemic, which justifies the use of TVP VAR framework. In particular, gross links of oil and gold with the other markets are visibly stronger in the pre-Covid period compared to the second part of the sample. The left panel of the figure also illustrates that on average the equity market is the major source of shocks in the system, whereas the role of bonds is far smaller. In turn, the right panel demonstrates that gross spillovers received from other markets are comparable across the markets and fluctuate around the average value of around 25%. The above gross spillovers structure implies that the stock market is a net transmitter and the bond market net receiver of shocks. Indeed, Figure 6 illustrates that there are several episodes during the equity market is a sizable source of markets connectedness, with net spillovers index reaching almost 100% at the end of 2019. The figure also confirms how intraday and daily spillovers indices diverged in times of Covid-19 lockdowns.

The information presented in Figures 4–6 is averaged over the entire sample and reported in Table 4. It shows that the mean value of the intraday TSI amounts to 23.8%, which is slightly below 25.8% for daily TSI. The BK decomposition of the intraday TSI indicates that around 50% of TSI can be attributed to spillovers at the shortest frequencies (up to 1 hour). The table also quantifies that the equity market is an important net transmitter of shocks, whereas the bond and exchange rate markets are net receivers of shocks. As regards the oil and gold market, on average their position is broadly balanced. Finally, the table shows that all five assets are on average broadly similar in terms of gross spillovers they receive, but are heterogeneous in terms of how much of spillovers they transmit.

Lastly, we provide an illustration on market connectedness across the entire sample and during the onset of the Russian invasion of Ukraine on Figure 7. Panel A clearly shows the dominating role of the stock market in transmitting volatility to other markets across the entire sample. In turn, the volatility flow to and from the oil market is much more balanced (as denoted by the relative width of arrows). The remaining three markets receive volatility in net terms. Interestingly, pairwise volatility spillovers for the bond market are all negative (i.e., the bond market is a net receiver of volatility from all other markets). During the onset of the Russian invasion of Ukraine (Panel B) the situation changes. The gold market transmits the majority of volatility to other markets (mostly the oil market), thus confirming the role of this market as a safe haven in times of large uncertainty. The volatility flow between the remaining markets is less pronounced.

Sentiment effect on oil market connectedness. The last question we examine in this study is whether sentiment drives connectedness among investigated markets. In answering this question, we put special emphasis on gross spillovers from and to the crude oil market. Let us recall that in the articles surveyed in subsection 2.2 this question was addressed by investigating on one or two *ad-hoc* selected sentiment measures and by applying various methodological approaches (linear and nonlinear Granger causality tests, quantile coherency analyses, quantile and predictive regressions or MIDAS approaches). Here, we are agnostic on which uncertainty or sentiment index drives connectedness among markets. In turn, we let the data speak and isolate a set of robust regressors among eight popular measures described in section 3. For that purpose, we apply the BMA framework (see section 4) to explain fluctuations in the total spillover index or gross spillover from and to the crude oil market.

Table 5 presents the results of the BMA regression for the total spillover index. The first main finding is that TEU is the strongest driver of TSI among eight investigated indices. This would imply that news appearing on Twitter are quickly and simultaneously interpreted by market participants, leading to significantly higher TSI. What is important, the BK decomposition shows that the effect of TEU is related to transitory (lasting up to one hour) rather than permanent changes in TSI. The second main finding is that all implied volatility measures are substantial drivers of TSI, with PIP amounting to around 0.80. Interestingly, coefficient estimates in 3 out of 4 cases indicate that higher implied volatility leads to a decrease in the TSI. The interpretation of this result is that implied volatilities are derived using options specific to individual markets (e.g., OIV for OIL). Consequently, they should capture expectations that are market-specific as well. Thus, their increases lead to the decoupling of one particular market from the others. It can be added that this decoupling of volatility dynamics is well seen at intraday, rather than daily frequency. The last main finding is that TEU and implied volatility based indices are dominating the three newspaper based sentiment measures (EPU, NSI and GPR), which are insignificant and characterized by very low PIP. This is probably due to the fact that information in newspapers is delivered to readers with a daily lag, hence does not provide any additional value compared to TEU and implied volatility indices (see discussion in Szafranek et al., 2023b).

Table 6, which reports the results of the BMA regression for the gross volatility spillovers from and to the crude oil market, allows us to better understand the results from Table 5 by analyzing the dynamics of individual market connectedness. First, the results in Table 6 reiterate the importance of TEU in driving connectedness among markets, especially its short-term fluctuations. The coefficient for TEU is again positive, significant, and of similar magnitude as in the TSI regressions. Second, the results shows that the impact of oil market specific implied volatility – OIV – is substantial and negative, while the impact of overall implied volatility is far weaker (but also negative). Moreover, the posterior mean of the coefficient is almost twice higher than in the TSI regression, which points to the decoupling of oil market volatility in response to OIV spikes. Third, it can be seen that the three newspaper based sentiment indices are again insignificant. Overall, it can be concluded that at intraday frequency, connectedness of the crude oil market with the remaining ones is driven mostly by TEU and OIV.

6 Conclusion and discussion

The joint dynamics of commodity and financial markets remains of high interest to a large number of economic agents, including investors and policy makers. These entities closely monitor market comovements at monthly, daily and even intraday frequency as unexpected price changes might affect their profits, lead to welfare losses or indicate a swiftly changing economic environment in a presence of a large shock. Against this backdrop, in this paper we have provided new insights to the literature on market connectedness by investigating interactions among five key markets (i.e., oil, currency, equity, gold and bonds) at intraday frequency. Our two-step approach consists in *i)* computing time-varying connectedness measures for these markets with the means of the spillover framework in time and frequency domains and *ii)* identifying robust determinants of the derived spillover indices among various popular uncertainty and sentiment measures.

Our main findings are threefold. First, we have shown that spillover indices calculated using intraday series are much different than those computed with daily data. The corresponding connectedness series are negligibly correlated and characterized by a different degree of persistence. This was especially evident during Covid-19 lockdowns. Second, at intraday frequency the equity market turns out to be the primary source and net transmitter of volatility shocks, while the bond and currency markets are found to absorb these shocks. In turn, the oil and gold market are occasionally significant for the volatility flow. Third, the BMA analysis has revealed that the Twitter-based Economic Uncertainty index is the strongest driver of the total spillover index, indicating that real-time news and sentiment from Twitter quickly spreads among market participants. Implied volatility measures, proxying market-specific uncertainty, are also significant for the development in the overall spillovers. However, quite surprisingly, an increase in implied volatility tends to decrease markets connectedness, which suggests the decoupling of markets following rising uncertainty. This is also well illustrated for the oil market, for which increases in oil price implied volatility leads to decreases in gross spillovers to and from the oil market. In turn, uncertainty measures derived from newspapers are typically not related to spillovers development.

Overall, our findings provide robust evidence that at intraday frequency sentiment changes are driving commodity and financial markets connectedness. We have identified that Twitter news transitorily increase volatility at all markets, whereas increases in implied volatility at a given market leads to its decoupling from the remaining ones. We have also emphasized the importance of using intraday data to better understand the join dynamics of commodity and financial markets.

References

Adekoya, O. B., Oliyide, J. A., 2021. How COVID-19 drives connectedness among commodity and financial markets: Evidence from TVP-VAR and causality-in-quantiles techniques. Resources Policy 70, 101898.

Adekoya, O. B., Oliyide, J. A., Yaya, O. S., Al-Faryan, M. A. S., 2022. Does oil connect differently with prominent assets during war? Analysis of intraday data during the Russia-Ukraine saga. Resources Policy 77, 102728.

Akyildirim, E., Cepni, O., Molnár, P., Uddin, G. S., 2022. Connectedness of energy markets around the world during the COVID-19 pandemic. Energy Economics 109, 105900.

Albulescu, C. T., Demirer, R., Raheem, I. D., Tiwari, A. K., 2019. Does the U.S. economic policy uncertainty connect financial markets? Evidence from oil and commodity currencies. Energy Economics 83, 375–388.

Algaba, A., Ardia, D., Bluteau, K., Borms, S., Boudt, K., 2020. Econometrics meets sentiment: An overview of methodology and applications. Journal of Economic Surveys 34 (3), 512–547.

Anand, B., Paul, S., 2021. Oil shocks and stock market: Revisiting the dynamics. Energy Economics 96, 105111.

Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2020. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. Journal of Risk and Financial Management 13 (4).

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., Perez de Gracia, F., 2018. Oil volatility, oil and gas firms and portfolio diversification. Energy Economics 70, 499–515.

Antonakakis, N., Gupta, R., Kollias, C., Papadamou, S., 2017. Geopolitical risks and the oil-stock nexus over 1899–2016. Finance Research Letters 23, 165–173.

Awartani, B., Aktham, M., Cherif, G., 2016. The connectedness between crude oil and financial markets: Evidence from implied volatility indices. Journal of Commodity Markets 4 (1), 56–69.

Awartani, B., Maghyereh, A. I., 2013. Dynamic spillovers between oil and stock markets in the Gulf Cooperation Council Countries. Energy Economics 36, 28–42.

Baker, S., Bloom, N., Davisc, S., Renaultd, T., 2021. Twitter-derived measures of economic uncertainty. Unpublished.

URL https://www.policyuncertainty.com/media/Twitter_Uncertainty_5_13_2021.pdf

Baker, S. R., Bloom, N., Davis, S. J., 2016. Measuring Economic Policy Uncertainty. Quarterly Journal of Economics 131 (4), 1593–1636.

Balcilar, M., Gupta, R., Wang, S., Wohar, M. E., 2020. Oil price uncertainty and movements in the US government bond risk premia. North American Journal of Economics and Finance 52, 101147.

Barunik, J., Krehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. Journal of Financial Econometrics 16 (2), 271–296.

Beckmann, J., Czudaj, R., 2013. Oil prices and effective dollar exchange rates. International Review of Economics & Finance 27, 621–636.

Benlagha, N., Karim, S., Naeem, M. A., Lucey, B. M., Vigne, S. A., 2022. Risk connectedness between energy and stock markets: Evidence from oil importing and exporting countries. Energy Economics 115, 106348.

Bernanke, B. S., 1983. Irreversibility, uncertainty, and cyclical investment. Quarterly Journal of Economics 98 (1), 85–106.

Bilgin, M. H., Gozgor, G., Lau, C. K. M., Sheng, X., 2018. The effects of uncertainty measures on the price of gold. International Review of Financial Analysis 58, 1–7.

Birru, J., Young, T., 2022. Sentiment and uncertainty. Journal of Financial Economics 146 (3), 1148–1169.

Bouri, E., Lei, X., Jalkh, N., Xu, Y., Zhang, H., 2021. Spillovers in higher moments and jumps across US stock and strategic commodity markets. Resources Policy 72, 102060.

Buckman, S. R., Shapiro, A. H., Sudhof, M., Wilson, D. J., 2020. News Sentiment in the Time of COVID-19. FRBSF Economic Letter 2020-08, 1–5.

Caldara, D., Iacoviello, M., 2022. Measuring geopolitical risk. American Economic Review 112 (4), 1194–1225.

Castelnuovo, E., 2023. Uncertainty before and during COVID-19: A survey. Journal of Economic Surveys, In Press.

Chen, Y.-C., Rogoff, K. S., Rossi, B., 2010. Can exchange rates forecast commodity prices? Quarterly Journal of Economics 125 (3), 1145–1194.

Cogley, T., Sargent, T. J., 2005. Drifts and volatilities: monetary policies and outcomes in the post WWII US. Review of Economic Dynamics 8 (2), 262–302.

Corbet, S., Goodell, J. W., Günay, S., 2020. Co-movements and spillovers of oil and renewable firms under extreme conditions: New evidence from negative WTI prices during COVID-19. Energy Economics 92, 104978.

Cui, J., Maghyereh, A., 2023. Higher-order moment risk connectedness and optimal investment strategies between international oil and commodity futures markets: Insights from the COVID-19 pandemic and Russia-Ukraine conflict. International Review of Financial Analysis 86, 102520.

Dabrowski, M. A., Papiez, M., Rubaszek, M., Smiech, S., 2022. The role of economic development for the effect of oil market shocks on oil-exporting countries. Evidence from the interacted panel VAR model. Energy Economics 110, 106017.

Dai, Z., Kang, J., 2021. Bond yield and crude oil prices predictability. Energy Economics 97, 105205.

Dai, Z., Zhu, H., 2023. Dynamic risk spillover among crude oil, economic policy uncertainty and Chinese financial sectors. International Review of Economics & Finance 83, 421–450.

Dai, Z., Zhu, H., Zhang, X., 2022. Dynamic spillover effects and portfolio strategies between crude oil, gold and Chinese stock markets related to new energy vehicle. Energy Economics 109, 105959.

Demirer, R., Ferrer, R., Shahzad, S. J. H., 2020. Oil price shocks, global financial markets and their connectedness. Energy Economics 88, 104771.

Diebold, F. X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting 28 (1), 57–66.

Diebold, F. X., Yilmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics 182 (1), 119–134.

Eicher, T. S., Papageorgiou, C., Raftery, A. E., 2011. Default priors and predictive performance in Bayesian model averaging, with application to growth determinants. Journal of Applied Econometrics 26 (1), 30–55.

Farid, S., Kayani, G. M., Naeem, M. A., Shahzad, S. J. H., 2021. Intraday volatility transmission among precious metals, energy and stocks during the COVID-19 pandemic. Resources Policy 72, 102101.

Fernández, C., Ley, E., Steel, M. F., 2001. Benchmark priors for Bayesian model averaging. Journal of Econometrics 100 (2), 381–427.

Gao, R., Zhao, Y., Zhang, B., 2021. The spillover effects of economic policy uncertainty on the oil, gold, and stock markets: Evidence from China. International Journal of Finance & Economics 26 (2), 2134–2141.

Gong, X., Xu, J., 2022a. Geopolitical risk and dynamic connectedness between commodity markets. Energy Economics 110, 106028.

Gong, X., Xu, J., 2022b. Geopolitical risk and dynamic connectedness between commodity markets. Energy Economics 110, 106028.

Gormus, A., Nazlioglu, S., Soytas, U., 2018. High-yield bond and energy markets. Energy Economics 69, 101–110.

Hoeting, J. A., Madigan, D., Raftery, A. E., Volinsky, C. T., 1999. Bayesian Model Averaging: A Tutorial. Statistical Science 14 (4), 382–401.

Husain, S., Tiwari, A. K., Sohag, K., Shahbaz, M., 2019. Connectedness among crude oil prices, stock index and metal prices: An application of network approach in the USA. Resources Policy 62, 57–65.

Iqbal, N., Bouri, E., Grebinevych, O., Roubaud, D., 2023. Modelling extreme risk spillovers in the commodity markets around crisis periods including COVID19. Annals of Operations Research, In Press.

Kang, W., Ratti, R. A., Yoon, K. H., 2014. The impact of oil price shocks on U.S. bond market returns. Energy Economics 44, 248–258.

Kass, R. E., Raftery, A. E., 1995. Bayes Factors. Journal of the American Statistical Association 90 (430), 773–795.

Koop, G., Korobilis, D., 2013. Large time-varying parameter VARs. Journal of Econometrics 177 (2), 185–198.

Koop, G., Korobilis, D., 2014. A new index of financial conditions. European Economic Review 71, 101–116.

Koop, G., Pesaran, M., Potter, S. M., 1996. Impulse response analysis in nonlinear multivariate models. Journal of Econometrics 74 (1), 119 – 147.

Ley, E., Steel, M. F., 2009. On the effect of prior assumptions in Bayesian model averaging with applications to growth regression. Journal of Applied Econometrics 24 (4), 651–674.

Li, S., Tu, D., Zeng, Y., Gong, C., Yuan, D., 2022. Does geopolitical risk matter in crude oil and stock markets? Evidence from disaggregated data. Energy Economics 113, 106191.

Lubik, T. A., Matthes, C., Owens, A., 2016. Beveridge curve shifts and time-varying parameter VARs. Economic Quarterly (3Q), 197–226.

Luo, J., Ji, Q., 2018. High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity markets. Energy Economics 76, 424–438.

Ma, Y.-R., Zhang, D., Ji, Q., Pan, J., 2019. Spillovers between oil and stock returns in the US energy sector: Does idiosyncratic information matter? Energy Economics 81, 536–544.

Maghyereh, A., Abdoh, H., 2022. COVID-19 and the volatility interlinkage between bitcoin and financial assets. Empirical Economics 63 (6), 2875–2901.

Maghyereh, A. I., Awartani, B., Bouri, E., 2016. The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. Energy Economics 57, 78–93.

Malik, F., Umar, Z., 2019. Dynamic connectedness of oil price shocks and exchange rates. Energy Economics 84, 104501.

Mensi, W., Ali, S. R. M., Vo, X. V., Kang, S. H., 2022a. Multiscale dependence, spillovers, and connectedness between precious metals and currency markets: A hedge and safe-haven analysis. Resources Policy 77, 102752.

Mensi, W., Vo, X. V., Kang, S. H., 2022b. COVID-19 pandemic's impact on intraday volatility spillover between oil, gold, and stock markets. Economic Analysis and Policy 74, 702–715.

Moral-Benito, E., 2016. Growth empirics in panel data under model uncertainty and weak exogeneity. Journal of Applied Econometrics 31 (3), 584–602.

Naeem, M. A., Karim, S., Yarovaya, L., Lucey, B. M., 2023. COVID-induced sentiment and the intraday volatility spillovers between energy and other ETFs. Energy Economics 122, 106677.

Narayan, P. K., Narayan, S., Zheng, X., 2010. Gold and oil futures markets: Are markets efficient? Applied Energy 87 (10), 3299–3303.

Nazlioglu, S., Gupta, R., Bouri, E., 2020. Movements in international bond markets: The role of oil prices. International Review of Economics & Finance 68, 47–58.

Obstfeld, M., Zhou, H., 2023. The global dollar cycle. NBER Working Papers 31004, National Bureau of Economic Research.

Okhrin, Y., Uddin, G. S., Yahya, M., 2023. Nonlinear and asymmetric interconnectedness of crude oil with financial and commodity markets. Energy Economics 125, 106853.

Ozcelebi, O., Tokmakcioglu, K., 2022. Assessment of the asymmetric impacts of the geopolitical risk on oil market dynamics. International Journal of Finance & Economics 27 (1), 275–289.

Pastor, L., Verones, P., 2012. Uncertainty about government policy and stock prices. Journal of Finance 67 (4), 1219–1264.

Peng, C., Zhu, H., Guo, Y., Chen, X., 2018. Risk spillover of international crude oil to China's firms: Evidence from granger causality across quantile. Energy Economics 72, 188–199.

Pesaran, H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Economics Letters 58 (1), 17 – 29.

Phan, D. H. B., Sharma, S. S., Narayan, P. K., 2016. Intraday volatility interaction between the crude oil and equity markets. Journal of International Financial Markets, Institutions and Money 40, 1–13.

Primiceri, G. E., 2005. Time varying structural vector autoregressions and monetary policy. Review of Economic Studies 72 (3), 821–852.

Raftery, A. E., Madigan, D., Hoeting, J. A., 1997. Bayesian model averaging for linear regression models. Journal of the American Statistical Association 92 (437), 179–191.

Rehman, M. U., Shahzad, S. J. H., Uddin, G. S., Hedström, A., 2018. Precious metal returns and oil shocks: A time varying connectedness approach. Resources Policy 58, 77–89.

Sala-i-Martin, X., Doppelhofer, G., Miller, R. I., 2004. Determinants of long-term growth: A Bayesian Averaging of Classical Estimates (BACE) approach. American Economic Review 94 (4), 813–835.

Sharif, A., Aloui, C., Yarovaya, L., 2020. Covid-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the us economy: Fresh evidence from the wavelet-based approach. International Review of Financial Analysis 70, 101496.

Smiech, S., Papiez, M., Rubaszek, M., Snarska, M., 2021. The role of oil price uncertainty shocks on oil-exporting countries. Energy Economics 93, 105028.

Szafranek, K., Kwas, M., Szafrański, G., Wośko, Z., 2020. Common determinants of credit default swap premia in the North American oil and gas industry. A panel BMA approach. Energies 13 (23), 6327.

Szafranek, K., Papiez, M., Rubaszek, M., Smiech, S., 2023a. How immune is the connectedness of European natural gas markets to exceptional shocks? Resources Policy 85, 103917.

Szafranek, K., Rubaszek, M., 2023. Have European natural gas prices decoupled from crude oil prices? Evidence from TVP-VAR analysis. Studies in Nonlinear Dynamics & Econometrics, In Press.

Szafranek, K., Rubaszek, M., Uddin, G. S., 2023b. Which uncertainty measure is most informative? a time-varying connectedness perspective. Unpublished.
URL `https://ssrn.com/abstract=4360009`

Uddin, G. S., Bekiros, S., Ahmed, A., 2018. The nexus between geopolitical uncertainty and crude oil markets: An entropy-based wavelet analysis. Physica A: Statistical Mechanics and its Applications 495, 30–39.

Umar, Z., Abrar, A., Hadhri, S., Sokolova, T., 2023. The connectedness of oil shocks, green bonds, sukuks and conventional bonds. Energy Economics 119, 106562.

Umar, Z., Aharon, D. Y., Esparcia, C., AlWahedi, W., 2022. Spillovers between sovereign yield curve components and oil price shocks. Energy Economics 109, 105963.

Wang, L., Ruan, H., Hong, Y., Luo, K., 2023a. Detecting the hidden asymmetric relationship between crude oil and the US dollar: A novel neural Granger causality method. Research in International Business and Finance 64, 101899.

Wang, Z.-X., Liu, B.-Y., Fan, Y., 2023b. Network connectedness between China's crude oil futures and sector stock indices. Energy Economics, 106848.

Wiggins, S., Etienne, X. L., 2017. Turbulent times: Uncovering the origins of US natural gas price fluctuations since deregulation. Energy Economics 64, 196–205.

Wu, H., Zhu, H., Huang, F., Mao, W., 2023. How does economic policy uncertainty drive time–frequency connectedness across commodity and financial markets? North American Journal of Economics and Finance 64, 101865.

Zhang, D., 2017. Oil shocks and stock markets revisited: Measuring connectedness from a global perspective. Energy Economics 62, 323–333.

Zhang, H., Demirer, R., Huang, J., Huang, W., Tahir Suleman, M., 2021. Economic policy uncertainty and gold return dynamics: Evidence from high-frequency data. Resources Policy 72.

Zhang, Y.-J., Wei, Y.-M., 2010. The crude oil market and the gold market: Evidence for cointegration, causality and price discovery. Resources Policy 35 (3), 168–177.

Tables and figures

Table 1: Descriptive statistics

Variable	Mean	Min.	Med.	Max.	Std. Dev.	Skew.	Kurt.	ADF	Nobs
	Intraday data								
OIL	0.118	0.000	0.068	50.964	0.268	53.604	7151.5	-217.6	289273
USD	0.016	0.000	0.011	1.683	0.018	12.208	710.1	-288.4	289273
SPX	0.046	0.000	0.027	3.085	0.068	7.343	129.0	-215.5	289273
GOLD	0.036	0.000	0.024	2.106	0.043	5.718	95.8	-258.3	289273
BONDS	0.013	0.000	0.012	0.503	0.015	3.906	48.6	-278.1	289273
	Daily data								
OIL	2.128	0.000	1.328	57.808	3.366	7.485	91.8	-12.5	1136
USD	0.280	0.000	0.218	1.686	0.233	1.554	7.0	-19.6	1136
SPX	0.867	0.000	0.590	11.663	1.044	4.128	31.0	-11.9	1136
GOLD	0.618	0.000	0.433	6.318	0.632	2.701	16.2	-18.9	1136
BONDS	0.219	0.000	0.164	2.118	0.212	2.532	14.6	-16.6	1136

Notes: The table reports descriptive statistics for volatilities calculated using intraday and daily data. The specification of the Augmented Dickey-Fuller (ADF) test includes a constant and one lag. The 1% critical value is -3.43.

Table 2: Correlations of volatilities

	Intraday data					**Daily data**				
	OIL	USD	SPX	GOLD	BONDS	OIL	USD	SPX	GOLD	BONDS
OIL	1.00					1.00				
USD	0.12	1.00				0.21	1.00			
SPX	0.24	0.24	1.00			0.38	0.29	1.00		
GOLD	0.16	0.29	0.27	1.00		0.18	0.28	0.27	1.00	
BONDS	0.10	0.22	0.30	0.25	1.00	0.20	0.26	0.40	0.29	1.00

Notes: The table reports Pearson's correlation coefficients for volatilities calculated using intraday and daily data.

Table 3: Correlations of sentiment measures

	VIX	OIV	GIV	BIV	EPU	TEU	NSI	GPR
	Levels							
VIX	1.00							
OIV	0.81	1.00						
GIV	0.78	0.76	1.00					
BIV	0.44	0.54	0.39	1.00				
EPU	0.61	0.62	0.70	0.13	1.00			
TEU	0.61	0.69	0.62	0.18	0.61	1.00		
NSI	0.58	0.66	0.66	0.11	0.63	0.75	1.00	
GPR	-0.03	0.03	-0.06	0.31	-0.11	-0.12	-0.11	1.00
	First differences							
VIX	1.00							
OIV	0.32	1.00						
GIV	0.24	0.19	1.00					
BIV	0.33	0.31	0.26	1.00				
EPU	-0.02	0.02	-0.04	0.03	1.00			
TEU	0.13	0.09	0.04	0.05	0.04	1.00		
NSI	-0.03	0.08	0.02	0.04	-0.02	-0.01	1.00	
GPR	-0.05	0.02	0.00	-0.02	0.05	0.00	0.07	1.00

Notes: The table reports Pearson correlation coefficients between the studied sentiment measures in levels and first differences.

Table 4: Average connectedness in the sample

	OIL	USD	SPX	GOLD	BONDS	From	Net
	All frequencies: DY connectedness for intraday data						
OIL	76.8	3.6	11.6	5.1	3.0	23.2	0.3
USD	4.0	76.9	7.1	8.3	3.7	23.1	-2.8
SPX	9.8	5.1	73.8	5.6	5.6	26.2	7.5
GOLD	6.0	7.6	7.4	74.2	4.8	25.8	-1.4
BONDS	3.7	3.9	7.6	5.4	79.3	20.7	-3.5
To	23.5	20.2	33.7	24.4	17.2	**23.8**	
	Short term: BK connectedness for frequencies up to 1 hour						
OIL	56.6	1.5	3.9	2.0	1.6	9.0	0.0
USD	1.7	63.8	3.0	5.5	2.5	12.7	-1.0
SPX	3.5	2.5	50.8	2.5	3.4	11.8	2.1
GOLD	2.1	5.1	2.9	59.4	3.2	13.2	0.3
BONDS	1.7	2.6	4.1	3.6	66.5	12.0	-1.4
To	8.9	11.7	13.9	13.5	10.6	**11.7**	
	Long term: BK connectedness for frequencies above 1 hour						
OIL	20.1	2.0	7.6	3.1	1.5	14.3	0.3
USD	2.3	13.1	4.1	2.8	1.2	10.4	-1.9
SPX	6.4	2.7	23.0	3.1	2.2	14.4	5.5
GOLD	3.9	2.5	4.6	14.8	1.6	12.6	-1.7
BONDS	2.0	1.3	3.5	1.8	12.8	8.7	-2.2
To	14.6	8.6	19.8	10.8	6.5	**12.1**	
	DY connectedness for daily data						
OIL	80.2	4.0	9.4	3.1	3.3	19.8	10.1
USD	7.4	74.8	7.0	6.9	4.0	25.2	-7.8
SPX	9.3	3.7	72.7	4.8	9.6	27.3	9.5
GOLD	6.8	6.6	6.6	73.3	6.8	26.7	-5.4
BONDS	6.5	3.2	13.8	6.5	70.0	30.0	-6.4
To	30.0	17.4	36.8	21.3	23.6	**25.8**	

Notes: The table presents average values of connectedness measures across the entire sample. For the DY connectedness the kj-th entry of the spillover matrix denotes the estimated contributions to the forecast error variance of variable k from variable j. The off-diagonal column sums ('To others') and row sums ('From others') are the gross directional spillovers transmitted and received, respectively. Taking their differences provides net spillovers. The total spillover index (in bold) can be calculated as the sum of the off-diagonal elements of the spillover matrix divided by the number of the variables in the system (or equivalently as the average of the 'From others' or 'To others' statistics). The sum of the respective BK connectedness measures at different frequencies is equal to the DY values.

Table 5: The effect of sentiment measures on the total spillover index

	Total		Short-term		Long-term	
	PIP	PM (PSD)	PIP	PM (PSD)	PIP	PM (PSD)
AR(1)	1.000	0.692$^{\bullet}$	1.000	0.573$^{\bullet}$	1.000	0.768$^{\bullet}$
		(0.022)		(0.025)		(0.019)
VIX	0.553	-0.070°	0.798	0.125*	0.999	-0.317$^{\bullet}$
		(0.072)		(0.079)		(0.068)
OIV	0.823	-0.167*	0.628	-0.103°	0.047	-0.004
		(0.096)		(0.091)		(0.031)
GIV	0.883	-0.147*	0.134	-0.014	0.077	-0.009
		(0.071)		(0.042)		(0.039)
BIV	0.815	0.134*	0.052	0.003	0.164	0.025
		(0.078)		(0.018)		(0.065)
EPU	0.037	0.000	0.986	-0.078$^{\bullet}$	0.034	0.000
		(0.005)		(0.021)		(0.006)
TEU	0.999	0.122$^{\bullet}$	0.999	0.117$^{\bullet}$	0.398	0.035
		(0.028)		(0.026)		(0.049)
NSI	0.044	-0.003	0.035	-0.002	0.040	0.000
		(0.021)		(0.016)		(0.026)
GPR	0.036	0.000	0.105	0.003	0.032	0.000
		(0.004)		(0.011)		(0.006)

Notes: PIP denotes the posterior inclusion probability, PM denotes the posterior mean, while PSD (in parentheses) stands for posterior standard deviation. $^{\circ}$, *and $^{\bullet}$report weak (50-75%), substantial (75-95%) and strong (above 95%) PIP values, respectively.

Table 6: The effect of sentiment on gross spillovers from and to crude oil.

	FROM OIL						**TO OIL**					
	Total		Short-term		Long-term		Total		Short-term		Long-term	
	PIP	PM (PSD)	PIP	PM (PSD)	PIP	PM (PSD)	PIP	PM (PSD)	PIP	PM (PSD)	PIP	PM (PSD)
AR(1)	1.000	0.694$^{\bullet}$	1.000	0.471$^{\bullet}$	1.000	0.742$^{\bullet}$	1.000	0.687$^{\bullet}$	1.000	0.519$^{\bullet}$	1.000	0.753$^{\bullet}$
		(0.022)		(0.026)		(0.020)		(0.022)		(0.025)		(0.019)
VIX	0.344	-0.060	0.999	0.273$^{\bullet}$	0.996	-0.427$^{\bullet}$	0.921	-0.206*	0.998	0.256$^{\bullet}$	0.999	-0.441$^{\bullet}$
		(0.094)		(0.055)		(0.089)		(0.091)		(0.030)		(0.088)
OIV	0.884	-0.288*	0.996	-0.316$^{\bullet}$	0.065	-0.012	0.671	-0.149°	0.936	-0.206*	0.062	-0.010
		(0.135)		(0.072)		(0.059)		(0.125)		(0.058)		(0.053)
GIV	0.106	-0.013	0.079	-0.007	0.038	-0.003	0.041	-0.002	0.044	-0.002	0.032	-0.001
		(0.046)		(0.031)		(0.030)		(0.018)		(0.080)		(0.022)
BIV	0.037	0.001	0.087	-0.009	0.034	0.002	0.061	0.005	0.041	-0.002	0.049	0.006
		(0.018)		(0.035)		(0.026)		(0.028)		(0.015)		(0.037)
EPU	0.037	0.001	0.037	-0.001	0.054	0.003	0.046	0.001	0.129	-0.005	0.147	0.011
		(0.007)		(0.006)		(0.015)		(0.008)		(0.017)		(0.031)
TEU	0.823	0.102*	0.998	0.161$^{\bullet}$	0.180	0.019	0.954	0.118$^{\bullet}$	1.000	0.152$^{\bullet}$	0.297	0.034
		(0.059)		(0.033)		(0.047)		(0.044)		(0.018)		(0.059)
NSI	0.117	0.023	0.117	0.018	0.111	0.026	0.036	0.001	0.038	-0.002	0.091	0.018
		(0.076)		(0.059)		(0.087)		(0.022)		(0.020)		(0.071)
GPR	0.041	-0.001	0.030	0.000	0.046	-0.002	0.063	-0.002	0.029	0.000	0.060	-0.003
		(0.007)		(0.004)		(0.013)		(0.010)		(0.004)		(0.015)

Notes: Standard errors are reported in parentheses. $^{\circ}$, *and $^{\bullet}$report weak (50-75%), substantial (75-95%) and strong (above 95%) PIP values, respectively.

Figure 1: Time series for levels, P_{it}, and volatility, $\tilde{V}_{it}$, of the analyzed assets

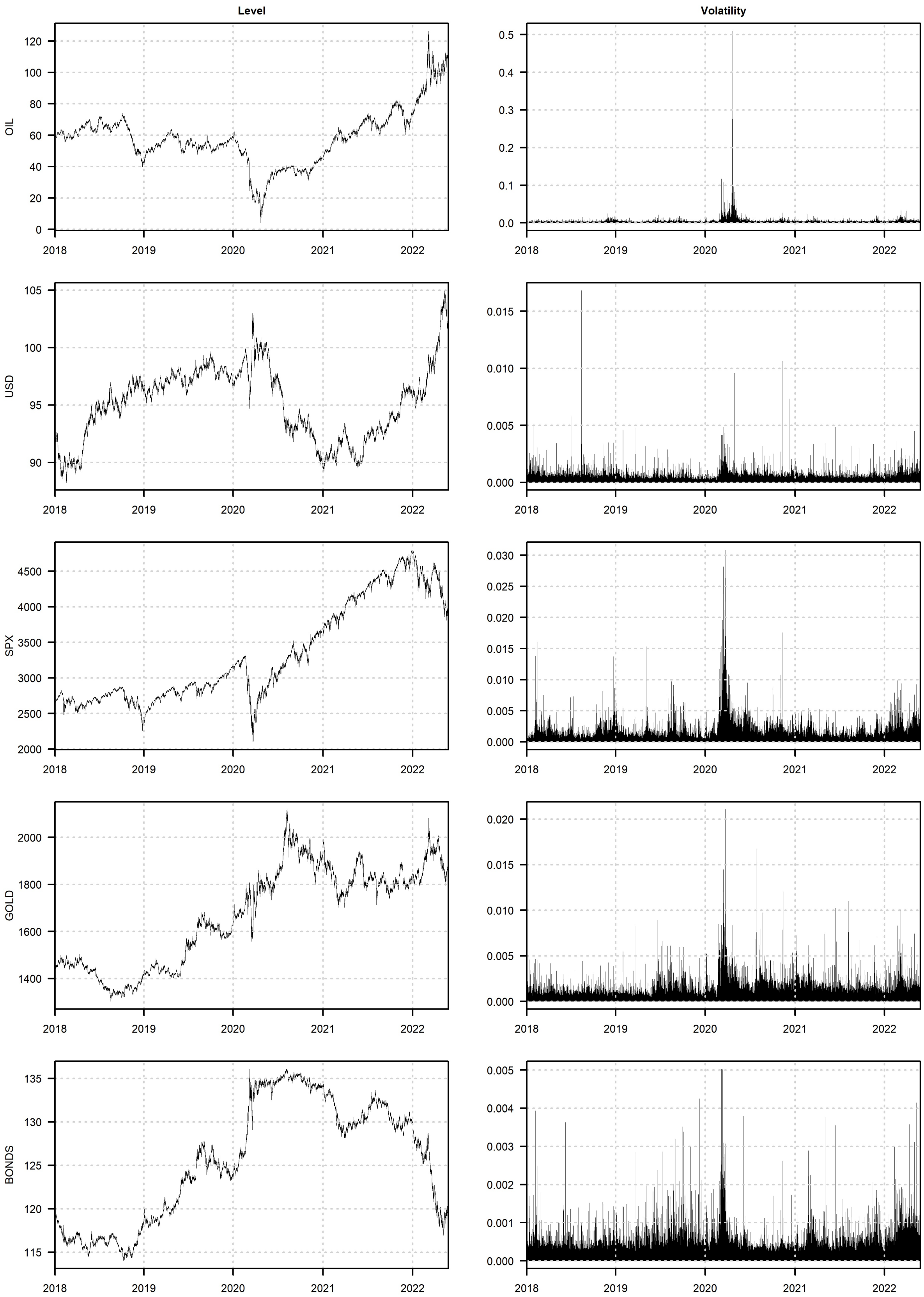


Figure 2: Time series for sentiment measures

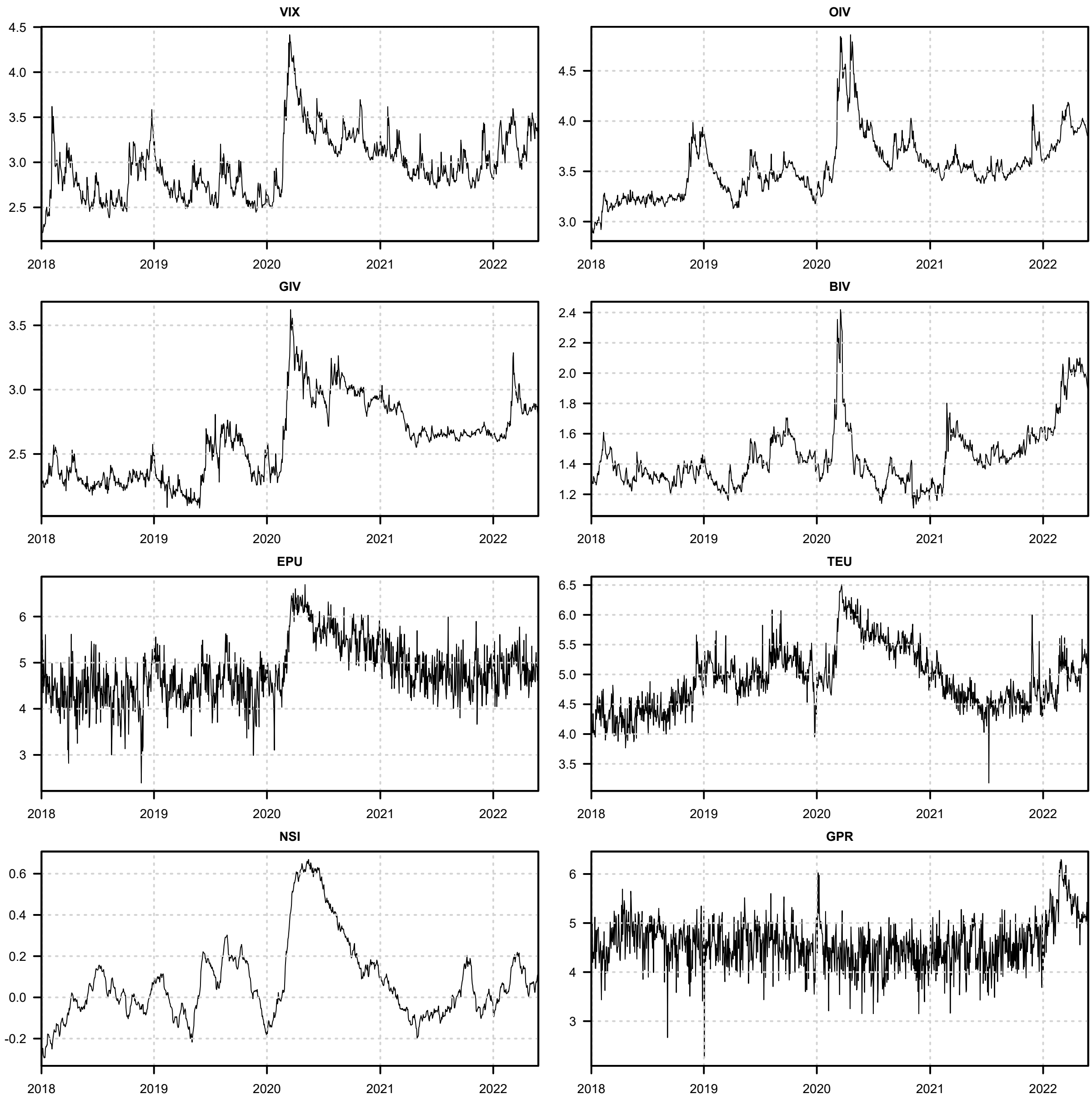
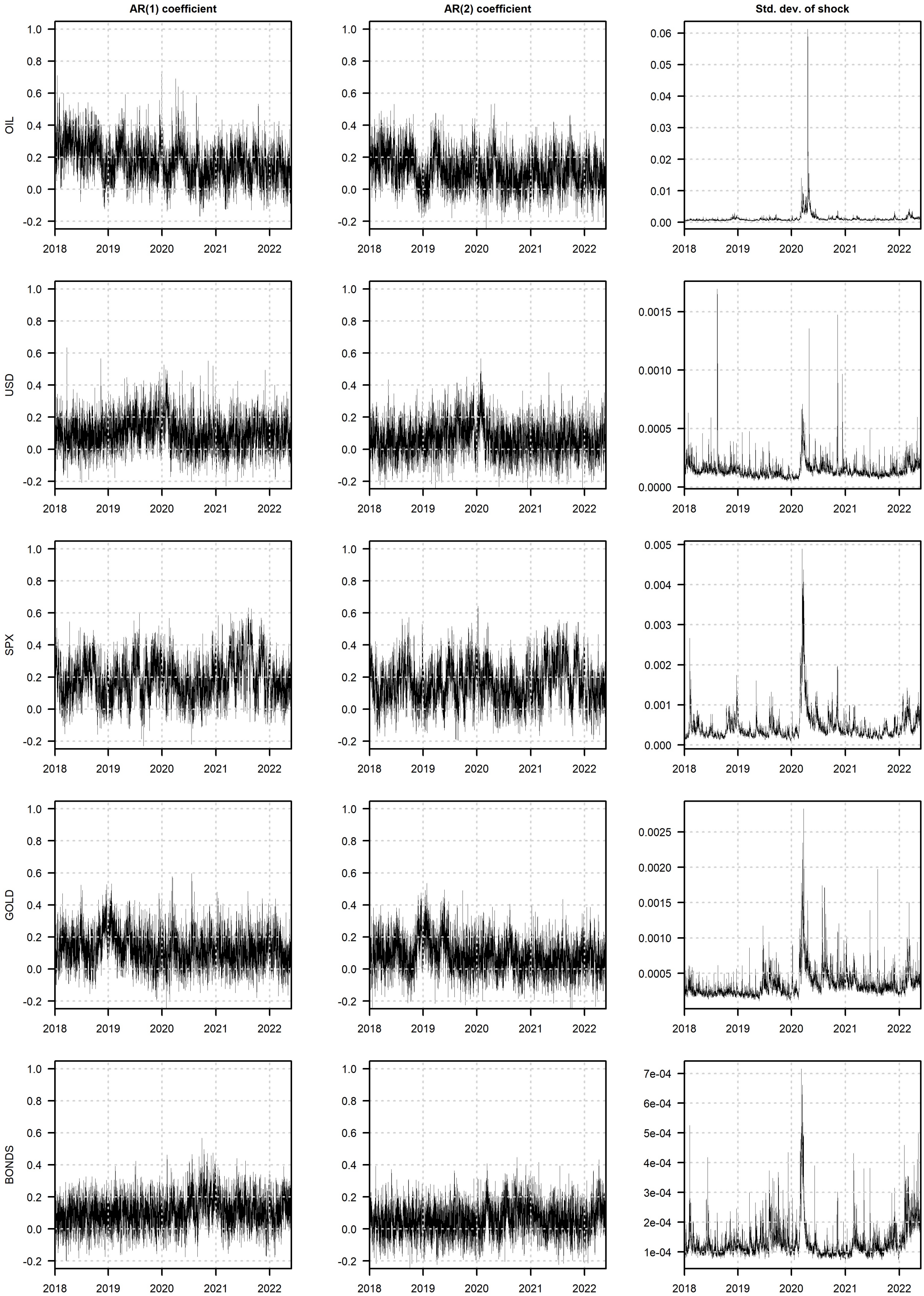


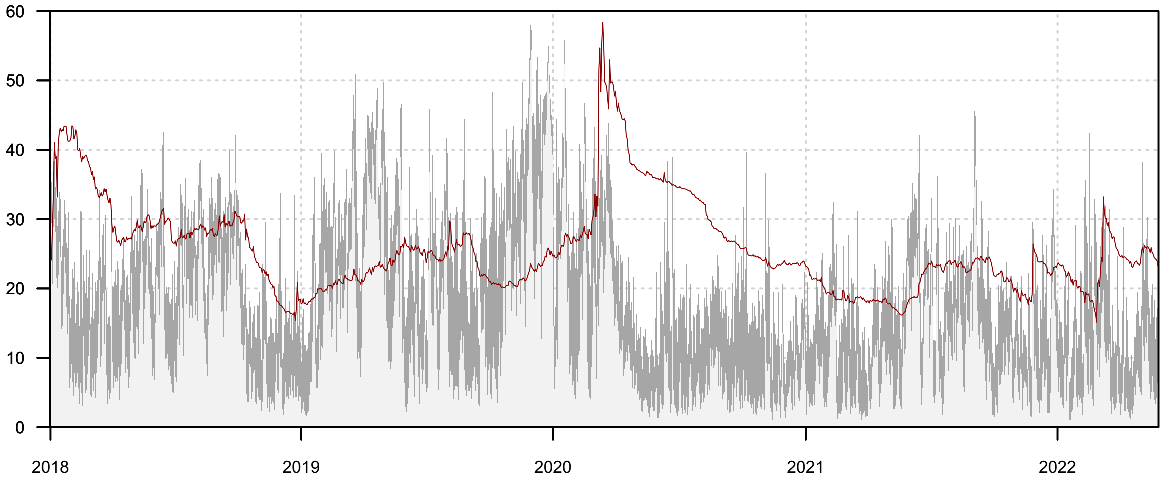
Figure 3: The evolution of selected coefficients in the TVP VAR model



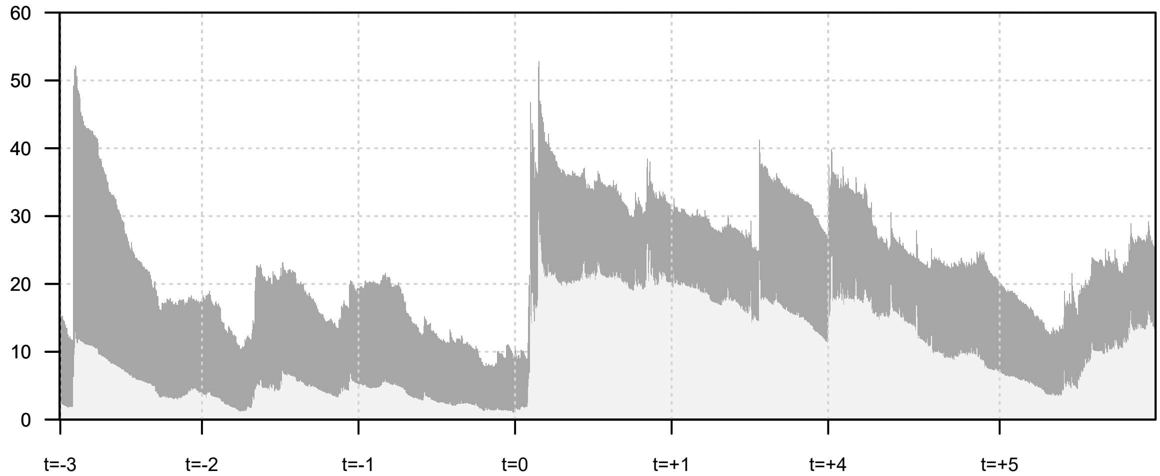
Note: The black solid line represents the time-varying estimates of autoregressive parameters and standard deviation of shocks.

Figure 4: Total spillover index

A) Entire sample

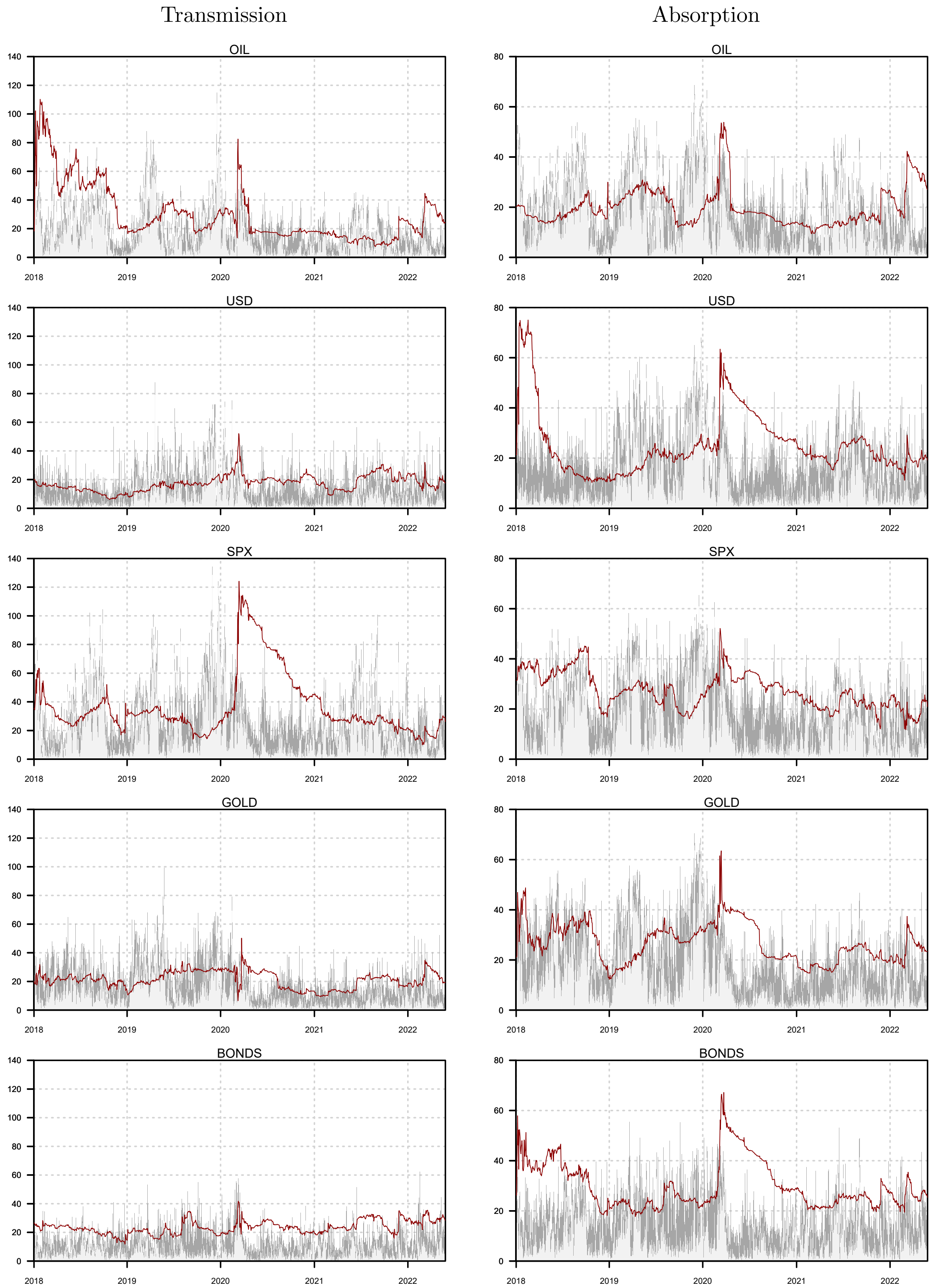


B) Russian invasion of Ukraine (24 February 2022)



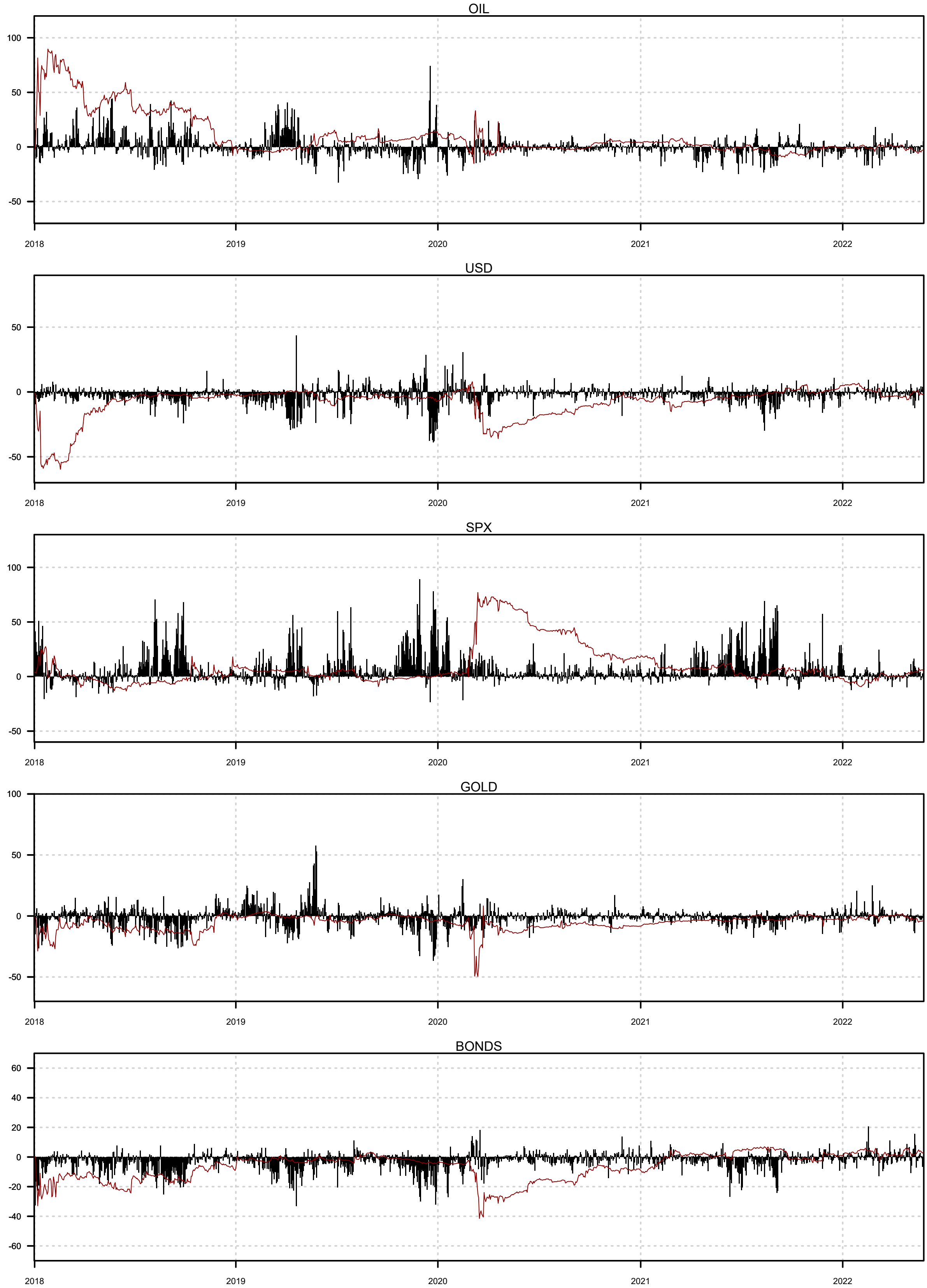
Notes: The figure presents the TSI ($S_t^g(H)$, panel A and B) decomposed using the BK approach into short (up to 1 hour, dark gray) and long-term frequencies (over 1 hour, light gray area). On panel A, the results for 5 minute interval are aggregated to daily data by taking averages, with red solid line indicating the TSI computed using daily data. On panel B the TSI and its decomposition based on intraday data for the Russian invasion of Ukraine (24 February 2022) is presented.

Figure 5: Gross directional spillovers



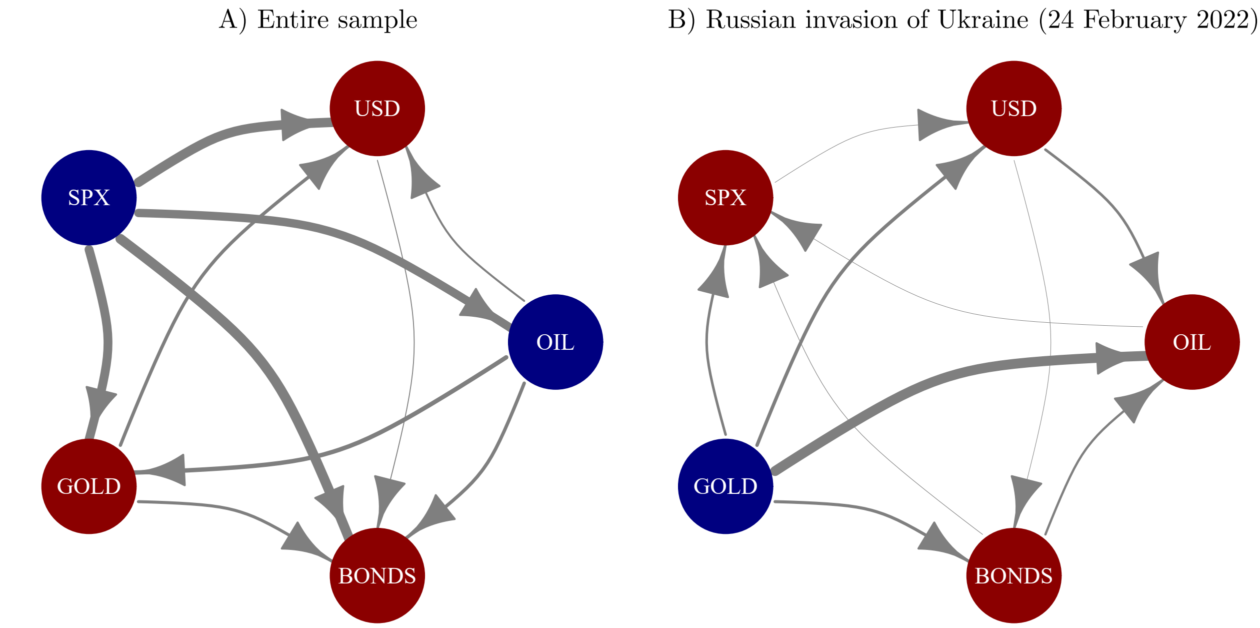
Notes: The Figure represents the gross directional spillovers (to others, $S^g_{\bullet\leftarrow k,t}(H)$, or from others, $S^g_{k\leftarrow\bullet,t}(H)$). These measures are decomposed using the BK approach into short (up to 1 hour, dark gray) and long-term frequencies (over 1 hour, light grey area). The results for 5 minute intervals are aggregated to daily data by taking averages. The red solid line represents spillovers computed using daily data.

Figure 6: Net directional spillovers



Notes: The figure presents net spillovers, $S^{g}_{k,t}(H)$. The results for 5 minute intervals are aggregated to daily data by taking averages. The red solid line represents net spillovers calculated using daily data.

Figure 7: Average market connectedness



Notes: The figure illustrates average market connectedness across the entire sample (Panel A) and on the day of the Russian invasion of Ukraine (24 February 2022, Panel B). Blue and red circles denote net volatility transmitters and receivers, respectively.

Appendix A The multivariate Kalman filter

TVP VAR. In this paper we use the TVP VAR model á la Koop and Korobilis (2014). The data generation process for vector y_t of size $m \times 1$ and unconditional mean equal to zero is:

$$y_t = \sum_{i=1}^{p} B_{i,t} y_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, Q_t) \tag{A.1}$$

where $(B_{1,t}, \dots, B_{p,t})$ are matrices of time-varying VAR coefficients and ε_t is the zero-mean Gaussian error term with time-varying variance-covariance matrix Q_t.

We reformulate the TVP VAR model as follows:

$$y_t = x_t B_t + \varepsilon_t \qquad \varepsilon_t \sim \mathcal{N}(0, Q_t) \tag{A.2}$$

$$\beta_t = \beta_{t-1} + \eta_t \qquad \eta_t \sim \mathcal{N}(0, R_t) \tag{A.3}$$

where $x_t = [y_{t-1}, y_{t-2}, ..., y_{t-p}]$, $B_t = [B_{1,t}, \cdots, B_{p,t}]'$, $\beta_t = [\text{vec}(B_{1,t})', \dots, \text{vec}(B_{p,t})']'$, $\text{vec}(B_{j,t})$ denotes the vectorization of matrix $B_{j,t}$. The VAR coefficients β evolve as multivariate random walks with the zero-mean disturbance term η_t with time-varying variance-covariance matrix R_t. All disturbance terms are uncorrelated over time and with each other.

We estimate the evolution of TVP VAR model parameters by using the Kalman filter method proposed by Koop and Korobilis (2014), where we initialize the filter by applying the Minnesota prior.[9] For Q_t we use exponentially weighted moving average estimator depending on the decay factor κ_2, while R_t is estimated using the forgetting factor κ_4. Both κ_2 and κ_4 are time-invariant and not estimated, since allowing them to vary over time significantly increases the computational burden of the Kalman filter (Koop and Korobilis, 2013) with no significant gains of this choice. Koop and Korobilis (2014) propose $\kappa_2 = 0.96$ and $\kappa_4 = 0.99$, but as we work with intraday data, we allow for very limited amount of variation in model parameters and volatility. Thus, we set $\kappa_2 = \kappa_4 = 0.99$.

Below we outline the subsequent steps for the multivariate Kalman filter we use to

[9] The alternative is to resort to the Primiceri (2005) prior based on presample information or to rely on uninformative priors. We check the stability of the results with respect to prior information and conclude that it does not affect our estimation outcomes.

estimate the TVP VAR model. The filter can be described as follows:

$$
\begin{aligned}
\beta_t | x_{1:t-1} &\sim \mathcal{N}(\beta_{t|t-1}, \Sigma^{\beta}_{t|t-1}) \\
\beta_{t|t-1} &= \beta_{t-1|t-1} \\
\Sigma^{\beta}_{t|t-1} &= \Sigma^{\beta}_{t-1|t-1} + \hat{R}_t \\
\hat{R}_t &= (1 - \kappa_4^{-1}) \Sigma^{\beta}_{t-1|t-1} \\
Q_t &= \kappa_2 Q_{t-1|t-1} + (1 - \kappa_2) \hat{\varepsilon}_t \hat{\varepsilon}_t^{'} \\
\hat{\varepsilon}_t &= y_t - y_{t-1} \beta_{t|t-1}
\end{aligned}
$$

Given the information set at time t, estimates are updated as follows:

$$
\begin{aligned}
\beta_t | x_{1:t} &\sim \mathcal{N}(\beta_{t|t}), \Sigma^{\beta}_{t|t}) \\
\beta_{t|t} &= \beta_{t|t-1} + \Sigma^{\beta}_{t|t-1} y_{t-1}^{'} (\hat{Q}_t + y_{t-1} \Sigma^{\beta}_{t|t-1} y_{t-1}^{'})^{-1} (y_t - y_{t-1} \hat{\beta}_{t|t-1}) \\
\Sigma^{\beta}_{t|t} &= \Sigma^{\beta}_{t|t-1} - \Sigma^{\beta}_{t|t-1} y_{t-1}^{'} (\hat{Q}_t + y_{t-1} \Sigma^{\beta}_{t|t-1} y_{t-1}^{'})^{-1} y_{t-1} \Sigma^{\beta}_{t|t-1} \\
Q_{t|t} &= \kappa_2 Q_{t-1|t-1} + (1 - \kappa_2) \hat{\varepsilon}_{t|t} \hat{\varepsilon}_{t|t}^{'} \\
\hat{\varepsilon}_{t|t} &= y_t - y_{t-1} \beta_{t|t}
\end{aligned}
$$

Appendix B The Diebold and Yilmaz (2012, 2014) connectedness approach

The starting point for integrating the DY framework and the TVP VAR model consists in writing down the forecast error at horizon H formulated at time t in the moving average representation:

$$y_{t+H} - E_t(y_{t+H}) = \sum_{s=0}^{H-1} \Lambda_{s,t} \varepsilon_{t+H-s}. \tag{B.1}$$

Matrices $\Lambda_{s,t}$ obey the recursion:

$$\Lambda_{s,t} = B_{1,t}\Lambda_{s-1,t} + B_{2,t}\Lambda_{s-2,t} + \cdots + B_{p,t}\Lambda_{s-p,t} \quad \text{for} \quad s > 0, \tag{B.2}$$

$\Lambda_{0,t} = I_5$ and $\Lambda_{s,t} = 0$ for $s < 0$. This representation is key to understanding the dynamics of the system.

Following DY, we denote by $\theta^g_{kj,t}(H)$ the contribution of shock j to forecast error variance of variable k at horizon H. The superscript g emphasizes the fact that the contribution is calculated with the KPPS generalized IRF method. In turn, the subscript t indicates that this statistic is time-varying. The formula for $\theta^g_{kj,t}(H)$ is as follows:

$$\theta^g_{kj,t}(H) = \frac{\sigma^{-1}_{jj,t} \sum_{h=0}^{H-1} (e'_k \Lambda_{h,t} Q_t e_j)^2}{\sum_{h=0}^{H-1} (e'_k \Lambda_{h,t} Q_t \Lambda'_{h,t} e_k)} \tag{B.3}$$

where Q_t is the variance-covariance matrix for the error vector ε_t, $\sigma_{jj,t}$ is the j element of the diagonal of the matrix Q_t at time t and e_k is the selection vector with 1 as the kth element and 0 otherwise.

As shocks to each variable are not orthogonalized, the sum of the contributions to the variance of the forecast error may not necessarily equal to 1. Therefore, DY normalize each entry of the variance decomposition matrix by the row sum, which we follow in our time-varying setting:

$$\tilde{\theta}^g_{kj,t}(H) = \frac{\theta^g_{kj,t}(H)}{\sum_{j=1}^{N} \theta^g_{kj,t}(H)}. \tag{B.4}$$

Consequently, in each period t the conditions $\sum_{j=1}^{N} \tilde{\theta}^g_{kj,t}(H) = 1$ is satisfied, which implies that $\sum_{k,j=1}^{N} \tilde{\theta}^g_{kj,t}(H) = N$. We will use $\tilde{\theta}^g_{kj,t}(H)$ to measure the evolution of own (for $k = j$) and cross (for $k \neq j$) spillovers between the studied asset classes.

Following DY, we calculate the overall connectedness as the total spillover index, using the normalized forecast-error variance contributions from the KPPS variance decomposition. In our case this measure is time-varying by construction and amounts to:

$$S^g_t(H) = \frac{\sum_{\substack{k,j=1\\k\neq j}}^N \tilde{\theta}^g_{kj,t}(H)}{\sum_{k,j=1}^N \tilde{\theta}^g_{kj,t}(H)} \times 100 = \frac{\sum_{\substack{k,j=1\\k\neq j}}^N \tilde{\theta}^g_{kj,t}(H)}{N} \times 100 \tag{B.5}$$

Employing the generalized VAR framework enables us to learn about the direction of the spillovers, since the outcome of this procedure does not depend on the ordering of variables. Therefore, we can exploit additional information from further connectedness measures introduced by Diebold and Yilmaz (2012) and refined in Diebold and Yilmaz (2014). Consequently, we focus on three additional measures. They are also time-varying and include:

1. Gross directional spillovers received by market k from all other markets j:

$$S^g_{k\leftarrow\bullet,t}(H) = \sum_{\substack{j=1\\j\neq k}}^N \tilde{\theta}^g_{kj,t}(H) \times 100, \tag{B.6}$$

   which illustrates to what extent volatility shocks from all other markets are absorbed by market k.

2. Gross directional spillovers transmitted by market k to all other markets j:

$$S^g_{\bullet\leftarrow k,t}(H) = \sum_{\substack{j=1\\j\neq k}}^N \tilde{\theta}^g_{jk,t}(H) \times 100, \tag{B.7}$$

   which shows to what extent volatility shocks originating in a particular market k are transmitted to other markets.

Based on measures (B.6) and (B.7) we compute net spillovers for variable k:

$$S^g_{k,t}(H) = S^g_{\bullet\leftarrow k,t}(H) - S^g_{k\leftarrow\bullet,t}(H), \tag{B.8}$$

which indicates whether market k transmits or receives shocks from other markets. Finally, this framework allows also to compute net pairwise spillovers as:

$$S^g_{kj,t}(H) = \tilde{\theta}^g_{jk,t}(H) - \tilde{\theta}^g_{kj,t}(H). \tag{B.9}$$

However, in this paper, we do not focus on differences between spillovers transmitted from market k to market j and those transmitted from j to market k.

Appendix C The Barunik and Krehlík (2018) connectedness approach

The starting point for the Barunik and Krehlík (2018) framework is to define for each frequency $\omega \in (-\pi, \pi)$ and period t the Fourier transform of the moving average representation coefficients Λ_t from equation (B.1):

$$\Lambda_{H,t}(exp\{-i\omega\}) = \sum_{s=0}^{H-1} exp\{-i\omega s\}\Lambda_{s,t}, \tag{C.1}$$

and the spectrum of forecast error at horizon H:

$$S_{y,t}(\omega, H) = \Lambda_{H,t}(exp\{-i\omega\})\Omega_t\Lambda'_{H,t}(exp\{i\omega\}), \tag{C.2}$$

so that the total forecast error variance amounts to $\frac{1}{2\pi}\int_{-\pi}^{\pi} S_{y,t}(\omega, H)d\omega$. Next, we notice that the contribution of shocks j to the spectrum of forecast error of variable k is:

$$\theta^g_{kj,t}(\omega, H) = \frac{\sigma^{-1}_{jj,t}|e'_k\Lambda_{H,t}(exp\{-i\omega\})\Omega_t)e_j|^2}{e'_k\Lambda_{H,t}(exp\{-i\omega\})\Omega_t\Lambda'_{H,t}(exp\{i\omega\})e_k},$$

which is the frequency equivalent of equation (B.3).

In our investigation we are interested in decomposing the value of $\theta^g_{kj,t}(H)$ defined in equation (B.3) into selected bands of frequencies. For that purpose, we need to weight $\theta^g_{kj,t}(\omega, H)$ by the share of frequency ω in the total variance of forecast for variable k:

$$\Gamma_{k,t}(\omega, H) = \frac{e'_k\Lambda_{H,t}(exp\{-i\omega\})\Omega_t\Lambda'_{H,t}(exp\{i\omega\})e_k}{\frac{1}{2\pi}\int_{-\pi}^{\pi} e'_k\Lambda_{H,t}(exp\{-i\lambda\})\Omega_t\Lambda'_{H,t}(exp\{i\lambda\})e_k d\lambda}. \tag{C.3}$$

Consequently, the contribution of frequencies within band $d = (a, b) : a, b \in (-\pi, \pi), a < b$ to the value of $\theta^g_{kj,t}(H)$ amounts to:

$$\theta^g_{kj,t}(d, H) = \frac{1}{2\pi}\int_d \Gamma_{k,t}(\omega, H)\theta^g_{kj,t}(\omega, H)d\omega, \tag{C.4}$$

so that $\theta^g_{kj,t}(D, H) = \theta^g_{kj,t}(H)$ for $D = (-\pi, \pi)$. In turn, the contribution of frequencies within band d to the normalized value $\tilde{\theta}^g_{kj,t}(H)$ defined in equation (B.4) can be easily calculated as:

$$\tilde{\theta}^g_{kj,t}(d, H) = \theta^g_{kj,t}(d, H) \times \frac{\tilde{\theta}^g_{kj,t}(H)}{\theta^g_{kj,t}(H)}. \tag{C.5}$$

Finally, the values of $\tilde{\theta}^g_{kj,t}(d, H)$ can be inserted to the nominator of equation (B.5) and equations (B.6)-(B.8) to compute the contribution of frequencies in the band d to DY spillover measures. The exact formulas are:

$$S_t^g(d,H) = \frac{1}{N}\sum_{\substack{k,j=1\\k\neq j}}^{N} \tilde{\theta}_{kj,t}^g(H) \times 100 \tag{C.6}$$

$$S_{k\leftarrow\bullet,t}^g(d,H) = \sum_{\substack{j=1\\j\neq k}}^{N} \tilde{\theta}_{kj,t}^g(d,H) \times 100 \tag{C.7}$$

$$S_{\bullet\leftarrow k,t}^g(d,H) = \sum_{\substack{j=1\\j\neq k}}^{N} \tilde{\theta}_{jk,t}^g(d,H) \times 100 \tag{C.8}$$

$$S_{k,t}^g(d,H) = S_{\bullet\leftarrow k,t}^g(d,H) - S_{k\leftarrow\bullet,t}^g(d,H) \tag{C.9}$$

Appendix D The BMA approach

The BMA framework ensembles individual models M_j of the form:

$$z_d = \alpha_0^{(j)} + X_d^{(j)}\beta^{(j)} + \xi_d, \xi_d \sim \mathcal{N}(0, h) \tag{D.1}$$

where $X^{(j)}$ is a vector of size k_j and constitutes a subset of vector X that collects all potential explanatory variables. The posterior probability of each model M_j, denoted as $p(M_j|z, X)$, is proportional its prior $p(M_j)$ and the conditional probability of observations, $p(z|M_j, X)$. In particular, the Bayes' theorem implies that:

$$P(M_j|z, X) = \frac{p(z|M_j, X)p(M_j)}{p(z|X)} \tag{D.2}$$

Consequently, computing $P(M_j|z, X)$ requires eliciting prior $p(M_j)$ and estimating the model to derive $p(z|M_j, X)$.

Let us discuss model prior. As a benchmark, we assume the uniform prior, which implies that each model is equally plausible: $p(M_j) = 2^{-K}$. As a robustness, we use fixed binomial model prior, which sets the prior on variable inclusion probability θ. It implies the expected model size of $\theta \times K$ and model probability $p(M_j) \propto (\theta)^{k_j}(1-\theta)^{K-k_j}$ (Sala-i-Martin et al., 2004). We also check random binomal model prior, in which θ is assumed to be a random variable $\theta \sim \text{Beta}(a, b)$ rather than a fixed scalar (Ley and Steel, 2009).

Regarding the estimation process of individual models M_j, we use a non-informative, improper prior on the constant and the error variance, thus assuming their even distribution over their domain, $p(\alpha^{(j)}) \propto 1$ and $p(h) \propto h^{-1}$, respectively. Moreover, we use a well-established prior structure called the Zellner's g prior for the regression coefficients, where for $\beta^{(j)}$ coefficients prior mean of zero is set to reflect the agnostic beliefs regarding regressors significance. As for the variance, we define it as follows:

$$\beta^{(j)}|g, h \sim N(0, hg(X^{(j)\prime}X^{(j)})^{-1})$$

where the hyperparameter g reflects the degree of certainty with respect to the value of parameters $\beta^{(j)}$ being 0. It can be noted that for $g \to 0$, the importance of the prior rises, whereas for $g \to \infty$ the prior becomes non-informative. In the benchmark, we use the unit information prior by setting $g = D$. This mean that the impact of the prior on the posterior is comparable to one additional observation. As a robustness, we also consider the so-called BRIC prior suggested by Fernández et al. (2001) that sets $g = \max\{D, K^2\}$.

Given that in our application various choices of priors yield very similar outcomes, in the paper we present solely the results for the benchmark.