How Connected is the Oil-Bank Network? Firm-Level and High-Frequency Evidence

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Abstract

By introducing a new generalized forecast error variance decomposition (GFEVD) approach that splits the same into its contemporaneous and lagged components, we investigate the risk spillover effects of different order moments, derived from intraday data, for the top 10 banks and top 10 oil and gas companies in the U.S., covering the period from December 29, 2017 to December 30, 2022. The study finds that, first, the dynamic total connectedness of all order moments is heterogeneous over time and economic events. Second, except realized volatility spillovers, the vast majority of overall spillovers are attributable to contemporaneous spillovers, while only a tiny fraction is associated with lagged spillovers. Finally, realized skewness (crash risk) and realized kurtosis (extreme events) in banks and oil and gas companies originate mainly from intra-industry rather than inter-industry transmission.

Keywords: Banking connectedness; TVP-VAR; higher moments; dynamic connectedness; GFEVD decomposition.
JEL codes: C50; F65; G15.

1 Introduction

With the increasing trend of economic globalization and financial integration, the information and risk connectedness of the global financial market has been increasing, and the contagion mechanism has become more and more complex. The lessons of the global financial crisis of 2008 have shown that systemic financial risks have the characteristics of concealment, scale, contagiousness, and destructiveness. In 2023, the world experienced a new round of financial turmoil. Silicon Valley Bank in the United States went bankrupt, Credit Suisse announced significant losses, and the Swiss federal government and regulatory authorities took several bailout measures. The banking turmoil in Europe and the United States is considered the largest systemic banking risk event in terms of scale and scope since 2008, triggering panic in the global banking sector. In this new era of global turbulence, it is critical to measure and monitor the stability and connectedness of the global banking system.

Recent studies have shown that banks have a close risk relationship with oil and gas companies through credit channels (Gilje, 2019; Wang, 2021). Under the international pressure of climate change, more and more European banks have increased their efforts to reduce or even stop financing new petrochemical projects. BNP Paribas, the European Investment Bank, and HSBC UK have announced restrictions on spending in the oil and gas sector, including canceling loans for financing offshore oil and gas projects and no longer cooperating with oil and gas firms that are primarily engaged in shale and oil sands (Urban and Wójcik, 2019). Collective action by banks could lead to defaults and stranded assets of oil and gas companies, which would not only bring down the quality of banks' assets but would also raise concerns in the market, causing investor confidence to erode and bank share prices to fall (Daumas, 2023). In the US, for example, banks have a high proportion of loans in the energy sector. They are, therefore, vulnerable to credit risk from oil and gas companies due to extreme oil price shocks (Nasim et al., 2023), which can propagate across banks and ultimately destabilize the entire banking system (Umar et al., 2021). Recent significant events (e.g., the fall in WTI prices during COVID-19 and the bankruptcy of Credit Suisse) have drawn further attention to this risk relationship from banking regulators, academics, and investors in the financial sector.

At the same time, the development of oil and gas companies is also affected by systemic risks in banks (Alodayni, 2016; Mirzaei and Moore, 2016). In the first half of 2022, the continued interest rate hikes by the Federal Reserve led to the continued festering of the U.S. banking crisis and increased systemic risks in the global banking sector. The cumulative effect of monetary tightening policies impacted international oil prices and oil and gas companies in two ways: by reducing crude oil futures trading activity and weakening oil production growth potential. On the one hand, banks are increasingly exposed to liquidity risk. Driven by risk aversion and recessionary expectations, market participants either transferred funds out of the crude oil futures market to higher return funding channels in search of returns or withdrew funds from the crude oil futures market in order to reduce risk (Abdel-Latif and El-Gamal, 2020). These have reduced the activity and trading volume in the crude oil futures market. If the investment capital in the oil and gas market is withdrawn significantly, it will amplify the panic of investors in the market in the short term and exacerbate the risk of falling oil prices (Qadan and Nama, 2018; Zhang and Li, 2019). On the other hand, due to the monetary tightening policy, market interest rates have increased (Kurov and Stan, 2018), and the financing cost of the oil and gas industry has increased significantly, which has a severe impact on small and medium-sized oil and gas companies. At the same time, due to the increasing downside risk of oil prices (Razmi et al., 2020), oil and gas companies are facing a decline in profitability, the willingness to invest in extraction will be further reduced, and the likelihood of a decline in oil production will increase. Therefore, the risk connectedness of the banking sector will have a significant impact not only on the financial system as a whole but also on the traditional oil and gas industry.

In this context, we examine credit risk spillovers among the top ten U.S. banks and the top ten oil and gas companies. Using a newly developed network topology methodology and high-frequency equity data, we can identify heterogeneous spillovers in both contemporaneous and lagged periods and further characterize the network of risk spillovers between banks and oil and gas firms, which may be of great interest to financial regulators and high-frequency traders, especially in times of crisis. Based on this, this paper attempts to answer three critical questions. 1) What is the dynamic evolutionary characterization of higher-order moments of spillovers between U.S. banks and oil and gas firms? 2) What causes higher-order moments of spillovers between U.S. banks and oil and gas firms? 3) Is the network connectedness between U.S. banks and oil and gas firms consistent across different moments of order? Therefore, the contribution of this paper is threefold. First, this is to the best of our knowledge the first study discussing higher moment transmission mechanisms using a time-varying parameter vector autoregressive (TVP-VAR) framework (see, He and Hamori, 2021; Apergis, 2023; Cui and Maghyereh, 2023). Second, this poses the first study that provides a detailed analysis of higher moments spillovers in the banking and oil and gas sector which is now more important than ever considering the default of Credit Suisse, as well as the Silicon Valley Bank, Signature Bank, and First Republic Bank, has wiped out far more money than the Great Financial Crisis of 2009. Third, we introduce a method on how to decompose the generalized forecast error variance decomposition (GFEVD) into its contemporaneous and lagged components and show that the fractions of contemporaneous and overall connectedness as well as the fractions of lagged and overall connectedness is independent of the employed normalization technique (Caloia et al., 2019; Chatziantoniou et al., 2021; Lastrapes and Wiesen, 2021; Balcilar et al., 2021).

The outline of the paper is as follows. Section 2 summarizes the recent developments in the area of higher moment connectedness. Section 3 introduces our proposed GFEVD decomposed connectedness strategy while Section 4 presents an overview of the employed datasets. Section 5 interprets and discusses the implications of the retrieved empirical results. Finally, Section 6 concludes the study.

2 Literature review

A growing body of research suggests that interbank connectedness is an essential determinant of systemic risk (Badarau and Lapteacru, 2020; Demirer et al., 2018). There are two main categories of connectedness in the banking sector. One is direct connectedness due to interbank activities such as peer-to-peer lending, deposits, and repo operations (Bluhm and Krahnen, 2014; Hale, 2012). Bilateral and multilateral linkages exist between banks, and when one bank defaults on its debt, it can cause financial institutions with direct linkages to be hit and their balance sheets to deteriorate. Second, indirect connectedness is caused due to holding common assets or liabilities and homogenization of structure and management models (Butzbach, 2016; Tonzer, 2015; Wang et al., 2022). Banks face common potential risk exposures, including asset price volatility and information spillovers, and when asset prices fluctuate dramatically, risks are rapidly transmitted between banks. This risk transmission leads to an increase in systemic risk in the banking sector and affects industries with a high percentage of loans, such as oil and gas, thus triggering bank-industry risk contagion.

Currently, there are many risk spillover analyses for interbanks. However, there are prominent areas for improvement in the risk portrayal of higher-order moments by considering only the risk spillover effects of first-order and second-order moments (return and volatility). First, the return distribution of financial assets usually deviates from the normal distribution, presenting asymmetric effects and extreme risks, which cannot be captured by considering only return and volatility. Second, skewness reflects asset returns and crash risk asymmetry, while kurtosis reflects extreme events and tail risk (Amaya et al., 2015; Greenwood-Nimmo et al., 2016). Higher-order moments help analyze spillover effects in the banking sector. Skewness spillovers describe how banks are linked by the degree of return asymmetry, while kurtosis spillovers explain how extreme events spread across banks. Thus, considering only low-order moments may underestimate risk, while higher-order moments can accurately portray risk spillovers.

Many scholars have recently introduced higher-order moments into the traditional financial analysis framework, opening up new research ideas in asset pricing and risk management. Many researchers have incorporated skewness into CAPM models, and many empirical studies have explored the relationship between skewness and risk premium (Harvey and Siddique, 2000; Kraus and Litzenberger, 1976). In addition to skewness, the effect of kurtosis on asset pricing has also received wide attention (Dittmar, 2002; Fang and Lai, 1997; Hwang and Satchell, 1999). Martellini and Ziemann (2010) introduced the idea of higher-order moments into the traditional portfolio framework, and the results showed that the modified portfolio model dramatically improves investor welfare. The empirical study of Jang and Kang (2017) demonstrated that incorporating higher-order moment preferences into intertemporal asset pricing models can significantly improve pricing accuracy. These studies only consider the effect of realized higher-order moments and asset pricing on low-frequency data. However, realized higher-order moments are more reflective of the relationship with asset prices under high-frequency data.

The increasing availability of data, econometric models, and algorithms has made it possible to study the impact of higher-order moments on asset pricing using higher-frequency data. High-frequency data contain more microstructural information and are more accurate in portraying risk. Merton (1980) first constructed an estimation method of realized volatility based on the sum-of-squares of intraday returns, which in turn yielded realized skewness and kurtosis, and the method has been widely used in the measurement of intraday higher-order moments. Along with the rapid development of financial technology and financial derivatives, researchers have begun to focus on the higher-order moments of connectedness between returns and risks in commodity markets. Bouri et al. (2021) calculated daily realized volatility, realized skewness, realized kurtosis, and jumps based on 5-minute data from 2006 to 2019 and used a time-varying parameter vector autoregression (TVP-VAR) model to reveal the spillovers between the U.S. stock market, crude oil, and gold. Zhou et al. (2023) analyzed the different roles of climate physical risk and transition risk on high moment-to-moment connectedness across commodity markets using the GJRSK model, the time-frequency connectedness framework, and the quartile-on-quartile methodology. Bouri et al. (2023) analyzed the impact of high moment-to-moment connectedness across commodity markets based on options data in precious metals (gold and silver) and energy (crude oil and natural gas) markets with spillovers from implied higher-order moments (i.e., volatility, skewness, and kurtosis), and find that system-wide connectedness weakens as the moment order increases. Nekhili et al. (2024) examined a European equity sector index's spillovers from higher-order moments (realized volatility, jumps, skewness, and kurtosis). The study finds that spillover shocks to other markets from volatility and jumps (bad volatility) associated with activity in the European energy and chemical industries, and skewness (asymmetry) and kurtosis (fat-tail) associated with activity in the European industrial and insurance sectors, are the largest sources of systemic risk.

With the continuous innovation and development of financial business, a complex and dense connectedness network has been formed among banks, leading to an increase in the channels and paths of systemic risk contagion. Against the above background, some scholars began applying complex network theory to study bank connectedness. Billio et al. (2012) constructed a risky connectedness network among financial institutions based on the Granger causality test, but this method could not identify the connectedness intensity. On this basis, Diebold and Yılmaz (2014a) proposed a spillover index model that can simultaneously portray bank connectedness's structure and strength. Härdle et al. (2016) combined the tail event and network approaches to propose the TENET methodology to measure the systemic risk of financial institutions in the U.S. Demirer et al. (2018) used the LASSO approach to select and estimate a sample of the world's top 150 banks from 2003-2014 and constructed static and dynamic network connectedness. Meanwhile, they point out that a critical reason for the lack of empirical studies on global bank connectedness is the high dimensionality of bank networks. In addition, existing studies showed that the dependence between financial assets is consistently characterized by nonlinearities, especially during economic downturns (He and Krishnamurthy, 2019), and ignoring this asymmetric and nonlinear effect may lead to a severe underestimation of systemic risk.

Existing literature provides a more in-depth study of high-frequency data portraying higher-order moment risk and bank connectedness, but things could still be improved. On the one hand, many scholars focus on risk spillovers among banks. However, the banking system is closely related to the oil and gas industry, and current studies on the impact of oil and gas prices on banks' systemic risk mainly use macro indexes, lacking studies that identify the micro transmission path of risk spillovers from the firm level. On the other hand, most of the existing studies explore inter-firm spillovers at the return and volatility level and only measure the degree of integration and risk contagion effects among banks or oil and gas companies under low-order moment conditions (Wu et al., 2021; Zhang et al., 2023). Excess higher-order moment features such as sharp peaks and thick tails are prevalent in financial institutions' asset returns and risks. However, little literature has quantified the risk spillover effects at higher-order moments (skewness and kurtosis), resulting in an incomplete portrayal of the risk spillover effects. Therefore, this paper uses high-frequency data to study the higher-order moments transmission mechanism between U.S. banks and oil and gas companies to provide theoretical support for financial risk prevention.

3 Methodology

In order to accurately estimate the transmission mechanism between the oil and banking sectors, we employ the TVP-VAR-based connectedness approach of Antonakakis et al. (2020). This approach has proven to be superior compared to the rolling-window VAR connectedness approach of Diebold and Yılmaz (2012, 2014b), as it overcomes several limitations such as (i) avoiding choosing an arbitrary window size, (ii) parameter changes are reflected more accurately, (iii) less outlier sensitive due to the multivariate Kalman filter approach, and (iv) no loss of observations.

We start by outlining the TVP-VAR(1) model as suggested by the Bayesian information criterion (BIC):

$$\boldsymbol{z}_t = \boldsymbol{B}_t \boldsymbol{z}_{t-1} + \boldsymbol{u}_t \qquad \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{H}_t) \tag{1}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{R}_t) \tag{2}$$

where $\boldsymbol{z}_t$, $\boldsymbol{z}_{t-1}$ and $\boldsymbol{u}_t$ are $K \times 1$ dimensional vectors in t, $t-1$, and the corresponding error term, respectively. $\boldsymbol{B}_t$ and $\boldsymbol{H}_t$ are $K \times K$ dimensional matrices demonstrating the TVP-VAR coefficients and the time-varying variance-covariances while $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $K^2 \times 1$ dimensional vectors and $\boldsymbol{R}_t$ is a $K^2 \times K^2$ dimensional matrix.

In order to compute the GFEVD proposed by Koop et al. (1996) and Pesaran and Shin (1998), the TVP-VAR is transformed to a TVP-VMA model using the Wold representation theorem: $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{B}_{i,t}\boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{j,t}\boldsymbol{u}_{t-j}$. Subsequently, the F-step ahead GFEVD represents the impact a shock in series j has on series i which is formulated as follows:

$$\phi_{ij,t}^{gen}(F) = \frac{\sum_{f=0}^{F-1}(\boldsymbol{e}_i'\boldsymbol{A}_{f,t}\boldsymbol{H}_t\boldsymbol{e}_j)^2}{\boldsymbol{H}_{jj,t}\sum_{f=0}^{F-1}(\boldsymbol{e}_i'\boldsymbol{A}_{f,t}\boldsymbol{H}_t\boldsymbol{A}_{f,t}'\boldsymbol{e}_i)} \tag{3}$$

where $\boldsymbol{e}_i$ is a $K \times 1$ dimensional zero vector with unity on its ith position. As shown by the unconditional connectedness measures of Gabauer et al. (2023), the contemporaneous effects of the GFEVD solely depend on $\boldsymbol{A}_{0,t}$ which is equal to the identity matrix, $\boldsymbol{I}_K$. Thus, without a loss of generality, the GFEVD can also be viewed as follows:

$$\begin{aligned}
\phi_{i\leftarrow j,t}^{gen}(F) =& \frac{\boldsymbol{H}_{ij,t}^2}{\boldsymbol{H}_{jj,t}\sum_{f=0}^{F-1}(\boldsymbol{e}_i'\boldsymbol{A}_{f,t}\boldsymbol{H}_t\boldsymbol{A}_{f,t}'\boldsymbol{e}_i)} &&+ \frac{\sum_{f=1}^{F-1}(\boldsymbol{e}_i'\boldsymbol{A}_{f,t}\boldsymbol{H}_t\boldsymbol{e}_j)^2}{\boldsymbol{H}_{jj,t}\sum_{f=0}^{F-1}(\boldsymbol{e}_i'\boldsymbol{A}_{f,t}\boldsymbol{H}_t\boldsymbol{A}_{f,t}'\boldsymbol{e}_i)} && (4)\\
=& \phi_{i\leftarrow j,t}^{gen,con}(F) &&+ \phi_{i\leftarrow j,t}^{gen,lag}(F) && (5)
\end{aligned}$$

where $\phi_{i\leftarrow j,t}^{gen,con}(F)$ and $\phi_{i\leftarrow j,t}^{gen,lag}(F)$ represent the contemporaneous and lagged component of the (unscaled) GFEVD. It should be noted that $\phi_{i\leftarrow j,t}^{gen,con}(F)$ is not purely contemporaneous as the denominator includes information about the lagged TVP-VMA coefficients, however, if $\phi_{i\leftarrow j,t}^{gen,lag}(F)$ would be equal to zero, we retrieve the same results as outlined in Gabauer et al. (2023). As the row sum of $\phi_{i\leftarrow j,t}^{gen}$ is not equal to unity, Diebold and Yilmaz (2012, 2014b) suggested normalizing $\phi_{ij,t}^{gen}(H)$ by dividing it by the row sum to obtain the scaled GFEVD, $gSOT_{ij,t}$:

$$\begin{aligned}
gSOT_{ij,t}(F) =& \frac{\phi_{ij,t}^{gen}(F)}{\sum_{k=1}^{K}\phi_{ik,t}^{gen}(F)} & (6)\\
=& \frac{\phi_{ij,t}^{gen,con}(F)}{\sum_{k=1}^{K}\phi_{ik,t}^{gen}(F)} + \frac{\phi_{ij,t}^{gen,lag}(F)}{\sum_{k=1}^{K}\phi_{ik,t}^{gen}(F)} & (7)\\
=& gSOT_{ij,t}^{con}(F) + gSOT_{ij,t}^{lag}(F) & (8)
\end{aligned}$$

Finally, the same concept can be applied to the total directional connectedness TO and FROM others as well as the net total directional connectedness measures

$$
\begin{aligned}
TO_{j,t} =& \sum_{k=1,k\neq j}^{K} gSOT_{kj,t}^{con}(F) + \sum_{k=1}^{K} gSOT_{kj,t}^{lag}(F) && (9)\\
=& TO_{j,t}^{con} + TO_{j,t}^{lag} && (10)\\
FROM_{j,t} =& \sum_{k=1,k\neq j}^{K} gSOT_{jk,t}^{con}(F) + \sum_{k=1}^{K} gSOT_{jk,t}^{lag}(F) && (11)\\
=& FROM_{j,t}^{con} + FROM_{j,t}^{lag} && (12)\\
NET_{j,t}^{con} =& TO_{j,t}^{con} - FROM_{j,t}^{con} && (13)\\
NET_{j,t}^{lag} =& TO_{j,t}^{lag} - FROM_{j,t}^{lag} && (14)\\
NET_{j,t} =& NET_{j,t}^{con} + NET_{j,t}^{lag}. && (15)
\end{aligned}
$$

While the $TO_{j,t}$ ($TO_{j,t}^{con}/TO_{j,t}^{lag}$) total directional connectedness demonstrates the overall (contemporaneous/lagged) impact series j has on all other series, the $FROM_{j,t}$ ($FROM_{j,t}^{con}/FROM_{j,t}^{lag}$) illustrates the overall (contemporaneous/lagged) influence all other series have one series j. Finally, if $NET_{j,t} > 0$ ($NET_{j,t} < 0$), series j is considered as a net transmitter (receiver) of shocks indicating that it influences all other series more (less) than being influenced by them. The contemporaneous and lagged net total connectedness measures can be interpreted in the same manner.

Lastly, we compute the total connectedness index (TCI), which is at the center of the connectedness approach as it represents the interconnectedness in the network and hence can be considered as a proxy for market risk. The TCI ranges between zero and unity and is formulated as follows,

$$
\begin{aligned}
TCI_t =& \frac{1}{K}\sum_{k=1}^{K} TO_{k,t} \equiv \frac{1}{K}\sum_{k=1}^{K} FROM_{k,t} && (16)\\
=& \frac{1}{K}\sum_{k=1}^{K}(TO_{k,t}^{con} + TO_{k,t}^{lag}) \equiv \frac{1}{K}\sum_{k=1}^{K}(FROM_{k,t}^{con} + FROM_{k,t}^{lag}) && (17)\\
=& TCI_t^{con} + TCI_t^{lag} && (18)
\end{aligned}
$$

where TCI_t^{con} and TCI_t^{lag} represent the contemporaneous and lagged TCI, respectively. The higher (smaller) the TCI, the higher (smaller) the market risk.

On another note, we can compute the fraction of lagged over contemporaneous GFEVD effects using the following formula:

$$f_{ij,t}^{con}(F) = \frac{gSOT_{ij,t}^{con}(F)}{gSOT_{ij,t}(F)} \tag{19}$$

$$= \frac{\phi_{i\leftarrow j,t}^{gen,con}(F)}{\phi_{i\leftarrow j,t}^{gen}(F)} \tag{20}$$

$$f_{ij,t}^{lag}(F) = 1 - f_{ij,t}^{con}(F) = \frac{\phi_{i\leftarrow j,t}^{gen,lag}(F)}{\phi_{i\leftarrow j,t}^{gen}(F)}. \tag{21}$$

The main advantage of computing the fraction of contemporaneous effects is that computation is independent of the employed normalization technique (Caloia et al., 2019; Chatziantoniou et al., 2021; Lastrapes and Wiesen, 2021; Balcilar et al., 2021). This fraction is not only interesting for the connectedness literature, but it is also far more general and is of crucial importance to all studies employing the GFEVD. It goes without saying that by processing the fractions $f_{ij,t}^{lag}(F)$ in the same fashion as the connectedness measure and combining them with the standard connectedness approach of Diebold and Yılmaz (2012, 2014b), we get retrieve all contemporaneous and lagged connectedness measures. For the special case when only contemporaneous effects are observed, $f_{ij,t}^{con}(F)$ will be equal to unity, and thus $TO_t = TO_t^{con}$, $FROM_t = FROM_t^{con}$, $TCI_t = TCI_t^{con}$, and TO^{lag}, $FROM^{lag}$ as well as TCI^{lag} will be equal to zero.[1]

4 Data

This study considers intraday data for the top 10 US banks and top 10 oil and gas companies. Our sample covers the period from December 29, 2017, to December 30, 2022, which, like this period, includes several market instabilities and crises (e.g., the COVID-19 pandemic, the Russia-Ukraine war, etc.). We exclude holidays such as Christmas Day, New Year's Day, and other dates not fully covered by trading hours. Inspired by Bollerslev and Zhou (2006) and Luo and Ji (2018), we set the sampling frequency to 5 minutes to reduce microstructure noise. Realized volatility, realized skewness and realized kurtosis are constructed using the 5-minute frequency data. Specifically speaking, We compute

[1] The analysis was conducted with the R package "Connectedness Approach" of Gabauer (2022).

the sum of squared intraday returns of the data and, thus, consider the classical estimator of realized variance Andersen and Bollerslev (1998). We obtain the realized variance as follows (we do not introduce a subindex to denote a company for notational convenience):

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2, \tag{22}$$

where $r_{t,i}$ denotes the intraday $M \times 1$ return vector, and $i = 1, ..., M$ denotes the number of intraday returns. Equipped with Equation (22), we compute the realized volatility as the standard deviation of the realized variance, i.e., $\sqrt{RV_t}$. We study RSK to trace the asymmetry of the returns distribution, while we use RKU to capture its extremes (Amaya et al., 2015). We calculate RSK and RKU as follows:

$$RSK_t = \frac{\sqrt{M} \sum_{i=1}^{M} r_{(i,t)}^3}{RV_t^{3/2}}, \tag{23}$$

$$RKU_t = \frac{M \sum_{i=1}^{M} r_{(i,t)}^4}{RV_t^2}. \tag{24}$$

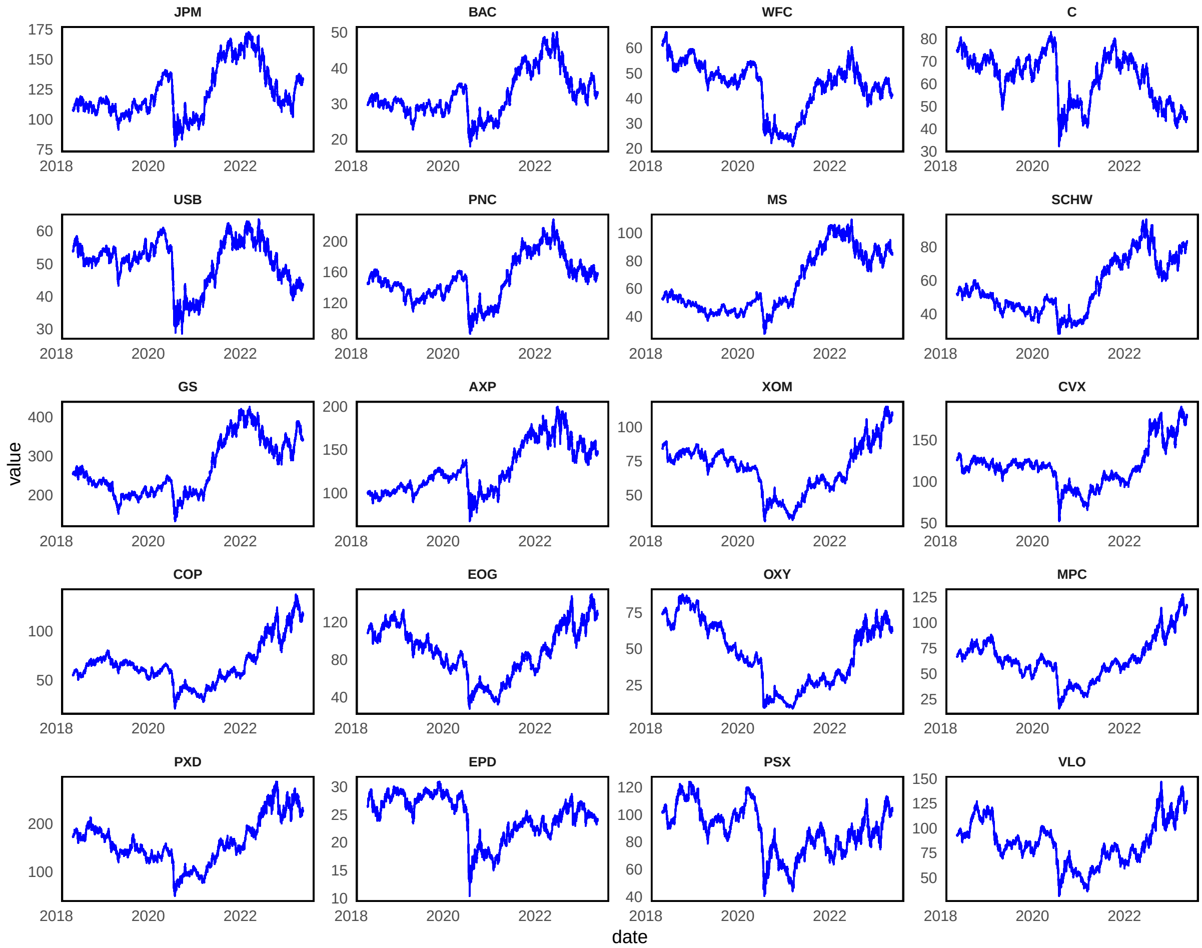
The scaling terms, $(M)^{1/2}$ and M, turn RSK and RKU into their daily values.

As shown in Figure 1, there is a high degree of similarity in the closing price movements of the stocks of the top ten U.S. banks and the top ten oil and gas companies. Between March 2020 and October 2020, both prices fell sharply to their lowest levels during the sample period due to the COVID-19 pandemic. After the outbreak of the Russian-Ukrainian conflict in 2022, the stock prices of the top ten banks trended downward, while the stock prices of the top ten oil and gas companies trended upward and even continued to set new highs.

Figure 2 illustrates the realized volatility of the top ten U.S. banks and oil and gas companies. Significant volatility clustering occurs during the February 2018 U.S. stock market crash and the March 2022 COVID-19 pandemic. This suggests that financial institutions and oil and gas companies exhibit more volatile characteristics during significant crises.

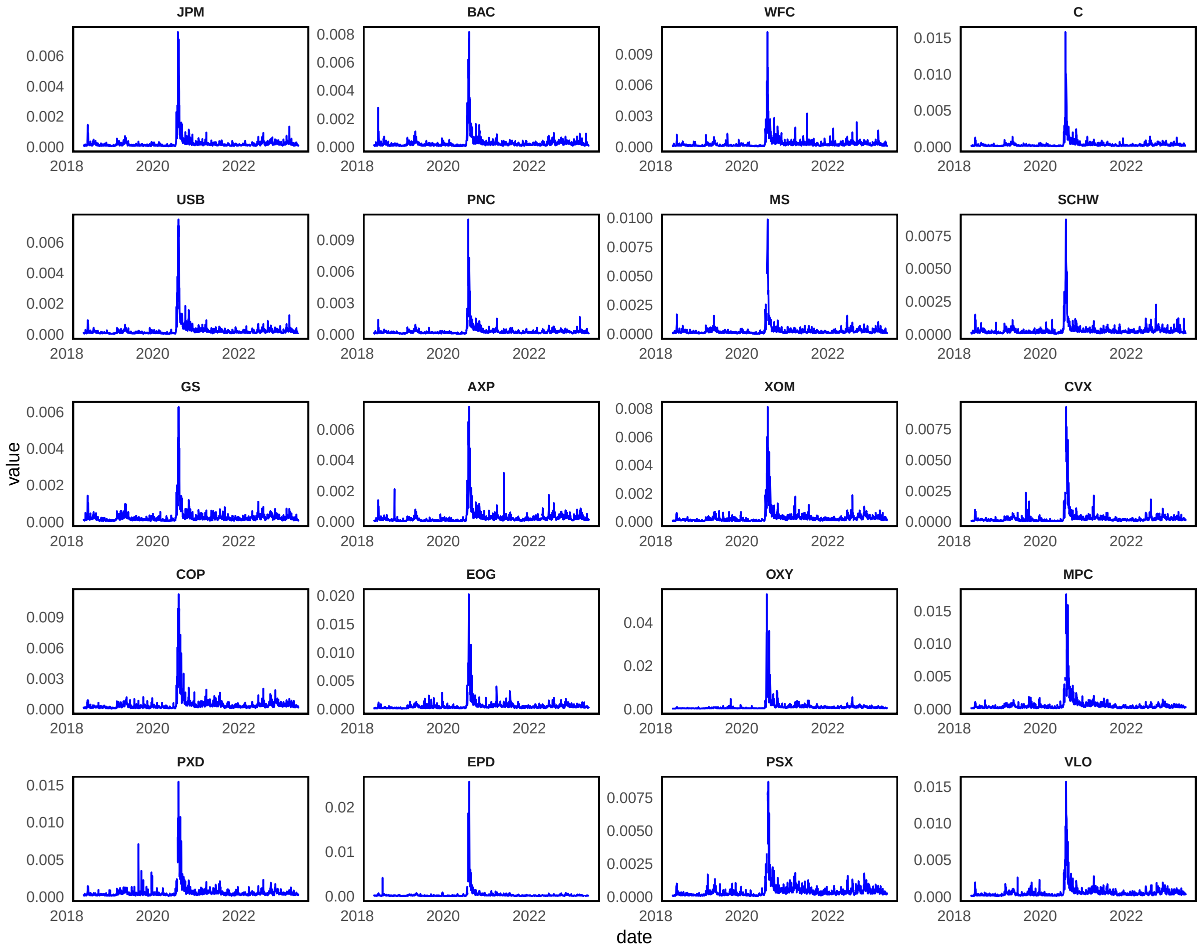
Figures 3 and 4 illustrate the realized skewness (third moment) and kurtosis (fourth moment) of the top ten U.S. banks and oil and gas companies. The stock prices of the

Figure 1: Intraday 5-min closing prices for banks and oil and gas companies



top ten U.S. banks are affected by various macro-factors such as the economic cycle, interest rate policy, and monetary policy. Thus, the realized skewness and kurtosis show more volatile characteristics. The realized skewness and kurtosis of the top 10 U.S. oil and gas companies are closely related to the geopolitical situation, supply and demand, and fluctuations in the U.S. dollar exchange rate. The escalation of tensions between the U.S. and Iran and the U.S. airstrikes in Iraq in January 2019 sparked geopolitical concerns, leading to fears of disruptions in the supply of oil, which in turn impacted the price of oil. This may have affected the concentrated movements in the share prices of oil and gas companies, increasing the magnitude of skewness volatility and kurtosis. In the first half of 2019, the downside risks to global economic growth and the extension of the OPEC+ production cut agreement affected the volatility of the share prices of oil and gas companies, increasing both skewness and kurtosis. Higher-order moments

Figure 2: Realized volatility for banks and oil and gas companies



measure better capture time-varying characteristics, highlighting the need to measure the interaction and connectivity between U.S. financial institutions and oil and gas companies from a higher-order moments perspective.

Figure 3: Realized skewness for banks and oil and gas companies

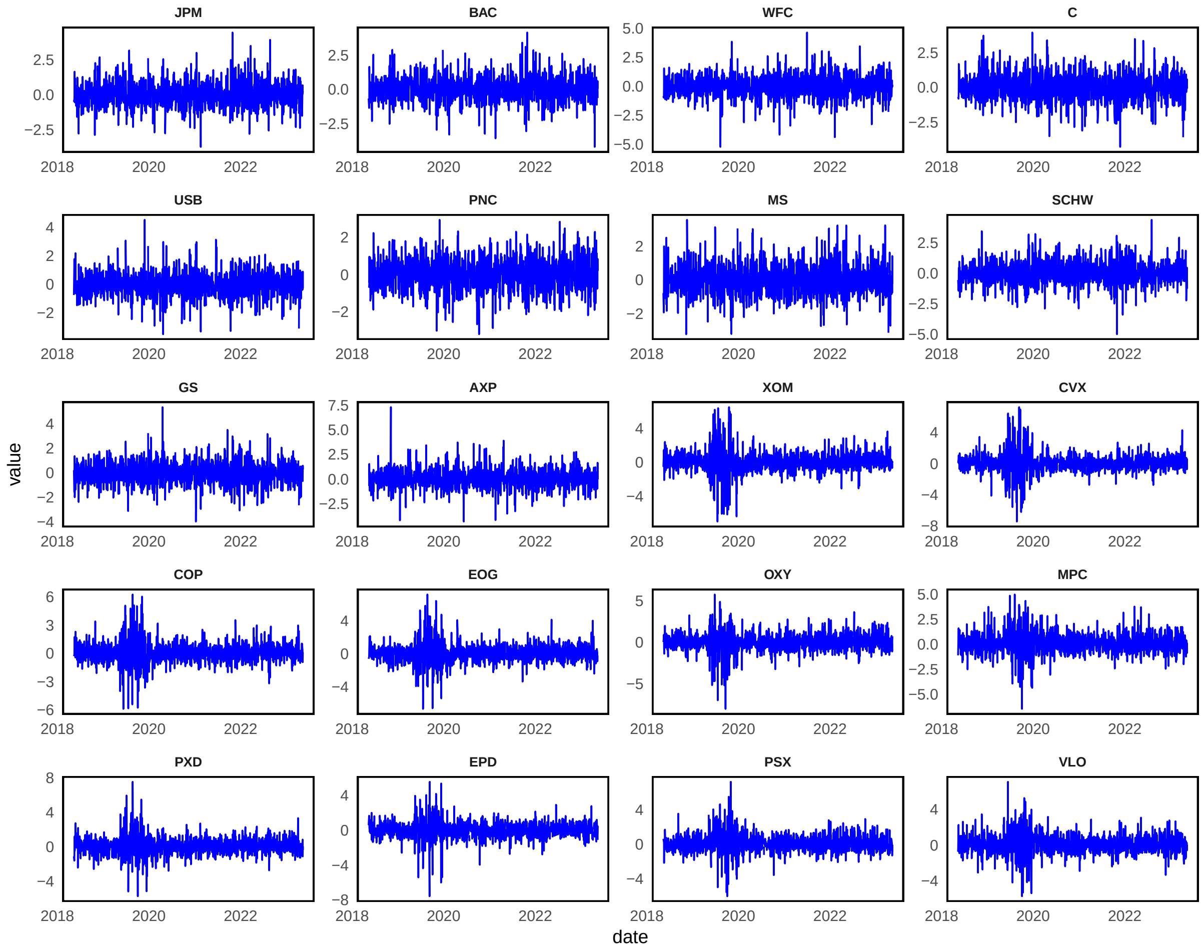
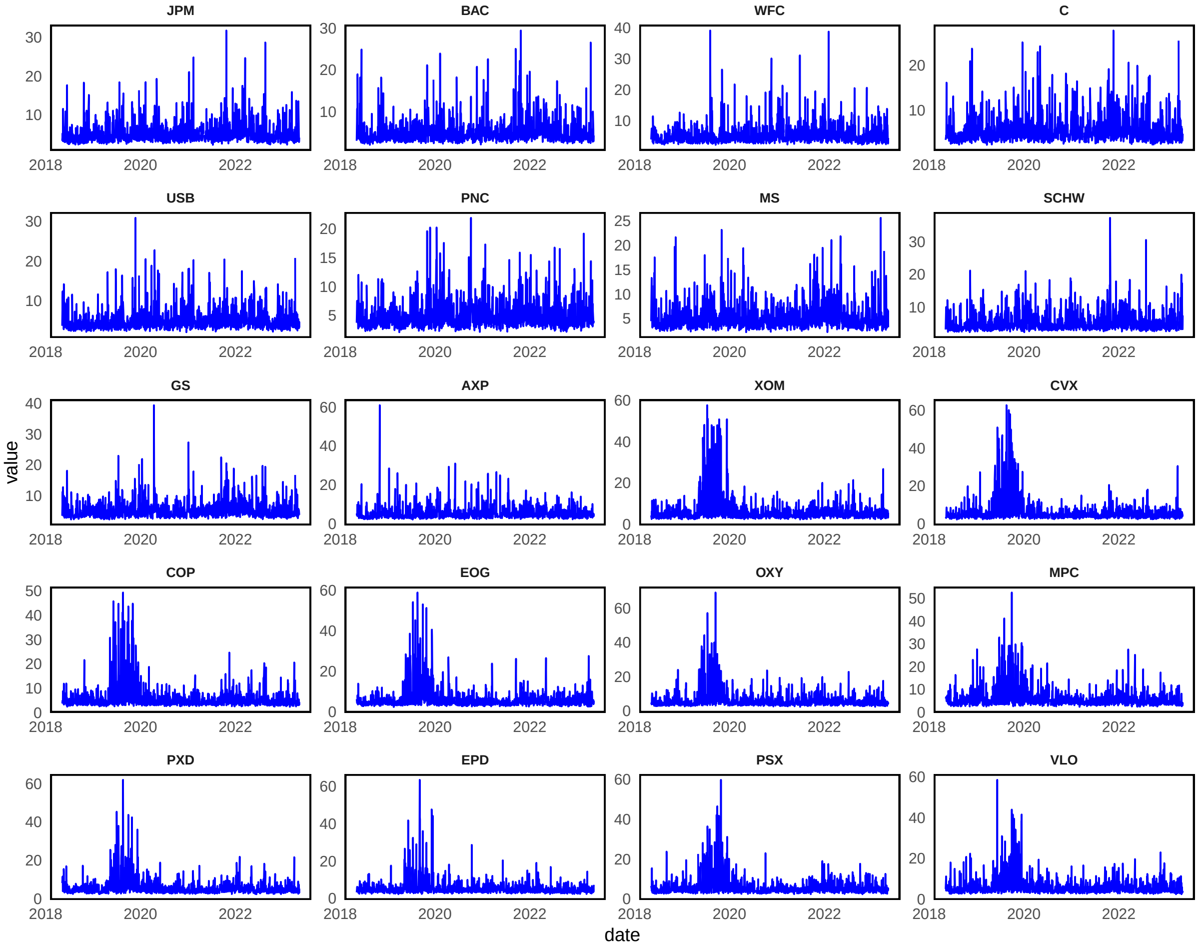


Figure 4: Realized kurtosis for banks and oil and gas companies



5 Empirical results

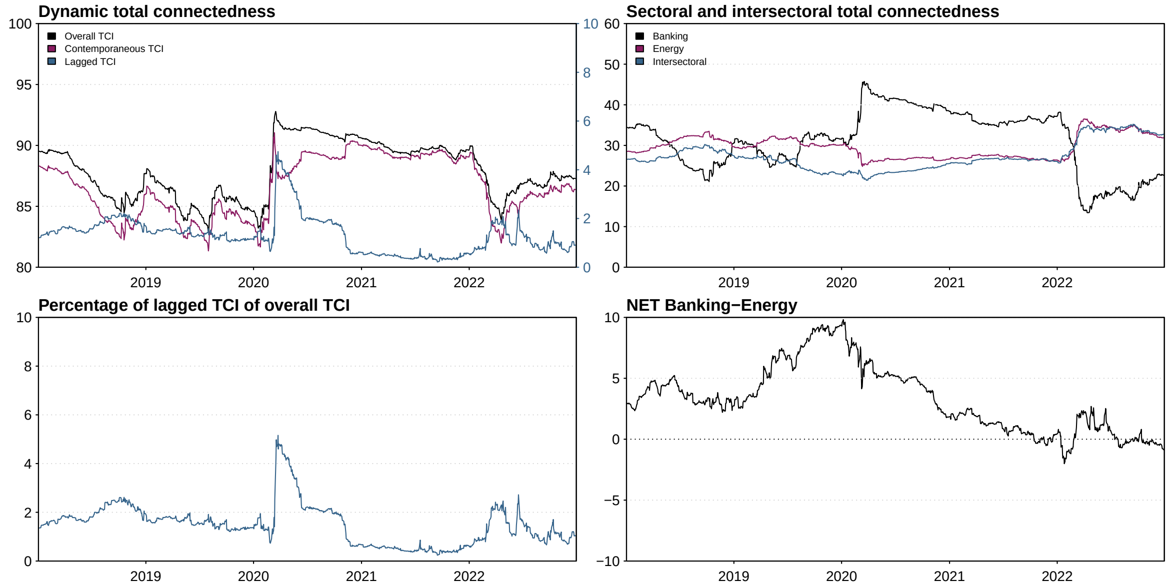
Contemporaneous rather than lagged effects can explain most dynamic total connectedness. When comparing the spillover results of the four order moments, realized volatility is the only exception whose dynamic total connectedness is mainly contributed by lagged effects. Sudden increases and decreases in connectedness signal increases in uncertainty and stability, respectively. Total directional net connectedness reveals whether a series is a net transmitter of spillovers (if total directional net connectedness is positive) or a net receiver of spillovers (if total directional net connectedness is negative). The network diagram portrays the node-pair spillover transmission mechanism at the overall, contemporaneous, and lagged levels. It should be noted that we have standardized the degree of spillovers for each network plot, as otherwise lagged interconnectedness is barely identifiable.

Figure 5 illustrates the dynamic total spillover sequence of returns, and we find that market risk increased sharply in the spring of 2020, probably due to a substantial increase in inter-market risk spillovers due to the increased market panic caused by the COVID-19 pandemic outbreak. Interestingly, the contemporaneous TCl remains high until the end of 2021. The lagged TCI declines rapidly to lower levels after market pessimism due to the outbreak subsides, but the overall level of risk in 2020 is still higher than the pre-pandemic market risk. The lagged TCI as a percentage of the overall TCI is consistently below 10%, only reaching its highest level in 2020 during the outbreak of COVID-19.

In addition, we also analyze sectoral and intersectoral connectedness spillovers. Banking sector spillovers are the main reason for the increase in market risk in 2020, while energy spillovers are associated with an increase in market risk in early 2022, which may be related to the Russian-Ukrainian war. Finally, we examine net return spillovers between the banking and energy sectors. The banking sector is the leading net transmitter of shocks for almost the entire sample period.

In Figure 6, we can draw the following conclusions. First, in terms of realized volatility, lagged TCI contributes more to the overall TCI than contemporaneous TCl. In particular, the lagged TCI reached its highest share of the overall TCI in the early 2020s, but it kept decreasing until the outbreak of the Russia-Ukraine war, after which it decreased further.

Figure 5: Return: Dynamic total connectedness



Notes: Results are based on a TVP-VAR model with a lag length of order one (BIC), $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition. The top left plot represents the overall, contemporaneous, and lagged dynamic total connectedness while the bottom left plot illustrates the effect the lagged TCI has on the overall TCI. Furthermore, the top right plot illustrates the banking, energy as well as intersectoral TCI based upon the connectedness decomposition approach of Gabauer and Gupta (2018) while the bottom right plot depicts the net sectoral spillover between the banking and energy sector.

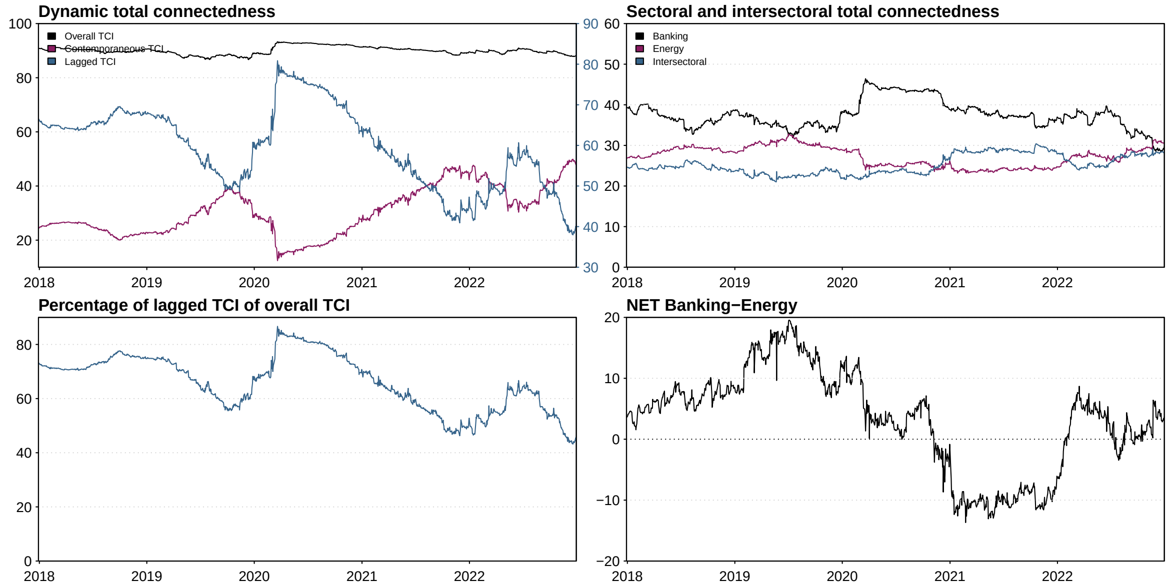
This behavior is to be expected, as realized volatility illustrates market uncertainty.

In addition, we also find that the increase in banking TCI in the early 2020s impacts the increase in market risk to some extent. Interestingly, energy TCI decreases while the transmission between banking and energy does not change. Moreover, over time, the banking TCI slowly decreases while the energy TCI gradually increases. Finally, the banking sector dominates the energy sector most of the time. The energy sector will become the dominant market risk player only from 2021 to early 2022, and there will be a net risk spillover from the energy sector to the banking sector.

The realized skewness in Figure 7 captures the asymmetry of asset returns and crash risk. The contemporaneous TCl is trending upward in line with the volatility of the overall TCI, which suggests that banks and energy companies in the U.S. are increasingly at risk of crashing. The lagged TCI was affected by COVID-19 in the second half of 2020 and became significantly more volatile, but the lagged TCI as a percentage of the overall TCI is always less than 8%.

We find that banking spillovers are significantly lower than energy and intersectoral

Figure 6: Realized volatility: Dynamic total connectedness



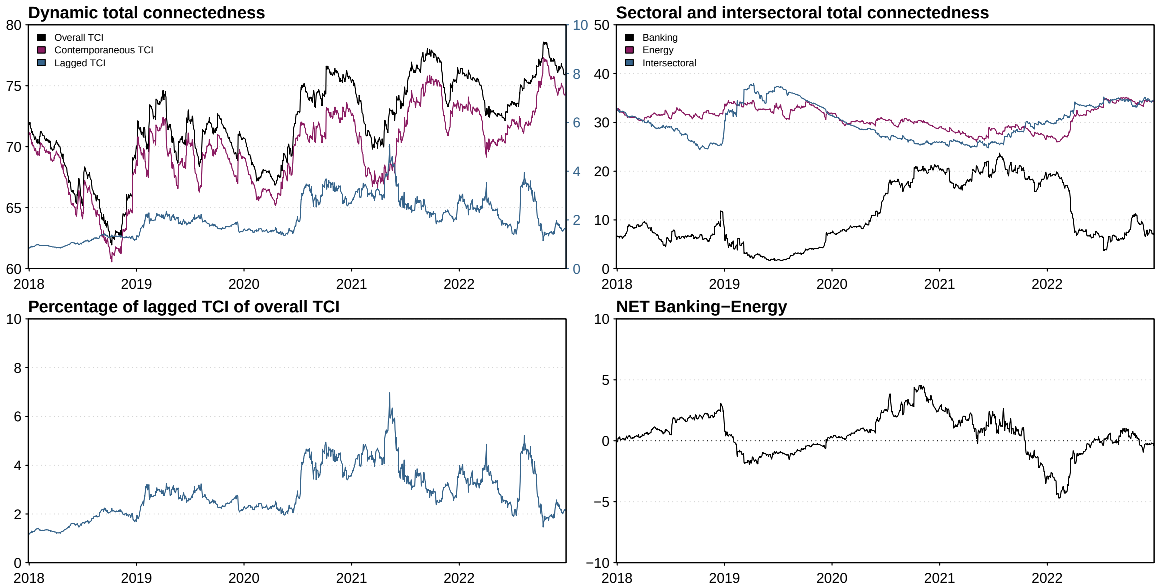
Notes: Results are based on a TVP-VAR model with a lag length of order one (BIC), $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition. The top left plot represents the overall, contemporaneous, and lagged dynamic total connectedness while the bottom left plot illustrates the effect the lagged TCI has on the overall TCI. Furthermore, the top right plot illustrates the banking, energy as well as intersectoral TCI based upon the connectedness decomposition approach of Gabauer and Gupta (2018) while the bottom right plot depicts the net sectoral spillover between the banking and energy sector.

spillovers for total intersectoral connectedness. The banking intersectoral spillover rose significantly in 2020 until the risk returned to pre-COVID-19 levels after omicron became the dominant transmission strain. When the bank TCI rises, there is little change in the connectedness between banks and energy. Similar to the conclusions obtained for returns and realized volatility, the banking sector mainly dominates the energy sector in realized skewness.

The realized kurtosis in Figure 8 depicts how extreme events and tail risks spread between banks and energy companies. The contemporaneous TCl is higher than the lagged TCI for almost the entire sample period. Starting in 2022, the overall TCI continues to rise, suggesting that tail risk for banks and energy companies increases as extreme events become more frequent. Meanwhile, lagged TCI as a percentage of overall TCI fluctuates between 5% and 22%.

Regarding intersectoral connectedness, bank spillovers are consistently the lowest, and intersectoral spillovers are the highest for almost the entire sample period. Moreover, in the spillover between banks-energy sectors with realized kurtosis, the energy sector is a

Figure 7: Realized skewness: Dynamic total connectedness



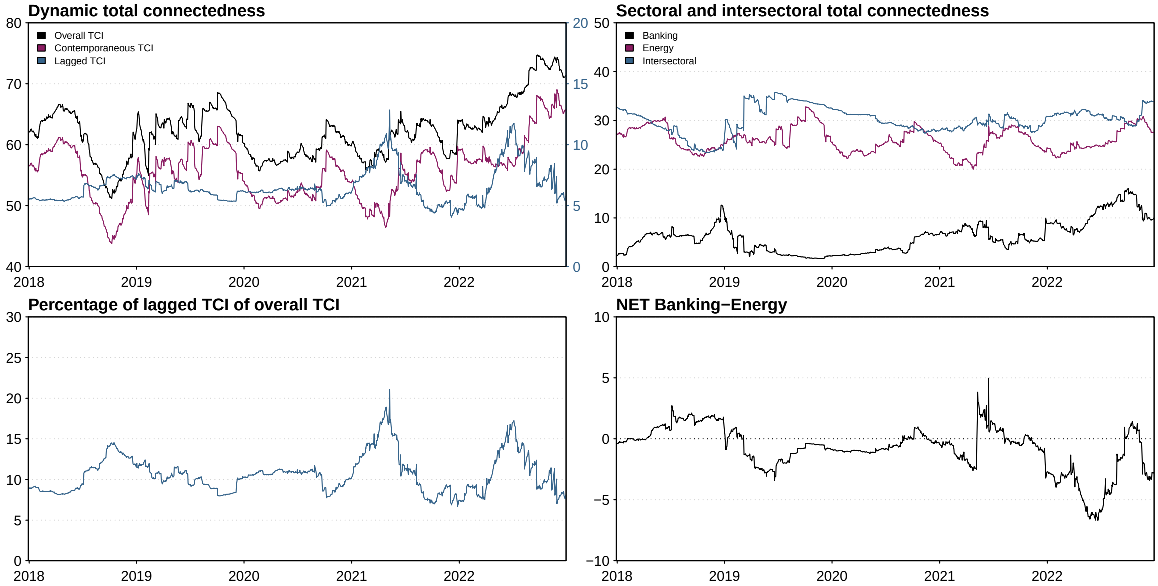
Notes: Results are based on a TVP-VAR model with a lag length of order one (BIC), $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition. The top left plot represents the overall, contemporaneous, and lagged dynamic total connectedness while the bottom left plot illustrates the effect the lagged TCI has on the overall TCI. Furthermore, the top right plot illustrates the banking, energy as well as intersectoral TCI based upon the connectedness decomposition approach of Gabauer and Gupta (2018) while the bottom right plot depicts the net sectoral spillover between the banking and energy sector.

solid net transmitter of spillovers when geopolitical crises arise. For example, tensions between the U.S. and Iran in 2019 and the outbreak of a Russian-Ukrainian war in 2022 led to energy price volatility.

Further, we carry out an analysis of the net total connectedness of individual firms. First, in the sequence of returns plotted in Figure 9, most banks are net transmitters of spillovers, while most oil and gas companies are net receivers of spillovers. After the COVID-19 outbreak in 2020, the net spillover values of banks started to decline, with several banks, including WFC, SCHW, and GS, experiencing longer periods of negative net spillover. This phenomenon may be because the outbreak led to a slowdown in the economy with rising unemployment and increased risk of loan defaults, which overlapped with bank interest rate cuts, affecting their profitability. EPD received the highest level of net spillover among all companies, which may be because the company is primarily engaged in oil and gas transportation, storage, and handling, and its production operations are subject to multiple impacts from bank loans and upstream supply.

Second, Figure 10 shows realized volatility. Contemporaneous net total directional

Figure 8: Realized kurtosis: Dynamic total connectedness

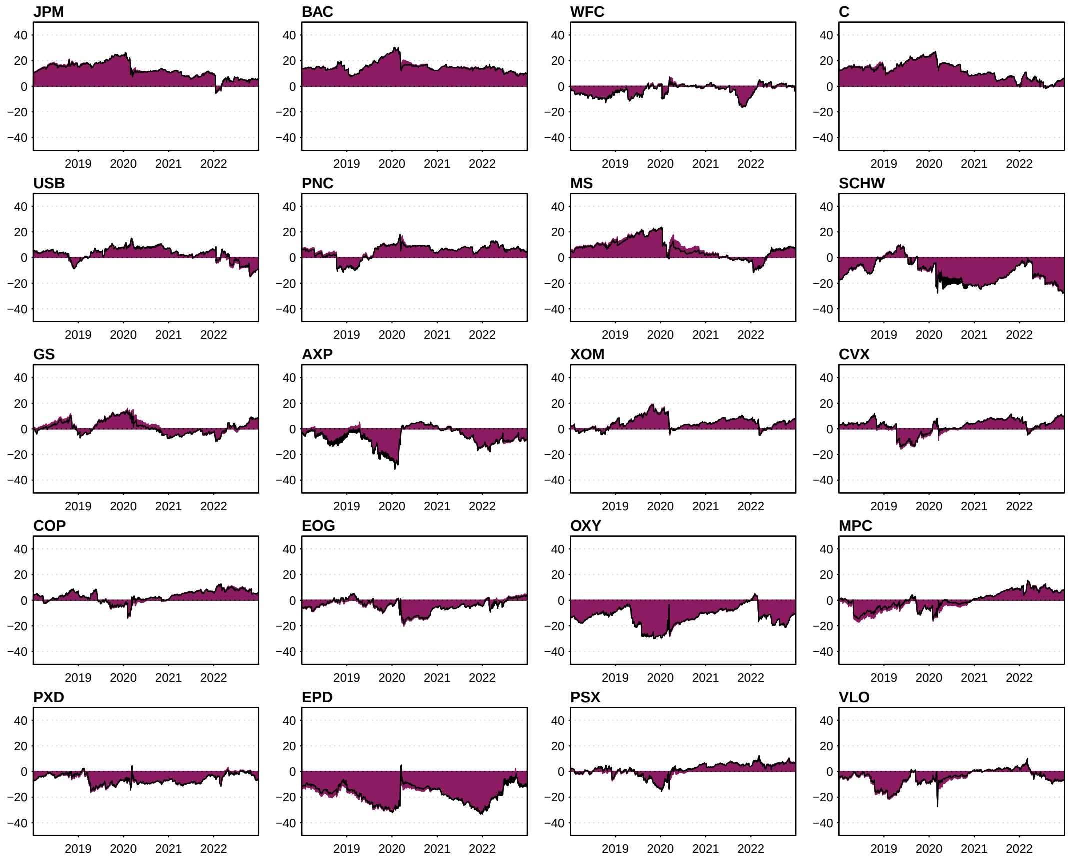


Notes: Results are based on a TVP-VAR model with a lag length of order one (BIC), $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition. The top left plot represents the overall, contemporaneous, and lagged dynamic total connectedness while the bottom left plot illustrates the effect the lagged TCI has on the overall TCI. Furthermore, the top right plot illustrates the banking, energy as well as intersectoral TCI based upon the connectedness decomposition approach of Gabauer and Gupta (2018) while the bottom right plot depicts the net sectoral spillover between the banking and energy sector.

connectedness contributes little to overall net total directional connectedness and is much smaller than lagged net total directional connectedness. Before COVID-19, net spillovers for banks were predominantly positive, indicative of the strong position of U.S. financial institutions, which changed after the epidemic outbreak. After the start of the Russia-Ukraine war in 2022, the volatility of net spillovers for almost all banks showed an upward trend, while a downward trend dominated oil and gas companies. The Russia-Ukraine war made U.S. stocks a better safe-haven asset, and investors went long in U.S. financial markets. Whereas geopolitical tensions have led to increased volatility in crude oil prices, the market is in a state of panic in the short term, and investors may reduce their investments in oil and gas companies.

Among all firms, MPC's realized volatility change trend is noteworthy. Its contemporaneous net total directional connectedness and overall net total directional connectedness change trends are almost identical and are negative before COVID-19 and after the start of the Russia-Ukraine war. Global oil and natural gas markets could be challenged by oversupply, demand volatility, and policy and environmental pressures during the COVID-19

Figure 9: Return: Net total directional connectedness

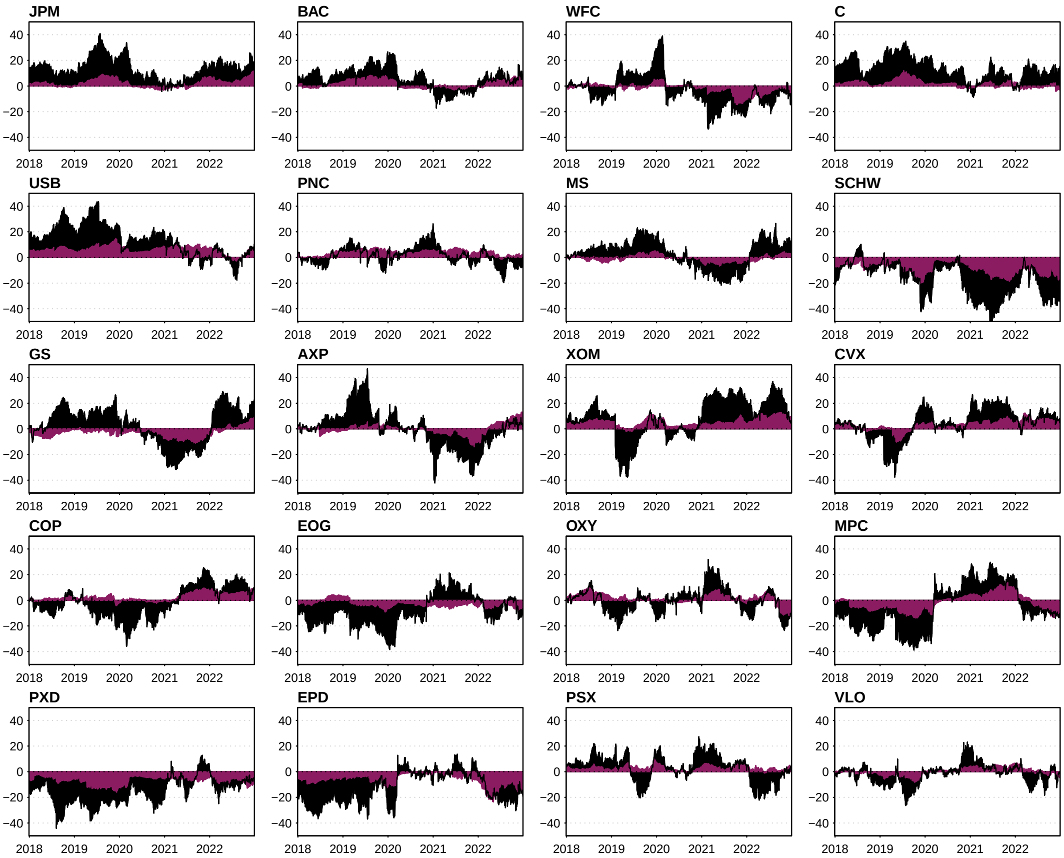


Notes: Results are based on a TVP-VAR model with a lag length of order one (BIC), $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition. The black areas represent the overall net total directional connectedness while the pink areas illustrate the contemporaneous net total directional connectedness.

pandemic. Marathon Petroleum's business is susceptible to oil price volatility as a refining and petroleum products distribution company. The Russia-Ukraine war has significantly impacted global energy markets, particularly in raising energy prices, disrupting supply chains, and increasing market uncertainty. For companies like Marathon Petroleum, this could mean higher costs, increased operational challenges and lower demand.

A combined analysis of Figures 11 and 12 reveals similar trends in net total directional connectedness changes for realized skewness and realized kurtosis for most firms. Realized skewness measures the asymmetry of the return distribution, while realized kurtosis measures the sharpness of the return distribution or the frequency of outliers. This implies that the shape of their return distributions maintains the consistency of market sentiment throughout the change, whether overly optimistic or overly pessimistic. This may lead to an increase in the frequency of asymmetric return distributions with outliers. In addition,

Figure 10: Realized volatility: Net total directional connectedness



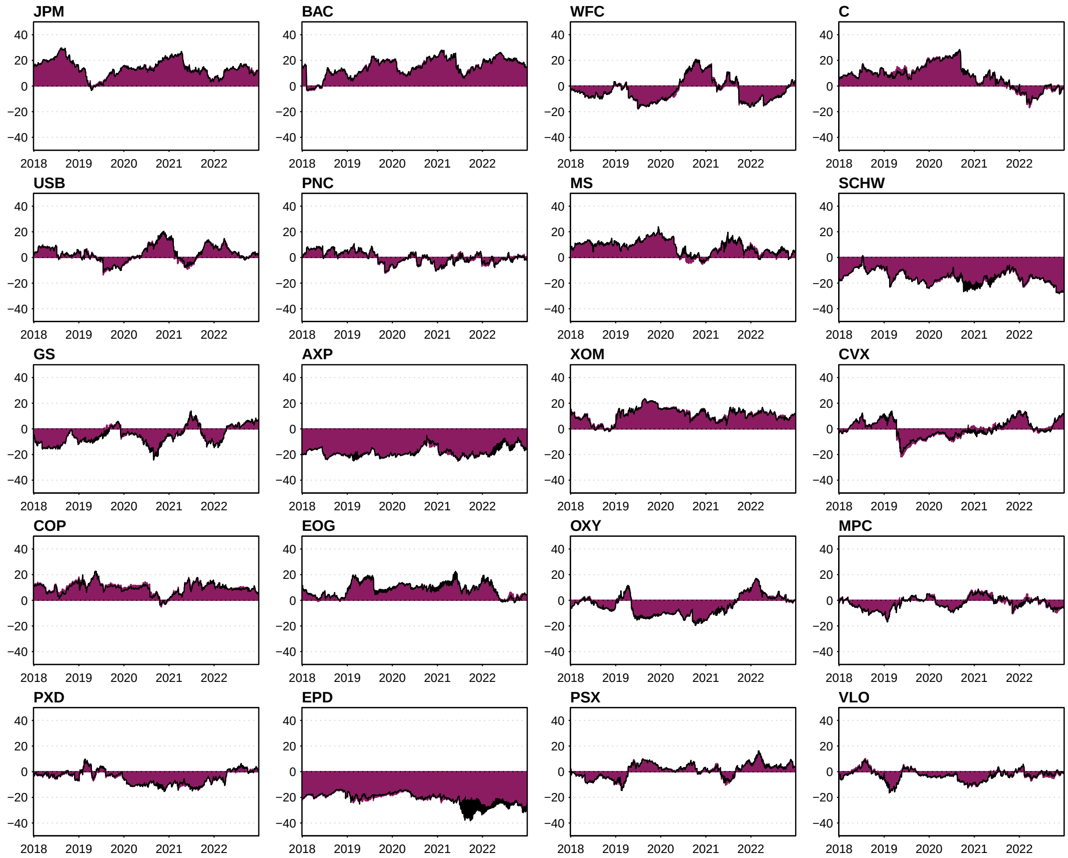
Notes: Results are based on a TVP-VAR model with a lag length of order one (BIC), $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition. The black areas represent the overall net total directional connectedness while the pink areas illustrate the contemporaneous net total directional connectedness.

similar trends may imply that markets are being affected by specific risk events. For example, a negative oil price shock could simultaneously cause the return distribution to become more skewed and sharp.

In addition, we graph the net pairwise directional connectedness network between all firm nodes. Blue nodes are firms with positive net spillovers, and yellow nodes are firms with negative net spillovers. Larger nodes indicate larger absolute values of net spillover. Directed lines between nodes indicate the spillover level between firms, with thicker lines representing higher spillover.

Figure 13 shows the return network, where most banks are spillover emitters in the overall connectedness network, illustrating that banks are influencers in the energy market. The contemporaneous connectedness network is similar to the overall connectedness network in that banks dominate. In contrast, all banks are net recipients of spillovers

Figure 11: Realized skewness: Net total directional connectedness

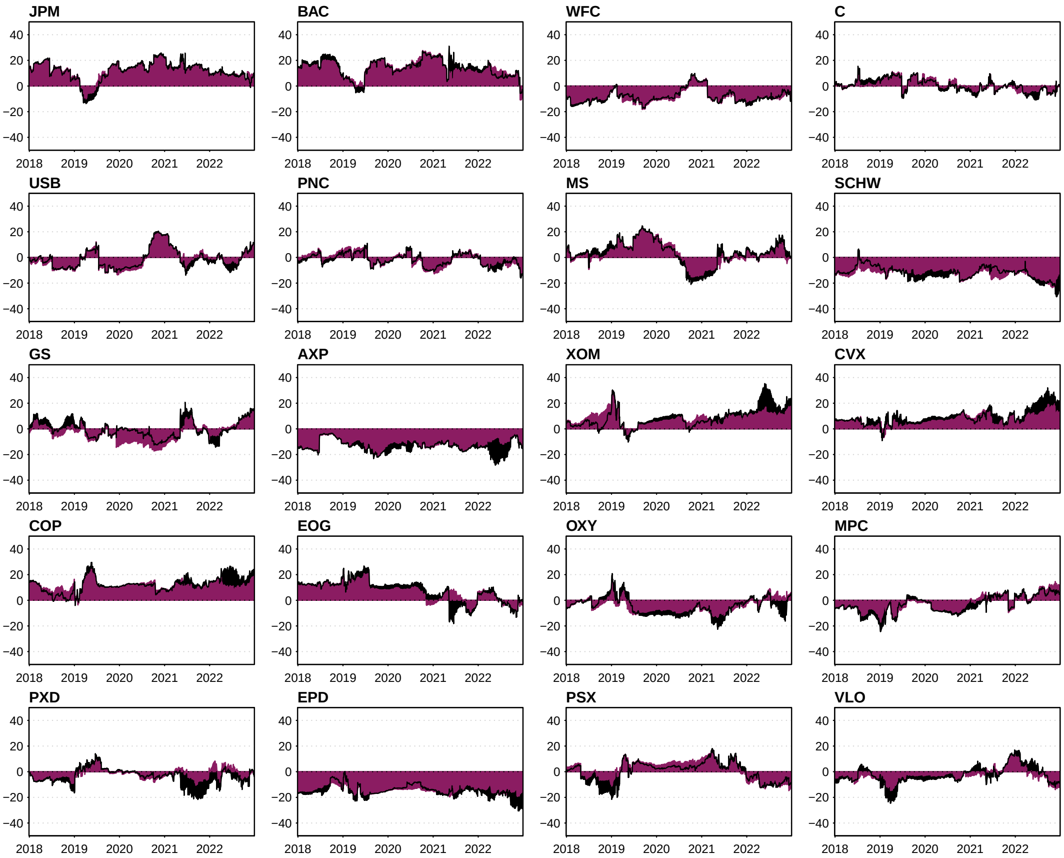


Notes: Results are based on a TVP-VAR model with a lag length of order one (BIC), $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition. The black areas represent the overall net total directional connectedness while the pink areas illustrate the contemporaneous net total directional connectedness.

except for USB, C, and JPM in the lagged connectedness network. This may suggest that spillovers are first passed from banks to oil and gas companies, and after some time, spillovers are passed from oil and gas companies back to banks. Banks are the leading lenders to oil and gas companies. When market conditions deteriorate, banks may tighten their credit conditions and increase the cost of financing for oil and gas companies, thereby passing on risk. Over time, the financial position of oil and gas companies may deteriorate, leading to an increased risk of default, affecting the banks that lend to them.

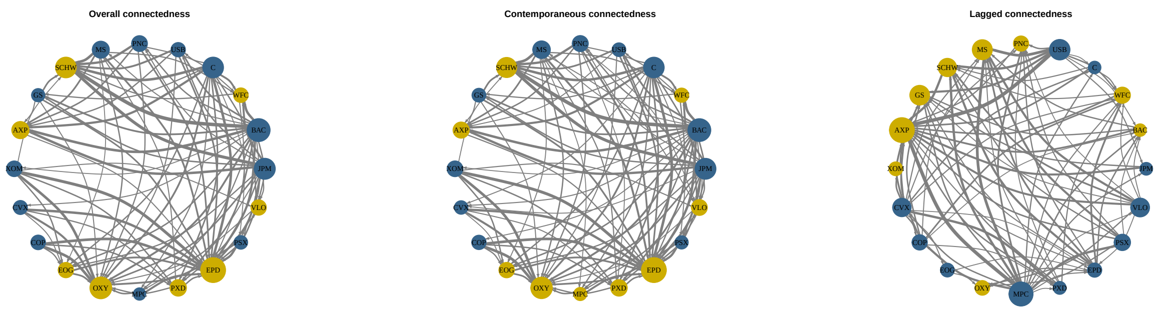
Figure 14 illustrates the realized volatility network. First, in the overall connectedness network, most oil and gas companies are net recipients of spillovers, which explains the vulnerability of most oil and gas companies to market volatility and the absorption of volatility from banks. The extent of risk spillovers between banks and oil and gas companies is significantly stronger than between cross-industry companies in the same

Figure 12: Realized kurtosis: Net total directional connectedness



Notes: Results are based on a TVP-VAR model with a lag length of order one (BIC), $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition. The black areas represent the overall net total directional connectedness while the pink areas illustrate the contemporaneous net total directional connectedness.

Figure 13: Return: Net pairwise directional connectedness



time period connectedness network. This suggests that the connectedness of inter-firm volatility is concentrated within the industry over the same period.

Second, lagged connectedness indicates how the volatility of a firm at one point in time affects the volatility of other firms at another point in time. The lagged and overall connectedness networks are very similar in structure. This confirms the conclusion above that lagged connectedness contributes more to overall connectedness in the realized volatility network. This phenomenon suggests a lag in the transmission of risk spillover from banks to oil and gas companies.

Finally, the particular firms in the graph can be analyzed based on their positive and negative net spillover values. JPM has the strongest risk spillover to SCHW of all the pairwise relationships. Due to JPM's large size and high market participation, its market actions and strategy changes may be interpreted by the market as signals about industry or economic trends affecting SCHW. In addition, USB is shown as a large blue node in all three graphs, suggesting that it has a strong influence and stability, which typically positively impacts market volatility. This characteristic of USB may result from its solid balance sheet, diversified revenue streams, or substantial risk management strategy. In contrast, PXD is presented as a large yellow node in all three graphs, which could imply that it is a receiver of volatility during periods of market turbulence, possibly due to its high sensitivity to crude oil prices or higher financial leverage.

Figure 14: Realized volatility: Net pairwise directional connectedness

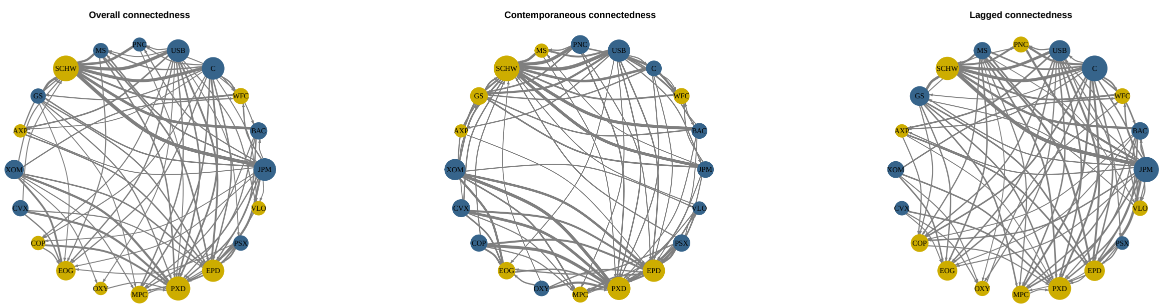
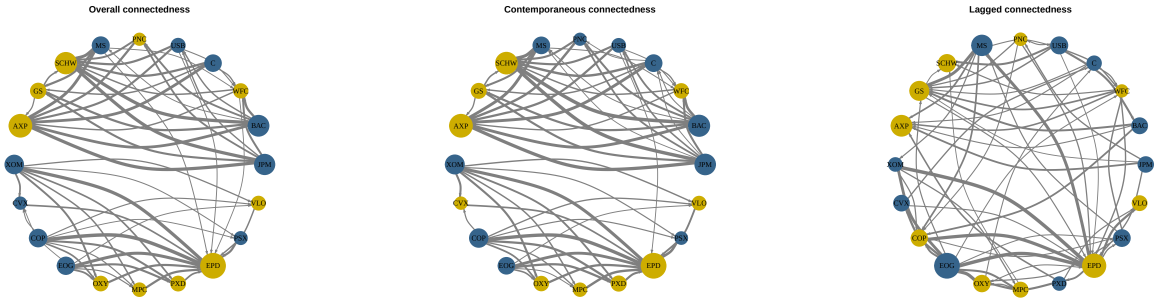


Figure 15 shows the realized skewness network. The contemporaneous connectedness network has a similar structure to the overall connectedness network, and its contribution is much more significant than that of the lagged connectedness network. In the banking and oil and gas industries, the distribution of positive and negative net spillover firms within the industry is balanced, and the risk spillover is mainly within the industry. This suggests that asset return asymmetries and crash risk for banks and oil and gas firms originate mainly within the industry.

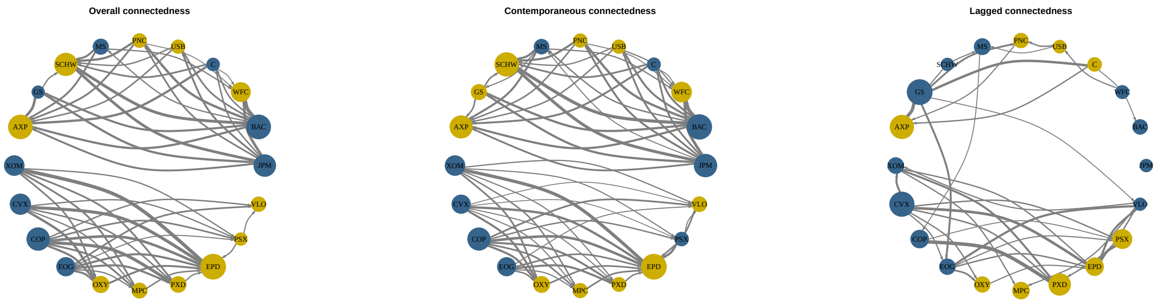
Figure 16 shows the realized kurtosis network. There are only intra-industry risk spillovers and no cross-industry spillovers in both the overall and contemporaneous con-

Figure 15: Realized skewness: Net pairwise directional connectedness



nectedness networks. The spillover relationships in the lagged connectedness network are concentrated in oil and gas companies, with only three pairs of cross-industry spillovers (GS-EOG, XOM-COP, GS-VLO). This phenomenon may be explained by extreme events and tail risks being predominantly diffused within the industry, and banking systemic risk has a limited impact on oil and gas systemic risk.

Figure 16: Realized kurtosis: Net pairwise directional connectedness



6 Concluding remarks

As the banking sector has been severely affected by the recent financial crises and, as the current bankruptcies of Credit Suisse, the second largest bank in Switzerland, as well as Silicon Valley Bank, Signature Bank, and First Republic Bank, demonstrate, these financial crises have been occurring with increasing frequency recently. At the same time, banks have close risk relationships with oil and gas companies through their credit channels. Monitoring and studying the transmission mechanisms of returns, realized volatility, realized skewness, and realized kurtosis of the top 10 banks and top 10 oil and gas companies in the United States are critical for global financial stability. As most research focuses solely on the first two moments, namely returns and volatility, necessary asymmetric measures such as downside and upside risk are often ignored. Thus, to understand the transmission mechanism of risk across markets more comprehensively, we considered the realized skewness and the realized kurtosis spillovers. Additionally, we introduce the new concept of GFEVD decomposed connectedness measures to separate the effects of contemporaneous and lagged spillover effects.

Our empirical results emphasize that spillovers from heterogeneous time-varying connectedness are primarily related to economic events. We also find that, except for realized volatility connectedness, most overall spillovers can be attributed to contemporaneous spillovers rather than lagged ones. Moreover, the highest level of connectedness occurs in realized volatility (where lagged connectedness is also the highest of the four moments), followed by return, realized skewness, and realized kurtosis spillovers. Finally, the net spillover network of higher-order moments suggests that crash and tail risks in banks and oil and gas companies originate mainly from intra-industry rather than inter-industry transmission. Therefore, it is vital to put policies in place to reduce simultaneous interdependence between firms within an industry or to reduce interdependence through hedging strategies to minimize adverse spillovers, which are propagated, especially in a contempraneous manner.

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A Appendix

A.1 Technical Appendix

The TVP-VAR is represented as follows:

$$\begin{aligned} \boldsymbol{z}_t =& \boldsymbol{B}_t \boldsymbol{z}_{t-1} + \boldsymbol{u}_t & \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{H}_t) \\ vec(\boldsymbol{B}_t) =& vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t & \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{R}_t) \end{aligned}$$

where $\boldsymbol{z}_t$, $\boldsymbol{z}_{t-1}$, and $\boldsymbol{u}_t$ represent $K \times 1$ dimensional vectors and $\boldsymbol{B}_t$ and $\boldsymbol{H}_t$ are $K \times K$ dimensional matrices. Furthermore, $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $K^2 \times 1$ dimensional vectors and $\boldsymbol{R}_t$ is an $K^2 \times K^2$ dimensional matrix.

An empirical Bayes prior is applied where the priors, $vec(\boldsymbol{B}_0)$ and $\boldsymbol{S}_0$, are equal to the estimation results of a constant parameter VAR estimation based on the full dataset.

$$\begin{aligned} vec(\boldsymbol{B}_0) \sim& N(vec(\boldsymbol{B}_{OLS}), \boldsymbol{R_{OLS}}) \\ \boldsymbol{H}_0 =& \boldsymbol{H}_{OLS}. \end{aligned}$$

The Kalman Filter estimation relies on forgetting factors ($0 \leq \kappa_i \leq 1$) which regulates how fast the estimated coefficients vary over time. If the forgetting factor is set equal to 1 the algorithm collapses to a constant parameter VAR. Since it is assumed that parameters are not changing dramatically from one day to another, κ_2 is set equal to 0.99:

$$\begin{aligned} vec(\boldsymbol{B}_t)|\boldsymbol{z}_{1:t-1} \sim& N(vec(\boldsymbol{B}_{t|t-1}), \boldsymbol{R}_{t|t-1}) \\ vec(\boldsymbol{B}_{t|t-1}) =& vec(\boldsymbol{B}_{t-1|t-1}) \\ \boldsymbol{R}_t =& (1 - \kappa_2^{-1}) \boldsymbol{R}_{t-1|t-1} \\ \boldsymbol{R}_{t|t-1} =& \boldsymbol{R}_{t-1|t-1} + \boldsymbol{R}_t \end{aligned}$$

The multivariate exponentially weighted moving average (EWMA) procedure for $\boldsymbol{S}_t$ is updated in every step, while κ_1 and κ_2 are set equal to 0.99 based on the sensitivity results provided by Koop and Korobilis (2014). Furthermore, Koop and Korobilis (2014) fix the forgetting factors, as well, even if the forgetting factors can be estimated by the data, as in Koop and Korobilis (2013). The main reason to fix the parameters is twofold (i) it increases computational burden substantially and (ii) the value added to the forecasting performance is questionable.

$$\begin{aligned}\hat{\boldsymbol{u}}_t =& \boldsymbol{z}_t - \boldsymbol{B}_{t|t-1}\boldsymbol{z}_{t-1}\\ \boldsymbol{H}_t =& \kappa_1 \boldsymbol{H}_{t-1|t-1} + (1-\kappa_1)\hat{\boldsymbol{u}}_t'\hat{\boldsymbol{u}}_t\end{aligned}$$

$vec(\boldsymbol{B}_t)$ and $\boldsymbol{R}_t$ are updated by

$$\begin{aligned}vec(\boldsymbol{B}_t)|\boldsymbol{z}_{1:t} \sim& N(vec(\boldsymbol{B}_{t|t}), \boldsymbol{R}_{t|t})\\ vec(\boldsymbol{B}_{t|t}) =& vec(\boldsymbol{B}_{t|t-1}) + \boldsymbol{R}_{t|t-1}\boldsymbol{z}_{t-1}'(\boldsymbol{H}_t + \boldsymbol{z}_{t-1}\boldsymbol{R}_{t|t-1}\boldsymbol{z}_{t-1}')^{-1}(\boldsymbol{z}_t - \boldsymbol{B}_{t|t-1}\boldsymbol{z}_{t-1})\\ \boldsymbol{R}_{t|t} =& \boldsymbol{R}_{t|t-1} + \boldsymbol{R}_{t|t-1}\boldsymbol{z}_{t-1}'(\boldsymbol{H}_t + \boldsymbol{z}_{t-1}\boldsymbol{R}_{t|t-1}\boldsymbol{z}_{t-1}')^{-1}(\boldsymbol{z}_{t-1}\boldsymbol{R}_{t|t-1})\end{aligned}$$

Finally, the variances, $\boldsymbol{H}_t$, are updated by the EWMA procedure

$$\begin{aligned}\hat{\boldsymbol{u}}_{t|t} =& \boldsymbol{z}_t - \boldsymbol{B}_{t|t}\boldsymbol{z}_{t-1}\\ \boldsymbol{H}_{t|t} =& \kappa_1 \boldsymbol{H}_{t-1|t-1} + (1-\kappa_1)\hat{\boldsymbol{u}}_{t|t}'\hat{\boldsymbol{u}}_{t|t}\end{aligned}$$