Interconnectedness in US futures markets during crisis periods.

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Abstract

This study contributes new empirical evidence on the interconnectedness of crude oil, precious metals, and financial futures during crisis/non-crisis periods. Dynamic spillovers from US to Europe and Asian futures markets are also examined. Empirical results show a significant and changing relationship among oil, gold, and financial futures, especially during the global financial crisis. Dynamic analysis (rolling window and subsamples) demonstrates that crude oil markets become notably more influential during the crisis, while gold turns from a net giver, in the pre- and post-crisis periods, to a net receiver during turbulent times. West Texas Intermediate and Brent provide valuable information about return dynamics, while S&P500 and FTSE100 play a key role in volatility spillovers. Asian futures markets are strongly influenced by changes in the US and UK oil and stock futures markets. Finally, using different permutations of Cholesky orderings (Klobner and Wagner, 2013), provides additional support that the spillover index for both return, and volatility is overestimated when the generalized forecast error decompositions are employed.

Keywords: Futures markets, Connectedness, Spillover effects, Volatility.

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1 Introduction

Spillover effects play an essential role in the financial world and have seen growing attention recently because of the global financial crisis (GFC) and the development of new econometric techniques (Diebold and Yilmaz, 2012, 2014). The US economy and its financial markets are the leading ones globally, while their fluctuations raise substantial concerns among market participants, policymakers, and researchers (Fung et al., 2001). Moreover, the Global Financial Crisis (GFC), that originated from the US, had a critical influence on many other markets and countries, and highlights the importance of investigating the dynamics and interconnectedness of futures markets domestically and abroad (Kang et al., 2017, Xiang et al., 2019).[1] Thus, the aim of this paper is to examine the interconnectedness among US futures markets during crisis/non-crisis periods and whether fluctuations in these markets have an impact on the European and Asian (futures) markets.[2] Given the increased uncertainty over the period from 2001 to 2018 in the US economy and internationally, some essential questions are yet to be answered.

Transmission of information across global markets has been a key research area. A range of studies try to find whether financial markets have short (simultaneous or feedback) and long-term (cointegrated) relationships using VAR models either for returns or different volatility proxies (Eun and Shim, 1989; Ng, 2000; Bekaert and Harvey, 1997; Wen et al., 2019). Alternatively, a number of researchers used different types of multivariate GARCH models to investigate the volatility spillovers among future and spot markets (Tse, 1999; Rittler, 2012). Their results show that there are spillover effects from futures to spot markets. Gannon (2005) found that the US contributes high spillover effects to Hong Kong's stock index futures market. Li (2007), using a multivariate GARCH model, find evidence of unidirectional (although weak) volatility spillovers from the stock exchange in Hong Kong to those in mainland China (Shanghai and Shenzhen).[3] Therefore, existing research on return and

[1] For example, the S&P500 stock index declined 57% from its peak in October 2007 to its trough in March 2009. More, the real Gross Domestic Product (GDP) decreased 4.3% from its peak in 2007 to its trough in 2009.

[2] Futures markets in US, Europe, and Asia have witnessed a high increase since the growth of world trade and globalization of the futures market. For example, Chinese futures exchanges such as the Shanghai Futures Exchange, Zhengzhou Commodity Exchange, the Dalian Commodity Exchange, and China Financial Futures Exchange are now classified as leading derivatives markets. Thus, it is essential to study the linkages of Chinese futures markets with other major international futures markets (Fung et al., 2013).

[3] The implication of low level of linkages is that the expected returns of investment in Chinese mainland stock exchanges would be determined by the country's exposure to firm-specific and country-specific risk factors. Another implication of the weak integration is that overseas investors will benefit from the reduction of diversifiable risk, and thus total portfolio risk, by adding the mainland Chinese stocks to their investment portfolio.

volatility spillovers consider whether a shock in one market can impact another domestic market or a foreign one, but only occasionally are both investigated at the same time. Put differently, existing studies do not examine the dynamic spillover effects for both return and volatility systems, while connectedness is not often examined across both domestic US futures markets and futures markets in Europe (UK) and Asia (Japan, China).

This study utilizes Diebold and Yilmaz's approach to investigate the interconnectedness between US stock index (S&P500), crude oil (WTI), Natural gas, precious metal (Gold, Silver), foreign currency (D-index) and bond (T-notes, T-bonds) futures markets. Further, the study explores spillover effects from US futures markets to UK (FTSE100, Brent oil) and Asian (NIKKEI225 stock index, Shanghai SE stock index) futures markets. Daily data from 2001 to 2018 is used to estimate return and volatility VAR models, while the 10-day ahead forecast error variance decompositions are of Cholesky (orthogonal) and generalized type (Pesaran and Shin, 1998).[4] Finally, the dynamic properties of the interconnectedness among futures markets is examined by utilizing a rolling window estimation and a sub-sample one based on the times of the global financial crisis. Overall, results show a significant relationship among US futures markets, both at return and volatility level, especially during crisis periods. More, Asian futures markets are strongly influenced by changes in US and UK stock and oil futures markets. Results also imply that US futures markets become substantially more interconnected during crisis periods (responding to same fundamental changes), while increased spillover effects to Asian markets demonstrate that their news-watchers and investors have a close eye to US and European financial markets.[5]

Finally, dividing the sample into three sub-samples provides more information on the dynamics of interconnectedness. For example, the crude oil market becomes more influential (towards others) during the crisis period, while gold turns from being a net giver, in the pre and postcrisis periods, into a net receiver, during the crisis. Analysis also shows that WTI and Brent contribute notably to other markets and play crucial roles in the return system, while in the volatility system, both US and UK indices show important spillover effects. Finally, using different permutations of Cholesky orderings (see Klob-

[4]Further, the spillover index is estimated by using Klobner and Wagner's (2013) divide and conquer strategy and large numbers of randomly chosen Cholesky orderings. The authors find that randomly choosing small number of orderings severely underestimates the true range of the spillover index, while using the generalized spillover index (does not depend on the ordering of variables) produces large values for the same index (see also Diebold and Yilmaz, 2012).

[5]Bailey and Chan (1993) provide evidence that the spread between commodity spot and futures prices (the basis) reflects the macroeconomic risks common to all asset markets. Yang et al. (2021) examine the volatility connectedness of commodity futures markets and show that commodity volatility spillovers can be explained by economic factors related to broad economic conditions.

ner and Wagner, 2013), provides additional support that the spillover index for both returns and volatility are generally overestimated when the generalized forecast error decompositions are used. Importantly, using Klobner and Wagner's approach on choosing Cholesky orderings, it is shown that shocks in the crude oil and precious metal futures returns affect the S&P500 index futures (Pineiro-Chousa et al. 2018), while a shock in S&P500 futures returns contributes to changes in US currency and bond (T-notes, T-bonds) future returns (Yoon et al. 2019). More, a shock in S&P500 futures volatility caused changes in the volatility of crude oil, precious metals, and currency markets (Husain et al. 2019), whereas a shock in crude oil market futures volatility does not exert any change in the volatility of major index futures markets such as S&P500 and FTSE100 (Soucek and Todorova, 2013).

The rest of this paper is structured as follows. Section two presents the literature and empirical findings of earlier works in futures markets such as US, Europe, and Asia. Econometric methodology is presented in section three, while section four describes the data and its summary statistics. Section five reports and discusses the empirical results. Section six presents robustness checks to the main empirical findings. Concluding comments and further research are put forward in section seven.

2 Literature review

Total volume of exchange-traded derivatives worldwide surpassed 62 billion contracts by 2021 (29.28 billion Futures contracts, 33.31 billion Options contracts). Exchanges in the Asia-Pacific region had the largest trading volume (30.55 billion contracts) followed by North America (15.38 billion contracts), Latin America (8.89 billion contracts) and Europe (5.45 billion contracts).[6] More, studies in the past demonstrated that stock index futures markets transmitted information more efficiently (Bohl et al., 2011) and more expeditiously (Koutmos and Tucker, 1996; Pizzi et al., 1998; Tse, 1999; Brooks et al., 2001; Chou and Chung, 2006) than spot markets. The interconnectedness of US, UK, and Asian markets, through the estimation and forecasting of their return and volatility spillovers, plays an essential role in asset valuation, portfolio diversification, and hedging.[7] Yang et al. (2021) examine volatility connectedness

[6] In terms of assets traded, equity-related derivatives accounted largely for the increase in trading activity in 2021 with futures and options in this category reaching 41.6 billion contracts. Trading of interest rate futures and options peaked at 4.58 billion contracts in 2021. In the commodity sector, trading of agricultural and metal futures and options increased importantly in 2021, but trading of energy futures and options fell on the same year (FIA 2022).

[7] Engle et al. (1990) find that volatility spillovers of foreign exchange markets are of meteor shower type as opposed to the heat wave type. The heat wave hypothesis is consistent with a view that major

in commodity futures markets and show that commodity volatility spillovers can be explained by economic factors related to broad economic conditions. Bailey and Chan (1993) provide evidence that the spread among commodity spot and futures prices (the basis) reflects macroeconomic risks common to all asset markets. The basis of commodities is correlated with the stock index dividend yield and corporate bond quality spread. Further tests showed that these associations are largely due to the presence of risk premiums, rather than spot price forecasts, in the basis.[8] Koijen et al. (2018) show that carry $((S_t - F_t)/F_t)$ predicts returns cross-sectionally and in time series for a host of different asset classes, including global equities, global bonds, commodities, US Treasuries, credit, and options. Carry is better explained by models with varying risk premia, in which carry strategies are commonly exposed to global recession, liquidity, and volatility risks. Finally, Henderson et al. (2015) and Shokin and Xiong (2015) show that non-information-based financial investments and informational frictions have important impacts on commodity prices and demand.[9] The literature on futures markets has concentrated on examining the relationship between crude oil and financial markets as well as modelling their volatilities (Arouri et al., 2011; Malik and Ewing, 2009; Khalfaoui et al., 2015; Tsuji, 2018). Nevertheless, many studies investigated the volatility spillover among energy markets and carbon (Ji et al., 2018; Batten et al., 2019) and other petroleum markets (Magkonis and Tsouknidis, 2017). In what follows, we review the literature on the interrelationship between oil, commodities, and financial markets.

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sources of disturbances are changes in country-specific fundamentals, and that one large shock increases the conditional volatility only in the country of origin. On the other hand, the meteor shower hypothesis implies that a shock increases volatility in geographically distant markets or outside the country. Put differently, conditional volatility will increase for all markets, not just for the market domestic to the shock.

[8] There are two popular theories of futures prices: the cost-of-carry hypothesis and the risk premium hypothesis (see Chow et al., 2000, for a review). The cost-of-carry hypothesis explains the difference between the spot (S) and futures price (F) as being due to the interest (R) foregone in storing the commodity, warehousing costs (W) and a convenience yield (C) from holding the inventory. The Risk Premium hypothesis sees a futures price as the forecast of the future spot price and an expected risk premium. When the level of inventory is sufficiently high, storage costs and convenience yields are exceptionally low relative to the spot price, and it is predicted that futures prices are below the expected spot price $F_{t+k|t} < E_t(S_{t+k})$ (normal backwardation). On the other hand, when stocks of the commodity are extremely low, the marginal convenience yield may exceed the marginal storage costs, and it is predicted that futures price is above the expected spot price, $F_{t+k|t} > E_t(S_{t+k})$ (normal contango). Although the Cost-of-Carry hypothesis is based on a no-arbitrage condition, it is often argued that the presence of speculators in the marketplace ensures that futures prices approximately equal the expected futures spot price. A large deviation between the futures price and the expected spot price would create attractive speculative opportunities. Due to market frictions which result in a 'no-arbitrage band' around $E_t(S_{t+k})$, the futures price, $F_{t+k|t}$, is only approximately equal to the expected future spot price.

[9] Additionally, Hamilton and Wu (2014) provide empirical evidence which is consistent with the claim that index-fund investing has become more important relative to commercial hedging in determining the structure of crude oil futures risk premia over time.

2.1 Crude oil and commodities

Nick and Thoenes (2014) examine the dynamic relationship between natural gas and other commodities using a structural VAR model. Their results indicate that natural gas, in the short term, was influenced by abnormal temperature and supply shocks. In the long term, the natural gas price developed and seemed to be close to coal and crude oil prices; this implies that there was a high performance of cross-commodity impacts. Soytas et al. (2009) employ a multivariate model to evaluate the relationship between crude oil, gold, silver, and several macroeconomic variables. Their results show that there was no proof of a causal relationship, either among silver and crude oil prices or between gold and oil prices. Liu and Chen (2013) investigate the link between UK natural gas, EUA future prices, Brent crude oil, and European coal by employing the FIEC-HYGARCH model. They find volatility spillover effects from the carbon market to natural gas and coal markets. Nevertheless, the carbon market was affected by natural gas and crude oil markets. Zhang and Wang (2014) studied return and volatility spillovers among Chinese and global petroleum markets (WTI and Brent). They document that world oil markets, through both return and volatility spillovers during the global financial crisis (GFC), strongly influenced the Chinese oil market.[10] Gong et al. (2021) using a TVP-VAR-SV model and the spillover method of Diebold and Yilmaz (2009, 2012, 2014) find that US crude oil and heating oil futures markets are main net transmitters of volatility risk information while gasoline and natural gas futures markets are net receivers.

2.2 Crude oil, commodities and financial markets

On crude oil markets, precious metals, and stock market indices, the number of studies investigating their volatility spillover and interconnection is limited. Junttila et al. (2018) investigate the link between both gold and crude oil futures and stock markets. Their findings show that while there was a negative correlation throughout financial meltdown days, gold, and oil offer diversification benefits. Oztek and Ocal (2017) model time-varying correlations between commodities and stock markets using both smooth and double smooth transition conditional correlation models. Their results suggest that investing across commodity and stock market gains more than just investing in the stock mar-

[10] Zhang et al. (2019) recently examined seven major regionally crude oil prices and provided evidence that they are dynamically connected. Further, high connectedness in both return and volatility shows that the findings support Adelman's claim that crude oil globally is 'one great pool'. Also, Batten et al. (2015) investigate the interconnectedness of four primary precious metals (i.e., silver, gold, platinum, and palladium) and find that the trend in spillover effects was changed by geopolitical and economic events

ket alone. Zhang (2017) studies the connectedness among different global stocks and crude oil markets. Results show that oil volatility made partial contributions to the stock markets worldwide. Recently, Xu et al. (2019) evaluated the asymmetric risk spillovers among crude oil and stock markets in US and China. They find that there exists an asymmetric spillover effect between the oil market and stock markets and that bad volatility spillover dominates good volatility spillovers across the sampling period.[11]

Husain et al. (2019) study the spillover effect among crude oil prices, stock index, and precious metal prices in the context of the US economy. Their results demonstrate that palladium, gold, platinum, and silver are net contributors of volatility spillover whereas crude oil, titanium, steel, and silver are net receivers of volatility spillover. Moreover, Mensi et al. (2013) examined the correlation and transmission of volatility across WTI, Brent, wheat, beverage spot prices, gold, and S&P500 stock index returns. They find significant volatility spillover effects between the crude oil market and the US or the European stock markets, respectively. Alotaibi and Mishra (2015) investigate return spillover effects from Saudi Arabia and US to the Gulf Cooperation Council (GCC), namely Qatar, Oman, Bahrain, Kuwait, and United Arab Emirates stock markets. They document important return spillover effects from US and Saudi Arabia to (GCC) stock markets.[12]

2.3 Financial crisis connectedness

Several studies that look at the spillover effects also examine their influence during crisis and non-crisis periods. Bampinas and Panagiotidis (2016) show that flights-to-alternative assets, from stocks to oil, are a common feature during three crisis periods (Mexican crisis, Asian crisis, dot.com bubble) except the recent global financial crisis.[13] The dynamic spillover connecting precious metals (gold, platinum, silver, and palladium) and stock markets (Asia, Japan, Europe, and the USA) was examined by Mensi et al. (2017a, 2017b). Their findings reported that commodities were receivers of spillover from stock markets during the European sovereign debt crisis and the Global Financial Crisis (GFC). Yoon et al. (2019) applied Diebold and Yilmaz's approach to study

[11] Bad volatility is volatility associated with negative innovations to quantities such as output and returns. In contrast, good volatility is volatility that is associated with positive shocks to these variables.

[12] Lean and Teng (2013) test integration between two developed countries, US and Japan, and two emerging markets, China and India, into the Malaysian stock market. They find that there is high integration between Malaysian and Chinese markets and between Malaysian and Indian markets. However, the volatility spillover effects disappear among the US and Malaysian markets in the short term.

[13] More, the view that stock and oil markets behave like 'a market of one' after the financialization of commodities is further supported by the presence of contagion between US stock markets and all benchmark oil markets.

the return spillovers from (Japan, Korea, Hong Kong, US, and China) stock markets to commodities (gold future, WTI crude oil), the US dollar index, and the 10-year US Treasury bond. They found that, during the GFC, spillovers among commodity and financial markets were intensive.

Moreover, the US stock market was an essential contributor to return and volatility spillovers across international stock markets, especially during the financial crisis. For example, Cheung et al. (2010) show that the US market contributes significantly to the UK, Hong Kong, Australia, Japan, and China. Kenourgios and Padhi (2012) assess the spillover effects of bond and equity in nine emerging and two developed countries. Their findings show substantial contagion during the Asian financial crisis, the Global financial crisis, and the Russian crisis. Gjika and Horvath (2013) evaluate the stock market comovements between the euro area and three Central European countries (Poland, Czech Republic, and Hungary). They find that correlations among stock markets in Central Europe and between Central Europe and the euro area are strong. Yilmaz (2010) studies spillover effects in both return and volatility systems across ten East Asian countries. Results show that return and volatility systems have varied impacts during crisis and non-crisis times. Bianconi et al. (2013) find an increase in dynamic conditional correlations, after the Lehman Brothers event in September 2008, among bond returns, stock returns, and US financial stress. Zhang and Broadstock (2020) find a dramatic change in the connectedness of global commodity prices following the global financial crisis. They show that co-dependence in price-changes among seven major commodity classes goes from a pre-crisis average of 14.82% to a strikingly larger average of 47.87% in the period following the crisis, which endured until lately. Of particular interest is the empirical behavior of the food commodity price index where its contribution to the system dynamics rises from less than 20%, in the period up to 2008, to more than 80%, thereafter.

3 Econometric methodology

To address questions empirically, this paper utilizes the recently developed approach by Diebold and Yilmaz (2009, 2012 and 2014). This method allows to examine the interconnectedness among major futures markets in the US and their dynamic spillovers to futures markets in the UK, China, and Japan. Estimation is based on a Vector Auto-Regressive (VAR) model and the generalized forecast error variance decomposition (GFEVD) that can be extracted.[14] The VAR model, as outlined in Diebold and Yilmaz (2009, 2012, and 2014), is expressed here as follows:

$$A_t = \sum_{i=1}^{P} \Psi_i A_{t-i} + \varepsilon_t, \tag{1}$$

Where A_t is an $N\times 1$ vector of endogenous variables,Ψ_i are $N\times N$ autoregressive coefficient matrices, and $\varepsilon_t \sim (0, \sum)$ is a vector of error terms with independent and identically distributed process. The moving average representation of the VAR(p) process is given by:

$$A_t = \sum_{i=1}^{\infty} Z_i \varepsilon_{t-i}, \tag{2}$$

Where $\mathrm{Z}_i = 0 \sim i < 0$, the $N\times N$ coefficient matrices Z_i are recursively defined as $\mathrm{Z}_i = \sum_{k=1}^{P} Z_{i-k}$ with Z_0 being the $N\times N$ identity matrix. We can estimate the generalized version of H-step-ahead forecast-error variance decomposition as follows:

$$c_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i^{'} Z_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i^{'} Z_h \sum Z_h^{'} e_j)}, \tag{3}$$

Where the term σ_{jj} is a vector of standard deviations of the error term for the jth equation and ith is an $N\times 1$ vector, which has 1 as the ith equation element and zero as the other components. And the term σ is a non-orthogonalised covariance matrix of error corresponding to the vector autoregressive system. In the connectedness table,$C_{i}^{H}{}_{\leftarrow j}$ indicates pairwise directional spillover from the market j to another market i as follows:

$$C_{i}^{H}{}_{\leftarrow j} = c_{ij}^{g}(H), \tag{4}$$

The directional connectedness from all other markets to the market i can be calculated as follows:

$$C_{i}^{H}{}_{\leftarrow \cdot} = \sum_{i,j=1 j\neq i}^{N} c_{ij}^{g}(H), \tag{5}$$

In contrast, the directional connectedness to other markets from j is calculated as:

$$C_{\cdot}^{H} \leftarrow_i = \sum_{i,j=1 j\neq i}^{N} c_{ij}^{g}(H), \tag{6}$$

[14] In line with Koop et al. (1996) and Pesaran and Shin (1998), we use generalized forecast error variance decompositions, which, unlike the traditional approach, do not require orthogonalization of shocks and are invariant to the ordering of the variables in the VAR.

The net directional connectedness can be expressed as:

$$C_i^H = C_{\cdot}^H \leftarrow_i - C_i^H \leftarrow_{\cdot}, \tag{7}$$

Finally, total connectedness (system-wide connectedness) is computed as

$$C^H = \frac{1}{N} \sum_{i,j=1 j \neq i}^{N} c_{ij}^g(H), \tag{8}$$

Moreover, in the volatility VAR model, we use the logarithm of variances to ensure that all variance forecasts are strictly positive (Callot et al. 2017). Dynamic connectedness measures are obtained using rolling-sample estimation of the VAR model, based on a fixed window of 200 observations. Rolling-window estimation of the VAR model has the advantages of clarity and coherence among several time-varying parameter mechanisms, though it has the limitation of discarding some observations and slightly increasing the persistence of the connectedness index (Koop and Korobilis, 2018). To build the network topology of connectedness between future markets, we follow Diebold and Yilmaz (2014) and interpret the pairwise connectedness table as the adjacency matrix of a weighted directed network. Diebold and Yilmaz (2014) merged VAR variance decompositions with network topology theory, and showed that variance decompositions of VARs form weighted directed networks, characterize connectedness in those networks, and in turn characterize connectedness in the VAR.

4 Data and summary statistics

The dataset of this paper consists of daily futures prices for stock market indices (S&P500, FTSE100, Shanghai SE, NIKKEI225), precious metals (Gold, Silver), crude oil and natural gas markets (West Texas Intermediate, Brent, and Natural gas) and the US bond (10-year Treasury notes, 30-year Treasury bonds) and currency markets (Dollar index). WTI and Brent are the primary benchmark prices in the crude oil market and have been employed extensively. Moreover, Natural gas is included as it is priced by indexing to oil prices. The four main stock index futures markets, chosen due to their high volume of trade and growth, are S&P500, FTSE100, NIKKEI225, and SSEC. Gold and silver futures are also employed in the study to capture the role of precious metals as an alternative investment. The 10-year Treasury note futures, and the 30-year Treasury bond are essential in capturing movements in the money market and investors' expectations about future changes in interest rates. Finally, Dollar-index futures is added to the VAR model owing to its close relationship with interest rates, stock, and gold prices.[15] Data runs from 02/01/2001 to 31/12/2018, which gives a total of 4417 daily observations. All data has been obtained from Bloomberg and Datastream. Returns of each variable are estimated by computing the log difference of the price level. For volatility, we employ Parkinson's High-Low volatility (HLV) estimator and the logarithm of variances to ensure that all variance forecasts are strictly positive (Callot et al., 2017). In particular, the time series entering the VAR equation is the log transformation of the Parkinson estimator. The purpose of using this proxy is that it uses crucial information that can enhance the accuracy of volatility estimator. Furthermore, the HLV estimator can deal with instability to trading hours, which implies that it is more efficient than the more intuitive close-to-close volatility estimator (Parkinson, 1980).

Parkinson's High-Low volatility (HLV) estimator can be calculated as follows:

$$Vol = \sqrt{100 * (\frac{1}{4 * \ln(2)}) * \ln(\frac{h}{l})^2} \tag{9}$$

where h and l are the highest and lowest prices on a given trading day.

Figures 1 and 2 show return and volatility patterns across different future markets in the US, UK, and Asia. Both figures show an important spike for all series during the global financial crisis. Also, most of the variables fluctuated in the second half of 2014 due to the drop in crude oil prices. Descriptive statistics for returns are reported in panel A of Table 1. Results show that the mean return across the whole sample is mostly positive. For example, Gold has the highest mean return, 0.04%, while Natural gas has the lowest mean return, -0.02%. Moreover, the highest daily price movement is observed in Natural gas, 32.44%, and the lowest price is obtained in Silver, -20.64%. The standard deviation is the highest for Natural gas, followed by WTI and Brent. Money market futures (10-year T-notes, 30-year T-bonds) and currency futures show the lowest return standard deviation. Overall, return distributions are characterized as fat tailed (excess kurtosis) and slightly skewed to the left (negative skewness).

Panel B of Table 1 presents the High-Low volatility statistics. S&P500, FTSE100, and NIKKEI225 index futures show similar levels of High-Low volatility with the Shanghai SE market documenting the highest one (0.06 vs. 0.08) among the index futures markets. Silver futures volatility (0.11) is almost two times higher than gold futures volatility (0.06). The two crude oil

[15] Tse and Zhao (2012) provide evidence of sizeable volatility spillover from stock returns to carry-trade returns, but not vice versa. The two markets are also more correlated in periods of high volatility.

futures markets, WTI and Brent, experience similar levels of High-Low volatility (0.13,0.12), while Natural gas futures show the highest volatility among all futures markets examined (0.18). Finally, money market and currency futures, as in the case of return standard deviation (see panel A), show the lowest High-Low volatility.

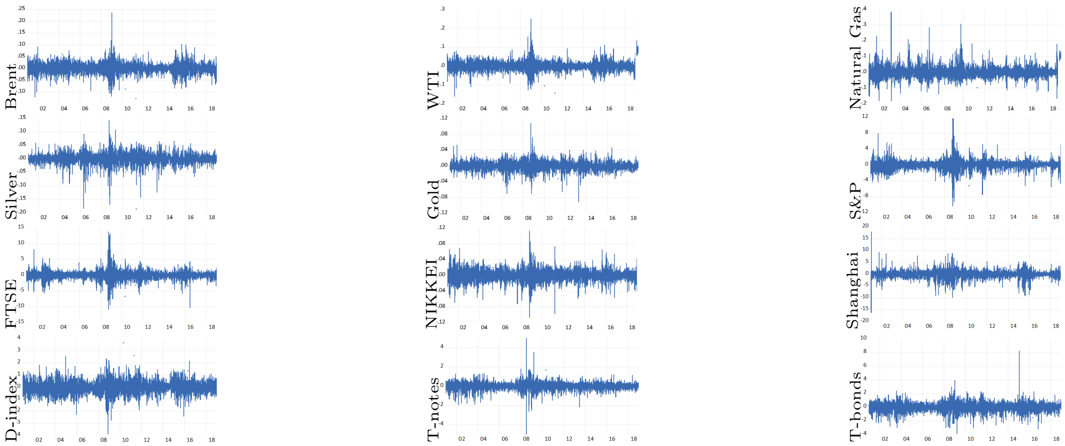

Figure 1: Plots of the Return Series.

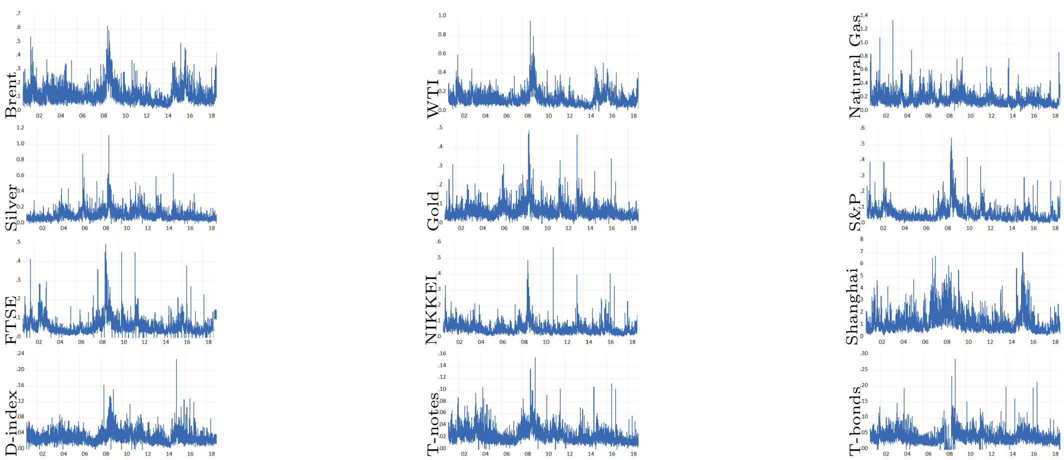

Figure 2: Plots of the Volatility Series.

Table 1: Descriptive Statistics.

	Brent	WTI	Natural gas	Silver	Gold	S&P500	FTSE100	NIKKEI225	Shanghai	D-index	T-notes 10	T-bonds 30
Panel A: Returns												
Mean	0.02	0.01	-0.02	0.03	0.04	0.01	0.00	0.01	0.01	0.00	0.00	0.01
Median	0.08	0.07	-0.10	0.08	0.05	0.07	0.06	0.04	0.05	0.00	0.02	0.03
Maximum	21.18	22.36	32.44	13.18	10.25	11.77	13.77	10.73	18.03	3.66	15.81	8.26
Minimum	-13.67	-17.46	-19.90	-20.64	-9.51	-10.40	-10.90	-11.27	-16.32	-3.87	-15.39	-3.88
Std. Dev.	2.19	2.39	3.41	1.95	1.12	1.23	1.39	1.50	1.66	0.52	0.52	0.67
Skewness	-0.10	-0.10	0.54	-1.35	-0.32	-0.10	-0.10	-0.31	-0.30	0.06	0.36	0.07
Kurtosis	7.95	9.05	9.23	15.59	8.86	13.61	14.61	7.28	12.47	5.63	374.38	9.92
Jarque-Bera	4513.8***	6743.6***	7358.1***	30503.8***	6381.4***	20724.6***	24788.5***	3446.8***	16553.7***	1271.3***	25378567***	8825.843***
Panel B: Volatility												
Mean	0.12	0.13	0.18	0.11	0.06	0.06	0.06	0.06	0.08	0.03	0.02	0.04
Median	0.10	0.11	0.16	0.09	0.05	0.05	0.05	0.05	0.06	0.03	0.02	0.03
Maximum	0.62	0.95	1.35	1.12	0.49	0.54	0.49	0.57	0.44	0.23	0.16	0.29
Minimum	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00
Std. Dev.	0.07	0.08	0.10	0.07	0.04	0.05	0.05	0.04	0.05	0.02	0.01	0.02
Skewness	1.94	2.35	2.48	3.04	2.74	3.09	3.08	3.60	2.18	2.15	2.19	1.98
Kurtosis	8.78	13.11	17.51	23.21	17.83	18.79	18.50	28.80	10.03	14.33	12.98	14.82
Jarque-Bera	8911.616***	22880.41***	43290.92***	81979.55***	46036.18***	52896.94***	51205.95***	132079***	12614.77***	27020.22***	21869.32***	28611.92***

Note:*** significant at the 1% level.

5 Empirical results

5.1 Connectedness in returns

5.1.1 Static results

The connectedness matrix for returns is given in Table 2.[16] The matrix provides how each pair of variables is connected, while off-diagonal elements explain whether a variable is a giver or receiver to other variables. Aggregating all row elements, except diagonal ones, allows to figure out how a variable is affected by all other variables (contributions from others) in the VAR system. Similarly, aggregating all column elements, except diagonal ones, tells how a variable contributes (contributions to others) to all other variables in the VAR model. The last row presents the net effect where positive values imply that they are contributors and the negative ones that they are receivers. Finally, the total spillover index appears in the lower right corner of the spillover table. For example, the total spillover index (or static connectedness) in the variables is 34.20%, indicating that, on average 34.20% of the return forecast error variance comes from spillovers among US financial futures markets and spillovers from European (UK) and Asian (China, Japan) futures markets.

Looking at directional spillovers (last row of table 2), five out of twelve markets are net givers, namely, WTI, Brent, S&P500, FTSE100, and Silver. The seven remaining markets (Natural gas, Gold, NIKKEI225, Shanghai SE, D-index, T-notes, T-bonds) are net receivers. For example, the S&P500 index futures return is the highest net giver, 17.43%, while the silver futures return is the lowest one, 6.24%. On the contrary, Nikkei225 and Shanghai SE index futures returns are the highest net receivers, -27.50% and -7.30%, respectively. In total, a range of directional spillovers across variables is observed, which is quite informative about the general dynamics across all futures markets in the VAR model. Having different contributors and receivers provides valuable information about the interconnectedness of futures markets and the risks involved.

Pairwise connections shed light on how one variable or market affects the other. For instance, spillover effects from WTI to Brent, and the opposite, are the highest on each other (34.32% vs 34.46%). In other words, US and UK crude oil markets have major spillover effects on each other and, thus, provide support for the 'one great pool hypothesis.'[17] The lowest spillover effect of

[16] The matrix of generalized forecasting error variance decomposition is based on a twelve variable VAR model for both the return and volatility series and considers a 10-day ahead forecast. The Bayesian information criterion (BIC) is used to check the order of the VAR models.

[17] One great pool hypothesis claims that markets from the same field influencing each other (Adel-

WTI and Brent are on T-bonds, 0.04%, and 0.08%, respectively. Moreover, FTSE100 index future returns have a high contribution to S&P500 futures returns, 22.67%, and low towards T-bonds ones, 0.11%. Further, S&P500 is considered as the highest contributor for both FTSE100, 22.78%, and NIKKEI225, 16.48%. Overall, S&P500 and FTSE100 index futures returns are set to be net contributors to all other markets.

A few interesting pairwise connections also arise in the case where the futures market is a net receiver. For example, Gold is an important contributor to Silver, 27.86%, and the D-index, 10.84%, despite being a net receiver overall. It also affects T-notes, 1.83%, but only casually affects T-bonds, 0.01%.[18] The Natural gas market is also a net receiver with both the US and UK crude oil (futures) markets being the main contributors to its return forecast error fluctuations. Furthermore, Asian stock markets (NIKKEI225, Shanghai SE) are notably influenced by S&P500 and FTSE100, while they have a very small contribution to all other markets. This is consistent with the fact that US and UK markets are still the major contributors to Asian stock markets (Zhang, 2017). As regards money market futures, T-notes (futures) returns are strongly influenced by S&P500, 4.79%, and FTSE100, 3.39%, index futures, with WTI, 1.99%, and Gold, 1.83%, showing some smaller impact.[19] Regarding T-bonds futures returns, they do not appear to affect or be affected by returns of other futures markets in US and Asia.

Lastly, D-index futures returns have substantial spillover effects on Gold and Silver, but these two markets exert even higher influence on D-index futures returns. Considering that US holds the largest Gold reserves worldwide and trade in Gold and Silver mostly happens in dollars, then any fluctuation in the dollar index is likely to influence Gold prices and the opposite (Capie et al. 2005).[20] Overall, results show that spillover effects are mostly evident between US and UK markets and rarely from Asian to US futures markets.

man,1984).

[18] Similarly, the contribution from Silver to Gold is the highest, 30.24%. Further, Silver has a substantial contribution to the D-index by 10.16% and a smaller one to the remaining markets

[19] This is consistent with Indriawan et al. (2019) who find that increased price discovery in the bond futures is related to returns and net order flows of the US stock market.

[20] Further, investors would buy gold in fear of currency devaluation, high inflation, and a declining stock market phase.

Table 2: Connectedness Matrix for Return Series.

	Brent	WTI	N-gas	Silver	Gold	S&P	FTSE	NIKKEI	Shanghai	D-index	T-notes	T-bonds	From
Brent	46.53	34.46	2.31	4.00	2.17	2.64	4.50	0.29	0.51	2.03	0.55	0.01	53.47
WTI	34.31	46.39	2.55	3.90	2.13	2.51	4.32	0.29	0.37	2.11	1.09	0.03	53.61
N-gas	4.50	5.01	88.17	0.61	0.42	0.17	0.29	0.10	0.01	0.64	0.02	0.06	11.83
Silver	4.15	4.08	0.33	48.20	27.86	1.60	3.87	1.40	0.40	8.01	0.08	0.01	51.80
Gold	2.45	2.42	0.25	30.24	52.30	0.19	0.76	0.80	0.10	9.28	1.19	0.03	47.70
S&P	3.25	3.28	0.08	1.74	0.03	62.32	22.67	1.49	0.47	0.92	3.66	0.07	37.68
FTSE	5.03	4.86	0.21	4.09	0.72	22.78	50.96	2.16	0.77	6.07	2.19	0.17	49.04
NIKKEI	1.44	1.37	0.08	2.10	0.94	16.48	11.34	61.27	1.42	2.48	1.02	0.05	38.73
Shanghai	1.25	0.92	0.02	1.06	0.20	2.43	2.93	2.07	88.08	0.66	0.37	0.02	11.92
D-index	2.66	2.81	0.45	10.16	10.84	1.39	7.07	2.52	0.17	61.02	0.88	0.04	38.98
T-notes	1.02	1.99	0.03	0.14	1.83	4.79	3.39	0.08	0.35	1.28	85.07	0.03	14.93
T-bonds	0.04	0.08	0.15	0.01	0.01	0.13	0.11	0.03	0.04	0.02	0.16	99.22	0.78
To Others	60.10	61.28	6.45	58.04	47.16	55.10	61.26	11.23	4.62	33.51	11.21	0.50	
Net	6.63	7.67	−5.38	6.24	−0.54	17.43	12.22	−27.50	−7.30	−5.47	−3.71	−0.28	**34.20**

Note: "To Others" is the aggregation of each column except diagonal elements."From" is the aggregation of each row except diagonal elements. The total connectedness is 34.20% and in bold. Net row reports the difference between "To Others" and "From" for each variable. All values are in percentage. A VAR lag length of 1 is chosen by using the (BIC).

5.1.2 Rolling-window results

As a result of the Global Financial Crisis (GFC), Europe's Sovereign Debt Crisis (ESDC), and conflict in the Middle East, markets and prices across the world have fluctuated substantially. Figure 3 presents the total spillover index after the estimation of a 200-day rolling window. Findings show that total connectedness ranges from 29% to slightly above 55%, while it is clear that most peaks occur during the crises. Figure 3 also indicates that total connectedness across all futures markets, during both crises, is between 45% and 55%. This implies that US futures markets become notably more interconnected during crisis periods (responding to same fundamental changes), while the increased spillover effects to Asian markets show that their news-watchers and investors have a close eye to US and European financial markets. Further, Figure 4 provides more information about how one market contributes to all other markets. Results provide substantial evidence of connectedness in most markets during crises, especially in WTI, Brent, S&P500, FTSE100, Gold, and Silver, implying that US and UK markets have the lead in contributing to all other futures markets. For example, US and UK stock index futures markets are increasingly influential towards other markets during the Global Financial Crisis and Europe's Sovereign Debt Crisis. Their effect decreases as the crisis repercussions wear out, and it slightly increases again when the bull market phase takes over after the crisis. On the contrary, Asian markets show that they have marginal contribution to US and UK futures markets.

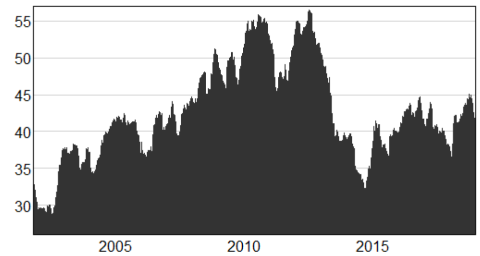

Figure 3: Overall Spillover (Return System).

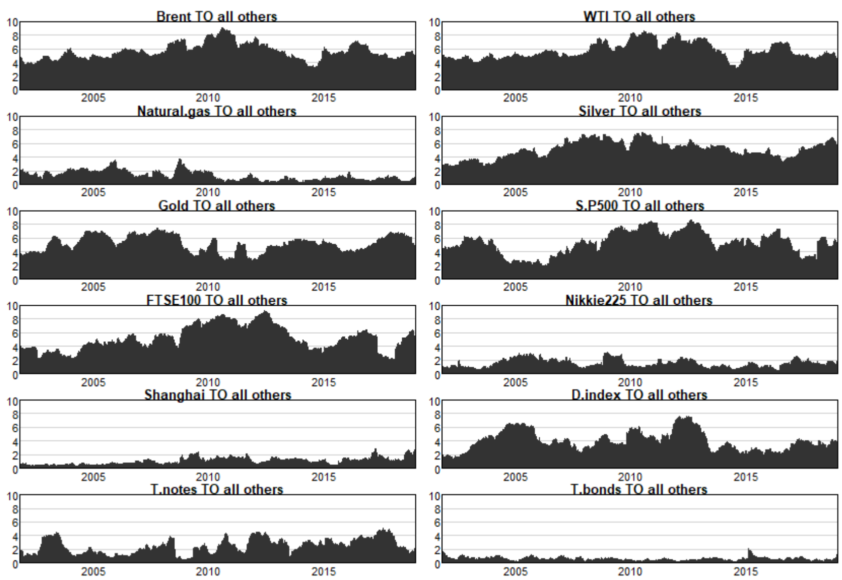

Figure 4: Rolling-window Contribution to All Others (Return System).

5.1.3 Sub-sample analysis

In this section, the full sample is divided into three sub-samples to examine the net directional connectedness during crisis and non-crisis periods. Three sub-samples are considered. The first period (precrisis) covers the years from 2001 to 2006, while the second one (during crisis) extends from 2007 to 2012. The third period (post-crisis) includes all years from 2013 to 2018. A few interesting results emerge from the sub-sample analysis presented in Table 3. First, futures markets are more interlinked during the crisis period compared to the pre- and postcrisis ones. In particular, the total spillover index reaches 42.70% compared to 28.90% and 33.32%, pre- and post-crisis, respectively. Second, S&P500, WTI, and Brent are the only markets that have positive net contributions (net givers) over the three sub-samples. In particular, the crude oil market becomes more influential during the crisis period. Third, although FTSE100, T-bonds, and Silver are ranked as net receivers in the pre-crisis period, their impact on other markets increased to become net givers (contributors) during and after the crisis period. For example, the net influence of the FTSE100 on other markets jumps from -2.22%, in the pre-crisis period, to 23.51% during the crisis period and falls back to 6.28% in the after crisis one. Fourth, Gold is a net giver in the pre- and post-crisis periods, but its contributions surprisingly fall to be a net receiver during crisis. Choudhry et al. (2015) find that gold may not perform well as a safe haven during the financial crisis period owing to the bidirectional interdependence among gold returns, stock returns and stock market volatility.[21] Finally, D-index, Natural gas, T-notes, Shanghai, and NIKKEI225 are net receivers throughout the three periods examined. All these markets are becoming increasingly sensitive to the changing (futures) returns of all other markets during the crisis period. Hence, financial and economic crises intensify total spillovers across future markets. Overall, findings confirm that US and UK futures markets are extensively interlinked, especially during crisis times.

Table 3: Net Contribution of A Futures Market to All Other Futures Markets.

	Pre-crisis	During crisis	Post-crisis
Brent	3.28	13.25	7.86
WTI	3.85	13.31	9.04
N-gas	−6.58	−7.94	−1.61
Silver	−1.19	9.90	4.23
Gold	7.67	−8.26	5.61
S&P	16.63	20.14	19.13
FTSE	−2.22	23.51	6.28
NIKKEI	−15.52	−38.61	−32.46
Shanghai	−1.50	−13.77	−9.03
D-index	−0.06	−4.56	−5.67
T-notes	−3.23	−7.09	−3.39
T-bonds	−1.13	0.09	0.02
NET Directional Connectedness	28.90	42.70	33.32

Note: Each columns report Net Directional Connectedness from one market to all other markets during three different sub-samples, while the last row shows the overall Net Directional Connectedness (or total spillover index) for the whole system. Pre-crisis period spans from 2001 to 2007, during crisis period spans from 2008 to 2012, and post-crisis period spans from 2013 to 2018.

[21] Authors also find that gold may be used as a hedge against stock market returns and volatility in stable financial conditions.

5.2 Connectedness in volatility

5.2.1 Static results

Volatility connectedness results are reported in Table 4. Analysis is also based on a twelve variable VAR model and 10-day ahead forecast error variance decompositions of the generalized type. As can be seen in Table 4, total connectedness is 38.72%, which is slightly higher than the return series. Put differently, 38.72% of the volatility forecast error variance is explained by the interconnectedness between various US financial futures markets and spillovers from/to European (UK) and Asian (China, Japan) futures markets. Further analysis shows that there is a difference between the return and volatility series, which means that each market's contribution to others varies when the return or volatility series is utilized. It is evident from Table 4 that volatility contributions ranged from 3.90% (from Natural gas to others) to 81.49% (from S&P500 to others) while return contributions ranged from 0.5% (from T-bonds to other) to 61.28% (from WTI to other).

A striking result emerging from empirical findings is that eight out of twelve markets are net receivers, namely, Brent, WTI, Natural gas, NIKKEI225, Shanghai, Silver, D-index, and T-notes, whereas the remaining markets are net contributors. Furthermore, it is observed that specific futures markets shift from being net givers to being net receivers compared to the return system. For example, WTI, Brent, and silver futures returns are net contributors to other markets, but their volatilities are strongly influenced by those of other futures markets (net receivers). Gold and T-bonds change from being net receivers to being net givers when return and volatility systems are considered, respectively. Additionally, S&P500 and FTSE100 contribute strongly to each other, as well as to other markets. Findings show that S&P500 has spillover effects on the D-index 6.21%, which is also consistent with the 'heat waves' hypothesis.[22] The 'meteor showers' hypothesis is further supported by the spillover effects from S&P500 to FTSE100.[23] Finally, parallels are also found in the results. For instance, S&P500 (NIKKEI225) is the most noteworthy contributor (receiver) to (from) other futures markets in both return and volatility series.

[22] Heat waves hypothesis means that there is a connection between two markets inside a country (Engle et al. 1988).

[23] Meteor showers hypothesis means that there is a connection between two similar markets in two different countries (Engle et al. 1988).

Table 4: Connectedness Matrix for Volatility Series.

	Brent	WTI	N-gas	Silver	Gold	S&P	FTSE	NIKKEI	Shanghai	D-index	T-notes	T-bonds	From
Brent	46.81	33.24	1.13	1.70	2.04	3.92	4.05	1.55	1.36	1.79	1.29	1.12	53.19
WTI	32.04	45.72	1.45	1.64	1.86	5.16	4.39	1.08	1.23	2.10	1.82	1.52	54.28
N-gas	1.60	2.36	94.29	0.18	0.17	0.29	0.28	0.18	0.12	0.10	0.20	0.23	5.71
Silver	1.74	1.48	0.11	54.10	26.11	3.97	3.78	0.46	0.96	4.73	2.27	0.30	45.90
Gold	2.15	1.72	0.17	24.52	46.98	5.99	7.04	1.40	0.83	5.56	3.24	0.39	53.02
S&P	2.21	2.41	0.18	2.03	3.30	46.64	27.81	3.55	0.86	2.71	6.47	1.84	53.36
FTSE	2.53	2.10	0.21	2.04	3.97	28.34	47.58	3.04	0.78	2.42	5.39	1.61	52.42
NIKKEI	1.90	1.17	0.04	1.87	4.52	12.87	10.38	62.68	0.81	0.99	1.93	0.85	37.32
Shanghai	1.44	1.38	0.01	2.10	1.47	1.69	1.19	0.54	88.90	0.63	0.55	0.10	11.10
D-index	3.41	3.28	0.17	6.17	8.04	6.21	5.33	0.48	0.65	56.62	7.77	1.88	43.38
T-notes	2.25	2.61	0.24	2.33	3.98	11.75	10.54	1.07	0.93	7.04	55.06	2.20	44.94
T-bonds	1.13	1.25	0.19	0.09	0.04	1.32	1.75	0.06	0.79	2.08	1.28	90.03	9.97
To Others	52.40	53.02	3.90	44.65	55.50	81.49	76.53	13.41	9.31	30.15	32.20	12.04	
Net	−0.79	−1.27	−1.82	−1.25	2.48	28.13	24.11	−23.91	−1.79	−13.23	−12.74	2.06	**38.72**

Note: "To Others" is the aggregation of each column except diagonal elements."From" is the aggregation of each row except diagonal elements. The total connectedness is 38.72% and in bold. Net row reports the difference between "To Others" and "From" for each variable. All values are in percentage. A VAR lag length of 3 is chosen by using the (BIC).

5.2.2 Rolling-window results

Rolling-window results show the time-varying connectedness among futures market volatilities. Figure 5 demonstrates the total spillover index and volatility connectedness dynamics of all future markets in this study. The overall spillover of the volatility system shows similarities to the return system. In particular, US, UK, and Asian futures markets are closely connected, especially during the Global Financial Crisis (GFC) and the European Sovereign Debt Crisis (ESDC). This can be seen from the range of total connectedness, which takes values from almost 35% to slightly above 55%. Connectedness gains an increasing trend on the most recent years of the sample. Overall, future markets have high uncertainties that feed into other markets in a time-varying style, especially during crisis times.[24]

The dynamic contribution of a futures market volatility to all others is plotted in Figure 6. This figure illustrates that WTI, Brent, S&P500, FTSE100, Gold, and Silver contribute highly to all others, whereas the remaining markets make a small contribution to all other futures markets. These results provide further support for the interconnectedness of crude oil, stock, and precious metal futures markets (Junttila et al., 2018; Mensi et al., 2017a, 2017b). The currency (D-index) and the bond market (T-notes) also show time-varying contributions to other markets, although to a lower degree. Like the overall spillover findings, individual futures market contributions towards other mar-

[24] These results are consistent with Xiao et al. (2019) who find that connectedness always increases in times of turmoil and that almost two-thirds of the volatility uncertainty for commodity futures are due to the connectedness of shocks across futures markets.

kets also show an increasing pattern during the two crisis periods (GFC and ESDC).

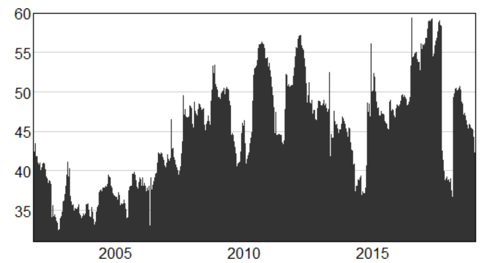

Figure 5: Overall Spillover (Volatility System).

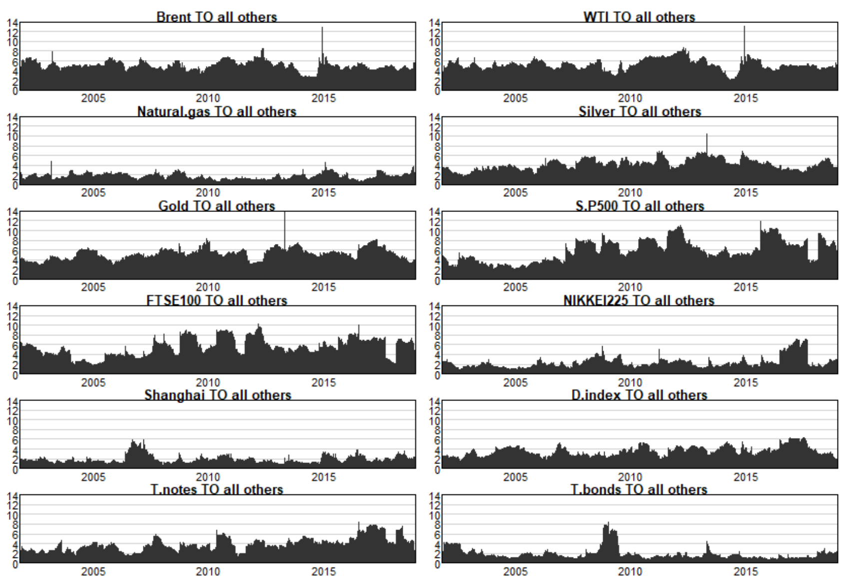

Figure 6: Rolling-window Contribution to All Others (Volatility System).

5.2.3 Sub-sample analysis

Sub-samples analysis is used again for the volatility VAR system to provide more information about the net directional connectedness across different periods. Results are reported in Table 5. First, by far the net directional connectedness of all markets is much higher during crisis periods compared to other times. Second, results show that FTSE100 is surprisingly the only market that significantly contributes to all other future markets throughout the three sub-samples. Third, WTI and Brent are contributors to the pre- and post-crisis times; however, they lose their influence during crisis. Fourth, S&P500 is a net receiver in the pre-crisis by -1.70%, but this figure increases considerably to a little above 44% during the crisis, which implies that it converts from a net receiver to the highest contributor in the system during the same time. Antonakakis et al. (2016) mentioned that during the GFC period, US markets (S&P500) lead other markets as the net spillover of S&P500 volatility towards other markets is positive. As regards T-bonds futures volatility, it exerts little spillover contribution during the first two sub-samples; nevertheless, it becomes a net receiver in the last sub-sample. Finally, findings show that six out of twelve markets are net receivers across all three sub-samples, namely, silver, Natural gas, NIKKEI225, Shanghai, D-index, and T-notes. In particular, their net directional connectedness grows during the crisis, which means that the overall response to the Global Financial Crisis is important. In other words, futures markets respond likewise to the announcement of bad news either because they depend on the same fundamentals or simply because international investors closely monitor the performance of the US economy and financial markets.

Table 5: Net Contribution of A Futures Market to All Other Futures Markets.

	Pre-crisis	During crisis	Post-crisis
Brent	2.04	−2.40	12.02
WTI	1.24	−4.33	14.67
N-gas	−2.34	−5.00	−4.09
Silver	−0.22	−3.39	−6.91
Gold	5.76	−1.52	3.92
S&P	−1.70	44.39	18.25
FTSE	12.43	28.38	7.97
NIKKEI	−8.65	−24.50	−20.36
Shanghai	−0.78	−9.96	−4.23
D-index	−3.38	−17.92	−10.54
T-notes	−4.79	−9.69	−6.20
T-bonds	0.39	5.96	−4.51
NET Directional Connectedness	24.11	49.25	42.89

Note: Each columns report Net Directional Connectedness from one market to all other markets during three different sub-samples, while the last row shows the overall Net Directional Connectedness (or total spillover index) for the whole system. Pre-crisis period spans from 2001 to 2007, during crisis period spans from 2008 to 2012 and post-crisis period spans from 2013 to 2018.

5.3 Pairwise net connectedness for return and volatility series

Figures 7 and 8 below illustrate the pairwise relationship networks between all markets in both systems (return and volatility); hence, essential information is demonstrated. Figures have three colors which explain the strength of the relationship among markets. Blue represents the lowest rank in the system. Red and Green nodes represent the highest and intermediate ranks, respectively. For returns (Figure 7), WTI has the highest place in the system, and this information implies that WTI plays an essential role in influencing all markets. Four markets, namely FTSE100, Gold, T-bonds, and T-notes, are placed at the intermediate level, and highlight that price dynamics provide further information about other markets and prices. At the bottom of the network is Asian markets which hardly provide any information to others.

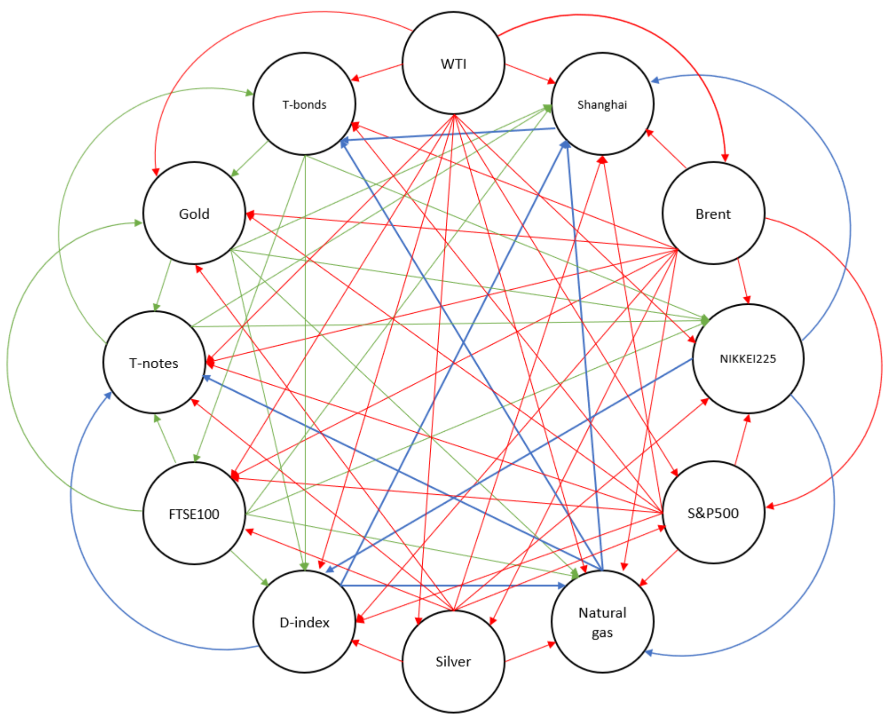

Figure 7: Pairwise Net Connectedness (Return System).

For volatility (Figure 8), S&P500 is the highest ranked, and it is a net contributor to all others. This also means that S&P500 is the most effective market in the volatility system. FTSE100, Brent, and T-bonds also contribute highly at volatility level. Gold, Silver, WTI, and Shanghai index futures provide less information and show contributions at an intermediate level in the volatility VAR model. Furthermore, the lowest-ranked markets are the Asian ones, with NIKKEI225 ranked at the bottom. Finally, results show that Asian markets contribute weakly to US and UK markets; however, these results do not alter the fact that US futures markets take the lead in contributing to all other markets.

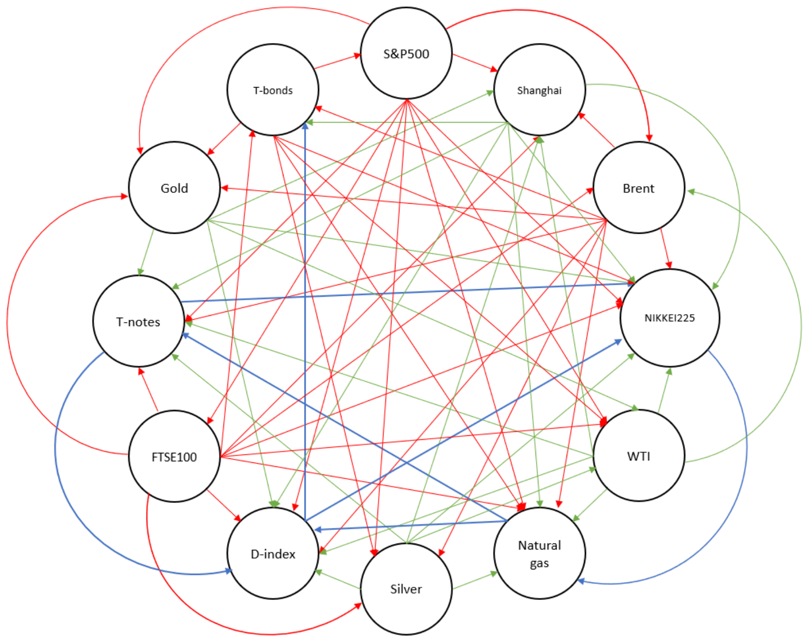

Figure 8: Pairwise Net Connectedness (Volatility System).

6 Robustness check

6.1 Different VAR lag order

To make sure that findings are robust, this study examines the sensitivity of return and volatility system's total spillover index to the VAR lag length. VAR orders of 3, 4 and 5 in the return system are employed, and the results (max, min, median) reported in Figure 9 show that there is no meaningful difference across the different VAR lag lengths, particularly during crisis periods. For example, the min-max range of total spillover in the pre-crisis period is just above 14%, while the min-max range during and after the crisis is about 10%. In the volatility system, VAR orders of 5 up to 8 are used, and Figure 10 shows similar findings. For instance, the min-max range in the pre-crisis period is around 9%, while the min-max range during and after the crisis is about 7%. Both figures indicate that result sensitivity to VAR orders during crisis is less compared to pre- and post-crisis periods. This is due to the fact that, during the crisis, it is the most recent news that matter and move prices eventually. Therefore, the total spillover plot is not sensitive to the VAR lag order, especially during crisis periods.

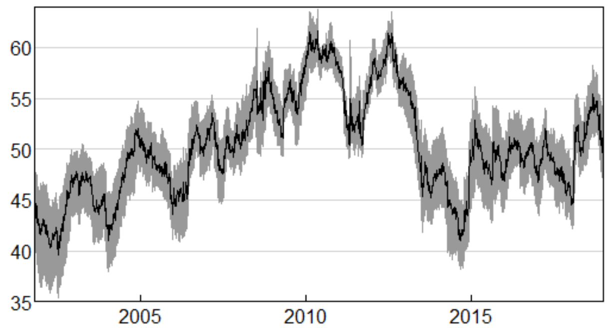

Figure 9: The Sensitivity of the Return System To VAR Lag.

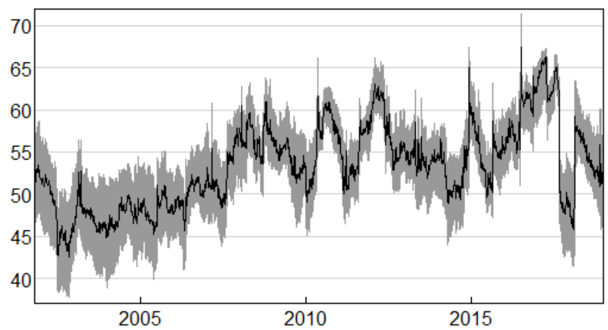

Figure 10: The Sensitivity of the Volatility System To VAR Lag.

6.2 Garman-Klass volatility estimator

Recall that volatility results are based on Parkinson's High-Low volatility (HLV) estimator. As mentioned earlier, this estimator provides valuable information and higher accuracy than close to close volatility estimators. To check for result sensitivity to the choice of volatility estimator, the spillover index is estimated using the Garman and Klass (1980) volatility proxy. This is a range-based volatility estimator which utilizes not only the High(H), and Low(L) prices but also the Open(O), and Close(C) ones. The Garman-Klass volatility proxy is more efficient compared to other estimators that utilize closing prices alone. Garman- Klass's volatility model can be estimated as follows:

$$Vol = \sqrt{(0.5 * (ln(h) - ln(l))^2 - ((2 * ln(2) - 1) * (ln(c) - ln(o))^2)} \qquad (10)$$

A comparison between Garman-Klass and Parkinson estimators shows that there is no meaningful difference in terms of spillover effects. For example, total contribution of S&P500 volatility to all other futures markets uncertainties is 81.49% using the Parkinson proxy compared to 83.6% using the Garman-Klass one. Also, the total spillover index is 38.72% using the Parkinson volatility proxy compared to 39.3% using the Garman-Klass one. Overall, findings remain qualitatively unchanged on the choice of range-based volatility estimator, Parkinson or Garman-Klass. Detailed results are not presented; nevertheless, are available from the authors upon request.

6.3 Different permutations of Cholesky orderings

Klobner and Wagner (2013) calculate the spillover index using a new divide and conquer strategy that swiftly calculates the spillover index's maximum and minimum over all possible Cholesky orderings.[25] They find that randomly choosing a small number of orderings severely underestimates the true range of the spillover index, while using the generalized spillover index (does not depend on variable ordering) produces large values for the same index (see also Diebold and Yilmaz, 2012). For this reason, the spillover index is estimated by using Klobner and Wagner's divide and conquer strategy as well as specific numbers of randomly chosen (Cholesky) orderings (ten thousand, one million and ten million permutations). Results from Table 6 are compared with those of Tables 2 and 4 and confirm that the spillover index, for both returns and volatility, is overestimated when the generalized forecast error decompositions are employed. For returns, the generalized spillover index is 34.20%, while, under the different permutations of Cholesky orderings, the spillover on average is 23.23% with a maximum value of 24.28%.

Similarly, for volatility, the generalized spillover index is 38.72%, but the randomly chosen Cholesky orderings produce a spillover index of 30.20% (the maximum value is 30.96%). In the final part of this section, Table 7 reports the Cholesky variable ordering of the VAR model that generates the maximum spillover index value. For futures returns, the variable ordering that produces the maximum spillover index is Nikkei225, FTSE100, Brent, WTI, Silver, Gold, S&P500, Dollar index, T-notes, Natural gas, Shanghai, and T-bonds.

Also recall that, with Cholesky decomposition, a shock on the first variable will affect (contribute to) all other variables in the VAR model, while a shock on the last variable will affect only itself. According to the return variable ordering, a shock in the crude oil and precious metal futures returns affects the S&P500 index futures (Pineiro-Chousa et al. 2018), while a shock in the

[25] Authors also calculate the spillover index exploring a specific number of randomly chosen Cholesky orderings under a static and a rolling window setting.

S&P500 futures returns will contribute mainly to changes in the US currency and bond (T-notes, T-bonds) future returns (Yoon et al. 2019). Moreover, the Shanghai SE futures returns appear to be affected by shocks to all major US futures markets. Finally, the variable ordering for the volatility VAR model that generates the maximum spillover is T-bonds, S&P500, FTSE100, WTI, Brent, T-notes, Gold, Silver, Shanghai, Dollar index, Nikkei225 and Natural gas. Here, a shock in the S&P500 futures volatility will contribute to changes in the volatility of the crude oil, precious metal, and currency markets (Husain et al. 2019), while a shock in the crude oil market futures volatility does not contribute to changes in the volatility of major index futures markets such as S&P500 and FTSE100 (Soucek and Todorova, 2013). Interestingly, a shock in the volatility of government bond futures (T-bond, T-notes) will have an impact on more futures markets than a shock in its return will do.

Table 6: Total Spillover Index Under Different Cholesky Orderings.

	Divide and Conquer	10000	1000000	10000000
Panel A: Return				
Average	23.23	23.24	23.23	23.23
Maximum	24.28	24.22	24.28	24.28
Panel B: Volatility				
Average	30.20	30.20	30.20	30.20
Maximum	30.96	30.93	30.94	30.95

Note: Each column reports the total spillover index under the divide and conquer strategy (see Klobner and Wagner, 2012) and 10,000, 1,000,000, and 10,000,000 randomly chosen permutations of Cholesky orderings. The results reported show the average and maximum value of the total spillover index.

Table 7: Maximum Permutations of Cholesky Orderings.

Panel A: Return												
Divide and Conquer	8	7	1	2	4	5	6	10	11	3	9	12
10000	8	4	5	7	2	6	10	11	12	9	3	1
1000000	8	4	5	7	1	9	2	6	12	3	10	11
10000000	8	7	1	2	4	5	6	10	11	12	3	9
Panel B: Volatility												
Divide and Conquer	12	6	7	2	1	11	5	4	9	10	8	3
10000	12	6	2	7	11	1	5	4	8	10	9	3
1000000	12	6	7	11	2	1	9	5	10	4	3	8
10000000	12	6	7	2	1	5	4	8	9	11	10	3

Note: The variable ordering reported is the one that produces the maximum total spillover index under different numbers of randomly chosen Cholesky orderings. The number of different permutations used are 10,000, 1,000,000 and 10,000,000. For details on choosing Cholesky ordering using the divide and conquer strategy, please see Klobner and Wagner (2013). The ordering of our variables in the dataset is Brent (1), WTI (2), N-gas (3), Silver (4), Gold (5), S&P500 (6), FTSE100 (7), NIKKEI225 (8), Shanghai SE (9), D-index (10), T-notes (11), T-bonds (12).

7 Conclusion

This study examines the dyamic spillover effects within US futures markets and explores further linkages with European (UK), and Asian (Japan, China) futures markets. We apply Diebold and Yilmaz's approach (2009, 2012, 2014) to daily futures market returns and realized volatility proxies for the period of January 2001 until December 2018. Empirical results highlight a significant link among US futures markets at both return and volatility levels, especially during crisis periods. Importantly, findings show that Asian futures markets are strongly affected by changes in the US and UK stock and crude oil futures markets. US futures markets become notably more interconnected during crisis periods as investors in various futures markets respond similarly to changes in economic fundamentals, while increased spillover effects to Asian markets show that their news-watchers and investors have a close eye to US and European financial markets.[26]

[26] Bailey and Chan (1993) provide evidence that the spread between commodity spot and futures prices (the basis) reflects macroeconomic risks common to all asset markets. Yang et al. (2021) examine the volatility connectedness of commodity futures markets and show that commodity volatility spillovers are

Dividing the sample into three sub-samples shows the changing character of interconnectedness and its high sensitivity to time-specific events such as the Global Financial Crisis (and the European Sovereign Debt Crisis). For example, the crude oil market becomes more influential (towards others) during the crisis period, while Gold changes from being a net giver, in the pre- and postcrisis periods, to a net receiver during the crisis. Hence, investors in futures markets will change their hedging strategies to manage their portfolios away from risk. Analysis also shows that WTI and Brent contribute particularly to other markets and play a crucial role on the return (VAR) system, while on the volatility model, both US and UK stock indices have considerable spillover effects. Robustness analysis proves that results are not sensitive to the choice of VAR lag order or volatility proxy (Parkinson, Garman-Klass). Critically, using deferent permutations of Cholesky orderings, according to Klobner and Wagner (2012), confirm that the spillover index for both returns and volatility is overestimated when the generalized forecast error decompositions are used. For instance, the generalized spillover index (in returns) is 34.20%, while under the different permutations of Cholesky orderings, the spillover on average is 23.23% with a maximum value of 24.28%. More, using Klobner and Wagner's approach on choosing Cholesky orderings, we show that shocks in crude oil and precious metal futures returns affect S&P500 index futures (Pineiro-Chousa et al. 2018), while a shock in S&P500 futures returns contributes mainly to changes in US currency and bond (T-notes, T-bonds) future returns (Yoon et al. 2019). Further, a shock in the S&P500 futures volatility contributes to changes in the volatility of crude oil, precious metal, and currency markets (Husain et al. 2019), whereas a shock in the crude oil market futures volatility does not contribute to changes in the volatility of major index futures markets such as S&P500 and FTSE100 (Soucek and Todorova, 2013). Finally, the network of return and volatility systems illustrates graphically the contributor or receiver of information, as well as the information networks across future markets in US, UK, and Asia. This provides policymakers with valuable information to propose a plan for managing systemic risk in future markets.

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