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Volatility spillovers during market supply shocks: The case of negative oil prices

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ABSTRACT

This paper applies a TVP-VAR model to explore dynamic connectedness between West Texas Intermediate crude oil and other US energy prices, stock prices and exchange rate markets during the April 2020 supply shock leading to negative WTI crude oil prices. This period, while coinciding with the escalation of the COVID-19 pandemic, is also associated with non-uniform government pandemic responses, widespread expectations of global economic slowdown, and the combined effects of international political influence, all of which generated immense financial stress. A number of distinct results are identified. Firstly, while WTI is broadly identified as a volatility receiver from all of the analysed markets, during the negative pricing events WTI rapidly becomes a volatility transmitter. The inherent signal within such an unexpected market movement sent very sharp contagion effects throughout traditional financial markets. Spillovers to stock, currency and futures markets are also substantial. This negative valuation event, although reaffirming the status of the efficient markets hypothesis, has potentially endangered the role of WTI as a safe-haven during future periods of financial stress and crises.

1. Introduction

Within the context of a number of substantial crises and shocks, the very nature of the collapse of West Texas Intermediate oil (WTI hereafter) prices to an all-time trading low price of -$40.32, before settling at -$37.63 per barrel on 20 April 2020 provided significant support to the efficient markets hypotheses. As per (Corbet et al., 2020a), negative WTI occurred for a number of substantial factors, such as the financial stresses inherent within the outbreak of COVID-19, a global reduction of oil demand due to falling economic activity and increased oil supply due to geopolitical issues. This research focuses specifically on the interactions between this negative WTI event and other traditional financial market products during this same period of time. In particular, we investigate volatility spillovers not only during the outbreak of the COVID-19 pandemic, but the ability of a market as central to world finances as that of WTI to simply fall to significant negative values. Such analysis presents valuable insights into not only how this phenomenon occurred, but also, as to how such an event generated contagion effects while further fuelling market panic within other related energy markets. Negative trading in the markets for WTI in Midland, Mars Blend, Light and Heavy Louisiana Sweet crude oil also presented a scenario where some oil producers began to offer oil at fixed prices to mitigate negative pricing effects.

As presented in Fig. 1, on 20 April 2020, the nearest futures contract closed at -$37.63 per barrel, however, all other futures remained positive. This was the penultimate day of trading before contract expiration, leading to a spread between the May 20 and June 20 contracts of $58.08 just before 2:30pm ET, before values quickly increased above $0.00 and as high as $10.01 at the end of the April 20 futures contract, with the May-June spread falling to just -$1.56 per barrel. Market sentiment appeared to have been largely driven by supply and demand imbalances along with a distinct lack of storage capacity in the US. Much of the imbalance was driven by OPEC and OPEC plus. Although OPEC Plus members had agreed to reduce supply, the production changes were not to begin until May 2020, therefore, concerns continued to increase around elevated production and a lack of storage availability. In January 2020, there were approximately 49.4 million barrels of oil in floating storage worldwide. Weekly global floating storage inflows exceeded 10 million barrels in early March, following the collapse of the first OPEC Plus agreement. During the first three weeks of April, the amount of oil in floating storage rose by almost 69 million barrels to approximately 127 million barrels. Forty million barrels had been added in the week before 20 April alone as the May Contract had entered its spot period, presenting evidence of the

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substantial pressures that were accumulating. This situation had been simultaneously exacerbated as Saudi Arabia signalled no breakthrough in the oil price war with Russia, despite US pressure to end the impasse. OPEC had recommended additional production cuts of 1.5 million barrels per day starting in April and extending into the short-term, but Russia had rejected the additional cuts. The crude oil industry's demand response to COVID-19 was faster than its supply response, leading to an increase in the oversupply problem in the crude oil markets. Consumption of refined production and crude oil fell at a rapid pace as the global economy slowed while attempts to curtail production lagged behind the dramatic demand loss. This created a buildup of oil that would be available for immediate use, pushing nearby prices lower. At the same time, the expectation that demand would recover in the future kept forward prices elevated. As more oil flowed into storage, particularly at Cushing, near-term prices continued falling, in part to discourage the continued flow of oil into facilities that were reaching their maximum operational capacity, further widening the spread between the May and June Contracts. All of these supply and demand dynamics, within the hostile financial environment driven by the outbreak of the COVID-19 pandemic generated difficult conditions for traders, many of which were at this point seeking investment safe-havens while attempting to make sense of the growing number of lockdowns and restrictions being imposed by many international governments. The dynamic volatility, and indeed, the spillover of such volatility are of interest, particularly due to the growing probability of re-occurrence of such events in the future.

In this paper, we use a combination of the DCC-GARCH type framework and a TVP-VAR approach, developing on the work of Antonakakis et al. (2020), to generate the volatility spillovers indexes of Diebold and Yilmaz (2012) in a time-varying fashion to test the interactions between the price of WTI and several US financial futures prices and market indices. We focus specifically on the time period surrounding the supply shocks that occurred in April 2020, which led to the unprecedented development of negative WTI prices. While the market for WTI has often acted as a safe-haven asset during periods of immense international turmoil, we find several interesting results that occur during the negative WTI event in April 2020. Firstly, while WTI is found to be a volatility receiver from all markets analysed, it becomes a volatility transmitter during the negative WTI price event. Such a result indicates, that while considering the inherent uncertainty contained within the development of the COVID-19 pandemic, the events that transpired within WTI markets during this short time-frame presented such a signal of market abnormality that the shock reverberated throughout many other traditional financial assets. Among all financial markets considered, the magnitude of volatility spillovers from the WTI market to US energy futures and US exchange rate markets are found to be largest while the volatility shocks to the stock markets are found to be smallest. However, the direction of the spillover of shocks remains consistent throughout all analysed assets. WTI has the largest volatility spillovers to the gasoline market among all the markets, followed by the exchange rate markets and NASDAQ 100. Historic market dynamics and correlations would present support for such a result. Evidence of volatility transfer from WTI towards both the Dow Jones Industrial Average and the S&P500 present substantial evidence as to how significant, and indeed, how unprecedented the April 2020 events within the WTI market had become. Significant spillovers sourced from WTI upon the VIX indicates how forward looking implied volatility increased as signals of such an incredibly rare event in the form of negative prices presented further evidence as to how perplexed the valuation process of short- and medium-term risk had become. While the COVID-19 pandemic had generated much confusion and fear, the timing of geopolitical confusion and intervention through the form of OPEC and OPEC plus action proved to be a substantial propellant of market anxiety, in an environment attempting to rationalise the effects of broad-ranging pandemic response, the rapid rise of quantitative easing and broad close-to-zero interest rate policy-making. Results are found to be robust across a variety of analysis time-frames.

The rest of this paper is structured as follows: Section 2 presents a concise overview of the previous literature relating to contagion effects, the outbreak of COVID-19, diversification behaviour during crises, and the selected methodologies. Section 3 presents an overview of the selected data used in this analysis, while 4 presents a concise overview of the methodology used. Section 5 presents an overview and discussion of the results with associated robustness testing results. Section 6 concludes.

2. Previous literature

Within the context of inter-market dynamics during financial crises, a number of areas of research provide the foundation for our structural and methodological selection. Firstly, we consider research that has focused on the volatility spillovers and dynamic interactions between financial markets surrounding, and inclusive of, periods of crises. Secondly, we develop our understanding of the breadth of research that has focused on the outbreak of the COVID-19 pandemic, and as to how this 'black swan' event has influenced traditional financial markets. Finally, we focus on the use of our selected methodological structure in previous analyses of financial market interactions.

Focusing on the international financial crisis of 2007–2012, Collet and Ielpo (2018) identified that volatility spillovers are high in the US credit market and that the insurance, goods and energy sectors have been net contributors to these shocks over the 1996–2017 period. For the same crisis, Bratis et al. (2020), amongst other results, found that financial spillovers intensified in the post-crisis period exhibiting cycles of inter-linkages among various assets classes. Kotkatvuori-Örnberg et al. (2013) identified dynamic correlations between fifty exchanges during key banking events in the same crisis period and Fry-McKibbin et al. (2021) showed that interdependence peaked during the global financial crisis with the covariance and co-volatility co-moments being the dominant factors. Mollah et al. (2016) identified that the bank risk transfer between the United States and other countries is the key transmission channel for cross-country correlations, whereas, both Kočenda and Moravcová (2019), Dimitriou and Kenourgios (2013) identified significant differentials in currency comovement during market distress, a result that is found to be present in a number of financial markets including credit default swaps (Tamakoshi and Hamori, 2016); precious metals (Mensi et al., 2020); volatility markets (Kenourgios, 2014); bond markets (Philippas and Siriopoulos, 2013); insurance markets (Slijkerman et al., 2013); and the market for diamonds (Auer and Schuhmacher, 2013). Bussière et al. (2015) found that hedge funds with a high commonality were affected disproportionately by illiquidity and exhibited negative returns during the subsequent financial crisis, thereby providing little diversification benefits to the financial system and to investors. Areal et al. (2015) verified that gold remained a safe haven during multiple recent crises. Other examples of dynamic interlinkage in crisis were also identified by Cioroianu et al. (2020), who found evidence of substantial corporate reputational pass-through during the Boeing 737-MAX disasters.

In relation to the recent COVID-19 pandemic, Mensi et al. (2020) identified strong evidence of asymmetric multifractality that increases as the fractality scale increases between gold and oil prices the period surrounding the pandemic. Ashraf (2020) identified significant stock market effects across sixty-four countries, results that are echoed in the works of Salisu and Vo (2020), Adekoya and Oliyide (2020), Smales (2021). Ji et al. (2020) identified that gold and soybean commodity futures remained robust as safe-haven assets during the pandemic, with gold found to be particularly susceptible to fear-driven volatility (Salisu and Vo, 2020; Sharif et al., 2020), while Hu et al. (2020a) add another dimension through the use of economic policy uncertainty indicators to test responses in the market for crude oil along with gold. Yarovaya

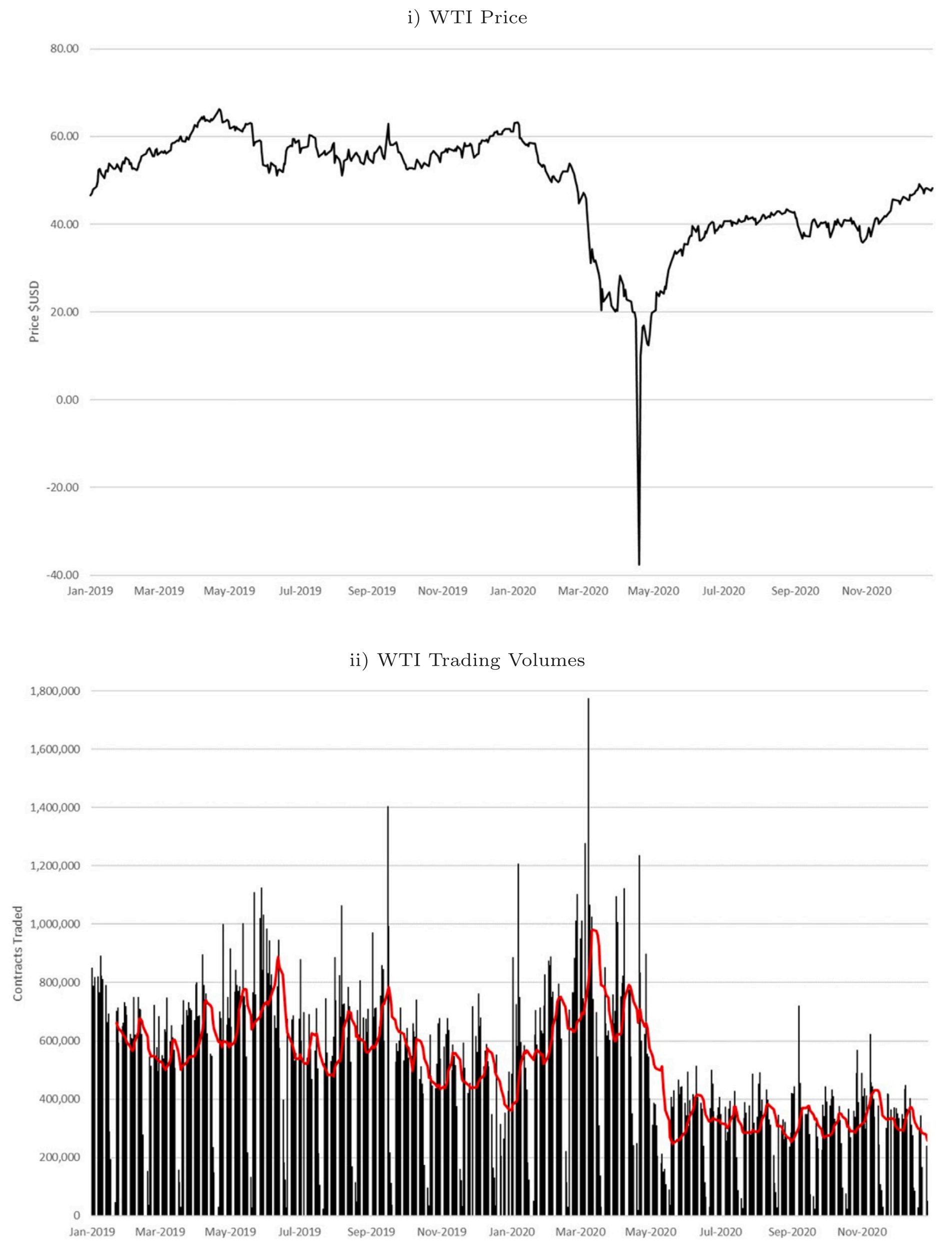

Fig. 1. Daily WTI price and trading volumes. Note: Further analysis and methodological variants were estimated by the authors. The red line indicates the ten-day moving average of WTI contract trading volumes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

et al. (2021) found that equity funds that were ranked higher in human capital efficiency outperformed their counterparts. Further, Corbet et al. (2020b) analysed the relationships between cryptocurrencies and traditional financial markets, finding evidence indication that such new financial products acted as a store of value during the escalation of the crisis. Other evidence of cryptocurrency dynamics during the COVID-19 crisis were provided by Conlon et al. (2020), Dutta et al. (2020), Corbet et al. (2020c).

Consideration of volatility spillovers builds directly on the work of Diebold and Yilmaz (2009, 2012, 2014), which has been previously used to identify spillovers in a number of markets including foreign exchange markets following the introduction of the Euro (Antonakakis, 2012), and that of cryptocurrency markets in more recent times (Hu et al., 2020b). Other, similar multivariate methodologies have been used to investigate spillovers including BEKK-GARCH (Katsiampa et al., 2019b,a); CCC-GARCH (Sadorsky, 2012); semi-parametric GARCH (Serra, 2011); and VAR-DCC-GARCH (Meegan et al., 2018; Corbet et al., 2020d). However, following a number of pre-estimation testing procedures, the work of Diebold and Yilmaz (2012) was found to best represent the methodology necessary to test for specific spillovers within short, dynamic, crisis-driven periods of time such as those specifically surrounding the negative oil price event. In terms of oil market research, the previous literature has identified a number of key characteristics relating to volatility spillovers both to and from traditional financial markets. Mensi et al. (2013) used a VAR-GARCH approach and found significant evidence of volatility spillovers and transmission between oil prices and the S&P500. Spillovers have also been identified between oil markets and agricultural commodity markets Mensi et al. (2014), while for the same markets, Du et al. (2011) identified evidence of crude oil price dynamics including mean-reversion, asymmetry between returns and volatility, volatility clustering, and infrequent compound jumps. Nazlioglu et al. (2013) found that volatility transmission dynamics are heavily influenced by crises. Dynamic spillovers also seem to exist between oil markets and equity markets in Europe (Arouri et al., 2012), Gulf Cooperation Council countries (Awartani and Maghyereh, 2013) and the US (Kang et al., 2015), while Maghyereh et al.

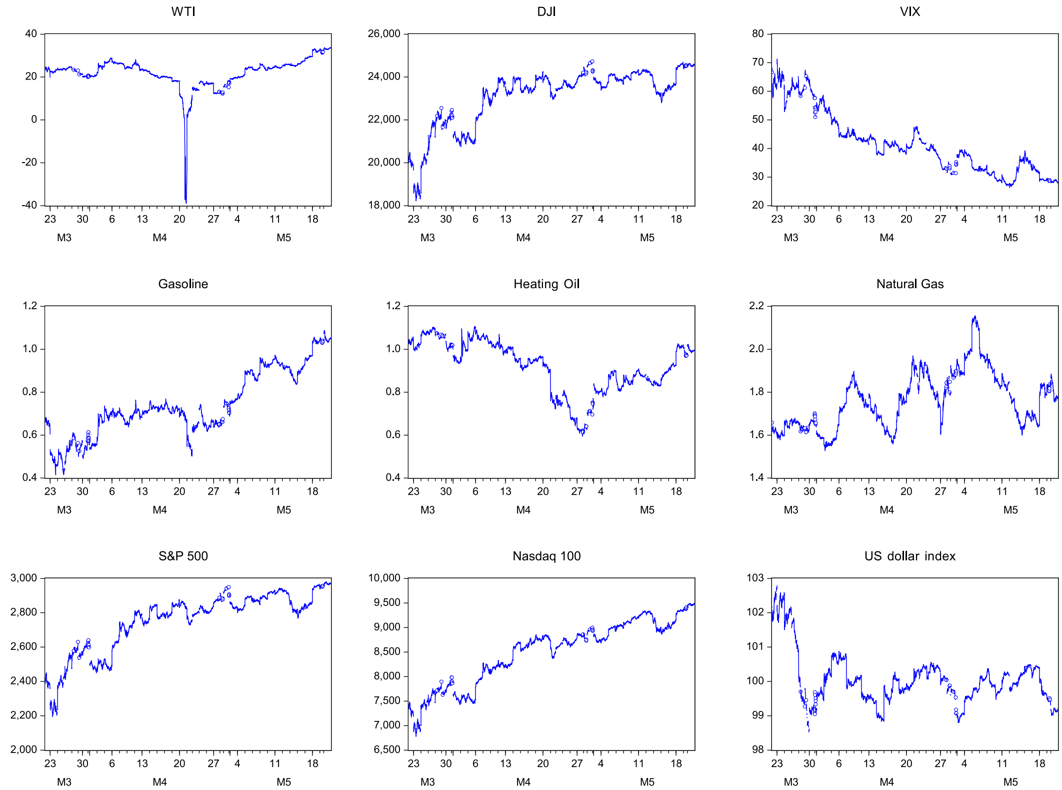

Fig. 2. Time series plot of 5-minute price data. Note: Our price data runs from 20 March 2020 throughout 20 May 2020.

(2016) identify post-crisis driven interactions for eleven major stock exchanges and oil when considering the role of volatility indices. Corbet et al. (2020a) identified significant volatility spillovers between the negative WTI price event of April 2020 upon energy sub-sectors, with differential effects observed in the markets for both coal and renewables which were found to be directly attributed to the negative WTI price event of April 2020 which was related to the onset of the COVID-19 pandemic.

3. Data

The data used comes from the Thomson Reuters DataScope Select database where we use the 5-minute high frequency data to best capture the volatility dynamics across different financial asset markets during the recent negative WTI oil prices on April 20, 2020. We select several US energy markets including the WTI crude oil futures, gasoline futures, heating oil futures and natural gas futures prices and three US stock market indexes (e.g., Dow Jones Industrial Average (DJIA), S&P 500 and NASDAQ 100). We also include the VIX index which is a measures of the 30-day expected volatility of the S&P 500 market. The VIX index is also known as the 'fear index' and it is the most recognised volatility estimator and is calculated on a real-time basis by the CBOE. In addition, we consider the US Dollar index, which is a measure of the value of the United States dollar relative to a basket of US trade partners' currencies, to represent the overall US exchange rate market.

A time series plot of these series is provided in Fig. 2 for the period 20 March through 20 May 2020 with 3,084 observations where the negative WTI oil event determines the choice of sample period for our empirical analysis. From this figure, we can observe a sudden and large drop in WTI crude oil futures prices on 20 April and the WTI price rebounds quickly after the negative oil prices. For the three US stock market indexes, we clearly see an increasing trend during the sample period, however, the VIX index exhibits a decreasing trend in general with several peaks over the sample. The movement of gasoline futures prices also shows an increasing trend, however, the gasoline price also falls after the WTI futures turned negative. We also notice the effects of the negative oil prices on heating oil with a sudden drop in value, whereas natural gas futures price oscillates and exhibits several peaks in March, April and May. The US Dollar index falls from 102 to 97 at the beginning of the sample period and then this index oscillates between 97 and 100 for the rest of the sample period.

Fig. 3 also plots the natural logarithmic returns for each index or price.[1] From this figure, we can clearly observe an episode of exceptional volatility in WTI when its price goes negative for first time during the global pandemic. We can also see that there are episodes of volatility movements in other financial markets, however, the movements of these returns are quite different. The volatility of DJIA returns is large in the early sample period during late March, where we also find similar effects for the S&P 500 and NASDAQ 100 indexes returns as the movement of returns, which are substantial at the end of March. There are exceptional episodes of movements in the energy markets, for example, the movement of gasoline futures returns reaches its maximum shortly after the negative oil price. The heating oil futures returns show the largest fluctuations between the end of April and early May and natural gas futures returns also show exceptional volatility during the entire sample period. The US Dollar index returns presents more negative movements in general while the positive movement occurs less frequently. The descriptive statistics for each logarithmic return series are presented in Table 1, where we provide mean, median, maximum, minimum, standard deviation, skewness and kurtosis information for each series. All nine series have very high kurtosis as we expect for typical financial time series. The Jarque–Bera test for normality for each series is also reported, suggesting a non-normal distribution.

[1] The returns are computed by taking first differences of the natural logarithms for each index or price except that we use only the natural logarithm for VIX.

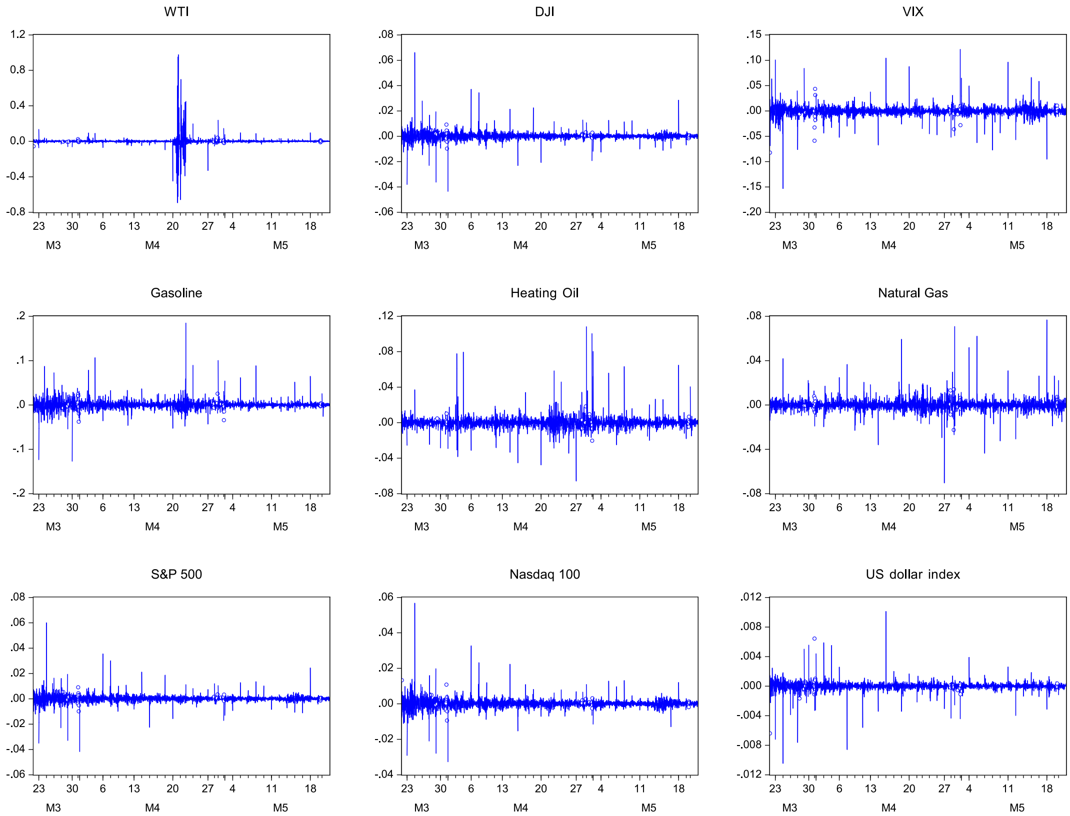

Fig. 3. Natural logarithm of 5-minute return series. Note: Our sample data runs from 20 March 2020 throughout 20 May 2020, representing 3,084 observations.

Table 1
Descriptive statistics of the 5-minute logarithmic returns.

Variable	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	J.B.	N
WTI	0.00037	0.00000	0.9762	−0.6931	0.0543	3.5416	143.7980	0.0000***	3,084
DJIA	0.00007	0.00004	0.0660	−0.0435	0.0032	2.0705	94.3628	0.0000***	3,084
Gasoline	0.00020	0.00000	0.1846	−0.1270	0.0106	2.0886	58.4788	0.0000***	3,084
Heating oil	0.00004	0.00000	0.1083	−0.0657	0.0071	4.0429	61.4854	0.0000***	3,084
Natural gas	0.00002	0.00000	0.0766	−0.0703	0.0053	2.2086	56.5041	0.0000***	3,084
S&P 500	0.00007	0.00005	0.0599	−0.0417	0.0030	1.6574	88.4031	0.0000***	3,084
NASDAQ 100	0.00008	0.00007	0.0567	−0.0326	0.0027	2.4275	83.1547	0.0000***	3,084
US Dollar index	−0.00001	0.00001	0.0100	−0.0104	0.0006	−1.7682	85.4335	0.0000***	3,084
VIX	−0.00033	−0.00033	0.1215	−0.1532	0.0104	−0.2196	45.2306	0.0000***	3,084

Note: The 5-minute return data runs from 20 March 2020 to 20 May 2020 with 3084 observations.

4. Methodology

The seminal paper of Diebold and Yilmaz (2012) develops a spillover measure based on forecast error variance decompositions from a generalised VAR framework. The covariance matrix is set to be time-invariant and is calculated under either the Cholesky factorisation or generalised decomposition. Gamba-Santamaria et al. (2017) is the first to construct volatility spillover indexes Diebold and Yilmaz (2012) using a DCC-GARCH framework to model the multivariate relationships of volatility among assets. The volatility can be computed directly from the covariance matrix obtained from the DCC-GARCH model of Engle (2002). Antonakakis et al. (2019) employ the time-varying parameter (TVP)-VAR-based approach of Antonakakis et al. (2020) to generate the spillover indices of Diebold and Yilmaz (2012) and the DCC-GARCH t-Copula model of Patton (2006). The TVP-VAR approach of Antonakakis et al. (2020) improves the approach of Diebold and Yilmaz (2012) in that it does not require setting a rolling window-size to undertake the time-varying estimation. The TVP-VAR approach has gained considerable support when it comes to exploring transmission spillovers, for example, see Antonakakis et al. (2018a,b), Gabauer and Gupta (2018), Antonakakis et al. (2019), Corbet et al. (2021). In this paper we use a combination of the DCC-GARCH framework and the TVP-VAR approach of Antonakakis et al. (2020) to investigate the dynamic volatility spillovers between the negative WTI price event and several selected US financial futures prices and market indexes.

4.1. Volatility spillover index

The following is derived from Antonakakis et al. (2020), who extend the spillover index approach of Diebold and Yilmaz (2012) by allowing the variances to vary via a stochastic volatility Kalman Filter estimation approach to explore the transmission mechanism as time-varying. This new approach does not require choosing a arbitrary rolling window-size, which could lead to a loss of valuable observations.

A TVP-VAR(1) model with time-varying volatility can be written as follows,

$$y_t = \beta_t z_{t-1} + \epsilon_t \qquad \epsilon_t | F_{t-1} \sim \mathrm{N}(0, S_t), \tag{1}$$

$$vec(\beta) = vec(\beta_{t-1}) + v_t \qquad \varepsilon_t | F_{t-1} \sim \mathrm{N}(0, R_t), \tag{2}$$

where y_t and $z_{t-1} = [y_{t-1}, \dots, y_{t-p}]'$ represent $N \times 1$ and $Np \times 1$ dimensional vectors. β_t is a $N \times Np$ time-varying coefficient matrix and ϵ_t is $N \times 1$ error disturbance vector and time-varying variance–covariance matrix of S_t. $vec(\beta)$, $vec(\beta)$ and v_t are $N^2p{\times}1$ dimensional vectors and R_t is an $N^2p{\times}N^2p$ dimensional matrix. The time-varying coefficients of the vector moving average (VMA) is the fundamental of the connectedness index introduced by Diebold and Yilmaz (2012) using the generalised impulse response function (GIRF) and the generalised forecast error variance decomposition (GFEVD) developed by Koop et al. (1996), Pesaran and Shin (1998). The GFEVD can be interpreted as the variance share one variable has on others and it can be calculated as follows:

$$\tilde{\phi}^g_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}} \tag{3}$$

where $\tilde{\phi}^g_{ij,t}(J)$ denotes the J-step ahead GFEVD. Using the GFEVD, variable i transmits its shock to all other variables j, representing the total connectedness index of the network by:

$$C^g_t(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\phi}^g_{ij,t}(J)}{\sum_{i,j=1}^{N} \tilde{\phi}^g_{ij,t}(J)} * 100 \tag{4}$$

$$= \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\phi}^g_{ij,t}(J)}{N} * 100. \tag{5}$$

The spillovers of all variables i to variable j, known as the total directional connectedness to others, is defined as:

$$C^g_{i\to j,t}(J) - \frac{\sum_{j=1, i\neq j}^{N} \tilde{\phi}^g_{ji,t}(J)}{\sum_{j=1}^{N} \tilde{\phi}^g_{ji,t}(J)} * 100 \tag{6}$$

Similarly, the spillovers of all variables j to variable i (or the directional connectedness variable i receives it from variables j), known as the total directional connectedness from others, is defined as:

$$C^g_{i\leftarrow j,t}(J) = \frac{\sum_{j=1, i\neq j}^{N} \tilde{\phi}^g_{ij,t}(J)}{\sum_{j=1}^{N} \tilde{\phi}^g_{ij,t}(J)} * 100 \tag{7}$$

The net total directional connectedness ($C^g_{i,t}$) is calculated using the total directional connectedness ($C^g_{i\to j,t}(J)$) to others minus total directional connectedness from others ($C^g_{i\leftarrow j,t}(J)$).

$$C^g_{i,t} = C^g_{i\to j,t}(J) - C^g_{i\leftarrow j,t}(J) \tag{8}$$

The sign of the net total directional connectedness illustrates whether a variable i is driving the network ($C^g_{i,t} > 0$) or driven by the network ($C^g_{i,t} < 0$). The net pairwise directional connectedness is calculated in the bidirectional relationships:

$$NPDC^g_{i,t} = \frac{\tilde{\phi}^g_{ji,t}(J) - \tilde{\phi}^g_{ij,t}(J)}{N} * 100 \tag{9}$$

The net pairwise volatility spillovers between markets i and j is simply the difference between the gross volatility shocks transmitted from variable i to variable j and those transmitted from variable j to variable i.

4.2. DCC-GARCH t-Copula

Copula functions can be used for modelling correlated random variables. Let X_i be a random variable with a marginal distribution F_i for $i = 1, 2, \dots, n$. As Sklar (1973) shows, each distribution function $F(x_1, \dots, x_n)$ can be represented as its marginal distribution by using a copula such as:

$$F(x_1, \dots, x_n) = C(F_1(x_1), \dots, F_n(x_N)). \tag{10}$$

An n-dimensional copula C determined in $[0,1]^n$ can be written as:

$$C(u_1, \dots, u_N) = F\left(F_1^{-1}(u_1), \dots, F_n^{-1}(u_n)\right), \tag{11}$$

for $\forall u_i \in [0,1], i = 1, \dots, N$. According to Patton (2006), copulas can be based on conditional distributions for estimating a DCC-GARCH t-copula model:

$$c(u_1, \dots, u_N | R_t, \eta) = t_\eta(F^{-1}_{X_1}(u_1|\bullet_1), \dots, F^{-1}_{X_N}(u_N|\bullet_N)) \tag{12}$$

$$= \int_{-\infty}^{F_1^{-1}(u_1)} \cdots \int_{-\infty}^{F_N^{-1}(u_N)} \frac{\Gamma(\frac{\eta+N}{2})}{\Gamma(\frac{\eta}{2})(\eta\pi)^{N/2}|R_t|^{1/2}} \times (1 + \frac{1}{\eta} z_t' R_t^{-1} z_t)^{(\eta+N)/2} dz_1, \dots, dz_N \tag{13}$$

where $F^{-1}_{X_1}(u_1|\bullet_1)$ represents the conditional distribution and $\bullet_1$ represents the estimated parameters of the univariate GARCH model. The DCC model is applied to study the time-varying correlations of asset returns where the time-varying variance–covariance matrix H_t is defined as:

$$H_t = D_t R_t D_t \tag{14}$$

where $D_t = diag(\sqrt{h11,t}, \dots, \sqrt{nn,t})$ is a diagonal matrix of square root conditional variances. R_t is the dynamic conditional correlations based on the standardised residuals' conditional variance–covariances, Q_t, that are followed a GARCH(1,1) model of Engle (2002):

$$Q_t = (1 - a - b)\bar{Q} + a z_{t-1} z'_{t-1} + b Q_{t-1} \tag{15}$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag Q_t^{-1/2} \tag{16}$$

where a and b are positive scalar parameters satisfying $a + b < 1$ to ensure stationarity. The DCC model is estimated under a multivariate Student-t distribution. The multivariate Student-t distribution is applied as the normality assumption of the innovations is rejected for each series. In this paper, the volatility is calculated directly from the covariance matrix obtained from a DCC-GARCH model.

5. Empirical results

In this section we investigate how negative WTI crude oil prices affected US energy, stock and exchange rate markets. Our primary goal is to estimate the significance of dynamic volatility spillovers between WTI and several selected US energy, stock and exchange rate markets, to understand any contagion effects of volatility shocks using the spillover index-based framework of Diebold and Yilmaz (2012), Gamba-Santamaria et al. (2017), Antonakakis et al. (2020). Our research question is of interest, as the volatility transmissions between the US crude oil and energy markets, stock markets, and exchange rate markets can provide unique new insights as to how the first negative WTI price event in US history influenced other traditional financial markets, during a global pandemic caused by COVID-19.

A nine-variable VAR model is initially estimated, including the WTI crude oil futures returns, gasoline futures returns, heating oil futures returns, natural gas futures returns, DJIA stock market returns, NASDAQ 100 stock market returns, S&P 500 stock returns, US Dollar index returns together with the CBOE volatility index. Our results are based on a VAR of order 4 and 10-day-ahead volatility forecast errors as suggested by Diebold and Yilmaz (2012). The WTI crude oil futures prices turned negative for the first time in history on 20 April 2020, where the price fell from \$17.85 per barrel at the beginning of the trading day to negative \$37.63 per barrel at the end of the trading day. 20 April is not only an occasion where we see a negative oil price but it is also the largest one day drop in US crude oil's history. The negative oil price represents a sharply reduced demand due to the pandemic, along with storage scarcity due to large supply increases.

Our empirical analysis will be divided into two parts. We first examine the contagion of volatility effects for our selected variables using high-frequency data in the period inclusive of both one month before, and one month after the negative WTI oil price event of 20 April 2020. A number of robustness checks are also undertaken to investigate the volatility spillovers, utilising the same variables, for a range of time periods.[2]

Our first model focuses on the volatility spillover effects between WTI and our selected financial assets for a two-month period (20 March-20 May 2020) using the 5-minute high frequency data. The plot of dynamic total connectedness and the net directional connectedness index of WTI is presented as Fig. 4, and is indicative of the overall volatility spillover transmissions and receptions for all nine variables considered in the model. As presented in the figure, the dynamic total connectedness is clearly time-varying and it fluctuates between 48 and 55 during the two-month sample period. There has been a significant slowdown in worldwide economic activities since the outbreak of COVID-19 at the beginning of 2020 and the linkages across all US financial markets are high as can be observed during our selected sample period. We can clearly see that there is a sharp increase in overall volatility spillovers during the negative WTI oil prices in April as the total connectedness rises sharply due to the effects of negative oil, indicating that sellers would have to theoretically pay buyers to take the oil off their hands. With many countries in lockdown due to the COVID-19 pandemic, many forecasted that global oil demand would fall sharply as lockdown restrictions reduce the demand of oil worldwide. Within these conditions, the dynamic net directional connectedness index of WTI is calculated as the volatility shocks transmitted from WTI to other financial assets minus the volatility shocks received by WTI from all other assets. As can be observed in Fig. 4, the net directional connectedness exhibits signs of time-variation. A negative (positive) value in the plot at a specific time indicates a net volatility receiver (transmitter) role at that time. The dynamic net directional connectedness of WTI is negative during most of the sample period except when the WTI oil price dropped below zero. In general, the dynamic net directional connectedness plot shows that volatility spillovers from all other financial assets to WTI play a dominant role most of the time as the WTI crude oil is a volatility receiver during the sample period. However, it should be noted that WTI crude oil is a volatility transmitter during the negative crude oil price period in April 2020, as we can see a substantial positive increase in the net directional connectedness index of WTI when the WTI crude oil prices fall below zero. This result is of particular interest, as it presents evidence that volatility spillovers originate from WTI and transfer to other financial assets during the short negative crude oil price period.

The dynamic net pairwise directional connectedness between WTI and other financial markets is shown in Fig. 5, where the estimates of pairwise connectedness index is labelled on the y-axis for each pair and the estimate of pairwise connectedness simply measures the intensity of volatility spillovers. In addition, the summary statistics of dynamic pairwise directional connectedness estimates between WTI and each market is provided in Table 2, where mean, median, minimum, maximum and standard deviation of the pairwise directional connectedness estimates are reported. In general, as illustrated by Fig. 5, the pairwise connectedness indexes are negative in most cases. This result is also reflected in Table 2 as the mean and median estimate of pairwise directional connectedness for each pair are all negative. However, there is a large variation between minimum and maximum estimate for the pairwise directional connectedness index. A negative pairwise connectedness index means that volatility shocks from the other market to WTI were larger than in the opposite direction. Therefore, a negative pairwise connectedness index implies that the other tested traditional markets influence WTI oil price directly through volatility spillovers. Similarly, a positive pairwise connectedness index would indicate that a volatility shock transmitted from WTI to the other market was larger than in the opposite direction. Hence, a positive pairwise connectedness index implies that the WTI oil price influences an index or asset price more than vice-versa.

A general finding from Fig. 5 suggests that, when focusing on a short negative oil price period for each pair, the negative WTI oil affects US energy, stock and exchange rate markets. Furthermore, we can see a change of net volatility transmission direction. Both prior to, and after the negative WTI oil price event, the net pairwise connectedness indices are generally negative while the net pairwise connectedness indexes become positive when oil price becomes negative. As can be seen, the intensity of volatility transmissions from WTI towards the other financial markets are quite different for each pair. We first explore how the negative WTI crude oil affects three US stock markets.

The dynamic volatility spillovers between WTI and DJIA, S&P 500 and NASDAQ 100 show that the corresponding pairwise connectedness indexes are negative for most of the sample except during a short period of negative oil prices, indicating that the volatility spillovers transmitted by each stock market to WTI are larger under most circumstances. For all three US stock markets, the magnitude of volatility spillovers towards the WTI market reach a peak at the end of March or early April as the corresponding pairwise directional connectedness index reach a local minimum. For example, we can see that the NASDAQ 100 market has the largest magnitude of volatility spillovers to the WTI market at the end of March compared to the other two stock markets. At that time, the estimate of pairwise directional connectedness for WTI-NASDAQ 100 is −1.30229, which is also the minimum estimate of the pairwise connectedness index for this pair. Shortly after the peak volatility transmission, the magnitude of net pairwise directional connectedness index between WTI and each stock market generally fall smaller especially for the NASDAQ 100 and S&P 500 markets.

It is particularly interesting that the volatility spillovers transmitted from WTI to each stock market are substantially larger that the absolute value in the opposite direction during the negative WTI oil event on 20 April, presenting evidence of the effects of negative oil prices on all three stock markets. The volatility spillovers transmitted by WTI to each stock market are much larger than the those received by WTI from US stock markets, indicating that the historic drop of US crude oil futures prices quickly sent massive shock waves to the US stock market. As a result, the Dow Jones fell by over 1200 points in the following two trading days, while the S&P 500 fell 1.79%. If we compare the net pairwise directional connectedness index on the y-axis for each stock market pair, the WTI market presents evidence of the stronger volatility transmissions to the NASDAQ 100 market compared to the DJIA and S&P 500 markets. From Table 2, the maximum estimate of the pairwise directional connectedness is 0.927 for the NASDAQ 100, 0.638 for S&P 500 and 0.407 for DJIA. Turning to the CBOE volatility index, the (VIX) also jumps to 43.83 at the end of 20 April from 38.15 of the previous day. This is further evidence of the significant volatility spillovers from WTI to the VIX index during the negative oil price period. This result is very interesting as it shows that uncertainty in the crude oil market also had an impact on the VIX index, a common measure of the volatility of the S&P 500 market.

Plots of dynamic net pairwise directional connectedness between WTI and three key US energy futures markets (gasoline, heating oil and natural gas) are presented as Fig. 5. For all three energy futures markets, the volatility spillovers from WTI to each energy futures market is generally smaller than those transmitted by each of the three energy futures markets to WTI except when the WTI crude oil turned negative. We can clearly see that the pairwise directional connectedness indexes are negative most of the time, suggesting that energy futures market influence WTI market more than vice-versa. This finding is further confirmed by Table 2, as the corresponding mean and median estimate of pairwise directional connectedness are negative.

For the WTI-gasoline pair, the volatility spillovers from the gasoline market to WTI are larger than in the opposite direction. However, the magnitude of volatility spillovers are generally trending slightly smaller. The net pairwise directional connectedness changes direction

[2] For brevity, only the two week period both before and after the identified date are presented, however, further results are available from the authors on request.

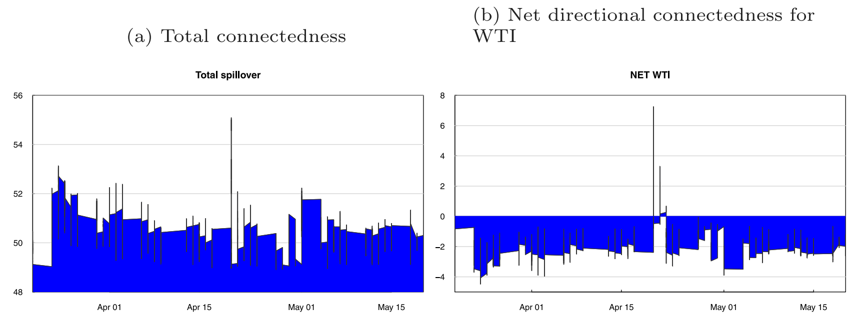

Fig. 4. Dynamic total connectedness index for all financial assets and net connectedness index for WTI between 20 March 2020 and 20 May 2020. Note: Our 5-minute sample data runs from 20 March 2020 throughout 20 May 2020, representing 3084 observations. Further analysis and methodological variants were estimated by the authors.

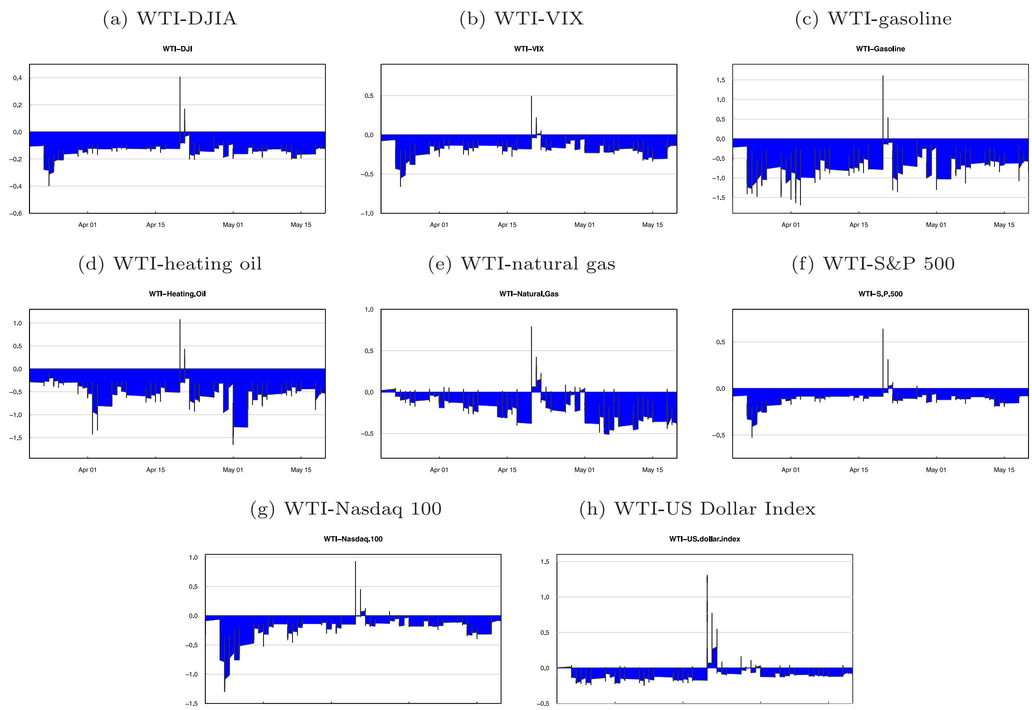

Fig. 5. Dynamic estimates for pairwise directional connectedness between the WTI and financial assets between 20 March 2020 and 20 May 2020. Note: Our 5-minute sample data runs from 20 March 2020 throughout 20 May 2020, representing 3084 observations. Further analysis and methodological variants were estimated by the authors.

for the negative WTI crude oil event on 20 April as the net pairwise directional connectedness index becomes positive in Fig. 5. We can conclude that the volatility spillovers transmitted by WTI to the gasoline market are much larger during the negative WTI crude oil prices. This result demonstrates that the negative oil prices had a very strong influence on the gasoline market. In fact, WTI generates the largest volatility spillovers to the gasoline market of any other market we consider as the WTI-gasoline pair has a maximum connectedness estimate of 1.60648. Apart from the negative WTI oil period, there are generally constant volatility spillovers from the market for gasoline through to WTI. Volatility transmissions mainly spillover from the heating oil market to WTI direction as can be seen in Fig. 5. The magnitude of volatility spillovers increase in size over the time period analysed with some sudden shifts in volatility spillover intensity. The first peak of volatility spillovers to the WTI market took place in early April and the second peak in early May. Between these two spikes in terms of volatility transmissions, the direction of volatility spillovers changed substantially during the negative oil prices, where the pairwise directional connectedness index shows a sharp positive increase. More importantly, we find that the net pairwise directional connectedness index for the WTI-heating oil pair is positive for the negative WTI oil event. For the WTI-natural gas pair, the volatility spillover from the natural gas market to WTI is also below zero throughout most of the sample period investigated, however, during the negative WTI prices, volatility shocks transmitted by WTI to the natural gas market dominate as we observe a positive spike in net pairwise directional connectedness index.

To summarise the key results for three energy futures markets, we find evidence of volatility spillovers from the WTI to each energy futures market during the negative WTI event on 20 April. Hence, the WTI influences these three energy futures markets more than the opposite direction at that time period. Moreover, we also find that the magnitude of volatility spillovers from the WTI market to the gasoline futures is largest during the negative oil price period followed by heating oil and natural gas futures. This is clearly shown in Table 2, where the corresponding maximum pairwise directional connectedness estimate are 1.60648 for gasoline, 1.07724 for heating oil and 0.79166 for natural gas.

The volatility spillovers from the US Dollar index to WTI are larger than in the opposite direction as the net pairwise directional connectedness index is negative, however, net pairwise directional connectedness index is positive when the WTI oil price turned negative, indicating

Table 2
Summary statistics of dynamic pairwise directional connectedness estimates between WTI price and financial assets based on 5-minute return data for the period 20 March 2020–20 May 2020.

WTI relationship with	Mean	Median	Min	Max	Std. Dev.
DJIA	−0.13514	−0.12842	−0.39784	0.40669	0.05591
VIX	−0.16988	−0.16222	−0.65995	0.49213	0.10482
Gasoline	−0.64293	−0.63677	−1.69138	1.60648	0.32910
Heating Oil	−0.47737	−0.45089	−1.65079	1.07724	0.23570
Natural gas	−0.14403	−0.12828	−0.51017	0.79166	0.14866
S&P 500	−0.11314	−0.10034	−0.52485	0.63761	0.08164
NASDAQ 100	−0.20431	−0.14435	−1.30229	0.92684	0.21343
US Dollar index	−0.07098	−0.08587	−0.25154	1.30681	0.11426

Note: Our sample data runs from 20 March 2020 throughout 20 May 2020, representing 3084 observations. The WTI oil prices dropped below zero on 20 April 2020.

Table 3
Summary statistics of dynamic pairwise directional connectedness estimates between WTI price and financial assets based on 5-minute return data for the period 06 April 2020–04 May 2020.

WTI relationship with	Mean	Median	Min	Max	Std. Dev.
DJIA	−0.33213	−0.34952	−0.72153	0.41789	0.17859
VIX	−0.51327	−0.54587	−1.19512	0.57881	0.34506
Gasoline	−0.97835	−1.02374	−2.43427	1.71048	0.56961
Heating Oil	−0.31759	−0.30765	−1.35506	1.14105	0.26489
Natural gas	−0.14509	−0.13357	−0.47257	0.73893	0.14115
S&P 500	−0.30107	−0.30812	−0.69010	0.51582	0.18066
NASDAQ 100	−0.57716	−0.59841	−1.41721	0.60923	0.39681
US dollar index	−0.40422	−0.43426	−1.00372	1.10473	0.31289

Note: Our sample data runs from 06 April 2020 throughout 04 May 2020, representing 1433 observations. The WTI oil prices dropped below zero on 20 April 2020.

that volatility spillovers transmitted by WTI to the exchange rate market exceed the opposite spillovers effects. Moreover, the intensity of volatility spillovers from WTI to the US Dollar index is larger than for most other asset pairs with a maximum of 1.3068, which is the second largest spillovers. Negative oil pricing is found to have had a significant impact on the US exchange rate market.

Finally, we complete a number of robustness checks using a variety of additional sample sizes. We present evidence of a shorter sample period between 06 April 2020 and 04 May 2020, consisting of 1433 observations at 5-minute frequency. This allows us to test for similar volatility spillovers between WTI and US financial markets. The dynamic total connectedness index and net directional connectedness index of WTI is provided in Fig. 6. The dynamic net pairwise directional connectedness index for each pair is presented in Fig. 7 together with summary statistics of pairwise directional connectedness in Table 3. Both Figs. 6 and 7 confirm that the results based on a short sample period are generally consistent with the conclusion we draw earlier. In Table 3, we identify the average spillover relationships for this short time-period of analysis. When comparing such results with the maximum values, each of which are identified specifically in the period in which negative WTI prices occurred, we further verify that heating oil and natural gas markets present the closest volatility relationship with WTI (−0.31 and −0.14 respectively, before increasing to +1.14 and +0.73 during negative WTI), while the market for gasoline is found to present the largest breadth of volatility spillovers with WTI (ranging between a minimum of −2.43 and maximum of +1.71 respectively). In each sample size, both substantial and significant short-term volatility spillovers are sourced within the negative WTI pricing event are identified.

Such results should be of interest to policy-makers and market participants alike. While broad confusion surrounded the severity and international breadth of the COVID-19 pandemic, as previously identified, traditional financial markets had somewhat failed to uniformly quantify the inherent risks. A number of distinct reasons can be offered, consisting of broad geopolitical risk within the quite unusual verbal jousting between international oil-supplying superpowers, the inherent side-effects associated with unprecedented quantities of global quantitative easing, close-to-zero interest rate policy implementation, and lack of uniform international response to the COVID-19 pandemic. While research suggests that Chinese-related COVID-19 cases can be identified as far back as November 2019, evidence suggests that there were no prior related media announcements before 17 November 2019. Such timing pre-dates the official WHO announcement of a global pandemic in early January 2020, and the imposition of strict, official Chinese government lock-downs in mid-January 2020. However, it is not until 9 March 2020 that lock-downs are implemented in Italy and Saudi Arabia, while in the following seven days, lock-downs are imposed in Ireland, Qatar, Bulgaria, Poland, Spain, Serbia and the Philippines. It is not until the 18 & 19 March 2020 that government lock-downs are imposed in Canada (British Columbia) and the United States (California and Nevada). Government agencies during this period attempted to make decisions surrounding freedom of movement and risk of infection, and financial markets appeared to have incorporated much of the valuation of associated risks associated with a 'black-swan' event such as COVID-19. However, the once-in-a-generation' event where WTI prices turned negative appears to have created a reality check on the true global-scale of the problems associated with the spread of the pandemic.

6. Conclusion

This paper applies a TVP-VAR model to explore dynamic connectedness between the WTI and US energy, stock and exchange rate markets for the effects of the first occurrence of negative WTI crude oil prices in history, which coincided with the COVID-19 pandemic. Using 5-minute high frequency data, our research provide insights into what is happening in various futures markets during time periods surrounding the WTI supply shocks that occurred on 20 April 2020 which led to the unprecedented development of negative WTI prices. During periods of immense financial market stress and chaos, such as that of the 2008 international financial crisis, the market for WTI has acted as a short-term investment safe-haven. However, during the onset of the COVID-19 pandemic, combined with substantial uncertainty surrounding non-uniform government responses to the pandemic, the variety of regional difficulties directly attributed to the pandemic, widespread expectations of global economic slowdown, and the effects of political influence from both OPEC and OPEC plus, the events of April 2020 have not only rendered those seeking financial shelter to be suspicious as to

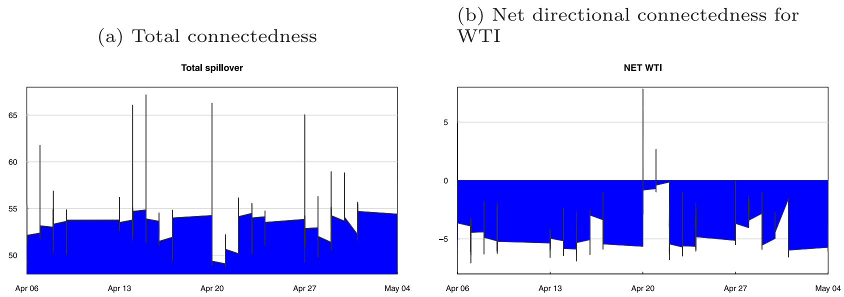

Fig. 6. Dynamic total connectedness index for all financial assets and net connectedness index for WTI between 06 April 2020 and 04 May 2020. Note: Our 5-minute sample data runs from 06 April 2020 and 04 May 2020, representing 1433 observations. Further analysis and methodological variants were estimated by the authors.

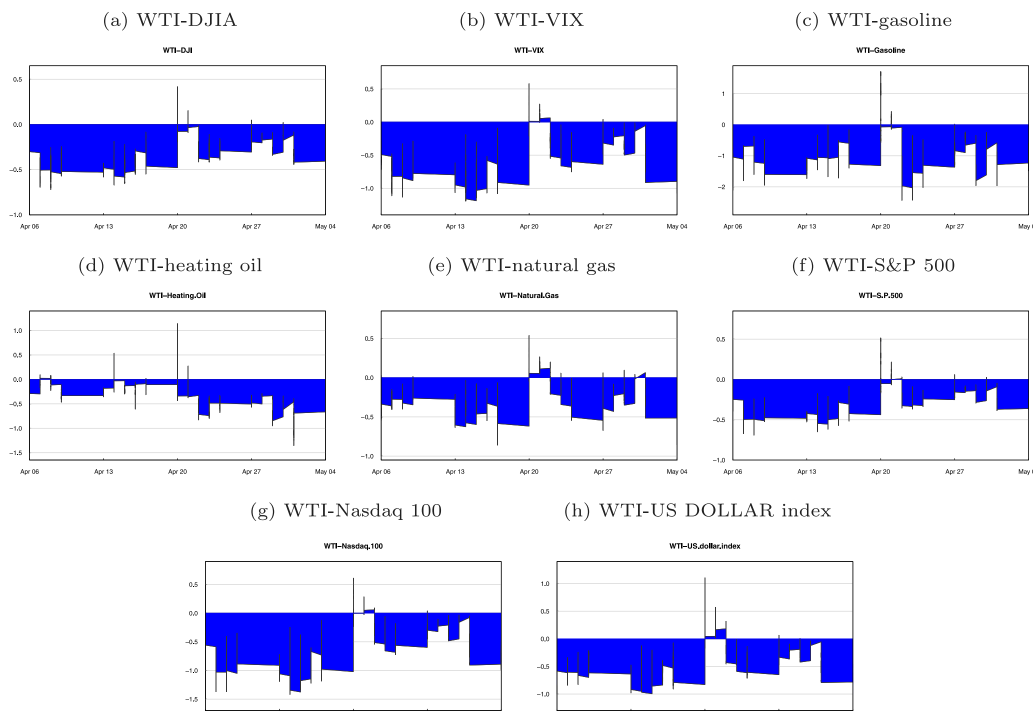

Fig. 7. Dynamic estimates for pairwise directional connectedness between the WTI and financial assets between 06 April 2020 and 04 May 2020. Note: Our 5-minute sample data runs from 06 April 2020 and 04 May 2020, representing 1433 observations. Further analysis and methodological variants were estimated by the authors.

the potential future safe-have properties of WTI, but also the potential spillover effects sourced within such markets during immense financial stress.

A number of distinct results are identified. First, WTI is found to be a volatility receiver from all of the analysed markets during most periods, however, it rapidly becomes a volatility transmitter in the period surrounding negative WTI pricing. This suggests that when considering the inherent uncertainty that occurred as the COVID-19 pandemic developed, the abnormality of structural changes in the market for near-contract WTI futures generated such market panic that it translated into significant volatility spillovers across a range of traditional financial market products. Among all financial markets considered, the magnitude of volatility spillovers from the WTI market to US energy futures and US exchange rate markets are found to be largest while the volatility shocks to the stock markets are found to be smaller, however, the direction of the spillover of shocks remains consistent throughout all analysed assets. Significant spillovers sourced from WTI upon the VIX shows that forward looking implied volatility increased as signals of this rare event of negative prices presented further evidence as to how confused the valuation process of short- and medium-term risk had become. This result coincides with significant volatility spillovers from WTI upon stock markets in the form of the Dow Jones Industrial Average, the NASDAQ 100 and the S&P500.

Policy-makers, regulators and market participants should proceed with particular caution during future episodes of significant financial crises, particularly those possessing the inherent risk of global economic slowdown. While the price of oil breached $100 per barrel during the international financial crisis of 2008, it broadened the range of investor expectations due to the use of the asset as a safe-haven investment while stock market investors re-calibrated their estimation of bank valuations. The very fact that oil prices have achieved negative valuation during the global pandemic of 2020 has generated uncertainty as to a possible recurrence of negative oil which may have damaged the potential for WTI to be considered as a safe-haven asset during future economics shocks.

CRediT authorship contribution statement

Shaen Corbet: Conceptualisation, Visualisation, Writing – review & editing, Data curation, Investigation. **Yang (Greg) Hou:** Conceptualisation, Visualisation, Writing – original draft, Writing – review & editing, Data curation, Methodology, Formal analysis. **Yang Hu:** Conceptualisation, Visualisation, Writing – review & editing, Data curation, Methodology, Formal analysis. **Les Oxley:** Conceptualisation, Writing – review & editing, Data curation, Investigation.

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