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Dynamic connectedness among the implied volatilities of oil prices and financial assets: New evidence of the COVID-19 pandemic☆

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A B S T R A C T

This paper examines the dynamic connectedness among the implied volatilities of oil prices (OVX) and fourteen other assets, which can be grouped into five different assets classes (i.e., energy commodities, stock markets, precious metals, exchange rates and bond markets). To do so we estimate a recently developed time-varying parameter vector autoregressive (TVP-VAR) connectedness approach using daily data spanning from March 16th, 2011 to March 3rd, 2021 — covering the first year of the COVID-19 pandemic. The empirical results suggest that connectedness across the different asset classes and oil price implied volatilities are varying over time and fluctuate at very high levels. The dynamic total connectedness ranges between 65% and 85% indicating a high degree of cross-market risk linkages. Furthermore, we find that the oil market is becoming more integrated with the financial markets, since it tends to be materially impacted by abrupt fluctuations of the global financial markets' volatilities. More specifically, the analysis shows that, throughout the period, OVX is a net receiver of shocks to the remaining implied volatilities. Finally, the net pairwise connectedness measures suggest that OVX is constantly at the net receiving end vis-a-vis the majority of the asset classes' implied volatilities. Those findings are of major importance for portfolio and risk management in terms of asset allocation and diversification.

1. Introduction

In the last two decades, financialization of crude oil has played an increasingly important role in the global economy. The rapid growth of financialization of crude oil has a significant impact on commodities and financial markets explaining the synchronized price boom and bust of a broad set of seemingly unrelated commodities (Tang & Xiong, 2012). In addition, the time-varying

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relationship between the crude oil and stock markets, as well as, their spillover effects, have been studied by the related economic and finance literature.[1]

For instance, Arouri et al. (2012) analyze the volatility transmission between oil and sectoral stock market in Europe and the US. Their results show significant volatility spillovers between oil and sectoral stock returns. Sadorsky (2012), on the other hand, focuses on the volatility spillovers between oil and the US stock prices of clean energy and technology companies. His findings confirm that stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices. In a related study, Phan et al. (2016) provide evidence of volatility spillover effects between the US stock market and oil prices. More recently, Antonakakis, et al. (2018) investigate volatility spillovers and co-movements among oil and stock prices of major oil and gas corporations, showing the existence of significant volatility spillover effects among oil and gas companies' stock volatility. Malik and Umar (2019) examine dynamic connectedness among oil price shocks and exchange rates, demonstrating that the former cannot transmit spillover effects to the exchange rates volatilities. Finally, Liu et al. (2020) document bi-direction spillover effects between implied volatility of oil prices and the US stock market.[2]

Despite the vast literature on potential spillover effects, that the oil market transmits to or receives from the financial markets, the main focus is on the oil-stock market nexus, with very few exceptions, ignoring the potential spillover effects among other asset classes (such as commodities, bonds, etc.). Even more, the majority of the studies focus on the spillover effects of market returns rather than volatilities and those that study volatility spillover effects, do not consider implied volatility indices, with the exception of Antonakakis et al. (2017) and Liu et al. (2020).

Yet, even these studies confine their interest in the oil-stock market relationship. Focusing on the interrelationship among implied volatilities is important for at least three reasons. First, implied volatilities are forward looking measures of uncertainty and thus have the ability to gauge investors' fear. Second, the implied volatility is a key determinant for option pricing. Third, the information content of implied volatility is used by financial investors for volatility trading. Thus, the linkages among the anticipated uncertainty of the different asset markets provides better understanding (i) for the future path of the underlying asset prices (this is of great importance for financial analysts, as well as, diversification strategies), (ii) for accurate option pricing, as well as, (iii) profitable trading strategies.

This paper fills all aforementioned voids by examining the dynamic connectedness among the crude oil price implied volatility and fourteen asset price implied volatilities[3] using a time-varying parameter VAR variant of the connectedness approach (Diebold & Yılmaz, 2012). In particular, we employ the time-varying parameter vector autoregressive (TVP-VAR) connectedness approach of Antonakakis, Chatziantoniou, and Gabauer (2020) to estimate spillover effects among the implied volatilities of the aforementioned asset classes, with the following benefits: (i) no arbitrarily chosen rolling-window size, (ii) no loss of observations, (iii) less outlier sensitive than the standard rolling-window VAR approach, and (iv) less volatile or flattened out parameters. Even more, the importance of using implied volatility indices from oil prices and fourteen other assets, which can be clustered in five asset classes (i.e. stock markets, exchange rates, energy commodities, precious metals and bonds), stems from the fact that these markets have become closer interrelated in recent years (see, Degiannakis & Filis, 2017; Phan et al., 2016; Souček & Todorova, 2014; Yang & Zhou, 2017). Hence, studying the dynamic connectedness among all these assets' implied volatilities can provide additional insights in the propagation mechanism of cross-market volatility shocks. We should mention here that we pay particular attention on the COVID-19 period, given the fact that this pandemic is one of the most important sources of uncertainty, at least over the last decades, for all asset markets.

Our findings show that the network connectedness, and hence cross-market risk transmission, steadily declines from the beginning of the sample until mid-2015 reaching its lowest point. Subsequently, we observe a rapid increase in connectedness which lasts until 2017 and coincides with several important political and economic events of that period (e.g. include the resurgence of the Middle-East unrest in 2015, the Chinese stock market crash in mid-2015, the Turkish coup d'état attempt in 2016, the Brexit vote in 2016 and the Iranian sanctions in 2017, to name a few). From 2017 until the spring of 2020 the cross-market volatility connectedness still fluctuates at high levels, yet at a relatively stable pattern until it has skyrocketed to its highest peak caused by the COVID-19 pandemic. This effect could be assigned to the event that the WTI crude oil price has closed at a negative price in April 2020, -$37.63/bb, which has never happened before. Afterwards, the market risk has decreased until the end of the sample although hovering at a high level. Moreover, the findings indicate that the OVX is at the net receiving end of spillover shocks throughout the period of analysis, whereas the main net transmitters of shocks are RVX, VIX, VXD, VXEEM, VXN and VXXLE. Analyzing the bidirectional spillovers with respect to OVX, revealed that OVX partially dominates GVZ, EVZ, VXSLV and VXTYN. By contrast, OVX is at the net receiving end with respect to all other implied volatilities, throughout the sample period. Overall, these results

[1] Some recent studies on the time-varying relationship and spillover effects among oil and financial markets see Antonakakis, Chatziantoniou, and Filis (2017), Antonakakis, Cunado, Filis, Gabauer, and De Gracia (2018), Arouri, Jouini, and Nguyen (2012), Balcilar, Gabauer, and Umar (2021), Broadstock and Filis (2014), Degiannakis, Filis, and Kizys (2014), Kang, McIver, and Yoon (2017), Khalfaoui, Boutahar, and Boubaker (2015), Liu, Tseng, Wu, and Ding (2020), Maghyereh, Awartani, and Tziogkidis (2017), Malik and Umar (2019), Phan, Sharma, and Narayan (2016) and Sadorsky (2012) among others.

[2] For additional recent references on volatility spillover in commodity markets see, for example, Dahl and Jonsson (2018) and Dahl, Oglend, and Yahya (2019).

[3] The selected series of implied volatility indices are defined in Section 3.1. OVX = CBOE crude oil ETF volatility index, GVZ = Gold ETF volatility index, EVZ = Euro/dollar currency volatility index, RVX = Russell 2000 volatility index, VIX = S&P 500 volatility index, VXD = CBOE DJIA Volatility Index, VXEEM = Emerging Markets ETF volatility index, VXEFA = EFA (Europe, Australia, Asia and the Far East) ETF volatility index, VXEWZ = Brazil ETF volatility index, VXFXI = China ETF volatility index, VXSLV = Silver ETF volatility index, VXN = NASDAQ100 volatility index, VXXLE = CBOE Energy Sector ETF volatility index, VXTYN = CBOE 10-Year Treasury Note volatility index, VXGS = CBOE Equity VIX on Goldman Sachs volatility index.

demonstrate the increased cross-market volatility linkages, which further suggests that the oil market has become more financialized and thus, it is impacted by different asset markets. Such findings have important implications for risk and portfolio managers.

The remainder of the paper is structured as follows. Section 2 discusses the employed methodology while the dataset and empirical results are presented in Section 3. Finally, Section 4 concludes the study.

2. TVP-VAR based connectedness approach

As previously mentioned, we are employing the recently developed TVP-VAR connectedness approach of Antonakakis et al. (2020) to examine the transmission mechanism across fifteen implied volatilities in a time-varying fashion. It should be noted that, the TVP-VAR connectedness approach extends the originally proposed connectedness approach of Diebold and Yılmaz (2012) by allowing the variance–covariance matrix to vary via a Kalman filter estimation with forgetting factors in the spirit of Koop and Korobilis (2014). By doing so, our methodology (i) overcomes the burden of the often arbitrarily chosen rolling-window size, that could lead to very volatile or flattened parameters, and (ii) avoids the loss of valuable observations. According to the Bayesian Information Criterion (BIC), a TVP-VAR model with a lag length of order one is estimated:

$$\boldsymbol{x}_t = \boldsymbol{\Phi}_t \boldsymbol{x}_{t-1} + \epsilon_t \qquad \epsilon_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{1}$$

$$vec(\boldsymbol{\Phi}_t) = vec(\boldsymbol{\Phi}_{t-1}) + \xi_t \qquad \xi_t \sim N(\boldsymbol{0}, \boldsymbol{\Xi}_t) \tag{2}$$

where $\boldsymbol{x}_t$, ϵ_t and ξ_t are $N \times 1$ vectors and $\boldsymbol{S}_t$, $\boldsymbol{\Phi}_t$ and $\boldsymbol{\Xi}_t$ are $N \times N$ dimensional matrices. The time-varying parameters of the vector moving average model (TVP-VMA) is the fundament of the connectedness approach (Diebold & Yılmaz, 2012) as the generalized forecast error variance decompositions (GFEVD), $\tilde{\phi}^g_{ijt}(J)$, of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) are utilizing. Hence, we are following the Wold representation theorem to obtain a TVP-VMA model: $\boldsymbol{x}_t = \sum_{i=1}^{p} \boldsymbol{\Phi}_{it} \boldsymbol{x}_{t-i} + \epsilon_t = \sum_{j=1}^{\infty} \boldsymbol{A}_{jt} \epsilon_{t-j} + \epsilon_t$. The GFEVD can be interpreted as the forecast error variance share variable i explains on variable j. Mathematically, it can be written as follows,

$$\phi^g_{ij,t}(J) = \frac{\boldsymbol{S}^{-1}_{ii,t} \sum_{t=1}^{J-1} (\boldsymbol{\iota}'_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{\iota}_j)^2}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} (\boldsymbol{\iota}_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{A}'_t \boldsymbol{\iota}_i)} \qquad \tilde{\phi}^g_{ij,t}(J) = \frac{\phi^g_{ij,t}(J)}{\sum_{j=1}^{N} \phi^g_{ij,t}(J)} \tag{3}$$

where $\boldsymbol{\iota}_i$ is a zero vector with unity on the i position, $\sum_{j=1}^{N} \tilde{\phi}^N_{ijt}(J) = 1$ and $\sum_{i,j=1}^{N} \tilde{\phi}^N_{ijt}(J) = N$. Based on the GFEVD, we construct the corrected total connectedness index (TCI) of Chatziantoniou and Gabauer (2021) and Gabauer (2021) representing the interconnectedness of the network:

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

Intuitively, it can be explained as the average (off-diagonal) spillover from all other assets to one asset — not taking under consideration the effect an asset has on itself through its lags. High $C^g_t(J)$ values are associated with high market risk and vice versa.

First, we are interested in the impact a shock in variable i has on all others j (*total directional connectedness to others*):

$$C^g_{i \to jt}(J) = \sum_{j=1, i \neq j}^{N} \tilde{\phi}^g_{jit}(J) \tag{5}$$

Second, we compute the impact a shock in all variables j has on variable i (*total directional connectedness from others*):

$$C^g_{i \leftarrow jt}(J) = \sum_{j=1, i \neq j}^{N} \tilde{\phi}^g_{ijt}(J) \tag{6}$$

Third, we calculate the differences between the *total directional connectedness to others* and *total directional connectedness from* others to obtain the *net total directional connectedness*:

$$C^g_{it} = C^g_{i \to jt}(J) - C^g_{i \leftarrow jt}(J) \tag{7}$$

The *net total directional connectedness* illustrates whether variable i is driving the network ($C^g_{it} > 0$) or is driven by the network ($C^g_{it} < 0$).

Finally, we break down the *net total directional connectedness* to examine the bidirectional relationships by computing the *net pairwise directional connectedness*:

$$NPDC_{ij}(J) = \tilde{\phi}_{jit}(J) - \tilde{\phi}_{ijt}(J) \tag{8}$$

If $NPDC_{ij}(J) > 0$ ($NPDC_{ij}(J) < 0$) variable i is influencing (influenced by) variable j more (less) than variable j influences variable i.

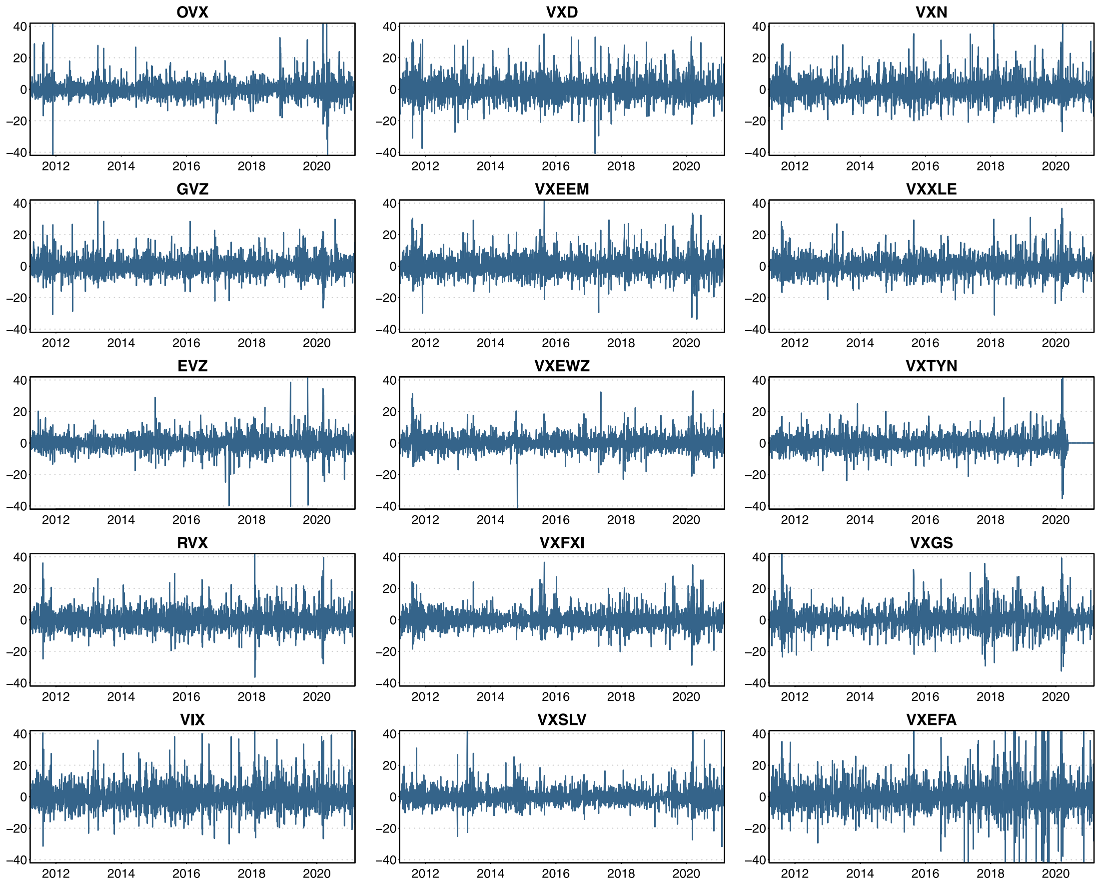

Fig. 1. Implied volatility returns.
Notes: OVX = CBOE crude oil ETF volatility index, GVZ = Gold ETF volatility index, EVZ = Euro/dollar currency volatility index, RVX = Russell 2000 volatility index, VIX = S&P 500 volatility index, VXD = CBOE DJIA Volatility Index, VXEEM = Emerging Markets ETF volatility index, VXEFA = EFA (Europe, Australia, Asia and the Far East) ETF volatility index, VXEWZ = Brazil ETF volatility index, VXFXI = China ETF volatility index, VXSLV = Silver ETF volatility index, VXN = NASDAQ-100 volatility index, VXXLE = CBOE Energy Sector ETF volatility index, VXTYN = CBOE 10-Year Treasury Note volatility index, VXGS = CBOE Equity VIX on Goldman Sachs volatility index.

3. Dataset and empirical results

3.1. Data description

In the present study, we consider the implied volatility of the crude oil prices and fourteen other implied volatility indices, which are clustered into five different assets classes (i.e. stock markets, precious metals, energy commodities, exchange rates and bonds). In particular, we consider the CBOE crude oil ETF volatility index (OVX) as our main variable of interest. From the stock markets asset class, we consider the implied volatility indices of Russell 2000 (RVX), S&P 500 (VIX), Dow Jones Industrial Average (VXD), NASDAQ-100 (VXN), EFA (Europe, Australia, Asia and the Far East) ETF (VXEFA), Emerging Markets ETF (VXEEM), Brazil ETF (VXEWZ), China ETF (VXFXI) and CBOE Equity VIX on Goldman Sachs (VXGS). From the exchange rates, we use the Euro/dollar currency volatility index (EVZ), whereas for the precious metals we use the Gold ETF volatility index (GVZ) and Silver ETF volatility index (VXSLV). Finally, we include the CBOE 10-Year Treasury Note implied volatility (VXTYN) as a proxy of the bond market and the CBOE Energy Sector ETF volatility index (VXXLE) representing the energy commodity asset class. All series are retrieved from the Federal Reserve Economic Data (FRED) and the CBOE website. The sample period ranges from March 16th, 2011 until March 3rd, 2021. The choice of the selected series and data period is purely dictated by the data availability.

As all implied volatility indices are non-stationary according to the ERS unit-root test (Elliott, Rothenberg, & Stock, 1996), we use implied volatility returns by calculating the first log-differences. The returns are shown in Fig. 1.

Table 1 presents the summary statistics of the implied volatility returns. According to Table 1 all returns are significantly right skewed, leptokurtic distributed and thus non-normally distributed according to the Jarque and Bera (1980) normality test. Furthermore, all series are significantly stationary on the 1% significance level (Elliott et al., 1996).

Table 1
Descriptive statistics.

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque–Bera	ERS	Obs.
OVX	−0.003	−0.380	85.770	−62.225	5.839	1.779 ***	35.650 ***	112680.7 ***	−23.539 ***	2507
GVZ	0.004	−0.426	48.073	−30.692	5.567	0.837 ***	8.612 ***	3582.4 ***	−13.337 ***	2507
EVZ	−0.026	−0.135	49.644	−40.175	5.163	0.246 ***	14.484 ***	13801.9 ***	−21.896 ***	2507
RVX	0.003	−0.311	54.045	−36.428	6.220	0.898 ***	8.748 ***	3788.3 ***	−7.214 ***	2507
VIX	−0.004	−0.621	76.825	−31.414	7.994	1.227 ***	9.915 ***	5624.9 ***	−6.483 ***	2507
VXD	−0.005	−0.448	35.114	−40.810	7.107	0.641 ***	6.671 ***	1579.6 ***	−6.091 ***	2507
VXEEM	−0.007	−0.570	50.486	−33.696	6.519	0.823 ***	7.634 ***	2526.7 ***	−7.161 ***	2507
VXEWZ	0.019	−0.284	33.084	−61.958	5.200	0.147 ***	15.063 ***	15209.0 ***	−10.789 ***	2507
VXFXI	−0.009	−0.422	36.577	−28.785	5.548	0.889 ***	7.461 ***	2409.0 ***	−4.220 ***	2507
VXSLV	−0.002	−0.257	56.610	−31.700	5.340	1.714 ***	16.677 ***	20767.8 ***	−15.217 ***	2507
VXN	0.004	−0.575	46.891	−26.884	6.833	0.932 ***	7.050 ***	2076.5 ***	−7.684 ***	2507
VXXLE	0.010	−0.401	36.621	−31.032	5.857	0.742 ***	6.529 ***	1530.9 ***	−6.075 ***	2507
VXTYN	−0.026	0.000	47.404	−35.353	5.007	0.653 ***	12.975 ***	10571.6 ***	−12.008 ***	2507
VXGS	0.004	−0.331	44.377	−32.508	6.549	0.676 ***	7.803 ***	2600.0 ***	−4.981 ***	2507
VXEFA	−0.025	−0.382	89.676	−102.744	10.461	0.179 ***	17.627 ***	22363.0 ***	−5.106 ***	2507

Notes: JB = Jarque and Bera (1980) test, ERS = Elliott et al. (1996) Augmented Dickey–Fuller with generalized least squares (ADF-GLS), LB(20) = Ljung–Box test for autocorrelation, LiMak(20) = Fisher and Gallagher (2012) test for ARCH effects. OVX = CBOE crude oil ETF volatility index, GVZ = Gold ETF volatility index, EVZ = Euro/dollar currency volatility index, RVX = Russell 2000 volatility index, VIX = S&P 500 volatility index, VXD = CBOE DJIA Volatility Index, VXEEM = Emerging Markets ETF volatility index, VXEFA = EFA (Europe, Australia, Asia and the Far East) ETF volatility index, VXEWZ = Brazil ETF volatility index, VXFXI = China ETF volatility index, VXSLV = Silver ETF volatility index, VXN = NASDAQ-100 volatility index, VXXLE = CBOE Energy Sector ETF volatility index, VXTYN = CBOE 10-Year Treasury Note volatility index, VXGS = CBOE Equity VIX on Goldman Sachs volatility index.

Table 2
TVP-VAR: Averaged dynamic connectedness table.

	OVX	GVZ	EVZ	RVX	VIX	VXD	VXEEM	VXEWZ	VXFXI	VXSLV	VXN	VXXLE	VXTYN	VXGS	VXEFA	FROM
OVX	32.9	3.1	2.0	5.5	5.6	4.9	6.8	5.0	5.1	3.4	5.4	9.6	2.5	3.9	4.3	67.1
GVZ	2.9	28.9	4.7	5.0	5.1	6.0	5.4	3.7	4.5	11.7	5.0	5.2	3.6	4.4	3.9	71.1
EVZ	2.2	5.5	36.8	4.9	4.9	5.5	5.3	4.3	4.4	3.5	4.7	5.0	4.6	3.6	4.7	63.2
RVX	2.5	2.6	2.1	14.0	11.3	10.1	8.5	5.2	6.6	1.8	11.2	8.7	2.4	6.7	6.4	86.0
VIX	2.5	2.5	2.1	11.0	13.6	11.3	8.4	5.1	6.4	1.7	11.4	8.4	2.4	6.5	6.6	86.4
VXD	2.3	3.2	2.6	10.3	11.9	14.4	7.8	4.9	6.0	1.6	10.6	8.3	2.5	6.8	6.7	85.6
VXEEM	3.3	2.9	2.3	8.8	9.0	7.9	14.5	7.3	9.1	2.3	8.9	8.1	2.6	6.0	6.9	85.5
VXEWZ	3.2	2.6	2.5	7.2	7.3	6.7	10.1	23.4	7.2	1.9	7.2	7.1	2.4	5.7	5.5	76.6
VXFXI	3.0	2.9	2.4	8.1	8.0	7.2	11.0	6.5	19.3	2.0	8.1	7.5	2.3	5.8	5.9	80.7
VXSLV	3.7	14.5	3.5	4.3	4.0	3.8	5.0	3.4	3.8	36.8	4.2	5.1	1.9	3.1	2.8	63.2
VXN	2.5	2.6	2.1	11.2	11.7	10.4	8.6	5.1	6.6	1.8	13.9	8.2	2.4	6.7	6.4	86.1
VXXLE	4.6	2.9	2.4	9.5	9.4	8.9	8.5	5.5	6.5	2.4	8.9	15.5	2.2	6.7	6.0	84.5
VXTYN	2.6	4.4	4.3	5.3	5.4	5.2	5.6	3.6	4.2	1.9	5.3	4.3	39.3	4.4	4.2	60.7
VXGS	2.4	3.0	2.2	8.9	8.9	8.7	7.7	5.4	6.2	1.6	8.9	8.1	2.6	19.5	5.7	80.5
VXEFA	2.6	2.5	2.7	8.3	8.8	8.4	8.6	5.2	6.2	1.6	8.4	7.3	2.4	5.7	21.3	78.7
TO	40.2	55.2	37.8	108.4	111.3	105.1	107.4	70.2	82.8	39.3	108.4	100.9	37.0	76.2	76.0	TCI
NET	−26.9	−15.9	−25.5	22.4	24.9	19.5	22.0	−6.5	2.1	−23.9	22.3	16.4	−23.7	−4.3	−2.8	82.6

Notes: Results based on the TVP-VAR model. Variance decompositions are based on 30-day-ahead forecast horizon. OVX = CBOE crude oil ETF volatility index, GVZ = Gold ETF volatility index, EVZ = Euro/dollar currency volatility index, RVX = Russell 2000 volatility index, VIX = S&P 500 volatility index, VXD = CBOE DJIA Volatility Index, VXEEM = Emerging Markets ETF volatility index, VXEFA = EFA (Europe, Australia, Asia and the Far East) ETF volatility index, VXEWZ = Brazil ETF volatility index, VXFXI = China ETF volatility index, VXSLV = Silver ETF volatility index, VXN = NASDAQ-100 volatility index, VXXLE = CBOE Energy Sector ETF volatility index, VXTYN = CBOE 10-Year Treasury Note volatility index, VXGS = CBOE Equity VIX on Goldman Sachs volatility index.

3.2. Empirical results

Table 2 presents the averaged connectedness table which illustrates the average impact variable j has on variable i.[4] We notice that the TCI presents a high value (82.6%) suggesting a large interdependence among the implied volatility returns which can be interpreted as high cross-market risk transmission. The TCI is significantly higher compared to the one presented in Maghyereh, Awartani, and Bouri (2016), which is slightly higher than 50%. This is suggestive of the fact that the inclusion of several asset classes – rather than solely oil and stock markets – provides additional information to the transmission mechanism of implied volatility returns.

Furthermore, the results highlight that the oil market is on average considered as a net receiver of shocks (−26.9%). The same holds for the EVZ (−25.5%), VXSLV (−23.9%), VXTYN (−23.7%), GVZ (−15.9%), VXEWZ (−6.5%), VXGS (−4.3%) and VXEFA

[4] Table A.1 presents the averaged connectedness measures of a 250-day rolling-window VAR model which is qualitatively similar to Table 2. We perform this estimation so to demonstrate that the TVP-VAR connectedness measures are qualitatively similar to the results of the originally proposed connectedness approach of Diebold and Yılmaz (2012), while they overcome the weaknesses identified in the latter framework (especially the fact that we do not lose any valuable observations).

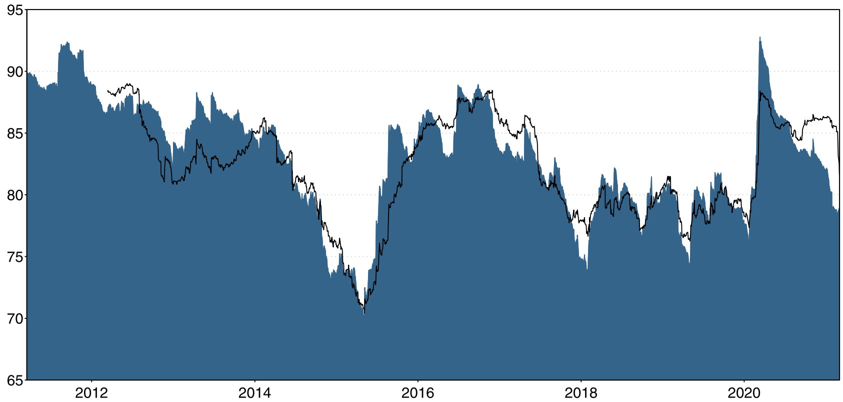

Fig. 2. Dynamic total connectedness. *Notes*: The dynamic total connectedness based upon the TVP-VAR is presented by the blue area while the black line represent the dynamic total connectedness of a 250-day rolling-window VAR. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(−2.8%) implied volatility indices, suggesting that overall commodities, precious metals and exchange rate implied volatilities are significantly impacted by the US and aggregate emerging markets implied volatilities. Interestingly enough, this finding does not corroborate Maghyereh et al. (2016) results showing that the oil implied volatility is indeed transmitting shocks to stock market volatility. Nevertheless, our findings are in-line with those studies who also maintain that it is primarily the stock markets that transmit volatility shocks to the oil market (see, for instance, Malik & Ewing, 2009; Mensi, Beljid, Boubaker, & Managi, 2013).

Next we focus on the time-varying total connectedness index, which is illustrated in Fig. 2. The results illustrate that the total connectedness index fluctuates at very high levels (between 75%–100%), reaching a trough in mid-2015. The latter finding suggests some reduction in the interconnectedness, which could be explained by the fact that during 2015 we notice a divergence in the behavior of implied volatility indices. In particular, we observe assets, such as oil and the US stock market indices, to exhibit a decreasing volatility during this period, whereas the reverse is true for the implied volatilities of precious metals (gold and silver) and the Euro/dollar currency. By contrast, a rather material increasing pattern in the dynamic total connectedness is observed after the mid-2015 until 2017, which could be related to the emergence of economic and political events that shocked all asset markets. These events include the resurgence of the Middle-East unrest in 2015, the Chinese stock market crash in mid-2015, the Turkish coup d'état attempt in 2016, the Brexit vote in 2016 and the Iranian sanctions in 2017. Such claim is based on the abundance evidence that shows the detrimental effects of political, geopolitical and economic uncertainty in global asset markets. More specifically, it has been suggested that events, such as the ones referred here, tend to cause significant declines in prices, pushing volatilities to higher levels, for all asset classes, which subsequently leads to greater cross-market linkages (see, for instance, Bouras, Christou, Gupta, & Suleman, 2019; Caldara & Iacoviello, 2022; Chau, Deesomsak, & Wang, 2014; Demirer, Omay, Yuksel, & Yuksel, 2018; Dogan, Majeed, & Luni, 2021; Liu, Shu, & Wei, 2017; Pástor & Veronesi, 2013, among others).

Furthermore, it is important to note that in the early period of our study we observe the highest level of interconnectedness among implied volatility indices. This is also anticipated given that during 2011 there were several geopolitical and economic events that triggered turbulence to all different asset classes, including the Arab Spring, the start of the Syrian Civil war, the European governmental debt crisis, as well as, the US debt-ceiling crisis. More recently, we see that the largest spike has been reached around April 2020 when the crude oil price settled into negative territory for the first time in history which has been a side effect of the COVID-19 pandemic. Even though the extraordinary high degree of market interconnectedness decreased soon afterwards, we still see that the market risk is still moderately high until the end of the sample period. The sudden spike in the dynamic total connectedness signifies the severe impact of COVID-19 pandemic, during its early stages, when asset markets experienced material increases in their volatilities, due to the uncertainty that the virus brought to the global economy. As mentioned previously, events that have global impact tend to create stronger cross-market linkages. It is worth mentioning here that the rapid decline of the connectedness in the months that followed suggests that markets absorbed the shock fairly quickly, which could be, at least partly, attributed to expansionary monetary and fiscal policies (Chadha, Corrado, Meaning, & Schuler, 2021; UN DESA, 2022). These expansionary policies have resulted in injecting liquidity in both asset markets and the real economy, which managed to reduce the financial distress and thus reduce stock market volatility.

Turning our attention to the net total directional connectedness (see, Fig. 3)[5] it is evident that OVX is not only at the receiving end of the spillover effects based on the averaged connectedness measures (as shown in Table 2), but also when investigating the dynamic connectedness measures. We further show that the volatility indices of GVZ, EVZ, VXSLV and VXTYN also exhibit a net

[5] The total directional connectedness FROM and TO all others are illustrated in Figures A.2 and A.1, respectively, in the online appendix A.

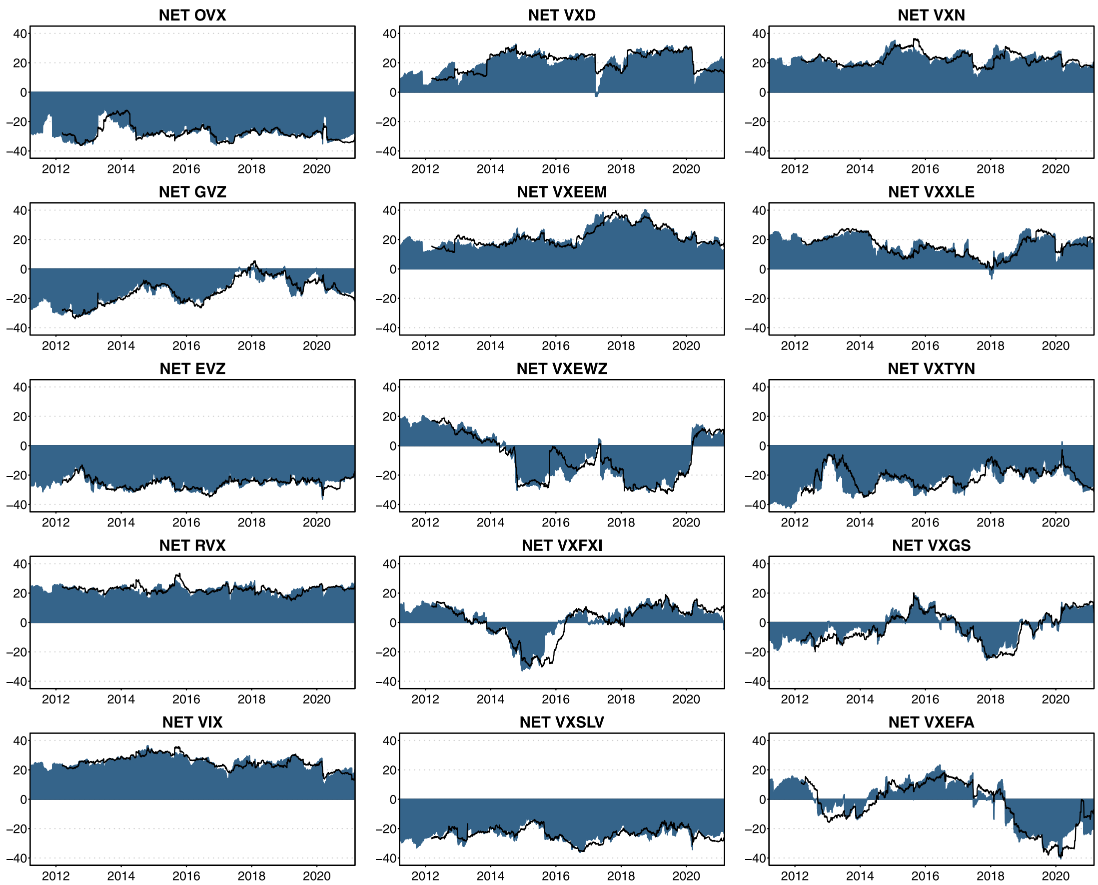

Fig. 3. Net total directional connectedness.
Notes: The TVP-VAR connectedness measures are presented by the blue areas while the black lines represent the connectedness measures of a 250-day rolling-window VAR. OVX = CBOE crude oil ETF volatility index, GVZ = Gold ETF volatility index, EVZ = Euro/dollar currency volatility index, RVX = Russell 2000 volatility index, VIX = S&P 500 volatility index, VXD = CBOE DJIA Volatility Index, VXEEM = Emerging Markets ETF volatility index, VXEFA = EFA (Europe, Australia, Asia and the Far East) ETF volatility index, VXEWZ = Brazil ETF volatility index, VXFXI = China ETF volatility index, VXSLV = Silver ETF volatility index, VXN = NASDAQ-100 volatility index, VXXLE = CBOE Energy Sector ETF volatility index, VXTYN = CBOE 10-Year Treasury Note volatility index, VXGS = CBOE Equity VIX on Goldman Sachs volatility index. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

receiving behavior throughout the sample period. By contrast, the VIX, as well as, the RVX, VXD, VXEEM, VXN, and VXXLE are those that propagate the volatility shocks for the majority of the time period. As expected, the highest net transmitter of volatility shocks is VIX (24.9%).

Overall, these findings complement those observed in Table 2 and suggest that it is primarily the stock market asset class that transmits volatility shocks to the remaining asset classes. It may be surprising that OVX is not a net transmitter of volatility spillover shocks, at least in the early part of the study (2011) or during the oil price collapse in 2014–2015, given that there is ample evidence that shows the reverse. Nevertheless, the net receiving character of the oil implied volatility could be explained by the fact that since the Global Financial Crisis of 2009, oil has become more integrated in the financial system and thus it is further affected by the various financial markets across the world (Zhang, 2017). This is further evidence of the higher financialization of the oil market (Creti, Nguyen, et al., 2015).

Interestingly enough, the VXEWZ, VXFXI, VXGS and VXEFA are the only ones that change their character in the post-2014 period. In particular, Fig. 3 indicates that VXEWZ, VXFXI and VXGS end up of being net transmitters of shocks whereas VXEFA ends up as a net receiver. This is rather interesting given that we have established so far from the averaged results that mainly the US stock market implied volatility indices are net transmitters of shocks. Nevertheless, we opine that the net transmitting character of the VXEWZ in the early part of our study (2011–2014) could be justified by the economic downturn of the Brazilian economy at that period, which was primarily caused by the reduction in both domestic and foreign demand for Brazilian products. Similarly, it is rather anticipated for VXEFA to transmit volatility shocks during the early period of our sample due to the developments in the European and Greek governmental debt crisis.

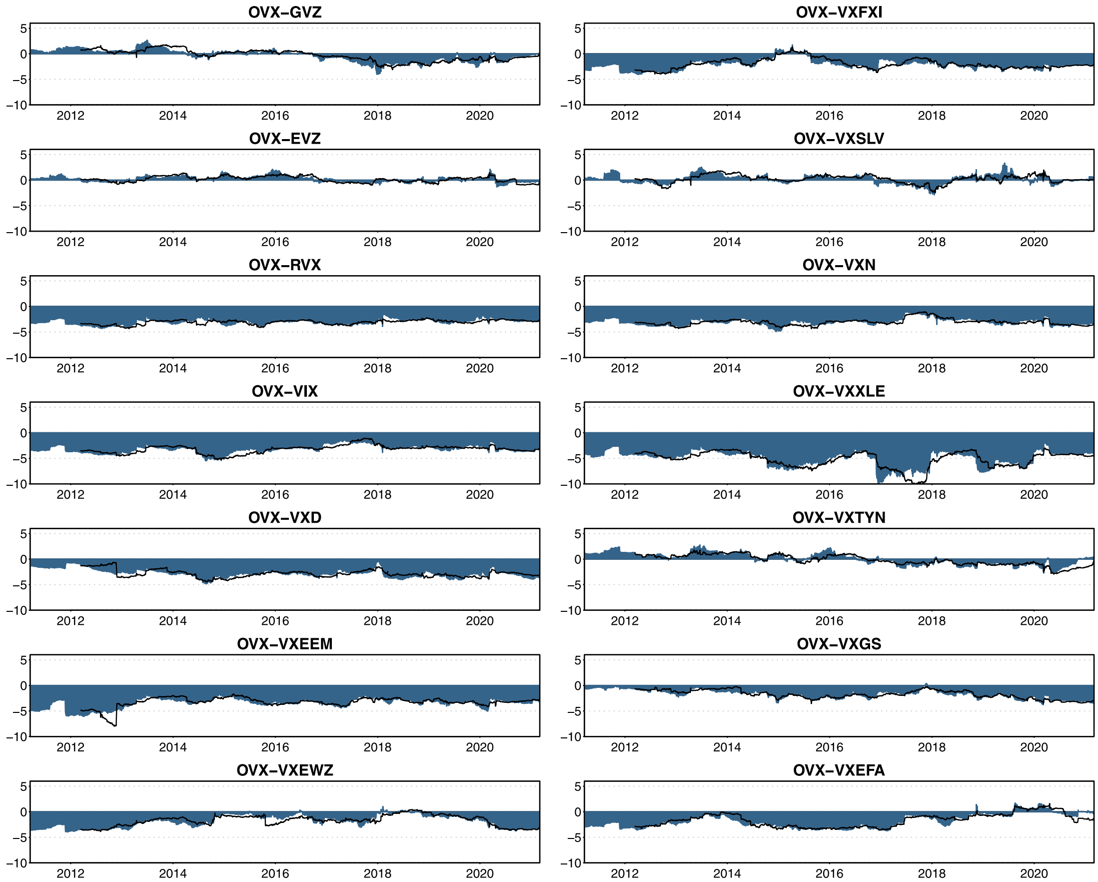

Fig. 4. Net pairwise directional connectedness.
Notes: The TVP-VAR connectedness measures are presented by the blue areas while the black lines represent the connectedness measures of a 250-day rolling-window VAR. OVX = CBOE crude oil ETF volatility index, GVZ = Gold ETF volatility index, EVZ = Euro/dollar currency volatility index, RVX = Russell 2000 volatility index, VIX = S&P 500 volatility index, VXD = CBOE DJIA Volatility Index, VXEEM = Emerging Markets ETF volatility index, VXEFA = EFA (Europe, Australia, Asia and the Far East) ETF volatility index, VXEWZ = Brazil ETF volatility index, VXFXI = China ETF volatility index, VXSLV = Silver ETF volatility index, VXN = NASDAQ-100 volatility index, VXXLE = CBOE Energy Sector ETF volatility index, VXTYN = CBOE 10-Year Treasury Note volatility index, VXGS = CBOE Equity VIX on Goldman Sachs volatility index. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Finally, we concentrate on the net pairwise directional connectedness to disentangle further the propagation mechanisms among the implied volatilities of oil and other asset classes. The results are shown in Fig. 4.[6] Fig. 4 strengthens our aforementioned findings that OVX is a net receiver of shocks, mainly from the stock market asset classes, as it is depicted by the net pairwise plots between OVX and RVX, VIX, VXD, VXEEM, VXEWZ, VXFXI, VXN, VXXLE, VXGS and VXEFA. Nevertheless, Fig. 4 provides some additional information which are particular interesting when analyzing the relationship between oil and asset classes beyond the stock markets, regarding precious metals and foreign exchange. In particular, OVX transmits at least temporarily shocks to GVZ, EVZ, VXSLV as well as, to VXTYN for most of the period under investigation. These findings complement those by Baffes (2007), Narayan, Narayan, and Zheng (2010) and Sari, Hammoudeh, and Soytas (2010), who maintain that there is a pass-through from crude oil returns to precious metals price changes. By contrast, we do not lend support to the results presented by Antonakakis and Kizys (2015), who provide evidence (for an earlier period) that precious metals and exchange rates are transmitting volatility spillover effects to oil.

In summary, we have identified four main trends that drives the connectedness among the selected implied volatilities: (i) the top three net receivers of shocks are oil, exchange rates and precious metals; (ii) the top three net transmitters of shocks are related with US stock market volatility — namely, S&P500, Russell 2000 and NASDAQ-100; (iii) the time-varying connectedness present the highest value around the beginning of the COVID-19; and (iv) the emerging volatility index – associated with emerging countries – is also a relevant net transmitter.

[6] We only show the net pairwise directional connectedness between oil and each of the remaining implied volatilities. The remaining net pairwise directional connectedness graphs are available upon request.

4. Concluding remarks

Although there is an abundance of empirical evidence regarding the linkage between financial assets and oil prices, this paper contributes to the related literature examining the dynamic connectedness among the implied volatility of oil prices and fourteen other assets (which represent five different asset classes - i.e. stock markets, precious metals, energy commodities, exchange rates and bonds), using the recently developed TVP-VAR based connectedness approach (Diebold & Yılmaz, 2012) a la Antonakakis et al. (2020) over the period from March 16th, 2011 to March 3rd, 2021. In addition, this paper also provides relevant insights in the propagation mechanism of cross-market volatility during the first year of the COVID-19 pandemic shock. Our findings indicate that spillovers among the different asset classes and oil price implied volatilities are time-varying and fluctuate at very high levels (between 75% and 100%). Furthermore, we show that OVX is not a net transmitter to stock market indices, but rather it is constantly at the net receiving end of spillover shocks across all bond and stock market implied volatilities.

Such findings imply that as the oil market is becoming more integrated with financial markets, it tends to be impacted more by abrupt fluctuations of different asset classes. Interestingly, this holds true even during the oil price collapse period of 2014–2015. Even more, the net pairwise connectedness results suggest that OVX transmits volatility shocks – at least temporarily – to GVZ, EVZ, VXSLV, as well as, to VXTYN for most of the period under investigation. The latter finding complements those by Baffes (2007), Narayan et al. (2010) and Sari et al. (2010), who concentrated on returns rather than volatilities, and showed that there is a pass-through from crude oil to precious metals returns. Finally, we want to emphasize the fact that OVX is a net transmitter of shocks to the VXXLE, which confirms the impact of oil to energy stocks.

Future studies should investigate the dynamic spillovers among the implied volatilities of oil and different agricultural commodities, given the fact that the latter is also becoming more financialized over the years. Finally, future research could investigate the predictive content of spillover effects when forecasting OVX. Overall, the study provides new insights regarding the dynamic spillover among the implied volatilities of oil and five different assets classes, which have relevant implications for portfolio and risk managers. We maintain that it is not only the asset price volatilities but also their dynamic spillovers that play an important role for practitioners and institutional investors in terms of asset allocation, hedging and diversification.

CRediT authorship contribution statement

Nikolaos Antonakakis: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Investigation. **Juncal Cunado:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Investigation. **George Filis:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Investigation. **David Gabauer:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Investigation. **Fernando Perez de Gracia:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Investigation.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.iref.2022.08.009.

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