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A closer look into the global determinants of oil price volatility

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ABSTRACT

In this paper we investigate global determinants of oil price volatility by employing a time-varying parameter vector autoregressive (TVP-VAR) model. We focus on realised volatility and consider the impact from a set of potential determinants including oil supply, oil demand, oil inventory, financial market uncertainty, financial interbank stress, as well as, financial trends in different currencies. We investigate the impact of these factors on realised volatility utilising monthly data over the period 1990:1–2019:5. Findings show that all factors can be conducive to higher levels of realised oil price volatility particularly in the short run. What can further be noticed, is that the magnitude of the corresponding impulse response functions may differ across time and this could largely be attributed to specific intervals of financial crises and economic recessions. Nevertheless, we show that shocks originating to the financial markets tend to be more important for oil price volatility. Our findings are closely linked to the implications regarding the financialisation of the oil market.

1. Introduction & Brief Review of the Literature

The examination of oil price volatility is essential as it helps improve our understanding in connection with changes in the level of uncertainty in the market for oil, which are typically reflected upon abrupt fluctuations in the price of oil. Clearly, oil price volatility contains information which is closely associated with developments in both the physical and the futures oil market. In turn, such information could potentially be utilised by energy traders who seek to effectively manage their asset portfolios and design hedging strategies. It follows that, oil price volatility has received considerable attention by the research community in recent years.

In fact, the investigation of oil price volatility has been the focal point of many studies in the field of forecasting. More particularly, we highlight the recent studies by authors such as Efimova and Serletis (2014); Phan et al. (2016); Degiannakis and Filis (2017); Chatziantoniou et al. (2019) who employ a variety of forecasting specifications in order to produce more accurate forecasts of oil price volatility. The general consensus from this strand of the literature is that oil price volatility forecasting has become increasingly more important in recent years mainly due to the financialisation of the oil markets and the fact that oil is now largely regarded as a financial asset by market participants – including hedge funds, insurance companies and pension funds (see, inter alia, Fattouh et al. 2013). It should also be noted that, existing literature in the field of forecasting has so far effectively reported the importance of oil market specific variables such as world crude oil production, US crude oil inventories, US petroleum inventories and NYMEX oil futures prices, for forecasting the price of oil (see, for instance, Baumeister and Kilian, 2012); nonetheless, such variables have rather been neglected when it comes to making predictions of oil price volatility. That is, existing literature in this field, mainly uses historical information in the form of price jumps rather than oil market fundamentals to produce forecasts of oil price volatility (see Prokopczuk et al., 2016).

Recent studies have also emphasized the role of oil price volatility as a leading macroeconomic indicator, since it provides significant information to energy traders, financial market participants and policymakers (see Efimova and Serletis 2014). Indeed, in an early study, Ferderer (1996) provides evidence that oil price volatility contains information that helps forecast industrial production growth in the US. Similarly, Pindyck (2004) explains that higher oil price volatility has a positive impact on demand for storage and thus subsequently affects both the spot price of oil and the convenience yield. Furthermore, in a recent study, Elder and Serletis (2010) find that oil price volatility has a negative impact on the US aggregate output, investment and consumption. In addition, Henriques and Sadorsky (2011) indicate that oil price volatility has an impact on the strategic investment decisions of

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US firms. They document that increased oil price volatility affects the cost of oil inputs and generates uncertainty not only around investment decisions but also with regard to firm valuation and firm profitability. In addition, Diaz et al. (2016) provide evidence that higher levels of oil price volatility negatively affect stock market returns in G7 economies. Finally, Bouri et al. (2018c) report a significant effect of oil price volatility on the sovereign credit risk of BRICS countries. In contrast with studies that assume a leading indicator role for oil price volatility, one of the objectives of this study is to investigate how well-established financial indicators such as the global financial market volatility, the global interest rate or the global exchange rate influence oil price volatility per se.

In this relatively scarce strand of the literature in connection with the investigation of factors that determine oil price volatility, Van Robays (2016) opines that increased macroeconomic uncertainty triggered by recessions and financial crises is rather conducive to higher levels of oil price uncertainty. More specifically, Van Robays (2016) explains that during periods of increased macroeconomic uncertainty, oil price volatility is driven by fundamental factors underpinning oil supply and demand shocks, which in turn, are largely associated with delays in production and consumption decisions from market agents. This is mainly because, higher macroeconomic uncertainty lowers the price elasticity of oil supply and oil demand and consequently increases oil price volatility.

Another interesting aspect with regard to oil price volatility and its determinants, relates to speculation in the market for oil and how the latter could potentially result in increased volatility. Van Robays (2016) argues that, changes in the price elasticity of oil supply and oil demand should not be attributed to changes in oil inventory holding-levels and that speculation should not really be regarded as a factor that contributes to changes in oil price volatility. Nonetheless, authors such as Beidas-Strom and Pescatori (2014) who utilise data on global oil inventories to approximate shifts in speculative demand for oil find a link between an increase in oil inventories and that in the price of oil. They conclude that financial speculation triggers short term oil price fluctuations between 3 and 22%.

What is more, Robe and Wallen (2016) investigate whether physical market fundamentals, financial and macroeconomic conditions drive oil price volatility at horizons of one to six months. Robe and Wallen (2016) use the term structure of oil option-implied volatilities and report that the VIX index significantly affects oil implied volatility, whereas both other macroeconomic variables and speculative activity do not seem to have a significant impact. On a parallel note, Caldara et al. (2019) examine sources of oil price movements. They indicate the importance of oil supply shocks and global demand shocks in driving oil price fluctuations. Specifically, they report that oil supply shocks and global demand shocks contribute to explain 50 and 35% of oil price fluctuations respectively.

Following from the above, the objective in this study is to focus on global determinants of oil price volatility in an effort to shed additional light upon the underlying factors of oil price fluctuations. To this end, we consider a broad set of factors such as global oil supply, global oil demand, global oil inventories, global financial market uncertainty, global financial interbank stress and global financial trends in currencies. To be more explicit, we examine whether unanticipated changes both in global, crude oil market-specific fundamental factors and in financial indicators are useful in explaining movements in oil price volatility and whether they subsequently help capture the uncertainty generated in the crude market for oil.

Our decision to employ fundamental and financial factors is strongly motivated by the fact that recent empirical evidence indicates that oil price fluctuations are not only traditionally determined by the fundamental factors of oil supply and oil demand but also driven by financial activity (see, for example Tang and Xiong 2012; Irwin and Sanders 2011). Indeed, the financialisation of the oil market refers to the increased participations of hedge funds, insurance companies and pension funds, among other financial participants, in the commodity futures markets. According to Tang and Xiong (2012), this investment has grown from $15 billion to $200 billion between 2003 and mid-2008, whereas Irwin and Sanders (2011) maintain that this investment raised to $250 billion in 2009, and further to $450 in 2011, as documented by Bicchetti and Maystre (2013). Overall, this recent development recognises that oil futures market derivatives can be used as financial assets in the attention of energy traders and portfolio managers who appear to increase their positions in the oil futures market both prior to the Global Financial Crisis of 2007–08 (henceforth, GFC 2007) and the period afterwards.

It should also be noted that, we focus on realised oil price volatility as opposed to conditional oil price volatility; although we do consider the latter alternative for robustness purposes. This decision is primarily based on Andersen and Bollerslev (1998); Andersen et al. (2003) as well as Hansen and Lunde (2006) who provide evidence that realised volatility is both a more accurate measure and more reliable in producing forecasts. In a relevant study involving the oil market, Herrera et al. (2018) also focus on realised oil price volatility arguing that the underlying volatility of crude oil returns is rather unobserved.

We contribute to existing literature in two ways. First, we investigate the said relationships utilising a time-varying parameter vector autoregressive (TVP-VAR) model. By allowing all parameters to vary over time, we are able to capture regular or unexpected variations to those parameters, securing both flexibility and accuracy. Second, we make use of a unique set of factors such as global oil supply, global oil demand, global oil inventory, global financial market uncertainty, global financial interbank stress and global financial trends in currencies. In this regard, we provide additional evidence on oil price volatility considering relationships that have so far been largely under-researched.

Our empirical findings suggest that all potential determinants affect the realised volatility of oil, mainly at short run horizons. In addition, impulse response functions vary over time and this might very well be attributed to changing economic conditions across time. More particularly, we note that the impact is stronger and shows peaks during severe episodes of economic recessions and financial crises. Overall, our results indicate that high levels of oil price volatility might indeed be determined both by oil fundamental and financial factors. More importantly, it has been illustrated that the greatest impact on oil price volatility is received by financial factors rather that fundamental factors.

The remainder of the paper is structured as follows: In Section 2 we describe the dataset and discuss the variables under investigation. In Section 3 we present the econometric methods that we employ in this study. In turn, in Section 4 we report and discuss the empirical results of the study. Finally, Section 5 summarises and concludes the paper.

2. Data Description & Preliminary Analysis

2.1. Explanatory variables

In this study, we use monthly data from January 1990 to May 2019 which is translated into 353 observations. The choice of the monthly time series and the sample period is governed by the data availability.[1] Additionally, the choice of the time period is motivated by the most significant changes and developments in the crude oil market.[2] We employ a set of potential global determinants of the oil price volatility which is used as a proxy of the crude oil market uncertainty. More specifically, we collect daily data on the Brent crude oil price which will be used to compute their monthly volatilities. The choice of Brent is attributed to

[1] More specifically, the start date is attributed to the fact that the VIX index data series is available from January 1990, whereas the end date is chosen due to the fact that data on the global economic activity index were available until May 2019 the period when we collected the sample data.

[2] Crude oil prices react to a variety of geopolitical, financial and macroeconomic events. For more information about the oil price chronology from 1970, the reader is referred to the EIA in the following link: http://www.eia.gov/finance/markets/reports_presentations/eia_what_drives_crude_oil_prices.pdf

the fact that it is widely considered as the global crude oil benchmark. Specifically, Brent is used to price crude oil that is produced and traded not only in Europe, the Mediterranean, and Africa, but also in Australia and some countries in Asia.[3] Data for the Brent crude oil price are extracted from Datastream and are expressed in dollar terms.

The crude oil-market specific factor of global oil supply is represented by the world oil production. Based on Kilian (2009) empirical work, we use this variable to evaluate unexpected changes in global oil supply. For example, an unexpected disruption in the world oil production attributed to OPEC's decision to cut its production quotas, leads to increases in oil prices and linked with fluctuations in oil price volatility. Data for the world oil production have been obtained from the Energy Information Administration (EIA).

In the same vein, the global economic activity index is used to approximate the crude oil-market specific factor of global oil demand. According to Kilian (2009), this index is designed to record shifts in the demand for industrial commodities responding to the global business cycle. Kilian and Murphy (2014) consider that this index is the only one appropriate indicator among other alternative proxies in the area of industrial commodities of capturing shifts in global demand. An advantage of this index is the inclusion of the real economic activity in the emerging economies of India and China (Kilian and Park 2009). We expect that an unexpected rise in global economic activity will drive up oil prices and associated with fluctuations in oil price volatility. The data for the global economic activity index are retrieved from Lutz Kilian's website.[4]

Based on the fact that there is no open data on global oil inventories, we follow Wang et al. (2017) who use the total US crude oil inventory including strategic reserves to approximate the factor of global oil inventories. The authors justify this choice by arguing that this is because the world total level of inventory is unavailable. We suggest that global oil inventories can be regarded as an additional crude oil-market specific factor. Since oil is a storable asset, unexpected changes in the demand for inventory are expected to affect movements in oil prices. For example, if shortages of barrels of oil are more likely to occur in the near future, an increase in the inventory demand in the oil physical spot market is likely to happen. The accumulation of inventories leads to a decline in the availability of crude oil for current use and tends to put an upward pressure on the oil price and related to significant variations in oil price. It should be mentioned that Kilian and Murphy (2014) provide evidence that fluctuations in global oil inventories are mainly driven by speculative activity and therefore reflect speculative trading. In other words, they argue that the use of global oil inventories help to identify the speculative component of the real price of oil. These data are collected from the EIA database.

To elaborate further on speculative activity, Fattouh (2012) and Fattouh et al. (2013) document that this can be associated with the increased participation of non-commercial traders, e.g. financial agents, in the oil market. In particular, non-commercial traders, such as hedge funds or money managers, tend to take long position in the oil futures or accumulate oil inventories, without having a commercial interest in oil market. Such activity tends to (i) significantly rise oil spot prices, (ii) increase oil price volatility and consequently cause greater uncertainty in the oil market, and (iii) cause a breakdown of the oil price-oil inventory relationship. For a detailed discussion of these aforementioned effects of speculative activity on oil markets the reader is directed to authors such as Adams et al. (2020); Nguyen et al. (2020); Baur and Dimpfl (2018); Zhang et al. (2017); Basak and Pavlova (2016); Adams and Glück (2015); Büyükşahin and Robe (2014); Cheng et al. (2015); Hamilton and Wu (2014); Morana (2013); Silvennoinen and Thorp (2013); Singleton (2014); Büyüksahin et al. (2009). Even more, an in-depth review on these effects can be found in Haase et al. (2016).

In addition, the volatility index (VIX) is used to approximate the global uncertainty in financial markets. The VIX index is provided by the CBOE and serves as a key measure of the expected volatility of the underlying S&P 500 stock index that reflects the market's expectation of 30-day volatility. However, the VIX index is also regarded as a benchmark not only for the S&P 500 stock index but also for the whole US stock market and further as a global measurement of market stress. In particular, Cai et al. (2009) argue that the VIX index is considered as the world's premier barometer to gauge investor fear. In addition, Sarwar (2012) documents that the VIX index measures the market fear in stock markets outside the US, such as those of Brazil, China and India. Finally, Bouri et al. (2018a, 2018b) argue that the US VIX index is a gauge of fear for emerging BRICS economies due to the massive size of the US stock market and the dominant role of the US VIX index to highly predict stock market returns and volatility in emerging markets. Given these characteristics, an increase in the expected stock market volatility results in negative market returns in international markets. Therefore, decreasing asset prices (including commodity/oil prices) are anticipated which implies deviations in oil price volatility. Data for the VIX are provided from Datastream.

Moreover, we use the TED spread as a proxy of global financial interbank stress which denotes interest rate fluctuations. The TED spread is the difference between the three-month US London Interbank Offered Rate (LIBOR) and the three-month US Treasury bill rate. It is used as an indicator of global interbank market stress which means that a rising TED spread signifies a higher risk of bank defaults and hence a lower economic activity. According to Basher et al. (2012), the TED spread can be used to approximate global interest rate movements and therefore to capture developments in future economic activity. In this regard, unexpected higher interest rates tend to rise the borrowing costs of oil companies and therefore affect negatively their revenues and profitability. Since oil extraction requires a huge amount of capital, higher interest rates reduce such investment and therefore limit future economic activity. This process is translated into a lower demand for oil and hence a fall in oil price which suggests an alteration in oil price volatility. Data on TED spread are extracted from Datastream.

What is more, the trade-weighted exchange rate index represents the weighted average of the foreign exchange value of the US dollar against the most widely traded currencies in the financial markets and hence it reflects global financial trends in currencies. Specifically, this index denotes financial trader's assessment of the dollar and used to approximate movements in global foreign exchange rates.[5] Even more, this index is used to measure financial stress on US dollar. Thus, a sudden higher value of this index denotes that the US dollar appreciates. Since crude oil is priced in US dollars, a stronger US dollar implies a higher oil supply and a lower oil demand. Therefore, the fall in oil price causes shifts in oil price volatility. Data on the trade-weighted exchange rate index are obtained from the Federal Reserve of St. Louis database (FRED).

2.2. Preliminary analysis

Fig. 1 illustrates diagrammatically visual representation of the series under consideration. It is evident that the realised oil price volatility exhibits a peak during the GFC 2007 which begins to emerge in the second half of 2008 and accords with the most serious stage of this crisis. It is worth mentioned that a significant peak is also observed during the period of 1990–1991 which is associated with Iraq's invasion of Kuwait

[3] The source of the information can be found on EIA: https://www.eia.gov/todayinenergy/detail.php?id=18571

[4] Global economic activity index is constructed by Lutz Kilian and the data can be found in his personal website: see https://sites.google.com/site/lkilian2019/research/data-sets.

[5] Based on the Board of Governors of the Federal Reserve System, the trade weighted exchange rate index of major currencies (TWEXMMTH) includes the Euro Area (euro), Canada (dollar), Japan (yen), United Kingdom (pound), Switzerland (frank), Australia (dollar), and Sweden (krona). For more information about trade-weighted indexes, please see http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf.

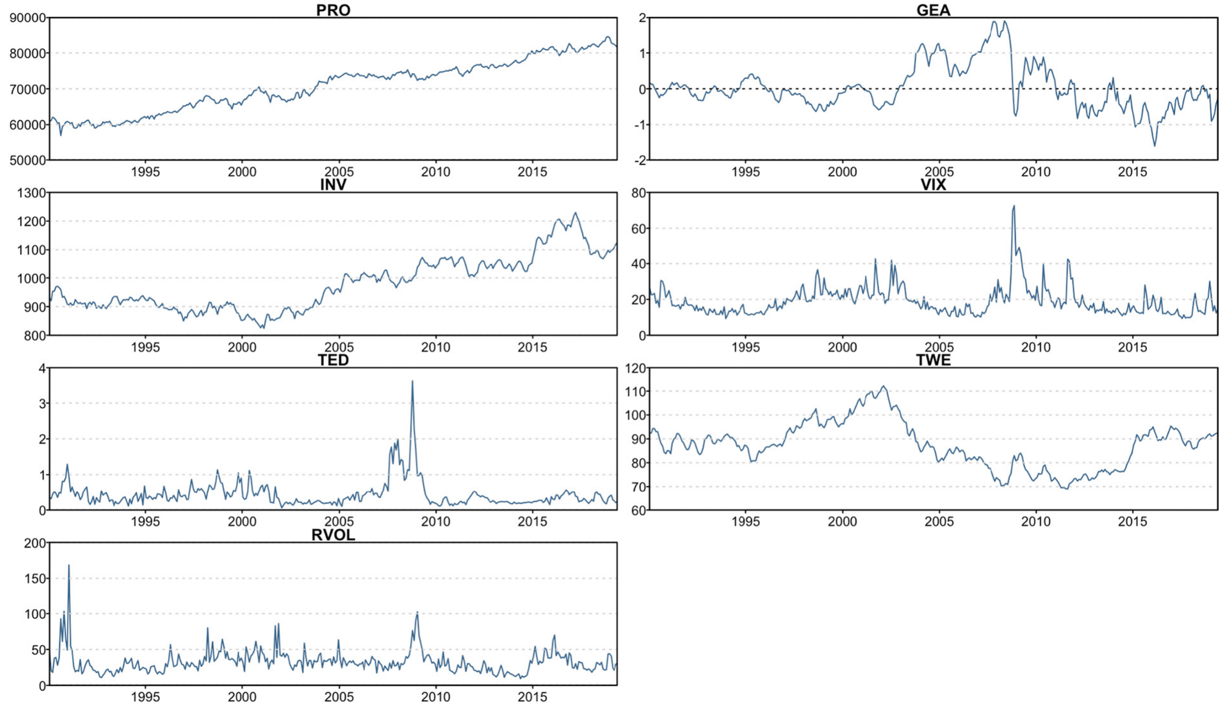

Fig. 1. Time series employed in the study. Note: This Figure exhibits the evolution of the series during the sample period. In the first column, world crude oil production, global crude oil inventories, TED spread and realised oil price volatility are represented. In the second column, the global economic activity index, VIX index and trade-weighted exchange rate index are depicted. The sample period runs from January 1990 to May 2019.

and the collapse of the former Soviet Union which was one of the largest oil-producer in the world. However, a higher oil price volatility is also spotted in 1998–1999 which coincides with two oil production cuts by OPEC in order to cause an end to declining oil prices, in late-2001 which is associated with 9/11 terrorist attack and 2016 which is attributed to speculation followed the OPEC's decision to cut production quota.

With reference to world crude oil production, there is a gradually increasing pattern for most of the period of investigation. However, there are only few periods of notable declining patterns such as the early-1998 (OPEC decisions), in 2000 (recession in the US market), during the GFC 2007 and the beginning of the Arab Spring in 2011. Global economic activity index experiences a boom since 2002 which is characterised by a surge in demand for industrial commodities mainly by emerging economies such as China and India. Nevertheless, global economic activity index exhibits a significant drop during the GFC 2007 and further in 2016 which can be influenced by a temporary weakness of the Chinese economy and other large emerging economies. Regarding the global crude oil inventories, the period from the mid-1990 through the early 2000 is mainly associated with low levels due to OPEC's production cuts. In addition, the accumulation of global crude oil inventories in 2003 is closely associated with the rapid growth in US shale oil production which was triggered by technological advances in drilling. In particular, shale oil production experienced an increase in 2003 and a rapid expansion in 2009, which resulted in almost half of US crude oil production coming from the accumulation of US shale oil production in 2014 (see, for instance, Kilian, 2016). Furthermore, these patterns can be also attributed to the decreasing demand for oil due to a drop in global economic activity. The rising pattern in oil inventories is observed until early-2017, when OPEC decided to cut oil production.

Turning to the VIX index, spikes are observed during periods of financial stress, such as the period from mid-1990 (the Asian financial crisis of 1997–98) to mid-2000 (the internet bubble burst together with the 9/11 terrorist attack). Since 2001 and until the GFC 2007, in the absence of financial turmoil, the VIX index experienced very low levels. This low risk environment was put at an end during the GFC 2007, when the VIX index reached unprecedented levels. Since then, the VIX index has reverted back to its pre-crisis levels. Similarly, the TED spread shows a historically significant peak during the GFC 2007 period attributed to solvency problems and restrictions to interbank lending by leading banks. It is also evident that both in the period before and after the GFC 2007, the TED spread was trading at fairly low basis points which is indicative of stability in the financial system and the lack of financial stress. Indeed, although the aforementioned episodes of the Asian financial crisis, the internet bubble burst and the 9/11 terrorist attack were suggestive of a relatively greater financial uncertainty prior to the GFC 2007, it appears that markets recognise only a small amount of financial risk after the GFC 2007 and even during the European sovereign debt crisis.

Finally, turning to the trade-weighted exchange rate index, a peak is detected in early-2002, which was the consequence of a persistent increasing trend since 1995 and attributed to the strengthening of the US economy compared to the economic weakness of the rest of the world.[6] Furthermore, a stronger US dollar is detected during the second half of 2008, whereas a sharp upward trend is detected in mid-2014 onwards. According to Fratzscher (2009), the appreciation of the US dollar since July 2008 is driven by the severe global financial turmoil originated from a negative US shock linked with the collapse of Lehman Brothers. This resulted in capital repatriation from foreign markets to the US market and hence contributed to convert foreign currencies into US dollars. The recent strength in the dollar value can be explained by the Federal Reserve (FED) decision to raise the US interest rates in the end of 2015.[7] In addition, a second explanation is attributed to the European Central Bank (ECB) decision to reduce the value of euro during the same year. Since euro accounts for the highest weight among

[6] See, for example, Blecker (2003) who explains the benefits of a lower dollar and how a higher dollar has negatively affected US manufacturing producers.

[7] The interested reader can find a relevant information at https://www.usnews.com

other currencies in the value of dollar, a weaker euro implies a stronger dollar.[8]

Having explained the most important patterns of our indices, we proceed to the descriptive statistics analysis of our variables which are reported in Table 1. Turning our attention to the kurtosis, a greater possibility of extreme movements is indicated by a value higher than 3, which practically implies that the leptokurtic distribution practically describes two of the determinants; that is, VIX and TED spread. What is more, the global crude oil inventories appear to be the only variable of the study that is negatively skewed, implying that this variable is characterised by speedy decrease and sluggish increase. For the rest of the variables that are positively skewed, this could be indicative of slow-moving declines and rapid-moving upturns. In addition, according to the Jarque-Bera test, three of the series are normally distributed; namely, oil global production, inventories and the trade-weighted exchange rate index.

Finally, the Augmented Dickey-Fuller (ADF) introduced by Dickey and Fuller (1981) unit root test guarantees that all variables are stationary. In this regard, the global economic activity index is stationary by construction reflecting the global business cycle index (see, Kilian and Murphy 2014). Moreover, the realised oil price volatility, the volatility VIX index and the TED spread are stationary in level and expressed in natural logarithms. On a final note, the natural logarithms of world crude oil production, global crude oil inventories, and trade-weighted exchange rate index are transformed to stationary series by taking the first differences.

Table 2 reports the unconditional correlation among the variables under consideration based on a linear relationship. We observe a weak negative unconditional correlation between our measure of oil price volatility and both the series of world crude oil production growth rate and global economic activity index. In addition, a weak positive unconditional correlation is evident between our measure of oil price volatility and the series of global crude oil inventories growth rate and the trade-weighted exchange growth rate. Finally, a relatively moderate positive unconditional correlation between our measure of oil price volatility and the series of the volatility VIX index and the TED spread is observed. These preliminary findings motivate our decision to proceed with a time-varying framework in which the parameters are allowed to change over time.

3. Methodology

This Section is organised as follows: Section 3.1 designates the estimation of oil price volatility. Section 3.2 presents the time-varying parameter vector autoregression (TVP-VAR) model.

3.1. Oil Price volatility estimates

Initially, it requires to estimate the realised volatility measures of oil price. It should be mentioned that the realised oil price volatility as well as the conditional oil price volatility which is used in a robustness check are regarded as current-looking market volatility measures which implies that oil price volatility is estimated at the current time by using the most recent available information. The annualised monthly realised volatility is computed as the square root of the sum of the squared daily prices and is shown as:

$$RV_t^m = 100\sqrt{12\sum_{j=1}^{\tau}\left(logP_{t,j} - logP_{t,j-1}\right)^2} \tag{1}$$

where RV_t^m represents the annualised monthly realised volatility and $logP_{tj}$ reflects the natural logarithm of the daily market price at day j of month t. Finally, we assume equal number of trading days by scaling RV_t^m with $\sqrt{\frac{22}{\tau}}$ (whereby τ is the number of trading days per month and 22 is the average number of trading days per month) due to the fact that volatility is expected to be higher during a month which has more trading days. A more technical information regarding this estimation can be found to Xekalaki and Degiannakis (2010).

3.2. Model specification

In order to capture the underlying dynamics, we employ the time-varying parameter vector autoregression (TVP-VAR) approach of Del Negro and Primiceri (2015). This model can be regarded as a generalisation of the standard constant parameter VAR (see Sims 1980). In effect, we assume that the volatility and the relationship across the relevant series changes over time as a result of events such as economic and financial crises, technological innovations, as well as, political developments. In this regard, we employ the TVP-VAR framework with stochastic volatility (SV) as this version of the VAR model is not restrictive and does not assume constant volatility of the coefficients of the model across time.

Furthermore, early work by Engle (1982) and Bollerslev (1986) has shown that volatility considerably varies over time, while, authors such as Hamilton (1989); Cogley and Sargent (2005) and Primiceri (2005) have shown that linkages across variables may very well differ across different periods. Therefore, the Del Negro and Primiceri (2015) framework of analysis is appropriate for the investigation of the very dynamic oil market, as it allows both volatilities and coefficients to change over time. The TVP-VAR model is derived from the basic constant parameter VAR model, with the latter defined as follows:

$$\boldsymbol{y}_t = \boldsymbol{B}_{1t}\boldsymbol{y}_{t-1} + \ldots + \boldsymbol{B}_{pt}\boldsymbol{y}_{t-p} + \boldsymbol{A}_t^{-1}\Sigma_t\boldsymbol{\varepsilon}_t \tag{2}$$

where $\boldsymbol{y}_t$ denotes an $m \times 1$ vector of observed variables, and $\mathbf{A}_t, \boldsymbol{B}_{it}, i = 1, \ldots, p, t = p+1, \ldots, T$ denote $m \times m$ matrices of coefficients. The composite error term, $\boldsymbol{A}_t^{-1}\Sigma_t\boldsymbol{\varepsilon}_t$, implies that the residual variance-covariance matrix varies over time. More precisely, the parameters are adjusted over time as follows:

$$\boldsymbol{y}_t = \boldsymbol{X}_t'\boldsymbol{B}_t + \boldsymbol{A}_t^{-1}\Sigma_t\boldsymbol{\varepsilon}_t \tag{3}$$

$$\boldsymbol{B}_t = \boldsymbol{B}_{t-1} + \boldsymbol{u}_{B,t} \tag{4}$$

$$\boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \boldsymbol{u}_{\alpha,t} \tag{5}$$

$$log\,\boldsymbol{\sigma}_t = log\,\boldsymbol{\sigma}_{t-1} + \boldsymbol{u}_{\sigma,t} \tag{6}$$

where $\boldsymbol{y}_t$ is an $m \times 1$ dimensional vector stacked at a given date, $\boldsymbol{X}_t' = \boldsymbol{I}_m \otimes (1, \boldsymbol{y}_{t-1}', \ldots, \boldsymbol{y}_{t-p}')$, $\boldsymbol{B}_t$ stacks all $\boldsymbol{B}_{it}$, $\boldsymbol{A}_t$ is a lower triangular matrix with ones on the diagonal and all other elements stacked in the vector $\boldsymbol{\alpha}_t$, Σ_t is a diagonal matrix with elements $\boldsymbol{\sigma}_t = diag(\Sigma_t)$, and $\boldsymbol{\varepsilon}_t, \boldsymbol{u}_{B,t}, \boldsymbol{u}_{\alpha,t}$, and $\boldsymbol{u}_{\sigma,t}$ are all independent from each other. The TVP-VAR model is estimated using Markov-Chain Monte-Carlo (MCMC) methods with Bayesian inference, based on 30,000 draws after an initial burn-in of 30,000 (i.e., we use a total of 60,000 iterations).

The generalised impulse response functions (GIRF) developed by Koop et al. (1996) and Pesaran and Shin (1998) are based on the time-varying coefficient and time-varying variance-covariance matrices retrieved from the TVP-VAR. For this reason the TVP-VAR has to be transformed to its vector moving average (VMA) representation via the Wold representation theorem which can be illustrated as follows: $\boldsymbol{y}_t = \sum_{i=1}^{p}\mathbf{B}_{it}\boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t = \sum_{j=1}^{\infty}\Lambda_{jt}\boldsymbol{\varepsilon}_{t-j} + \boldsymbol{\varepsilon}_t$.

The GIRFs represent the responses of all variables following a shock in variable i. Since we do not have a structural model, we compute the differences between a K-step-ahead forecast where once variable i is shocked and once where variable i is not shocked. The difference can be accounted to the shock in variable i, which can be calculated by

[8] For more information the interested reader should refer to https://www.theguardian.com

Table 1
Descriptive statistics.

	ΔL(PRO)	GEA	ΔL(INV)	VIX	TED	ΔL(TWE)	RVOL
Mean	1.141	0.037	0.59	18.846	0.431	0.296	32.125
Median	1.17	−0.069	0.403	16.82	0.341	0.52	30.309
Maximum	7.35	1.892	10.325	72.67	3.619	19.949	168.61
Minimum	−4.243	−1.616	−11.479	9.31	0.061	−15.003	9.314
Std.Dev.	2.114	0.627	3.796	8.192	0.369	6.999	15.268
Skewness	0.111	0.766***	−0.061	2.499***	3.767***	0.174	3.112***
	(0.396)	(0.000)	(0.637)	(0.000)	(0.000)	(0.184)	(0.000)
Kurtosis	−0.031	0.552*	0.271	10.191***	21.084***	−0.077	20.126***
	(0.948)	(0.057)	(0.261)	(0.000)	(0.000)	(0.905)	(0.000)
JB	0.709	37.653***	1.260	1830.460***	7122.843***	1.804	6305.624***
	(0.702)	(0.000)	(0.533)	(0.000)	(0.000)	(0.406)	(0.000)
ADF	−5.216***	−3.368**	−3.513***	−5.637***	−5.170***	−4.914***	−7.102***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)

Note: This Table summarises descriptive statistics (sample mean, median, maximum, minimum, standard deviation, skewness, kurtosis, the Jarque-Bera test statistic, and the *p*-value associated to the Jarque-Bera test statistic) of the natural logarithm of realised oil price volatility (RVOL), the first difference of the natural logarithm of world crude oil production (ΔL(PRO)), the global economic activity index (GEA), the first difference of the natural logarithm of global crude oil inventories (ΔL(INV)), the natural logarithm of volatility VIX index (VIX), the natural logarithm of TED spread (TED) and the first difference of the natural logarithm of trade-weighted exchange rate index (ΔL(TWE)). Regarding the JB, asterisk * (**, ***) denotes the 10% (5%, 1%) significance level. ADF denotes the Augmented Dickey-Fuller unit root test with 10%, 5% and 1% critical values of −2.571, −2.869 and − 3.448, respectively. The ADF tests the null hypothesis that the series features a unit root. The sample period runs from January 1990 to May 2019.

Table 2
Unconditional correlations among variables under consideration.

	ΔL(PRO)	GEA	ΔL(INV)	VIX	TED	ΔL(TWE)	RVOL
ΔL(PRO)	1.000	0.140	−0.035	−0.150	−0.107	0.025	−0.067
GEA	0.140	1.000	−0.079	−0.022	0.260	−0.542	−0.077
ΔL(INV)	−0.035	−0.079	1.000	0.049	−0.125	0.224	0.232
VIX	−0.150	−0.022	0.049	1.000	0.530	0.146	0.461
TED	−0.107	0.260	−0.125	0.530	1.000	0.033	0.337
ΔL(TWE)	0.025	−0.542	0.224	0.146	0.033	1.000	0.158
RVOL	−0.067	−0.077	0.232	0.461	0.337	0.158	1.000

Note: Unconditional correlations of the natural logarithm of realised oil price volatility (RVOL), the first difference of the natural logarithm of world crude oil production (ΔL(PRO)), the global economic activity index (GEA), the first difference of the natural logarithm of global crude oil inventories (ΔL(INV)), the natural logarithm of volatility VIX index (VIX), the natural logarithm of TED spread (TED) and the first difference of the natural logarithm of trade-weighted exchange rate index (ΔL(TWE)). The sample period runs from January 1990 to May 2019.

$$GIRF_t(K, \boldsymbol{\iota}_{i,t}, \boldsymbol{I}_{t-1}) = E(\boldsymbol{y}_{t+K}|\boldsymbol{\iota}_{i,t}, \boldsymbol{I}_{t-1}) - E(\boldsymbol{y}_{t+K}|\boldsymbol{I}_{t-1}) \quad (7)$$

$$\Psi^g_{i,t}(K) = \Sigma_{ii,t}^{-\frac{1}{2}}\Lambda_{K,t}\Sigma_t\boldsymbol{e}_{i,t}\Sigma_{ii,t}^{-\frac{1}{2}}\boldsymbol{\iota}_{i,t}, \qquad \boldsymbol{\iota}_{i,t} = \Sigma_{ii,t}^{\frac{1}{2}} \quad (8)$$

$$\Psi^g_{i,t}(K) = \Sigma_{ii,t}^{-\frac{1}{2}}\Lambda_{K,t}\Sigma_t\boldsymbol{e}_{i,t} \quad (9)$$

where K represents the forecast horizon, $\boldsymbol{e}_{i,t}$ the selection vector with one on the ith position and zero otherwise.

4. Empirical results

This Section presents the empirical findings associated with the impact of global potential determinants on realised oil price volatility. It should be noted that, given the time-varying character of the analysis, we illustrate generalised impulse response functions on 3D-plots (i.e., GIRFs vary over time). Furthermore, given that this is not a constant variance – constant parameter model, no confidence bands have been included on the graphs. Figs. 2–7 report the results of the TVP-VAR model and show the median impulse response functions for horizons up to 60 months at each point in time.

4.1. Oil supply

Starting with the impact of a positive shock in oil production on realised oil price volatility, it is evident in Fig. 2 that in between years 1990–2019 the initial response from the latter appears to be positive (i.e., on the plot, we note that, during the first months of the GIRF purple colour progressively turns into green and in some cases into yellow). Oil price volatility is expected to respond positively to a positive global oil supply shock. Notably, a positive global oil supply shock signifies an increasing world oil production related to technological advances to extract oil or to OPEC's decision to increase oil quotas. This reduces the oil price and adds to higher levels of oil price volatility. What is more, this positive response is rather more pronounced around years 1990 and 1999 (i.e., when GIRFs are marked by yellow).

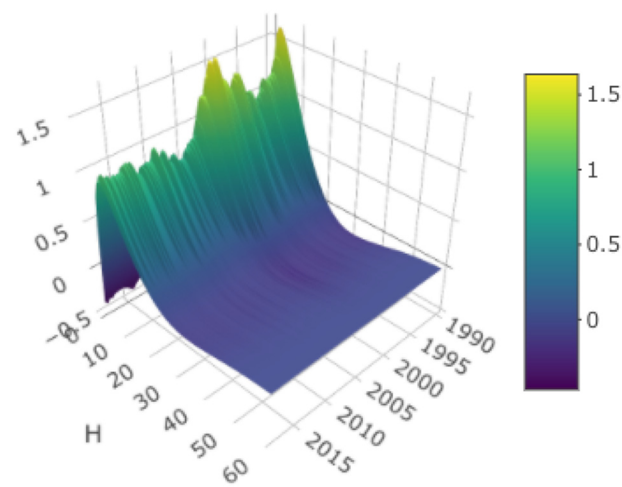

Fig. 2. Median impulse response of realised oil price volatility to a global oil supply shock.
Note: This Figure exhibits the evolution of the time-varying median impulse response of realised oil price volatility to a global oil supply shock approximated by the world crude oil production growth rate. The right front axis represents the time (years), the left front axis denotes the impulse response function monthly horizon and the vertical axis depicts the change. The vertical colour bar to the right side of the plot displays the colour scale and specifies the mapping of data values. The sample period runs from January 1990 to May 2019.

Our plot shows that a significant rise in realised oil price volatility is caused during the period of 1990–1991 which is associated with Iraq's invasion of Kuwait and the collapse of the former Soviet Union, one of the three largest oil producers in the world in 1991 as well as during 1998–1999 which coincides with oil production cuts by OPEC. Regarding the period of 1990–1991, oil price fluctuations are attributed to flow supply shocks together with speculative demand shocks that occurred at the same time as documented by Kilian and Murphy (2014), whereas Hamilton (2009) suggests that flow supply shocks itself contributed to oil price fluctuations. Turning to the higher oil price volatility of 1998–1999, Kilian and Murphy (2014) show that this was not only caused by OPEC's production cuts decisions (supply-side shock), but also by higher flow demand (aggregate demand shock) and higher speculative activity (speculative shocks). The discussion on the effects of the latter two shocks on oil price volatility is discussed in sections 4.2 and 4.3.

4.2. Global economic activity

Turning to the impact of a positive shock in global economic activity on realised oil price volatility, as we can see in Fig. 3, between years 1990–2019 the initial response from the latter appears to be negative (i.e., on the plot, we note that, during the first months of the GIRF green and in some cases yellow colour progressively turns into purple). Oil price volatility is expected to respond negatively to a positive global aggregate demand shock. In particular, a positive global aggregate demand shock suggests a higher global demand for industrial commodities including oil. This reflects positive developments in global macroeconomic activity despite the oil price increase and consequently reduces the levels of oil price volatility. Furthermore, this impact appears to be more pronounced prior to 2008 and after 2010 (i.e., when GIRFs progressively turn into purple).

Plausibly, the pattern prior to 2008 can be explained by the unexpected economic growth of the main emerging Asian economies such as China and India. In this regard, Kilian and Hicks (2013) refer to the period between 2003 and mid 2008 that contributed to an intense surge in the price of oil. In particular, they not only report economic growth surprises of the emerging economies but also lesser growth surprises that associated with OECD advanced economies during the aforementioned period. Similarly, the period after 2010 represents the recovery of global markets and hence a reduction in uncertainty regarding the macroeconomic activity. The increase in global demand was accompanied with an increase in oil demand and hence higher oil prices were associated with lower oil price volatility. Overall, our findings are not in line with the findings by Robe and Wallen (2016) who conclude that their proxies for aggregate demand do not significantly affect oil price volatility.

4.3. Global oil inventory

As far as the global oil inventory is concerned, the initial impact of this shock on realised oil price volatility is positive throughout the period of analysis. As we illustrate in Fig. 4, this persistent positive response is rather more pronounced between 1998 and 2005 (i.e., when GIRFs assume a yellow colour). Oil price volatility is expected to respond positively to a positive global inventory demand shock. Particularly, a positive global inventory shock which originates from increasing oil supply relative to oil demand, acts as a signal to market participants that this rising inventory levels could drive the oil price at lower levels which in turn increases oil price volatility. In addition to this, a positive global inventory shock could represent increasing speculative demand due to changes in the expectations for the future availability of oil and thus changes in the future oil price movements. This is associated with the sudden accumulation of inventories in the very short run which may cause a reduction in the availability of barrels of oil for current use in the market and consequently increasing levels of oil price volatility. With reference to the expectations for the future availability of oil, these are related to changes in the accumulation of oil inventories and as such they are captured by the speculative demand shock (or global inventory shock), similarly to Kilian and Murphy (2014). In addition, according to Alquist and Kilian (2010) speculative purchases may also be precautionary in that they reflect increased uncertainty about future demand or supply conditions.

Following the Iranian oil crisis (1979–1980), and prior to mid-1990's the oil inventories level remained fairly high. However, the period from the mid-1990 through the end of 2000 is closely associated with the sharp drop of oil inventories due to OPEC's production cuts with the exception of a recovery between 1998 and 1999 due to OPEC's overproduction (Lynch 2002). In addition, the period from 2000 to 2005 is characterised by adjustments in oil production from OPEC's member countries in an attempt to prevent oil inventories to be accumulated (Verleger Jr 2009). These episodes together with the weak global demand caused by the Asian financial crisis of 1997–98 and the

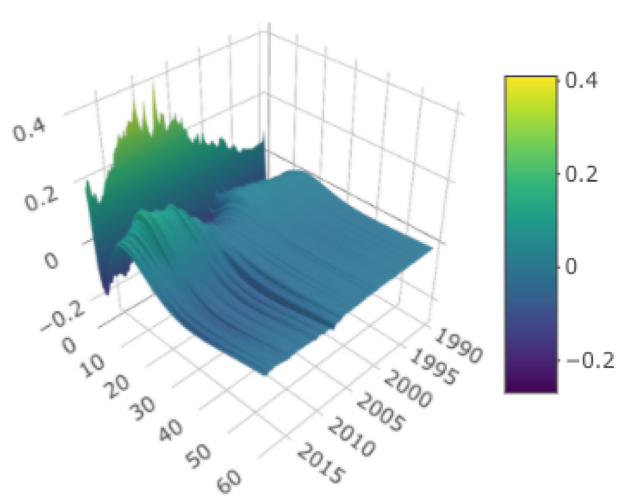

Fig. 3. Median impulse response of realised oil price volatility to a global oil demand shock. Note: This Figure exhibits the evolution of the time-varying median impulse response of realised oil price volatility to a global oil demand shock approximated by the global economic activity index. The right front axis represents the time (years), the left front axis denotes the impulse response function monthly horizon and the vertical axis depicts the change. The vertical colour bar to the right side of the plot displays the colour scale and specifies the mapping of data values. The sample period runs from January 1990 to May 2019.

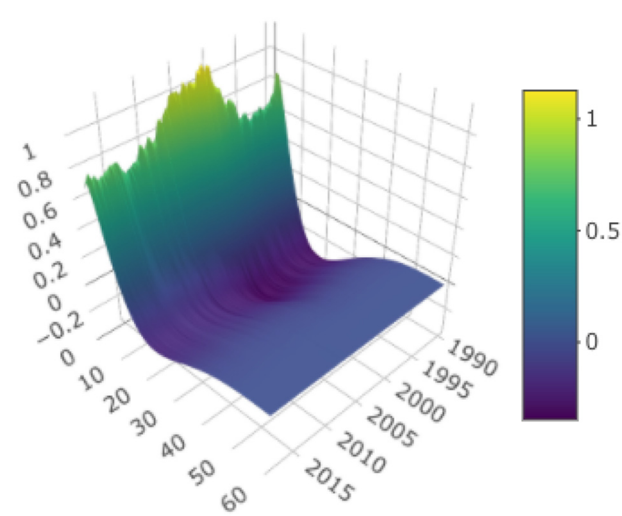

Fig. 4. Median impulse response of realised oil price volatility to a global oil inventories shock. Note: This Figure exhibits the evolution of the time-varying median impulse response of realised oil price volatility to a global oil inventories shock approximated by the global crude oil inventories growth rate. The right front axis represents the time (years), the left front axis denotes the impulse response function monthly horizon and the vertical axis depicts the change. The vertical colour bar to the right side of the plot displays the colour scale and specifies the mapping of data values. The sample period runs from January 1990 to May 2019.

uncertainty triggered by the terrorist attack crisis of September 2001, resulted in a sharp decline in oil prices and further to higher levels of oil price volatility. Such findings confirm the asymmetric volatility phenomenon (Bekaert and Wu 2000; Wu 2001). Overall, this period roughly matches the period from 1998 to 2005 in which our findings indicate higher levels of realised oil price volatility.

4.4. Volatility in financial markets

The initial impact of a shock in the volatility (VIX) index on realised oil price volatility as observed in Fig. 5, is rather positive throughout the period of analysis; however, the effect is clearly more pronounced during periods of recession that fuel global economic uncertainty. Oil price volatility is expected to respond positively to a positive global financial market volatility shock. Precisely, a positive global financial market volatility shock represents rising uncertainty about future stock price fluctuations and contributes to negative returns in global stock markets including oil returns. Thus, a higher level of financial uncertainty is indicative of worsening economic conditions and associated with higher oil price volatility. We can clearly discern the positive response from the realised oil price volatility during the recessions in the early-1990s and the 2000s, during the months of the GFC 2007, as well as more recently, during the intervals that include the European sovereign debt crisis (since 2009) and the oil price collapse of 2014. Apparently the period that marks the largest positive response from the realised oil price volatility is the GFC 2007.

Indeed, we observe the realised oil price volatility to show peaks when financial market volatility exhibits large spikes mainly during times of economic and financial turbulence. For instance, the Persian Gulf War (1990–1991), the early-2000 US recession, the GFC 2007, the European sovereign debt crisis (since 2009) and the oil price crash (2014). Linking these global episodes of financial uncertainty with the oil market, we note that all of them are associated with a collapse or a sudden significant fall of the global oil prices. The only exception was the Persian Gulf War during which oil prices climbed speedily and related to geopolitical turmoil. In turn, such developments drive oil price volatility to substantial spikes. Specifically, the finding related to the significance of VIX index has also been reported by Robe and Wallen (2016) who signify the importance of the financial market uncertainty to drive oil price volatility.

4.5. Interest rates

The GIRFs that correspond to a positive shock in the TED spread appear to follow those of a shock in the VIX. To put differently, GIRFs apparently assume very large values during well-defined crisis periods, particularly during the crisis in the early-1990s and the GFC 2007. GIRFs in connection with the TED spread are illustrated on Fig. 6. The only difference between the VIX GIRFs and the TED spread GIRFs is that realised oil price volatility seems to be relatively more (less) responsive to VIX (TED spread) shock during the two crisis periods. Oil price volatility is expected to respond positively to a positive global interest rate shock. Specifically, a positive global interest rate shock which is a money market shock causes the cost of borrowing to increase and discourages investment. This development generates uncertainty in global markets and causes a reduction in aggregate demand. In turn, oil demand and consequently oil price are expected to fall which implies increases in oil price volatility.

We notice that realised oil price volatility exhibits two large spikes when financial health approaches higher levels of stress. Since TED spread is considered as a principal indicator of financial health, we expect that when the TED spread is widened (narrowed) it is a signal of worsening (improving) financial stress and consequently leads to a higher (lower) possibility of a credit crisis. In this regard, the observed peaks in realised oil price volatility are associated with jumps in TED spread in two periods of financial crisis. Indeed, we refer to the early-1990 recession related to Iraq's invasion of Kuwait which was following the wave of late-1987 (Black Monday) stock market crash as well as the persistent wave of GFC 2007.

4.6. Exchange rates

Finally, with regard to the TWE, the initial response from realised oil price volatility to a shock in the TWE appears to be positive throughout the period of analysis, as evident in Fig. 7 (i.e., GIRFs show a purple colour which progressively turns into green and in some cases into

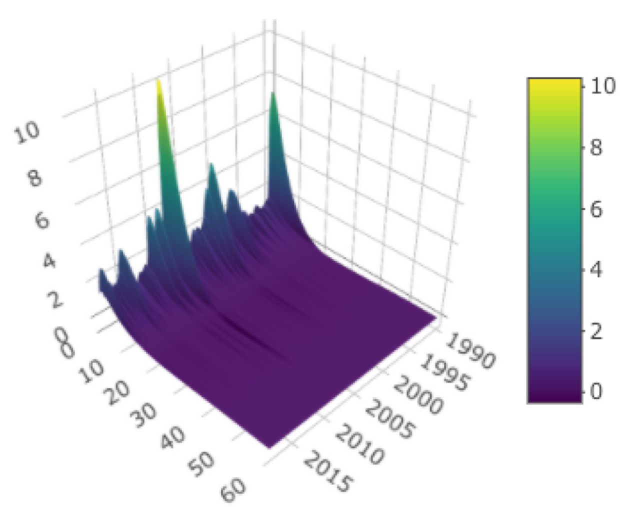

Fig. 5. Median impulse response of realised oil price volatility to a global financial market uncertainty shock. Note: This Figure exhibits the evolution of the time-varying median impulse response of realised oil price volatility to a global financial market uncertainty shock approximated by the volatility VIX index. The right front axis represents the time (years), the left front axis denotes the impulse response function monthly horizon and the vertical axis depicts the change. The vertical colour bar to the right side of the plot displays the colour scale and specifies the mapping of data values. The sample period runs from January 1990 to May 2019.

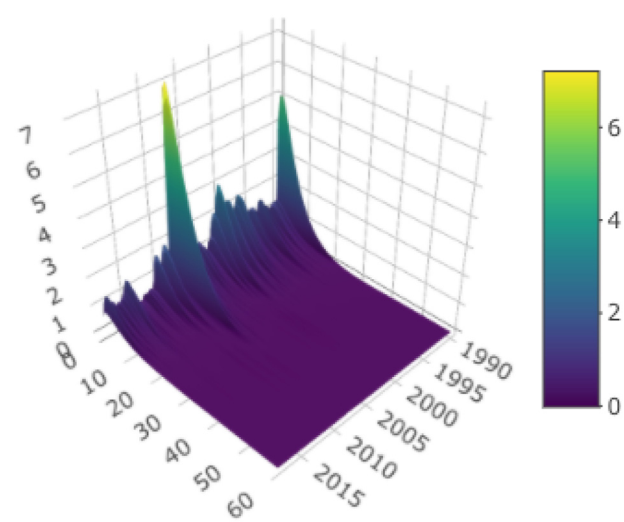

Fig. 6. Median impulse response of realised oil price volatility to a global financial interbank stress shock. Note: This Figure exhibits the evolution of the time-varying median impulse response of realised oil price volatility to a global financial interbank stress shock approximated by the TED spread. The right front axis represents the time (years), the left front axis denotes the impulse response function monthly horizon and the vertical axis depicts the change. The vertical colour bar to the right side of the plot displays the colour scale and specifies the mapping of data values. The sample period runs from January 1990 to May 2019.

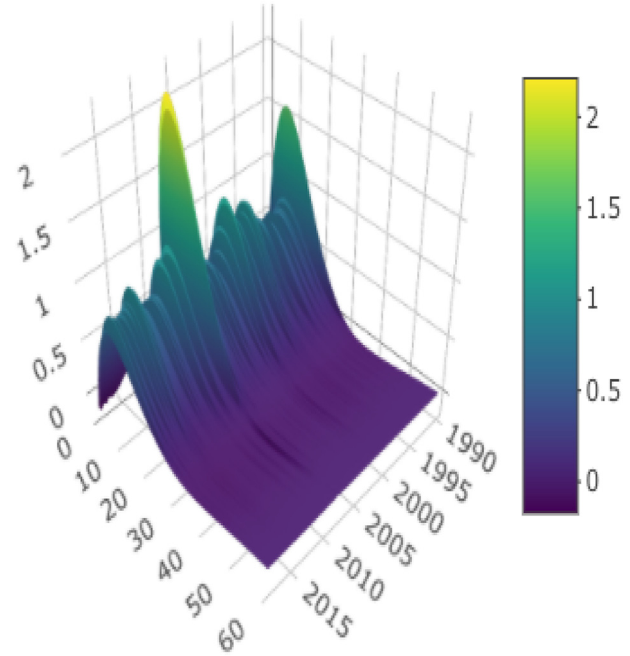

Fig. 7. Median impulse response of realised oil price volatility to a global financial currencies trend shock. Note: This Figure exhibits the evolution of the time-varying median impulse response of realised oil price volatility to a global financial currencies trend shock approximated by the trade-weighted exchange growth rate. The right front axis represents the time (years), the left front axis denotes the impulse response function monthly horizon and the vertical axis depicts the change. The vertical colour bar to the right side of the plot displays the colour scale and specifies the mapping of data values. The sample period runs from January 1990 to May 2019.

yellow). Oil price volatility is expected to respond positively to a positive global exchange rate shock. Principally, a positive global exchange rate shock is associated with an appreciation in the value of the US dollar which indicates a rise in the price of oil. However, global demand for oil with the exception of the US market will be reduced and consequently causes oil prices to fall. This weakness in global economy results in higher oil price volatility. As has already been underscored in the analysis regarding the impact of a shock in either VIX or the TED spread, it is rather evident that in the case of a shock in exchange rates, both the recessionary period of the early-1990s and the GFC 2007 also result in positive GIRFs of very large magnitude.

On the basis of the above findings, changes in the trade-weighted exchange rate index appear to influence the realised oil price volatility in a higher degree through the early-1990s and the GFC 2007 and in a lower degree through 1995–2000 and 2010–2015. Regarding the early-1990s and specifically the Persian Gulf War (1990–1991), the general consensus implies that wars trigger significant depreciation in the value of the US dollar. Furthermore, the trade-weighted exchange rate index exhibits a persistent increasing trend and peaks during periods of financial turmoil. For example, during 1995–2000, we focus on the Asian financial crisis (devaluation in Southeast Asian currencies), during GFC 2007, we highlight the financial markets crash (capital repatriation from foreign markets to the US market which led to convert foreign currencies into US dollars) and during 2010–2015, we indicate the European sovereign debt crisis (purchase of US dollars by investors). Clearly, realised oil price volatility appears to be influenced by periods of financial turmoil and unexpected wars that generate different trends in different currencies.

Following the previous findings for VIX and the TED spread, we notice that the impact magnitude of the TWE on realised oil price volatility is significantly larger and more persistent. This signifies that the TWE generates a relatively more sustainable impact on oil price volatility during the sample period. According to He et al. (2010) a 1% increase in the US dollar index is associated with a 0.70% decrease in crude oil prices, whereas Davig et al. (2015) find that a 1% appreciation of the US dollar exerts a fall in oil prices by 2.3%. Evaluating the year 2014, Davig et al. (2015) document the considerable appreciation of the US dollar against other currencies caused a decline in oil demand for non-US oil consumers and thus a reduction in oil price which triggered higher levels of oil price volatility.

4.7. Summary of findings

Overall, we document that our set of potential determinants (at the global level) appears to influence the realised oil price volatility and therefore our study adds to the examination of oil price volatility behaviour.[9] We argue that fundamental and financial (non-fundamental) shocks are drivers of realised oil price volatility. It should be mentioned though, that if we consider the magnitude of these responses, we document that there are certain differences among the GIRFs responses of oil price volatility to positive global shocks. Indeed, financial shocks appear to exert a stronger impact on oil price volatility. We point out that a common feature of our findings is associated with the impact response of our potential global determinants which appears to be the expected. Specifically, the initial impact takes approximately 10 months ahead to progressively decay and then to level off. We could say that short run effects can be associated with oil market fundamentals that appear to exhibit such effects due to supply and demand imbalances. In addition, financial indicators, incorporate information content which drives the price of oil away from its fundamentals and consequently generates similar effects. However, the oil market has the mechanism to adjust in new information and absorb the temporary imbalances. In turn, this process reduces the uncertainty in oil price and drives the volatility at very low levels in the long run.

On the whole, our findings support the evidence provided by Van Robays (2016) who demonstrates that recessions and financial crises trigger higher oil price uncertainty. On general principles, we suggest that realised oil price volatility movements are attributed to changes in oil market fundamentals of oil supply and oil demand (including oil inventories) and also we suggest the importance of financial shocks that transmit information which has contributed to significant variation in oil price. We are in line with Kilian (2010) who discusses the origin and impact of oil price volatility and argues that expectations of forward-looking traders, flow supply of oil and flow demand for oil are reflected in oil price changes. Our findings support the evidence provided by Caldara et al. (2019) who emphasise the importance of oil supply shocks and global demand shocks in driving oil price fluctuations. Similarly, our suggestions appear to be in line with Beidas-Strom and Pescatori (2014) who underline the short run impact of speculation on oil price fluctuations. By contrast, our findings do not appear to be in line with Van Robays (2016) who documents that speculation does not contribute to changes in oil price volatility. In particular, we show that speculative shocks, as depicted by the global oil inventory shocks, trigger a material positive response of the oil price volatility, which is relatively higher in amplitude compared to the responses of the latter to supply and aggregate demand shocks. As such, the accumulation of oil inventories arising from forward-looking market participants, in anticipation of rising oil prices in the future, tend to destabilise the market now and hence increase its uncertainty. To this end, Dvir and Rogoff (2009) also document that oil price volatility rises when the increase in oil storage is subject to speculative demand.

[9] We note that our findings regarding the impact from each potential global determinant on conditional oil price volatility do not provide heterogeneous responses. Therefore, we point out that our robustness check findings are qualitatively similar to those in the main analysis related to realised oil price volatility. For brevity we do not show the results here, but they are available upon request.

Finally, we argue that our findings could be associated with recent evidence in connection with the financialisation of the oil market (see, Büyükşahin and Robe 2014; Fattouh et al. 2013; Tang and Xiong 2012; Irwin and Sanders 2011). Oil prices are not only determined by oil market imbalances of supply and demand but also driven by increasing financialisation. Our findings provide support to the evidence provided by Fratzscher et al. (2014) who report that oil responds instantaneously to news incorporated in other asset prices such as stock returns, interest rates and exchange rates, which, in turn, implies that oil behaves like any other financial asset. According to our findings, global financial market uncertainty, global financial interbank stress and global financial trends in currencies are all expected to generate global economic uncertainty. In turn, economic activity and consequently oil demand will be reduced and oil price volatility will be increased.

5. Conclusion

In this study we attempt to investigate whether unanticipated changes in global crude oil-market specific fundamental factors and financial indicators could be regarded as uncertainty transmission to the oil market and cause oil price volatility. We employ a time-varying parameter vector autoregression model. We use monthly data over the period from January 1990 to May 2019.

Our main findings can be summarised as follows. First, crude oil-market specific fundamental factors and financial indicators (both at the global level) appear to influence the evolution of realised oil price volatility. Second, the impact varies over time and it is evident in the short run horizon. Third, the effect is mainly attributed to severe episodes of economic recessions and financial crises. Fourth, the greatest influence is attributed to the financial indicators and thus we lend support to the financialisation of the oil markets.

These findings could suggest important implications for policy makers and investors who are interested in receiving information related to the extent to which oil price volatility has influenced by global determinants. Increasing (decreasing) oil price volatility could be indicative of higher (lower) uncertainty and consequently generates an unstable (stable) financial and macroeconomic environment. For investors, increasing oil price volatility implies a reduction in planning and investment decisions as well as less effective fiscal and monetary tools for policy makers. This situation could lead to reallocation of resources which in turn affects negatively market productivity and further economic growth. It should be mentioned that periods of persistently increasing oil price volatility could be possibly influence the use of renewable energy sources by policy makers which could lead to reduced levels of oil price volatility.

Having documented that there is an increased financialisation of oil market and speculative activity in the market, our findings have important policy implications. Before presenting these implications it is important to mention that speculation could be beneficial for commercial consumers and commercial producers given that it provides liquidity to the market (see, Fattouh 2010). However, when speculators attempt to dominate the market by holding an enormous share of the futures market (excessive speculation), this results to the destabilisation of the price discovery and consequently negatively affects commercial users regarding their hedge capacity. Therefore, excessive speculation could be considered a rather important source of growing oil price volatility. In the presence of excessive speculation, policy makers need to impose regulatory tools to restrict such activities in commodity futures markets and hence to control their market share, as also suggested by Fattouh (2010). Even more, regulators should incorporate the developments in the oil market in both their micro and macroprudential policy decisions, since the fact that the oil market behaves as any other financial asset (due to its financialisation), it makes it prone to bubbles, which could then contribute to both systemic and non-systemic crises.

Furthermore, turning to a more detailed analysis of the importance of our findings to investors, traders and portfolio managers who are interested in the oil market, we should highlight the fact that their investment decisions should be dependent on the uncertainty that surrounds the financial markets. Hence, those investors who are interested in oil market returns should intensify their hedging strategies or exit the oil market when there is increased uncertainty in the financial world. Obviously, higher uncertainty in the latter is anticipated to lead to increased oil price volatility and thus lower oil prices. On the other hand, investors who are interested in trading oil market volatility, they should increase their long positions in the latter (via long straddles using options for example) when the uncertainty in the financial markets is anticipated to increase.

Finally, a promising area for future study could model additional variables. Indeed, the examination of whether other key oil-specific and global business cycle variables (oil futures spreads, producer price index for oil, gasoline price spreads, capacity utilisation rate, Baltic Dry index), financial variables (aggregate stock prices, firm level oil stock prices) and commodity variables (gold, natural gas) could provide explanatory value to capture movements in oil price volatility. Furthermore, future research may examine the leading role of oil price volatility in influencing macroeconomic indicators, given the fact that volatile oil prices lead to rising uncertainty in the economic activity.

Authors' Contributions

All authors of the study, have all contributed to the conceptualisation, development, analysis and writing of the paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2020.105092.

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