Bournemouth University

BAFES –
Bournemouth Accounting, Finance & Economic Series

NO 13 / 2018

Oil Price Shocks and Uncertainty: How stable is their relationship over time?

Stavros Degiannakis, George Filis, and Sofia Panagiotakopoulou

Oil Price Shocks and Uncertainty: How stable is their relationship over time?

Stavros Degiannakis[1,2], George Filis[3,*] and Sofia Panagiotakopoulou[1]

[1]Department of Economics and Regional Development, Panteion University of Social and Political Sciences, 136 Syggrou Avenue, 17671, Greece.

[2]Postgraduate Department of Business Administration, Hellenic Open University, Aristotelous 18, 26 335, Greece.

[3]Department of Accounting, Finance and Economics, Bournemouth University, 89 Holdenhurst Road, BH8 8EB, Bournemouth, UK

*Corresponding author: gfilis@bournemouth.ac.uk

Abstract

This paper investigates the time-varying relationship between economic/financial uncertainty and oil price shocks in the US. A structural VAR (SVAR) model and a time-varying parameter VAR (TVP-VAR) model are estimated, using six indicators that reflect economic and financial uncertainty. The findings from the SVAR model reveal that uncertainty indicators do not respond to supply-side oil shocks, whereas they respond negatively to aggregate demand and oil specific demand shocks. However, the TVP-VAR model shows that the uncertainty responses to the three oil price shocks are heterogeneous both over time and over the different oil price shocks. More specifically, we show that the behaviour of responses changes in the post global financial crisis period, suggesting a shift in the relationship between oil shocks and uncertainty indicators. The findings are important to policy makers and investors, as they provide new insights on the said relationship.

Keywords: Economic policy uncertainty; financial uncertainty; realized volatility; oil price shock; SVAR; TVP-VAR; US.
JEL: C32; C51; G15; Q40.

1. Introduction

Focusing on the US economy, the aim of this paper is to investigate the time-varying effects of oil price shocks, namely supply-side, aggregate demand and oil specific demand shocks, on economic uncertainty. The study focuses on different types of economic uncertainty, which capture the different sectors of an economy, namely macroeconomic-related, policy-related, commodity-related and financial-related uncertainty.

The interest on the drivers of economic uncertainty has reemerged since the last financial crisis of 2007-09, the ongoing European debt crisis, the oil price collapse since 2014 and more recently the Trump's victory in the US elections and the Brexit vote in the 2016 UK's referendum (see, *inter alia*, Bloom, 2009; Baum *et al*., 2010; Bachmann *et al*., 2010; Popescu and Smets, 2010; Antonakakis *et al*., 2013; New York Times, 2016; Bloomberg, 2017; Caggiano, 2017).

Interestingly enough, though, the literature has remained relatively silent on the effects of oil prices on economic uncertainty, despite the ample evidence on the effects of oil prices (i) on the economy since the 1980s and the seminal paper by Hamilton (1983), as well as (ii) on the financial markets, since the seminar paper by Kaul and Jones (1996) [1]. The wealth of literature has established that oil prices affect the wider economy, via their influence on productivity, inflation, unemployment, etc[2].

Nevertheless, examining the effects of oil prices on economic uncertainty is rather important, given the effects of the latter to the wider economy, as established by Bernanke (1983), Marcus (1981) and Rodrik (1991), among others. More specifically, examining the sources of economic uncertainty is of major importance as the latter affects the business cycle through its influence on economic activity (Pindyck, 1990; Bloom, 2009; Kang *et al*., 2014; Visco, 2017), either via household consumption decisions or firm investments decisions. Put it simply, the higher the economic uncertainty the lower the household consumption and the higher the delays in capital investments.

Recent literature shows that increased oil prices exert significant influences on inflation and production, leading to higher macroeconomic-related uncertainty (Natal, 2012; Montoro, 2012). In addition, El Anshasy and Bradley (2012) claim that higher

---

[1] See, Sadorsky (1999), Park and Ratti (2008), Filis (2010), Cunado and Perez de Gracia (2014), Angelidis *et al*. (2015), Boldanov *et al*. (2016) and Antonakakis *et al*. (2017), among many others.

[2] See, *inter alia*, Hamilton (1988, 1996), Hooker (1996), Abel and Bernanke (2001), Lee and Ni (2002), Hooker (2002), Bernanke (2006), Hamilton (2008, 2009), Lippi and Nobili (2012).

oil prices lead to greater government size for the oil-exporting countries, which obviously raised issues in terms of the efficient operation of the government, as also emphasized by Antonakakis *et al*. (2014). Along a similar vein, Kang and Rati (2013) maintain that economic policy-related uncertainty decreases (increases) in response to aggregate demand oil price shocks (oil specific demand shocks). By contrast, they find that supply-side oil price shocks do not impact economic policy uncertainty.

Turning our attention to the linkages between oil prices and financial-related uncertainty, the literature is extremely scarce. It is only Degiannakis *et al*. (2014) who provide evidence that oil price changes due to aggregate oil demand shocks lead to reduction in financial uncertainty, whereas supply side shocks and oil-specific demand shocks do not seem to exert any impact.

Finally, there is an emerging strand in the energy finance literature which is motivated by Filis *et al*. (2011), Degiannakis *et al*. (2013) and Broadstock and Filis (2014), among other, that show time-varying spillover effects between the aforementioned oil price shocks and economic policy uncertainty. For instance, Antonakakis *et al*. (2014) report that the aggregate demand oil price shocks mainly lead to a reduction in economic policy uncertainty, whereas oil specific demand shocks and supply-side shocks do not exhibit any strong spillover effects.

Against this backdrop, we maintain that it is important to assess how oil price shocks could also trigger changes in other sources of economic uncertainty, such as commodity-related and macroeconomic-related, rather than solely on economic policy and financial uncertainty, which is the main focus of the existing literature. This paper aims to fill this void.

The contribution of this paper can be described succinctly. First, it adds to the extremely limited empirical findings on the linkages between oil price shocks and economic uncertainty. Second, we investigate for the first time in the literature whether the responses of economic uncertainty indicators to the three oil price shocks, are time-varying. To do so, this study concentrates on six key US economic uncertainty indicators for the period January 1994 to March 2015 and uses a structural VAR (SVAR) model, as well as, a Time-Varying Parameter VAR (TVP-VAR).

Our results can be outlined as follows. The responses of the uncertainty indicators to the three oil price shocks, as these were estimated by the SVAR model, reveal that oil supply shocks do not exercise any significant impact on uncertainty indicators. Furthermore, we find that the two demand-side oil shocks trigger lower uncertainty. More importantly, though, through the TVP-VAR model we show for the first time that the impulse responses of the uncertainty indices to the three oil price shocks are not constant over time, but rather they vary over time. The time-varying impulse responses show that uncertainty indices exhibit heterogeneous responses to all three shocks, as well as, during different time periods. More specifically, we show that the behaviour of responses changes in the post global financial crisis period, suggesting a shift in the relationship between oil shocks and uncertainty indicators.

The rest of the paper is structured as follows. Section 2 describes the data employed in this study, whereas Section 3 details the methodology. The empirical findings of the research are presented in Section 4, whereas Section 5 summarises the results and concludes the paper.

2. *Data Description*

In this study we employ world oil production (in thousand barrels, PROD), Lutz Kilian's global real economic activity index (GEA)[3] and Brent crude oil price returns (ROIL), which are used for the construction of the three oil price shocks (supply-side, aggregate demand and oil specific demand shocks). We also use six measures of economic and financial uncertainty in the US, which capture macroeconomic-related, policy-related, commodity-related and financial-related uncertainty.

More specifically, we use (i) The *Chicago Fed National Activity Index* (CFNAI), which is constructed as a weighted average of four broad categories; the production and income index, the employment, unemployment and hours indicator, the broad personal consumption and housing index and the sales, orders and stocks index; (ii) The *Economic Policy Uncertainty Index* (EPU), which is constructed based on three components, i.e. newspaper articles of the ten largest newspapers of the US, the temporary provisions of the tax code expiration of the US and the factor of disagreement between the opinions of economic forecasters; (iii) The *Equity Market Uncertainty Index* (EMU), which is based on an automated text-search process from Access World News's NewsBank service news articles that contain terms related to "uncertainty", "economy", "stock price" and "equity market"; (iv) The *Implied*

[3] The Kilian's index became popular selection for the real economic activity worldwide as it captures business cycle fluctuations in global base about commodity markets of industrial sector and is used by many authors such as; Antonakakis *et al*. (2014), Apergis and Miller (2009), Baumeister and Kilian (2014) and Alquist and Kilian (2010), among others.

Volatility Index of S&P500 (VIX), which is often characterized as the "fear index" and it is the leading measure of market expectations of the implied volatility of S&P500 index options over the upcoming 30-day period; and finally (v) the *Conditional Oil Price Volatility* (OCV), which is a measure of commodity uncertainty. For this particular uncertainty indicator, we construct an additional oil price volatility series (vi), namely the *Realized Oil Price Volatility* (denoted as ORV) for robustness purposes. The usage of these two volatility series is justified by the fact that realized volatility is a more precise and less noisy estimator, according to the literature (e.g. Andersen and Bollerslev, 1998), but it requires no-freely available data for its construction, which are not always available to researchers. On the other hand, the conditional volatility is a widely applied and accepted volatility estimator and requires daily data.

All data span from January 1994 to March 2015, with only exception the ORV data which span from August 2003 to March 2015, due to the unavailability of longer period of the tick-by-tick data. The EPU and EMU have been extracted from Baker *et al*. (2013)[4]. In addition, Brent crude oil prices and the world oil production is obtained from the Energy Information Administration. The GEA is taken from Lutz Kilian's personal site[5], whereas the VIX and CFNAI come from FRED database.

For the construction of the OCV we collect daily Brent crude oil prices from Energy Information Administration, whereas tick-by-tick data of Brent crude oil prices, which are collected for the ORV, are obtained TickData. The construction of the two oil price volatility series is presented in Sections 3.1 and 3.2. We do not consider implied volatility given that this is not available for the Brent crude oil prices.

We convert oil production data in its first-log differences, whereas GEA and all uncertainty indices are expressed in levels.

[4]In more details, the US policy uncertainty index appears at http://www.policyuncertainty.com/us_monthly.html and the equity market uncertainty index appears at http://www.policyuncertainty.com/equity_uncert.html.

[5] Lutz Kilian's GEA index comes from http://www-personal.umich.edu/~lkilian/paperlinks.html and especially from the link: Updated version of the index of global real economic activity in industrial commodity markets, proposed in "Not all oil price shocks are alike ...", monthly percent deviations from trend, 1968.1-2015.9.

3. Methodology

3.1. Oil price realized volatility

Let us consider as $logP_{t_j}$ the observed Brent crude oil log-price at trading day t and j intra-day point. For j=1,..,τ equidistant intervals at each trading day, Andersen and Bollerslev (1998) provided evidence that the daily realized volatility is estimated to be the sum of squared intra-day returns:

$$DRV_t^{(\tau)} = \sqrt{\sum_{j=1}^{\tau}\left(logP_{t_j} - logP_{t_{j-1}}\right)^2}. \tag{1}$$

The realized volatility converges in probability to the integrated volatility, $IV_t \equiv \int \sigma^2(t)dt$, as the number of sub-intervals tends to infinity, $\tau \to \infty$. However, the microstructure frictions (i.e. discreteness of the data, transaction costs, taxes, regulatory costs, properties of the trading mechanism, bid-ask spreads, ect.) add more noise to the estimated volatility when the sampling frequency converges on zero. Thus, there is a trade-off between the bias that is inserted in the realized volatility measure and its accuracy.

The daily variance, $(logP_t - logP_{t-1})^2$, can be decomposed into the intra-day variance, $DRV_t^{2(\tau)}$, and the intra-day autocovariance, $\sum_{j=1}^{\tau-1}\sum_{i=j+1}^{\tau}\left(logP_{t_i} - logP_{t_{i-1}}\right)\left(logP_{t_{i-j}} - logP_{t_{i-j-1}}\right)$:

$$\begin{gathered}(logP_t - logP_{t-1})^2 = \\ DRV_t^{2(\tau)} + 2\sum_{j=1}^{\tau-1}\sum_{i=j+1}^{\tau}\left(logP_{t_i} - logP_{t_{i-1}}\right)\left(logP_{t_{i-j}} - logP_{t_{i-j-1}}\right).\end{gathered} \tag{2}$$

The intra-day autocovariance represents the bias that is induced in the realized volatility measure, with $E\left(\left(logP_{t_i} - logP_{t_{i-1}}\right)\left(logP_{t_{i-j}} - logP_{t_{i-j-1}}\right)\right) = 0$, for $j \neq 0$. Fang (1996) and Andersen *et al*. (2006) suggested the optimal sampling frequency being the highest frequency that minimises the autocovariance bias. In the case of Brent crude oil the $\left(\sum_{j=1}^{\tau-1}\sum_{i=j+1}^{\tau}\left(logP_{t_i} - logP_{t_{i-1}}\right)\left(logP_{t_{i-j}} - logP_{t_{i-j-1}}\right)\right)$ is minimized at τ=23. Hence, the optimal sampling frequency is defined in 23 minutes.

Furthermore, it is well established that when markets are closed, i.e. during night-time periods, holidays, and weekends, information still flows. Hansen and Lunde (2005), in order to account for changes in the asset prices during the hours that the market is closed, proposed to adjust the intra-day volatility with the close-to-open inter-day volatility, as:

$$DRV_{t,(HL)}^{(\tau)} = \sqrt{\omega_1\left(logP_{t_1} - logP_{t-1_\tau}\right)^2 + \omega_2\sum_{j=2}^{\tau}\left(logP_{t_j} - logP_{t_{j-1}}\right)^2}, \tag{3}$$

where[6] the weights ω_1 and ω_2 are such that minimise the difference between the realized volatility and the integrated volatility, i.e. $\min E\left(DRV_{t,(HL)}^{2(\tau)} - IV_t\right)^2$. Of course, the IV_t is unobservable. Thus, Hansen and Lunde (2005) proposed to solve $\min V\left(DRV_{t,(HL)}^{2(\tau)}\right)$, as they have stated that $\arg\min E\left(DRV_{t,(HL)}^{2(\tau)} - IV_t\right)^2 = \arg\min V\left(DRV_{t,(HL)}^{2(\tau)}\right)$. Finally, the annualised monthly realized volatility series, $ORV_t^{(m)}$, is constructed, as follows:

$$ORV_{\mathrm{t}}^{(\mathrm{m})} = 100\sqrt{12\sum_{t=1}^{22} DRV_{t,(HL)}^{2(\tau)}}. \tag{4}$$

3.2. Oil price conditional volatility

We estimate the conditional volatility of the oil daily log-returns using Ding's *et al*. (1993) APARCH model, in the spirit of Degiannakis *et al*. (2014). The APARCH model is estimated as:

$$\begin{gathered} y_t = c_0 + \varepsilon_t \\ \varepsilon_t = \sigma_t z_t \\ \sigma_t^{\delta} = a_0 + a_1\left(\left|\varepsilon_{t-1}\right| - \gamma_1\varepsilon_{t-1}\right)^{\delta} + b_1\sigma_{t-1}^{\delta} \\ z_t \overset{i.i.d.}{\sim} T(0,1;\nu) \\ f_{(t)}(z_t;\nu) = \frac{\Gamma((\nu+1)/2)}{\Gamma(\nu/2)\sqrt{\pi(\nu-2)}}\left(1 + \frac{z_t^2}{\nu-2}\right)^{-\frac{\nu+1}{2}}, \end{gathered} \tag{5}$$

where $a_0 > 0$, $\delta > 0$, $b_1 \geq 0$, $a_1 \geq 0$ and $-1 < \gamma_1 < 1$, $\nu > 2$.

The APARCH model is considered as one of the best models for estimating conditional volatility (for technical details, please see Xekalaki and Degiannakis, 2010).

We compute the annualised monthly conditional volatility, $OCV_t^{(m)}$, as:

$$OCV_{\mathrm{t}}^{(m)} = 100\sqrt{12\sum_{t=1}^{22} \sigma_{t/t-1}^2}, \tag{6}$$

[6] The subscript (HL) denotes the $DRV_{t,}$ measure according to Hansen and Lunde's adjustment.

where $\sigma^2_{t/t-1}$ denotes the daily conditional variance for the t=1,...,22 trading days of month m.

3.3. Structural VAR framework

Prior to the examination of the time-varying responses of the uncertainty indicators to oil price shocks, we employ a Structural Vector Autoregressive (SVAR) model in order to explore the impact of oil price shocks (supply-side, aggregate demand and oil specific demand shocks) on the respective six uncertainty indices (*UNCERT*), based on the full sample. The supply-side shocks (SS) reflect unexpected changes in world oil production of crude oil (*PROD*), the aggregate demand shocks (ADS) are identified from global real economic activity (*GEA*) and oil specific demand shocks (SDS) are estimated from changes in crude oil prices (*ROIL*). The generic name of uncertainty series is *UNCERT*. Our SVAR model has been adopted by Kilian and Park (2009).

The standard representation of a general pth order SVAR model expresses as the following form:

$$\mathbf{A}_0\,\mathbf{y}_\mathrm{t} = \mathbf{c}_0 + \sum_{\mathrm{i}=1}^{\mathrm{p}} \mathbf{A}_\mathrm{i}\,\mathbf{y}_{\mathrm{t-i}} + \boldsymbol{\varepsilon}_\mathrm{t}, \tag{7}$$

where, $\mathbf{A}_0$ represents the $[4 \times 4]$ matrix that summarizes the contemporaneous relationship between the variables of the model, $\mathbf{c}_0$ is a $[4 \times 1]$ vector of constants, $\mathbf{A}_\mathrm{i}$ are $[4 \times 4]$ autoregressive coefficient matrices and $\boldsymbol{\varepsilon}_\mathrm{t}$ is a $[4 \times 1]$ vector of error terms "*structural shocks*" assumed to have zero covariance and be serially uncorrelated, $E(\boldsymbol{\varepsilon}_\mathrm{t}) = 0$, $E(\boldsymbol{\varepsilon}_\mathrm{t}\boldsymbol{\varepsilon}'_\mathrm{t}) = \boldsymbol{D}$ and $E(\boldsymbol{\varepsilon}_\mathrm{t}\boldsymbol{\varepsilon}'_{\mathrm{t-i}}) = \mathbf{0}$. Finally, $\mathbf{y}_\mathrm{t}$ is a $[4 \times 1]$ vector of 4 endogenous variables and specifically $\mathbf{y}_\mathrm{t} = [PROD_t, GEA_t, ROIL_t, UNCERT_t]'$, where $UNCERT_t$ refers each time at one of the six uncertainty indicators that are considered in this study.

The variance-covariance matrix of the structural shocks where all the elements off the main diagonal are zero is typically normalized that:

$$E(\boldsymbol{\varepsilon}_\mathrm{t}\boldsymbol{\varepsilon}'_\mathrm{t}) = \boldsymbol{D} = \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 \\ 0 & 0 & 0 & \sigma_4^2 \end{bmatrix} \tag{8}$$

The reduced form of our structural model is estimated by multiplying both sides with $\mathbf{A}_0^{-1}$ as that:

$$\mathbf{y}_{\mathrm{t}} = \mathbf{B}_0 + \sum_{\mathrm{i}=1}^{\mathrm{p}} \mathbf{B}_{\mathrm{i}}\, \mathbf{y}_{\mathrm{t-i}} + \mathbf{e}_{\mathrm{t}} \qquad (9)$$

where, $\mathbf{B}_0 = \mathbf{A}_0^{-1}\mathbf{c}_0$, $\mathbf{B}_{\mathrm{i}} = \mathbf{A}_0^{-1}\mathbf{A}_{\mathrm{i}}$ and $\boldsymbol{e}_{\mathrm{t}} = \mathbf{A}_0^{-1}\,\boldsymbol{\varepsilon}_{\mathrm{t}}$, i.e. $\boldsymbol{\varepsilon}_{\mathrm{t}} = \mathbf{A}_0\ \boldsymbol{e}_{\mathrm{t}}$. The reduced-form errors $\boldsymbol{e}_{\mathrm{t}}$ are linear combinations of the structural errors$\boldsymbol{\varepsilon}_{\mathrm{t}}$, with a covariance matrix of the form can be expressed as $E(\boldsymbol{e}_{\mathrm{t}}\boldsymbol{e'}_{\mathrm{t}}) = \mathbf{A}_0^{-1}\,\mathbf{D}\,\mathbf{A'}_0^{-1}$.

In order to obtain the structural shocks we need to impose suitable short-run restrictions on $\mathbf{A}_0$, as follows:

$$\begin{bmatrix} \varepsilon_{1,t}^{SS} \\ \varepsilon_{2,t}^{\mathrm{ADS}} \\ \varepsilon_{3,t}^{\mathrm{SDS}} \\ \varepsilon_{4,t}^{\mathrm{UNS}} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \times \begin{bmatrix} e_{1,t}^{\mathrm{PROD}} \\ e_{2,t}^{\mathrm{GEA}} \\ e_{3,t}^{\mathrm{ROIL}} \\ e_{4,t}^{\mathrm{UNCERT}} \end{bmatrix}. \qquad (10)$$

In which $\varepsilon_{1,t}^{\mathrm{SS}}$ captures the supply side shocks (SS), $\varepsilon_{2,t}^{\mathrm{ADS}}$ reflects the aggregate oil demand shocks (ADS), $\varepsilon_{3,t}^{\mathrm{SDS}}$ denotes the oil specific demand shocks (SDS) and $\varepsilon_{4,t}^{\mathrm{UNS}}$ measures the uncertainty shocks (UNS). We should emphasize here that we run six separate SVAR models, one for each uncertainty indicators[7]. Once again, we should highlight that the short-term restrictions which are necessary in the context of structural vector autoregressive models are egged by Kilian and Park (2009).

In particular, according to Kilian and Park (2009), oil production does not respond contemporaneously to shocks in oil demand and oil prices, due to the high adjustment costs. By contrast, changes in the world oil production have an immediate effect on oil demand and they are instantly captured in oil price fluctuations, hence both aggregate demand and oil prices are allowed to receive contemporaneous effects from changes in the world oil production. Furthermore, given the time lag that is required for the global economy to respond to changes in oil prices, we do not allow for a contemporaneous effects on the global economic activity to changes in oil prices. However, shocks in aggregate economic activity are anticipated to trigger immediate (and thus contemporaneous) effects on oil prices. Finally, we posit that

[7] The length of the lags for the SVAR models is determined by Akaike information criterion (AIC). The AIC criterion for each of the six SVAR models is the following; model with CFNAI with three lags, models with EPU, EMU, VIX and OCV with two lags and model with ORV with five lags. All SVAR models satisfy the stability condition. We do not use all six indicators in one SVAR model, given that we are primarily concerned with the effects of oil price shocks and each of the uncertainty indicators, rather than the interactions among the sources of uncertainty.

economic/financial uncertainty responds contemporaneously to all aforementioned oil price shocks, whereas the reverse does not hold true.

3.4. Time-Varying Parameter Vector AutoRegression

In the paragraphs follow, we illustrate the Bayesian analysis of the time-varying parameter VAR model (TVP-VAR). The TVP-VAR is presented as:

$$\mathbf{y}_{\mathrm{t}} = \mathbf{B}_{0,\mathrm{t}} + \sum_{\mathrm{i}=1}^{\mathrm{p}} \mathbf{B}_{\mathrm{i,t}}\, \mathbf{y}_{\mathrm{t-i}} + \mathbf{e}_{\mathrm{t}}, \tag{11}$$

where $\mathbf{y}_{\mathrm{t}} = [PROD_t, GEA_t, ROIL_t, UNCERT_t]'$ is the $[4 \times 1]$ vector of the endogenous variables, $\mathbf{B}_{0,\mathrm{t}}$ is a $[4 \times 1]$ vector of time-varying coefficients, $\mathbf{B}_{\mathrm{i,t}} = \begin{bmatrix} \beta_{1,1,i,t} & \cdots & \beta_{1,4,i,t} \\ \vdots & \ddots & \vdots \\ \beta_{4,1,i,t} & \cdots & \beta_{4,4,i,t} \end{bmatrix}$ are matrices of time-varying coefficients and $\boldsymbol{e}_{\mathrm{t}} \sim N(\mathbf{0}, \boldsymbol{\Omega}_t)$. The time-varying covariance matrix is recursively identified by the decomposition:

$$\boldsymbol{\Omega}_t = \mathbf{A}_{\mathrm{t}}^{-1} \boldsymbol{\Sigma}_t \boldsymbol{\Sigma}'_t \mathbf{A}'^{-1}_{\mathrm{t}}, \tag{12}$$

where $\mathbf{A}_{\mathrm{t}}$ is a lower-triangular matrix with the diagonal elements equal to one, and $\boldsymbol{\Sigma}_t = diag(\sigma_{1,t}, \dots, \sigma_{4,t})$. All the elements of the time-varying matrices are stacked in row vectors such as:

$$\boldsymbol{\alpha}_t = (\alpha_{1,\mathrm{t}}, \dots, \alpha_{6,\mathrm{t}})', \tag{13}$$

$$\boldsymbol{\beta}_t = (\beta_{1,1,1,t}, \dots, \beta_{4,4,1,t}, \dots, \beta_{1,1,p,t}, \dots, \beta_{4,4,p,t})', \tag{14}$$

$$\boldsymbol{\sigma}_t = \left(log(\sigma_{1,t}^2), \dots, log(\sigma_{4,t}^2)\right)'. \tag{15}$$

The time-varying parameters follow the random walk process:

$$\boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \boldsymbol{u}_{(\alpha),t},\ \boldsymbol{\alpha}_t \sim N(\boldsymbol{\mu}_{(\alpha)}, \boldsymbol{\Sigma}_{(\alpha)}), \tag{16}$$

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \boldsymbol{u}_{(\beta),t},\ \boldsymbol{\beta}_t \sim N(\boldsymbol{\mu}_{(\beta)}, \boldsymbol{\Sigma}_{(\beta)}), \tag{17}$$

$$\boldsymbol{\sigma}_t = \boldsymbol{\sigma}_{t-1} + \boldsymbol{u}_{(\sigma),t},\ \boldsymbol{\sigma}_t \sim N(\boldsymbol{\mu}_{(\sigma)}, \boldsymbol{\Sigma}_{(\sigma)}), \tag{18}$$

where $\begin{bmatrix} \boldsymbol{u}_{(\alpha),t} \\ \boldsymbol{u}_{(\beta),t} \\ \boldsymbol{u}_{(\sigma),t} \end{bmatrix} \sim N\left(\mathbf{0}, \begin{bmatrix} \boldsymbol{\Sigma}_{(\alpha)} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma}_{(\beta)} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{\Sigma}_{(\sigma)} \end{bmatrix}\right)$. Denoting as $(\boldsymbol{\Sigma}_{(\alpha)})_i$ the i^{th} diagonal element of matrix $\boldsymbol{\Sigma}_{(\alpha)}$, the prior distributions employed are: $(\boldsymbol{\Sigma}_{(\alpha)})_i^{-2} \sim G(2, 0.01)$, $(\boldsymbol{\Sigma}_{(\beta)})_i^{-2} \sim G(20, 0.01)$ and $(\boldsymbol{\Sigma}_{(\sigma)})_i^{-2} \sim G(2, 0.01)$, where $G(.,.)$ is the Gamma distribution. The Gibbs sampler of the Markov chain Monte Carlo (MCMC) method[8] is implemented to generate samples from the posterior distributions of $\boldsymbol{\alpha}_t$, $\boldsymbol{\beta}_t \boldsymbol{\sigma}_t$.

4. *Empirical Results*

4.1 Descriptive statistics

Figures 1 to 2 plot the evolution of all the data series over time. The figures depict the peaks and troughs of world oil production, global real economic activity, oil log-returns and uncertainty measures. The selected time period of data includes the early-2000 recession in the US, the Global Financial Crisis (GFC) of 2007-09 and the ongoing European debt crisis. As evident by Figures 1 and 2 most series exhibit either unprecedented peaks or troughs during the GFC. Interestingly, the EMU reached its unprecedented levels during the early-2000 recession and EPU in 2011 and 2013, which are the periods characterised by the debt ceiling dispute and the fears for government shutdown, respectively. Another notable observation is that GEA has reached its lowest level during our sample period.

[FIGURE 1 HERE]

[FIGURE 2 HERE]

Table 1 presents the descriptive statistics of the chosen variables[9]. It is evident that the most volatile uncertainty index is this of CFNAI, followed by the EMU and EPU. Interestingly enough, the least volatile uncertainty series is the VIX. Furthermore, as depicted by the skewness, kurtosis and Jarque-Bera test, none of the series under consideration are normally distributed, where most series exhibit a leptokurtic distribution. In addition, CFNAI is negatively skewed, whereas the reverse holds true for the remaining uncertainty indicators. Finally, according to the ADF test all variables are stationary.

[TABLE 1 HERE]

4.2 Structural Impulse Responses to Oil Price Shocks: SVAR

First, we examine the dynamic adjustment of each uncertainty measure to unexpected structural oil price shocks as referred to Kilian and Park (2009) for the full sample period and then we will proceed with the results of the TVP-VAR.

[8] Technical information for the Bayesian estimation of the models is available in Nakajima (2011), Koop and Korobilis (2010) and Primiceri (2005).

[9] We should highlight that increases in CFNAI values suggest reduction in economic uncertainty, whereas for all other measures the reverse holds true.

Figure 3 reports the accumulated impulse responses of each uncertainty series to one standard deviation structural shocks from the oil supply side, the aggregate demand of crude oil and the oil-specific demand for a time period of 24–months.

[FIGURE 3 HERE]

Starting the analysis from an unexpected positive oil supply shock (Shock 1) and specifically looking at the first column of Figure 3, we observe that none of the uncertainty indicators exhibits any significant response to oil supply shock. A plausible explanation is that the oil supply shocks are anticipated, as markets and economies worldwide are familiar with OPEC practices, hence, they do not react to such oil price shocks (Kilian, 2009). More specifically, OPEC usually decides not to reduce production levels to maintain its market share, as competition from other sides intensifies with undeniable example the shale oil production from the United States. The aforementioned findings find support from the existing literature, such as, Kilian and Park (2009), Kilian (2009), Hamilton (2009), Bloom (2009), Alquist and Kilian (2010), Filis *et al*. (2011), Stock and Watson (2012), Degiannakis *et al*. (2014), Antonakakis *et al*. (2014) and Aloui *et al*. (2015) who maintain that disturbances from the supply-side shall result in small and transient changes in oil prices and therefore do not significantly affect economic and financial indicators.

Focusing on the second column of Figure 3, we show the uncertainty responses to positive aggregate demand shocks (Shock 2). Interestingly enough the responses are not homogeneous, which suggests that the multiple faces of uncertainty within the economy could be impacted differently by oil price shocks. Hence, monitoring the different responses from each uncertainty indicators is essential in disentangling how oil price shocks propagate their effects in the different uncertainty sources of economic activity. More specifically, four out of the six uncertainty series are affected, namely the CFNAI, VIX, OCV and ORV; however, the latter two exhibit a significant response only in the very short-run (the response become insignificant after 3 months). Even more we find that positive aggregate demand shocks lead to positive (negative) responses from CFNAI (VIX, OCV and ORV). This is rather expected as aggregate demand shocks are related to increased global economic activity, which can be regarded as positive news for the business and the financial sectors leading to lower uncertainty. The finding for VIX echoes this by Degiannakis *et al*. (2014) who maintain that European stock market volatility responds negatively to positive aggregate demand shocks. It is interesting that economic policy uncertainty

(EPU) does not respond to aggregate demand shocks, which are not in line with the findings reported by Kang and Ratti (2013) and Antonakakis *et al*. (2014) who find evidence that aggregate demand shocks exercise a significantly negative effect on EPU. Such difference could lie in the fact that this study is using a different time period, which could suggest that these relationships vary depending on the time period.

Finally, the effects of an unanticipated positive oil specific demand shock (Shock 3) are presented in the third column of Figure 3. Once again heterogeneity in responses of the uncertainty indices is evident. In particular, we observe a positive response from CFNAI and negative responses from VIX, OCV and ORV. By contrast, no responses are observed for EPU and EMU. The results for the OCV and ORV are somewhat expected, given that increases in oil prices, regardless the source of the oil shock, reduce oil price volatility. On the other hand, though, the findings for CFNAI and VIX are rather counter-intuitive. More specifically, a positive oil specific demand shock suggests great uncertainty about the future availability of oil and, thus, it should trigger a negative response from CFNAI and positive from VIX. A plausible explanation of this finding could be that the behaviour of the uncertainty indices to oil price shocks is changing over time and thus we cannot observe similar findings with the previous literature (e.g. Antonakakis et al., 2014; Degiannakis et al., 2014). Thus, we need to proceed with the estimation of a TVP-VAR, which will allow us to assess if these responses are indeed time-varying.

4.3. Structural Impulse Responses to Oil Price Shocks: TVP-VAR

Having examined the results for the full sample period, we proceed with the TVP-VAR model which allows us to investigate the impulse responses at different time periods, without estimating a model for each separate time period.

The time-varying responses to shocks for 0, 1, 3, 6, 12 and 18 months horizons are presented in Figures 4 and 5.

[FIGURES 4 and 5 HERE]

It is evident that impulse responses vary at different time periods, which provides support to the estimation of a TVP-VAR model. Furthermore, apart from the time-varying character of the impulse responses, we observe that these responses are quite heterogeneous depending on the shock and the uncertainty indicator.

Starting from the supply-side shocks, the responses are mainly negative for all uncertainty indices (expect from the CFNAI where the response is positive) in the shorter run horizons (up to 3 months), suggesting that positive supply-side shocks lead to a reduction in economic and financial uncertainty (we should note that increases in CFNAI suggest reduction in economic uncertainty). These findings are rather interesting, as they are in contrast to the majority of the studies, which report insignificant effects of supply-side shocks in the economy (see, for instance, Filis *et al*., 2011; Degiannakis *et al*., 2014; Antonakakis *et al*., 2014; Aloui *et al*., 2015). Furthermore, we can observe that magnitude of the responses is not constant and in cases such as VIX and CFNAI a declining pattern is evident, suggesting that in the more recent years, these two uncertainty indicators do not really react to supply-side shocks. By contrast, EMU and EPU seem to be more responsive to these shocks since 2003.

We further our analysis with the examination of the aggregate demand shocks. In Section 4.2 we concluded that uncertainty indicators respond favourably to these shocks, given that CFNAI's response was positive, whereas VIX's response was negative. Nevertheless, the TVP-VAR results suggest that even though a favourable response prevails (i.e. negative impulse responses), there are periods where positive aggregate demand shocks lead to increased uncertainty, especially in the medium run (between 3 and 6 months ahead). This is particularly evident in the period 2010-2014 and, primarily, for the financial and commodity uncertainty indicators. This is a very interesting finding, which further justifies the use of a time-varying environment in order to unravel the relationship between uncertainty and oil shocks. A plausible explanation could be found in the fact that, in the post-GFC period, we observe that even though GEA is exhibiting a declining trend, the financial uncertainty is also reaching its lowest levels (at least in our sample period), as shown in Figure 1. Thus, we maintain that even though the economic uncertainty has not been resolved in the post-GFC period, financial uncertainty has been kept at low levels and, thus, the positive impulse responses.

We finalise the analysis with the time-varying responses to oil specific demand shocks. We show that there are periods where these shocks increase the economic and financial uncertainty, as expected. However, we also show that there are periods where the opposite behaviour is observed, i.e. where a positive oil specific demand shock (i.e. an uncertainty-generating source) triggers negative responses from the uncertainty indicators (i.e. reduces uncertainty)[10], which is rather unexpected. More specifically, we notice that this unexpected finding is mainly associated with the latter part of our sample period. A closer investigation, though, suggests that such finding is not unexpected at all. In particular, in the post-GFC period a series of conflicts that raise geopolitical unrest (the main source of the oil specific demand shocks) have taken place (e.g. the Libyan political turmoil, the political turbulence in Egypt, Yemen, and Bahrain and the war in Syria), however, oil prices exhibited a declining pattern, which gave rise to increased speculation in the oil market and accumulation of oil reserves. Hence, due to the accumulation of these oil reserves, the oil specific shocks in the latter part of our study period do not lead to higher economic and financial uncertainty. Thus, we can conclude that the previous findings which suggest that oil specific shocks are expected to trigger higher uncertainty do not hold throughout the study period but rather responses are indeed time-varying.

5. Conclusion

This study adds to the extremely scarce literature on the effects of oil price shocks on economic and financial uncertainty. Even more, we assess whether these effects are time-varying. In particular, we focus on the US economic and financial uncertainty using monthly data over the period from January 1994 to March 2015. Economic and financial uncertainty is approximated by six indicators, namely, CFNAI, EPU, EMU, VIX, OCV and ORV. The study uses a Structural VAR model, similar to Kilian and Park (2009), as well as, a TVP-VAR.

The impulse responses to structural oil price shocks from the SVAR model reveal that oil supply shocks do not exercise any significant impact on uncertainty indicators. Such findings lend support to the existing literature (see, *inter alia*, Degiannakis *et al*., 2014; Antonakakis *et al*., 2014; Aloui *et al*., 2015) who argue that oil supply-side shocks do not exert a significant impact in the economy or the financial markets. Furthermore, we report that aggregate demand shocks trigger lower uncertainty, which is in line with Degiannakis *et al*. (2014). Finally, based on the SVAR results we cannot claim that oil specific demand shocks are uncertainty enhancing shocks.

[10] We note that the literature has documented that positive oil price shocks trigger negative responses from financial markets (i.e. negative returns). We, thus, claim that our finding is rather unexpected, given that negative returns should be associated with increased uncertainty rather than the opposite.

The TVP-VAR results suggest that the responses of the uncertainty indices to the three oil price shocks are indeed time-varying and, thus, static approaches could result in counter-intuitive results. The time-varying impulse responses show that uncertainty indices exhibit heterogeneous responses to all three shocks, as well as, during different time periods. Nevertheless, we notice that for the largest part of our sample period, supply-side and aggregate demand oil price shocks tend to decrease the level of economic and financial uncertainty in the US.

We are aware that economic and financial uncertainty indicators are considered as key elements for policy making and investment decisions, and thus, our findings are important for policy makers, as well as, investors. Overall, we show that the effects of oil price shocks to the different faces of economic uncertainty are not only time-specific but also depend on the source of the uncertainty that one examines. Hence, given that oil price shocks could destabilize the policy outcome, policy makers should take into account the sources of oil price shocks at the time of the decision and the uncertainty sources that they are targeting, when making informed decisions on macroeconomic policies that resolve economic uncertainty. Furthermore, our results should be considered when investors make decisions regarding the investment in volatility indices or risk management strategies.

Further research could investigate as to whether oil shocks trigger time-varying responses on other economic and financial indicators. Finally, given the increased importance of uncertainty indicators in economic and financial decision making, it is important to examine the ability of oil price shocks to improve the forecasting accuracy of these indicators.

Acknowledgements

George Filis and Stavros Degiannakis acknowledge the support of the European Union's Horizon 2020 research and innovation programme, which has funded them under the Marie Sklodowska-Curie grant agreement No 658494.

References

Abel, A.B., and Bernanke, B.S. (2001). *Macroeconomics*. Addison Wesley Longman Inc.

Aloui, R., Gupta, R., and Miller, S.M. (2015). Uncertainty and Crude Oil Returns. *University of Connecticut, Department of Economics Working Paper Series*, 1-21.

Alquist, R., and Kilian, L. (2010). What Do We Learn from the Price of Crude Oil Futures? *Journal of Applied Econometrics* 25, 539-573.

Andersen, T. G., and Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, 885-905.

Andersen, T. G., Bollerslev, T., Christoffersen, P. F., and Diebold, F. X. (2006). Volatility and correlation forecasting. *Handbook of Economic Forecasting* 1, 777-878.

Angelidis, T., Degiannakis, S., and Filis, G. (2015). US stock market regimes and oil price shocks. *Global Finance Journal* 28, 132-146.

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2013). Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. Economics Letters, 120(1), 87-92.

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2014). Dynamic Spillovers of Oil Price Shocks and Economic Policy Uncertainty. *Energy Economics*, 44, 433-447.

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2017). Oil shocks and stock markets: Dynamic connectedness under the prism of recent geopolitical and economic unrest. *International Review of Financial Analysis*, 50, 1-26.

Apergis, N., and Miller, S.M. (2009). Do Structural Oil - Market Shocks Affect Stock Prices? *Energy Economics* 31(4), 569-575.

Bachmann, R., Elstner, S., and Sims, E.R. (2010). Uncertainty and Economic Activity: Evidence from Business Survey Data. *NBER Working Papers 16143, National Bureau of Economic Research, Inc.*

Baum, C.F., Caglayan, M., and Talavera, O. (2010). On the Sensitivity of Firms's Investment to Cash Flow and Uncertainty. *Oxford Economic Papers* 62(2), 286-306.

Baumeister, C., and Kilian, L. (2014). What central bankers need to know about forecasting oil prices. *International Economic Review* 55(3), 869-889.

Bernanke, B.S. (2006). *The Economic Outlook*. *Remarks before the National Italian American Foundation*. New York: 2006.

Bernanke, B.S. (1983). Irreversibility, Uncertainty, and Cyclical Investment. *The Quarterly Journal of Economics* 98(1), 85-106.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica* 77, 623-685.

Bloomberg. (2017). Trump's uncertainty principle, Bloomberg Business Week 26/01/2017, https://www.bloomberg.com/news/articles/2017-01-26/trump-s-uncertainty-principle.

Boldanov, R., Degiannakis, S., and Filis, G. (2016). Time-varying correlation between oil and stock market volatilities: Evidence from oil-importing and oil-exporting countries. *International Review of Financial Analysis* 48, 209–220.

Broadstock, D., and Filis, G. (2014). Oil price shocks and stock market returns: New evidence from the United States and China. *Journal of International Financial Markets, Institutions and Money* 33, 417–433.

Caggiano, G., Castelnuovo, E., and Figueres, J.M. (2017). Economic policy uncertainty and unemployment in the United States: A nonlinear approach. Economics Letters, 151, 31-34.

Cunado, J., and de Gracia, F. P. (2014). Oil price shocks and stock market returns: Evidence for some European countries. *Energy Economics* 42, 365-377.

Degiannakis, S., Filis, G., and Floros, C. (2013). Oil and Stock Returns: Evidence from European Industrial Sector Indices in a Time-Varying Environment. *Journal of International Financial Markets, Institutions and Money* 26, 175–191.

Degiannakis, S., Filis, G., and Kizys, R. (2014). The Effects of Oil Price Shocks on Stock Market Volatility: Evidence from European Data. *The Energy Journal* 35(1), 35-56.

Ding, Z., Granger, C.W.J., and Engle, R.F. (1993). A Long Memory Property of Stock Market Returns and a New Model. *Journal of Empirical Finance* 1(1), 83-106.

El Anshasy, A.A., and Bradley, M.D. (2012). Oil Prices and the Fiscal Policy Response in Oil-Exporting Countries. *Journal of Policy Modeling* 34(5), 605–620.

Fang, Y. (1996). Volatility Modeling and Estimation of High-Frequency Data with Gaussian Noise. PhD dissertation, MIT Sloan School of Management.

Filis, G. (2010). Macro Economy, Stock Market and Oil Prices: Do Meaningful Relationships Exist among Their Cyclical Fluctuations? *Energy Economic* 32(4), 877-886.

Filis, G., Degiannakis, S., and Floros, C. (2011). Dynamic Correlation between Stock Market and Oil Prices: The Case of Oil-Importing and Oil-Exporting Countries. *International Review of Financial Analysis* 20(3), 152–164.

Hamilton, J.D. (1983). Oil and the Macroeconomy since World War II. *Journal of Political Economy* 228-248.

Hamilton, J.D. (1988). A Neoclassical Model of Unemployment and the Business Cycle. *Journal of Political Economy* 96, 593-617.

Hamilton, J.D. (1996). This is What Happened to the Oil Price Macroeconomy Relationship. *Journal of Monetary Economics* 38, 215-220.

Hamilton, J.D. (2008). *Oil and the Macroeconomy*. In the New Palgrave Dictionary of Economics: Eds.S. Durlauf and L. Blume, Palgrave McMillan Ltd.

Hamilton, J.D. (2009). Understanding Crude Oil Prices. *Energy Journal* 30(2), 179–206.

Hansen, P. R., and Lunde, A. (2005). A forecast comparison of volatility models: does anything beat a GARCH (1, 1)?. *Journal of Applied Econometric*s 20(7), 873-889.

Hooker, M.A. (1996). What Happened to the Oil Price–Macroeconomy Relationship? *Journal of Monetary Economics* 38, 195–213.

Hooker, M.A. (2002). Are Oil Shocks Inflationary? Asymmetric and Nonlinear Specifications versus Changes in Regime. *Journal of Money, Credit and Banking* 34, 540-561.

Jones, C.M., and Kaul, G. (1996). Oil and the Stock Markets. *Journal of Finance* 51, 463-491.

Kang, W., and Ratti, R.A. (2013). Oil Shocks, Policy Uncertainty and Stock Market Return. *Journal of International Financial Markets Institutions and Money* 26, 305-318.

Kang, W., Lee, K. and Ratti, R.A. (2014). Economic policy uncertainty and firm-level investment. *Journal of Macroeconomics*, 39, 42-53.

Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review* 99, 1053-1069.

Kilian, L., and Park, C. (2009). The impact of oil price shocks on the U.S. stock market. *International Economic Review* 50, 1267-1287.

Koop, G., and Korobilis, D. (2010). *Bayesian multivariate time series methods for empirical macroeconomics*. Now Publishers Inc.

Lee, K., and Ni, S. (2002). On the Dynamic Effects of Oil Price Shocks: A Study Using Industry Level Data. *Journal of Monetary Economics* 49, 823-852.

Lippi, F., and Nobili, A. (2012). Oil and the Macroeconomy: A Quantitative Structural Analysis. *Journal of the European Economic Association* 10(5), 1059–1083.

Marcus, A.A. (1981). Policy Uncertainty and Technological Innovation. *The Academy of Management Review* 6(3), 443-448.

Montoro, C. (2012). Oil Shocks and Optimal Monetary Policy. *Macroeconomic Dynamics* 16(02), 240–277.

Nakajima, J., Kasuya, M., and Watanabe, T. (2011). Bayesian analysis of time-varying parameter vector autoregressive model for the Japanese economy and monetary policy. *Journal of the Japanese and International Economies* 25(3), 225-245.

Natal, J. (2012). Monetary Policy Response to Oil Price Shocks. *Journal of Money, Credit and Banking* 44(1), 53–101.

New York Times. (2016). An index of uncertainty surges after 'Brexit', 29/06/2016. https://www.nytimes.com/2016/07/01/upshot/an-index-of-uncertainty-surges-after-brexit.html?_r=0.

Park, J., and Ratti, R.A. (2008). Oil Price Shocks and Stock Markets in the U.S. and 13 European Countries. *Energy Economics* 30, 2587-2608.

Pindyck, R.S. (1990). Irreversibility, uncertainty, and investment. National Bureau of Economic Research, W3307.

Popescu, A., and Smets, F.R. (2010). Uncertainty, Risk-taking, and the Business Cycle in Germany. *CESifo Economic Studies* 56(4), 596-626.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies* 72(3), 821-852.

Rodrik, D. (1991). Policy Uncertainty and Private Investment. *Journal of Development Economics* 36, 229-242.

Sadorsky, P. (1999). Oil Price Shocks and Stock Market Activity. *Energy Economics* 21, 449-469.

Stock, J.H., and Watson, M.W. (2012). Disentangling the Channels of the 2007-2009 Recession. *NBER Working Paper* No. 18094, 1-55.

Visco, I. (2017). Financial Market Volatility and Global Policy Uncertainty: a Conundrum, Istituto Affari Internazionali, Major Challenges for Global Macroeconomic Stability – The Role of the G7, 27/03/2017. http://www.iai.it/sites/default/files/visco-dinner_address_170327.pdf.

Xekalaki, E., and Degiannakis, S. (2010). *ARCH Models for Financial Applications*. Wiley, New York.

Tables

Table 1. Descriptive statistics of the series. The period spans from January 1994 to March 2015.

Series	Obs	Mean	Std. Dev.	Max.	Min.	Skew.	Kurt.	Jarque-Bera	ADF
PROD	254	0.0013	0.0078	0.0259	-0.0249	-0.1724	3.913	10.0917***	-13.764**
GEA	254	0.0309	0.2703	0.6248	-0.6386	0.2667	2.310	8.0743**	-2.928**
ROIL	254	0.0054	0.0885	0.2007	-0.3109	-0.7609	4.242	40.8410***	-13.034***
CFNAI	254	-0.1331	0.8548	1.5000	-4.6500	-2.0504	9.892	683.4492***	-2.984**
EPU	254	1.0450	0.3612	2.4512	0.5720	1.1199	3.586	56.9578***	-4.360***
EMU	254	0.7243	0.6207	4.9603	0.1309	2.7976	1.370	1547.7201***	-6.727***
VIX	254	0.2040	0.0807	0.6264	0.1082	1.8723	8.618	484.3670***	-3.708***
OCV	254	0.3381	0.1147	0.8438	0.1439	1.3976	6.419	207.2584***	-4.123***
ORV	140	0.2848	0.1282	0.9375	0.0998	2.3276	10.786	480.0866***	-2.582*

*, **, and *** indicate significance at 10%, 5% and 1% level, respectively.

Figures

Figure 1. Changes in World Oil Production (PROD), Global Real Economic Activity (GEA) and Changes in Crude Oil Prices (ROIL) from January 1994 to March 2015.

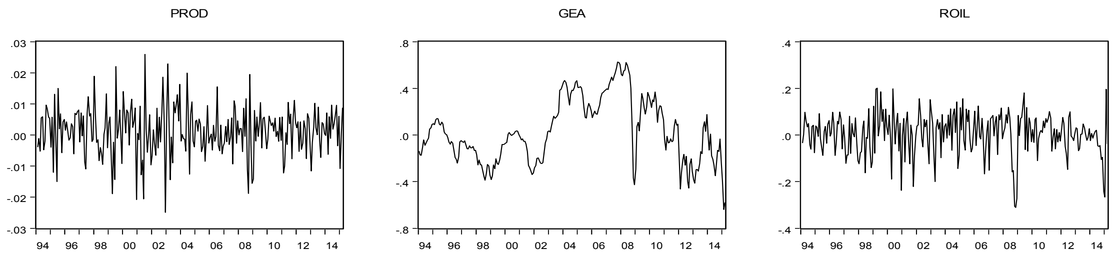
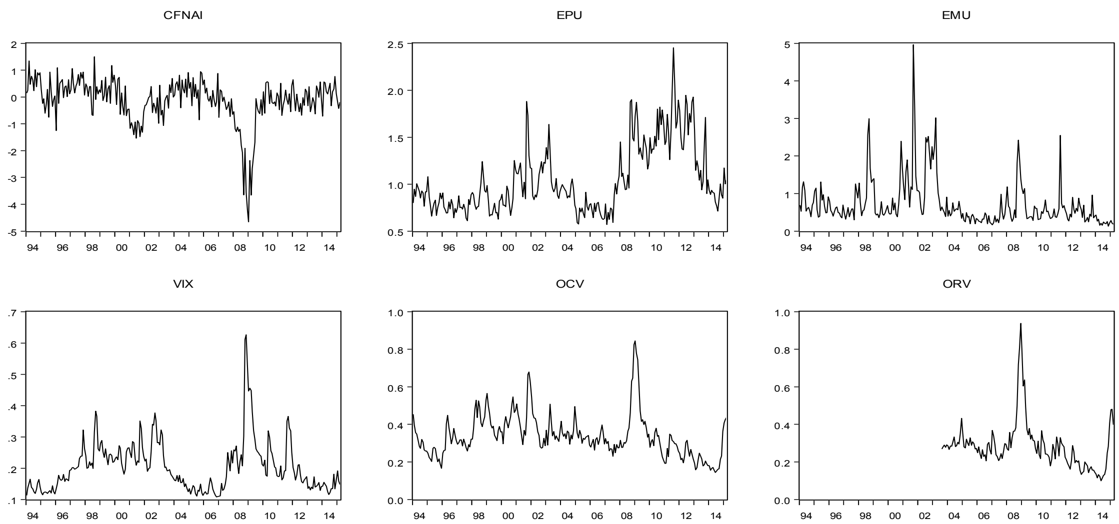
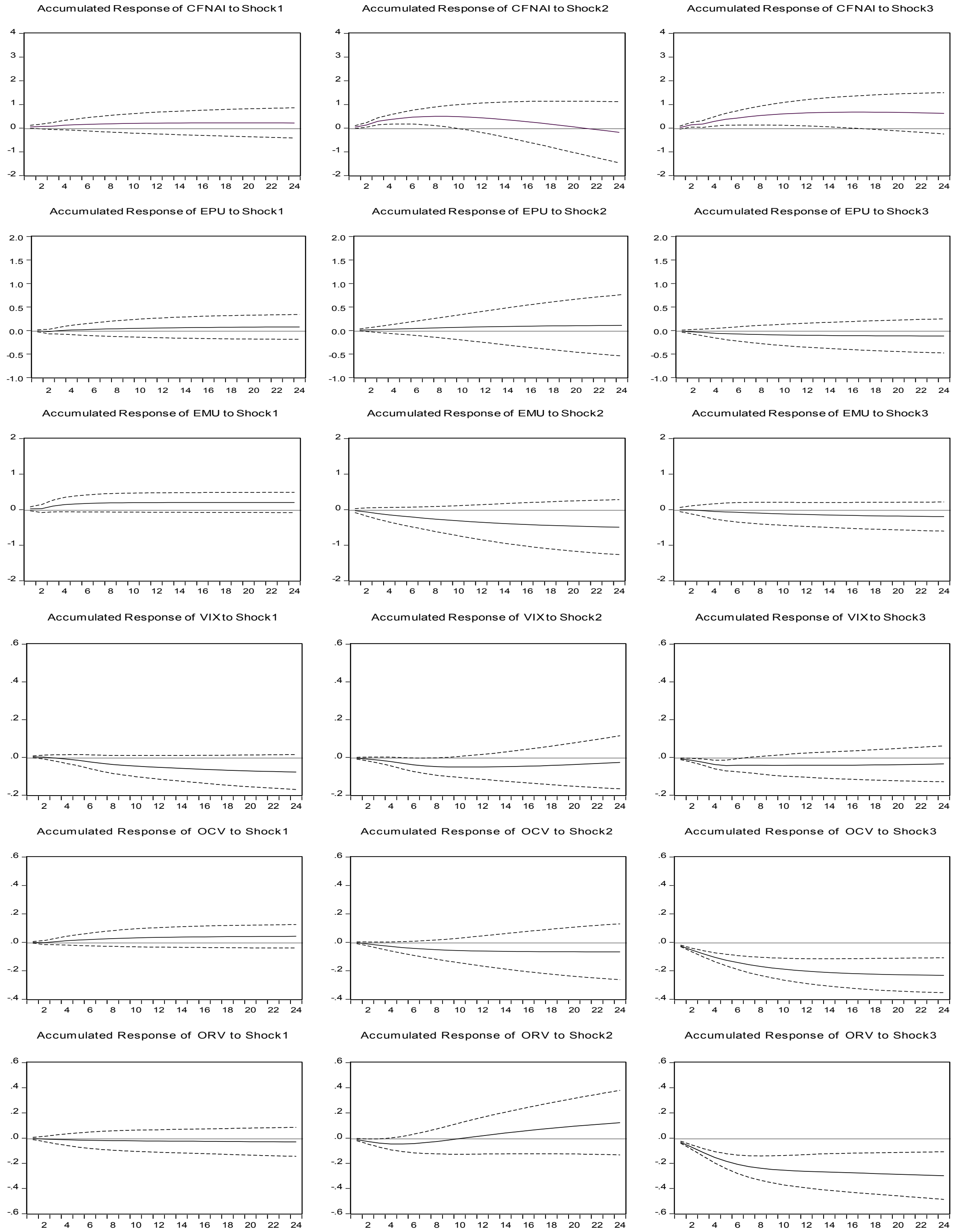


Figure 2. The US uncertainty measures from January 1994 to March 2015.



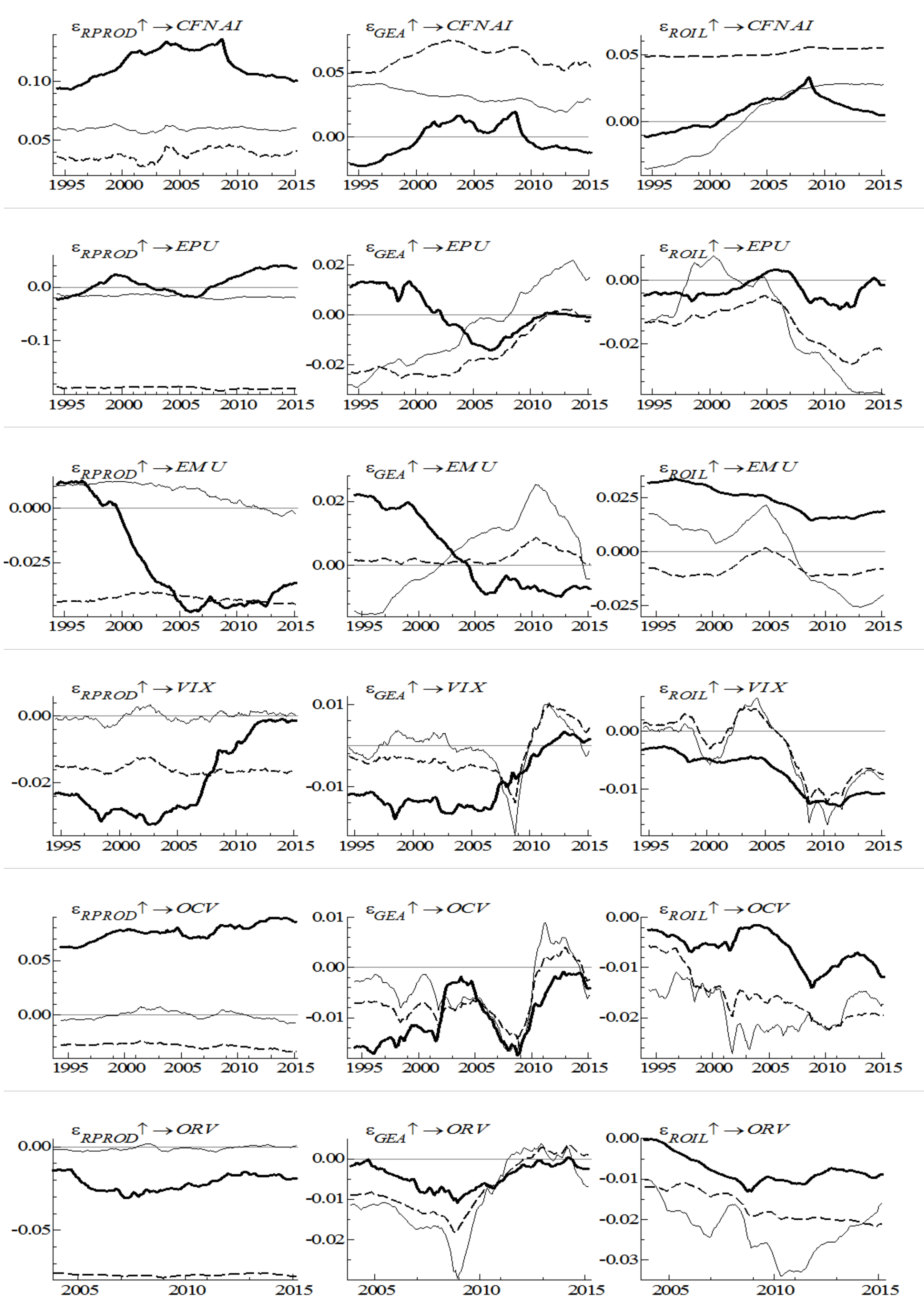
Note: CFNAI= Chicago Fed National Activity Index, EPU = Economic Policy Uncertainty, EMU = Equity Market Uncertainty Index, VIX = Implied Volatility Index of S&P500, OCV = Oil Conditional Volatility, ORV = Oil Realized Volatility.

Figure 3. Accumulated impulse responses of the uncertainty indices to oil price shocks (Shock 1: SS, Shock 2: ADS, Shock 3: SDS), based on the SVAR model.



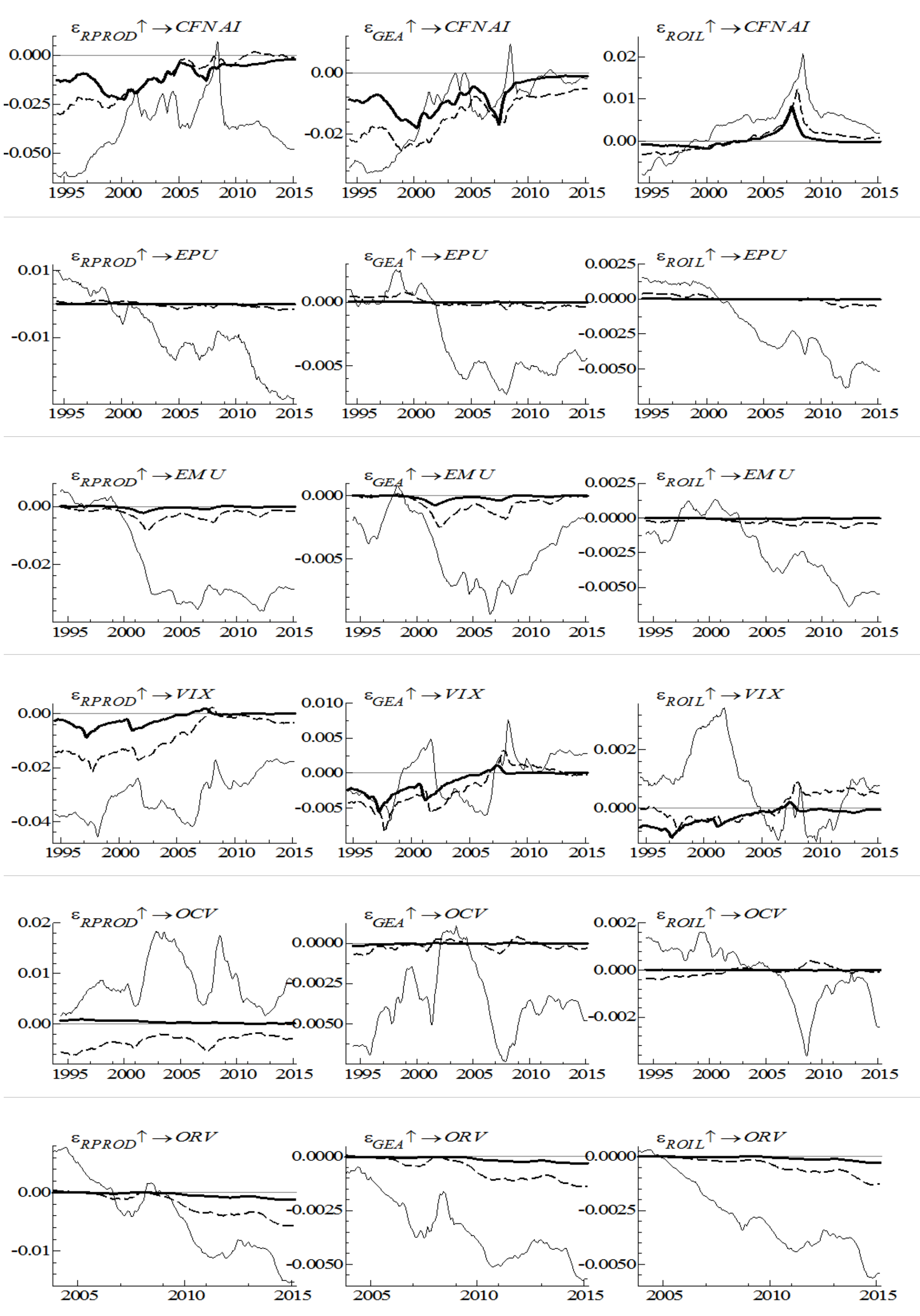
Note: Shocks successively refer to: Shock 1 to *Oil Supply Shocks* (SS), Shock 2 to *Aggregate Oil Demand Shocks* (ADS) and Shock 3 to *Oil-Specific Demand Shocks* (SDS). The series of the uncertainty measures (UNCERT), vertically, are the following: *Chicago Fed National Activity Index* (CFNAI), *Economic Policy Uncertainty Index* (EPU), *Equity Market Uncertainty Index* (EMU), *Implied Volatility Index of S&P500* (VIX), *Oil Conditional Volatility* (OCV) and *Oil Realized Volatility* (ORV).
Dotted lines depict the 90% confidence intervals.

Figure 4. Impulse responses of the uncertainty indices to oil price shocks for 0, 1 and 3 months ahead, based on the TVP-VAR.



Note: The thin, dotted and bold lines correspond to the responses of the uncertainty indices to oil price shocks for 0, 1 and 3 months ahead, respectively.
Impulse responses for the ORV start in 2003, whereas for the remaining uncertainty indicators the starting data of the impulse responses is 1994.

Figure 5. Impulse responses of the uncertainty indices to oil price shocks for 6, 12 and 18 months ahead, based on the TVP-VAR.



Note: The thin, dotted and bold lines correspond to the responses of the uncertainty indices to oil price shocks for 6, 12 and 18 months ahead, respectively.
Impulse responses for the ORV start in 2003, whereas for the remaining uncertainty indicators the starting data of the impulse responses is 1994.