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NGUYEN, Bao H.
Australian National University

OKIMOTO, Tatsuyoshi
RIETI

TRAN, Trung Duc
University of Melbourne

Research Institute of Economy, Trade & Industry, IAA

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Uncertainty-Dependent and Sign-Dependent Effects of Oil Market Shocks*

Bao H. Nguyen†
Australian National University
University of Economics Ho Chi Minh City

Tatsuyoshi Okimoto‡
Australian National University
Research Institute of Economy, Trade and Industry

and

Trung Duc Tran§
University of Melbourne

Abstract

This paper investigates the uncertainty-dependent and sign-dependent effects of the oil market fundamental shocks, namely supply, aggregate demand and oil-specific demand shocks. We do so by first proposing a novel oil uncertainty index that is measured by the stochastic volatility of the unpredictable component of oil prices. Second, we employ a nonlinear model to show that the structural oil market shocks have distinguishable effects in regimes that are characterized by high versus low oil price uncertainty. Finally, the model is extended to accommodate positive and negative oil market shocks to examine the possible asymmetric effects. In relation to real economic activity, we find that both supply shocks and oil-specific demand shocks have negligible impacts in periods of low oil price uncertainty, but they have sizeable effects in a high-oil-price-uncertainty regime. The effects of oil supply shocks are asymmetric, but oil-specific demand shocks are not, indicating that the (a)symmetric reaction of the real economic activity depends on the underlying oil market shocks.

Keywords: Oil price uncertainty, Oil price shock, Real economic activity, STVAR model, Asymmetric effects
JEL classification: C32, E32, Q43

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† Lecturer, Crawford School of Public Policy, Australian National University, Australia, and Lecturer, School of Economics, University of Economics Ho Chi Minh City (UEH), Vietnam. Email: bao.nguyen@anu.edu.au.

‡ Associate Professor, Crawford School of Public Policy, Australian National University, and Visiting Fellow, RIETI. E-mail: tatsuyoshi.okimoto@anu.edu.au.

§ PhD candidate, Department of Economics, University of Melbourne. Email: brian.tran@unimelb.edu.au.

1 Introduction

It is well-known that not all oil price shocks are alike (Kilian, 2009).[1] An increase in the price of oil, for example, could be caused by a disruption in global oil production or an increase in the demand for crude oil. In addition, an increase in the demand for crude oil could be induced by an increase in the aggregate demand or a surge in oil-specific demand. The underlying cause of oil price shocks, in turn, has different effects on real economic activity (Kilian, 2009; Lippi and Nobili, 2012; Baumeister and Peersman, 2013; Cross and Nguyen, 2017). In addition to distinguishing the three oil market shocks, the current paper considers the importance of the uncertainty-dependent and sign-dependent effects of oil market shocks to extend our understanding of the relationship between oil and the real economy. In particular, we question whether (i) the oil market reacts differently depending on the level of oil price uncertainty; and (ii) there is asymmetry in the effects of positive or negative oil market shocks on real economic activity under the presence of uncertainty regimes.

It is conceivable that the effect of an oil market shock depends on regimes that characterised by oil price uncertainty. Recent studies by, among others, Bernanke (1983), Dixit (1989), Pindyck (1991), Lee et al. (1995), Bloom et al. (2007), Elder and Serletis (2010), Pinno and Serletis (2013), Kellogg (2014), Jurado et al. (2015) and Bloom et al. (2018) have provided evidence that uncertainty, including oil price uncertainty, is important for real economic activity. The recent literature also shows that the international oil market and the relationship between oil price shocks and the macroeconomy behave in a regime-dependent manner (Holm-Hadulla and Hubrich, 2017; Datta et al., 2018; Hou and Nguyen, 2018; Bjørnland et al., 2018; Nguyen and Okimoto, 2019). For instance, Nguyen and Okimoto (2019) highlight that the effect of an adverse oil price shock during a recession tends to be much larger than that of the same shock happening in normal times. However, surprisingly little research has investigated the reactions of the oil market and global economic activity to the oil market shocks when regimes characterised by oil price uncertainty are taken into account. Thus, this prompts the need to differentiate between high- and low-oil-price-uncertainty regimes when analysing the relationship between the oil market and the real economy.

The literature shows that a positive and negative oil price shocks do not exert the same effect on the real economy. The theoretical prediction seems to agree that economic activity contracts when oil prices increase but does not expand very much when oil prices fall. One of the plausible explanations for the asymmetric relationship between the movement of oil prices and economic activity is the real options theory, which is detailed

[1] In this paper we use "oil price shocks" and "oil market shocks" interchangeably.

in Bernanke (1983), Brennan and Schwartz (1985) and Majd and Pindyck (1987).[2] The real options theory explains the possibility of the asymmetric effects of oil price shocks on economic activity from the perspective of uncertainty; it argues that a decline in the price of oil creates an expansionary effect on real output, but at the same time, it also tends to generate an increase in uncertainty about the future oil prices, holding back consumption and investment spending. As a result, the contractionary effect of uncertainty offsets the stimulating effect of the favourable oil price shock. Therefore, it is useful to further distinguish between positive and negative changes in oil supply and demand in the presence of different uncertainty regimes.

Our contribution is twofold. First, in the spirit of Jurado et al. (2015), we construct a novel oil uncertainty index based on the stochastic volatility (SV) of one-period-ahead forecast error of a forecasting regression. The novelty of this construction approach lies in its flexibility in including a large amount of additional information that is important in explaining fluctuations in oil prices, such as exchange rate, oil production, global economic condition and comovement in the fuel market. In this sense, the index can capture uncertainty in oil price rather than volatility as measured by both the generalised autoregressive conditional heteroskedasticity (GARCH) and SV in mean models.[3] Second, we offer fresh empirical estimates on the uncertainty-dependent and sign-dependent effects of oil market shocks to extend the literature on the relationship between oil and the real economy. More specifically, we extend the benchmark linear vector autoregressive (VAR) model, which is based on Kilian (2009) and Jo (2014), to a smooth transition VAR (STVAR) model by employing the novel oil uncertainty index as a transition variable. To further explore the asymmetric relationship between global economic activity and oil price shocks, the model is also estimated using the identified set of positive and negative changes in oil supply and demand. The method of nonlinear transformation used in the analysis is somewhat similar to Mork (1989) and Hamilton (2003), who evaluate the asymmetric impact of positive versus negative oil price shocks.

Our results are as follows: First, we find that the propagation of the structural oil market shocks is uncertainty dependent. In particular, shocks to the demand for crude oil arising from sudden increases in global economic activity have persistent impacts on

[2] Another explanation is that lower oil prices would increase the expenditure on energy-intensive durables and thus cause a reallocation of capital and labour towards the energy-intensive sectors. If capital and labour are specific and cannot move easily, the reallocation will dampen the economic expansion caused by unexpected declines in the price of oil while amplifying the recessionary effects of unexpected increases in the price of oil (Hamilton, 1988; Bresnahan and Ramey, 1993).

[3] It is important to remove predictable information to capture uncertainty; as stated by Jurado et al. (2015): "... what matters for economic decision making is not whether particular economic indicators have become more or less variable, but rather whether the economy has become more or less predictable."

oil prices, regardless of the uncertainty, but on global oil production only in times of low uncertainty. In contrast, when uncertainty is high, shocks to oil-specific demand have a magnified impact on oil production. In relation to real economic activity, we find that both supply shocks and oil-specific demand shocks have negligible impacts in periods of low oil price uncertainty but sizeable effects in periods of high oil price uncertainty. Second, we find that the asymmetric effects of oil price increases or decreases depend on the underlying oil market shocks. The effects of oil supply shocks are asymmetric, but oil-specific demand shocks are not. Taken together, our findings offer new explanations for the contrasting results found in the literature. Third, our additional analysis indicates that our findings of uncertainty-dependent responses cannot be observed by looking at stock market uncertainty; indeed these uncertainty-dependent responses only emerge when the uncertainty about oil prices is taken into account. Thus, considering the oil market uncertainty is crucial to correctly understand the uncertainty-dependent oil-output relationship.

The remainder of the paper is organised as follows: Section 2 reviews the related literature to clarify our contributions to it, while Section 3 describes the method that we construct the index of oil price uncertainty. Section 4 outlines the data and the econometric methodology, including the STVAR model specification and estimation of the models. The identification strategy of the oil market shocks is also discussed in this section. Section 5 then presents our results. In this section, we first analyse the uncertaity-regime-dependent impulse responses obtained from the STVAR model, and then, we evaluate the asymmetric effects of positive and negative oil price shocks to global economic activity. Section 6 reports the additional results and the robustness check. Finally, Section 7 concludes the paper.

2 Related Literature

Our paper is closely related to two strands of literature that focus on modelling the oil market and oil price uncertainty. The first strand acknowledges that the movement of oil prices could be driven by underlying shocks associated with unpredicted changes in oil supply or demand (Kilian, 2009; Kilian and Murphy, 2012; Baumeister and Peersman, 2013; Aastveit et al., 2015; Baumeister and Hamilton, 2019). For instance, Kilian (2009) uses a linear VAR model and finds that rather than supply shocks, a combination of global aggregate demand shocks and oil-specific demand shocks are the main factor driving the price of oil. A key difference of our work relative to these contributions is that we explicitly take the oil price uncertainty into consideration by allowing the market to react distinguishably between a high-oil-price-uncertainty regime and a low-oil-price-uncertainty regime.

This strand of literature also provides contradicting empirical evidence of the asymmetric effects of oil price shocks on economic activity. For instance, Mork (1989) and Hamilton (2003, 2011) show that oil price increases are much more important than oil price decreases, as the real options theory indicates. On the contrary, Kilian and Vigfusson (2011) and Herrera et al. (2011) provide little evidence of asymmetric feedback from oil price increases and decreases to U.S. aggregate and disaggregate industrial production. A possible explanation of the contradicting evidence is that these studies focus solely on quantifying the magnitude of outputs responding to a positive and negative change in oil prices without taking the underlying market shocks and uncertainty into consideration. We contribute the literature by providing new evidence of sign-dependent effects of oil price shocks in addition to the uncertainty-dependent effects.

The second strand of literature relates to the works that measure and study the effect of oil price uncertainty. Early theoretical discussions, for example Bernanke (1983), Dixit (1989) and Pindyck (1991), show that firms may delay their investments in response to higher oil price uncertainty. This theoretical prediction is later supported by Kellogg (2014), who uses data on oil producers in Texas and finds that increases in the expected volatility of the future price of oil are associated with decreases in drilling activity. In addition, the works by Lee et al. (1995) and Ferderer (1996) highlight the importance of taking into account the variance of oil prices, as a measure of uncertainty, in forecasting economic activity.

A key drawback of these studies is that they implicitly treat oil prices, and hence oil price volatility, as exogenous to the economy. To overcome this issue, researchers have augmented the linear VAR model to incorporate the GARCH in mean errors, or GARCH-in-Mean VAR for short (Elder and Serletis, 2009, 2010; Bredin et al., 2011; Elder and Serletis, 2011; Rahman and Serletis, 2011). In this approach, a measure of oil uncertainty is derived from the conditional standard deviation of the forecast error for the change in the price of oil, and thus, oil price uncertainty is simultaneously estimated within the VAR model. Those studies based on GARCH-in-Mean VAR model typically find that uncertainty about the oil price has a negative effect on real economic activity, as measured by GDP, investment, consumption in the U.S. and different countries. Although the GARCH-in-Mean VAR framework has become popular in such analyses, Jo (2014) argues that oil price uncertainty as defined under this approach is fully determined by changes in the level of oil price. As a result, it is not possible to disentangle uncertainty about the oil price and changes in the oil price level. Jo (2014) then proposes a new measure of oil price uncertainty by utilising a stochastic volatility in mean VAR model. In this framework, oil price uncertainty is modelled as the time-varying stochastic volatility of the oil price changes, and thus, it evolves independently of any change in the oil price level. Jo (2014) finds that oil price uncertainty, which is independent from changes in the price of oil, has a significant negative effect on global real economic activity, but the magnitude is much smaller than what has been found in previous studies. Our paper differs from Jo (2014) in three ways: (i) it proposes a novel construction of the oil price uncertainty index that is free from the structure of any specific theoretical model; (ii) it quantifies the uncertainty-regime-dependent responses of the oil market to its fundamental shocks; and (iii) under each uncertainty regime, it also explores the asymmetric reaction of global economic activity to positive and negative oil price shocks that are generated separately by typical supply and demand drivers.

3 Construction of the oil price uncertainty index

In the spirit of Jurado et al. (2015), our oil price uncertainty index (OPU) is based on the SV of one-period-ahead forecast error of a forecasting regression. By definition, the h-period-ahead uncertainty, $U_t(h)$, of an oil price series, y_t, is the conditional volatility of the unforecastable component. That is:

$$U_t(h) = \sqrt{E\left[\left(y_{t+h} - E[y_{t+h}|I_t]\right)^2 |I_t\right]} \tag{1}$$

where the expectation $E(\cdot|I_t)$ is formed with respect to the information available at time t. Uncertainty about oil prices will thus be higher when the expectation today of the squared error in forecasting y_{t+h} rises.

We consider uncertainty in the crude oil (petroleum) price index published by the IMF, which is a simple average of three spot prices: Dated Brent, West Texas Intermediate, and Dubai Fateh from 1994M1-2017M6. To construct the one-period-ahead oil price uncertainty index ($h = 1$), the conditional expectation in Equation (1) is replaced by the forecast based on the following:

$$y_{t+1} = \sum_{i=0}^{3} \phi_i y_{t-i} + X_t + \upsilon_{t+1}. \tag{2}$$

This step is critical because it ensures that the forecast error is "purged" of predictive content. The predictive model (2) for oil prices at time $t+1$ includes AR(4) terms and additional information that is considered robust in predicting and explaining movement in commodity or oil prices in the literature, such as the 'commodity currency' exchange rate, oil production and global economic activity, U.S. uncertainty and the comovement in the fuel market.[4] The reason for using these variables is that they have been shown

[4]There could be other ways to specify this predictive equation, but we find that the estimated uncertainty is consistent across different specifications, as in Appendix B

to be important drivers of the price of oil and/or commodities. For instance, Chen et al. (2010) shows that commodity currency exchange rates including the Australian, Canadian and New Zealand dollars, as well as the South African rand and the Chilean peso, have remarkably robust power in predicting global commodity prices. Kilian (2009) shows that aggregate supply and global economic activity are both important to explain the oil prices. Joëts et al. (2017) find that U.S. uncertainty can also affect commodity price uncertainty. Finally, to capture the fact that commodity prices can move together beyond what can be explained by fundamentals (Pindyck and Rotemberg, 1990; Ohashi and Okimoto, 2016), comovement in the fuel market is captured by including the first principle component and the quadratic terms of the principal component of oil prices and natural gas prices.[5]

Following Bai and Ng (2008), the predictors ultimately used in the predictive equation (2) only include those that have significant predictive power (t-stat > 2.575). However, we find that additional predictors typically do not improve the predictability of oil prices on top of the AR(4) terms.[6] We then calculate the stochastic components of the forecast error variance according to Equations (3) and (4) below. Let $\upsilon_{t+1} = \sigma_{t+1}\epsilon_{t+1}$ with $\epsilon_{t+1} \sim$ *iid* $N(0,1)$, following Jurado et al. (2015), and the parametric stochastic process is defined as[7]

$$\log \sigma_{t+1}^2 = \alpha + \beta \log \sigma_t^2 + \tau \eta_{t+1}, \tag{3}$$

where η_{t+1} are *iid* $N(0,1)$ disturbances. Using this definition, the one-period-ahead uncertainty is equal to the expected value of the SV in residual terms:[8]

$$U_t(1) = \sqrt{E[(\upsilon_{t+1})^2 | I_t]} = \sqrt{E(\sigma_{t+1}^2 | I_t)} \tag{4}$$

Figure 1 plots the OPU as defined by (4). The level of oil price uncertainty is relatively high during the Great Recession and is more volatile afterwards. In fact, there are three separate periods where we observe distinct peaks in oil price uncertainty. The first peak from 2000 to 2002 seems to coincide with the East Asian Crisis and the Second Gulf War in Iraq. The second peak in 2009 occurs during the Global Financial Crisis and the last peak during 2015-2016 comes because of the sharp drop in the oil prices, from a peak of \$115 per barrel in June 2014 to under \$35 at the end of February 2016.

We also observe that oil price uncertainty is distinct from other sources of uncertainty. Figure 2 compares the dynamics of OPU with other major uncertainty proxies commonly

[5]Fuel group commodities include coal, crude oil, and natural gas prices.

[6]See Appendix A for a discussion on the role of these predictors.

[7]The SV parameters are estimated by using the STOCHVOL package in R.

[8]Jurado et al. (2015) shows that when $h > 1$, the uncertainty is not based solely on the SV in residual $\upsilon_{j,t+1}$. There are also autoregressive terms, stochastic volatility in additional predictors, and covariance terms.

used in the literature, namely the Oil Price Volatility (OVX) index, the Global Economic Policy Uncertainty (EPU) index proposed by Baker et al. (2016), the CBOE Volatility Index (VIX) index and the U.S. uncertainty (JLN) index constructed by Jurado et al. (2015). The dynamics of the OPU are the most consistent with the OVX index, as seen by the moderately high correlation between the two series. The major distinction between the OPU and the OVX indexes is that the OPU does not report any heightened uncertainty around 2011. Next, oil uncertainty is highly different from economic policy uncertainty, as seen by the lack of correlation with the EPU index. Last, although oil price uncertainty correlates moderately with stock market uncertainty (VIX) or macroeconomic uncertainty in the U.S. (JLN), there are still some notable differences. The OPU does not pick up high uncertainty about the dotcom crisis or the European debt crisis, which are detected by the VIX, because those events are more relevant to the stock exchange. In addition, neither the VIX nor the JLN macro uncertainty index detects any surge in oil uncertainty during 2000-2002 and 2015-2016. Taken together, this indicates that the OPU index picks up uncertainty events that are highly specific to the oil market.

4 Data and empirical methodology

This section begins by describing the data, which is followed by a description of the baseline model that is based on Kilian (2009) and Jo (2014). The linear setting enables us to understand the behaviour of the oil market, under the assumption that the effects of uncertainty about oil prices remain time-invariant. A key contribution of our paper is that we relax this assumption by considering a nonlinear specification, namely a STVAR model. This model allows us to capture any regime changes and is well suited to our research questions.

4.1 Data

Along with the realised oil-price-uncertainty index computed in the previous section, we use monthly data between 1994M7 and 2017M6 on three variables of interest, as in Kilian (2009) and Jo (2014): the real price of oil, oil quantity and a measure of global economic activity. Regarding the price of oil, in line with our oil uncertainty measure, we use the simple average of three spot prices reported by the IMF: Dated Brent, West Texas Intermediate, and the Dubai Fateh. We note that the existing literature also considers two other alternative measures of oil prices: the U.S. refiners' acquisition cost (RAC) for imported crude oil and the West Texas Intermediate (WTI) price of crude oil. To address this concern, we also use RAC and WTI as a robustness check, as in, among many others, Herrera (2018) and Bjørnland and Zhulanova (2018). The real oil price is obtained by deflating the nominal price by the U.S. consumer price index taken from the Federal Reserve Bank of St. Louis FRED database. Next, the quantity of oil is measured by the amount of world crude oil production (thousand barrels per day) as provided by the U.S. Energy Information Administration. Finally, we measure the global economic activity using the global industrial production index for the OECD plus six other major emerging economies (Brazil, China, India, Indonesia, the Russian Federation and South Africa) published by OECD Main Economic Indicators and extended from November 2011 by Baumeister and Hamilton (2019).[9] The oil price uncertainty index enters the model in levels, while the other variables are transformed to growth rates by taking the first difference of the natural logarithms multiplied by 100. Figure 3 plot the evolution of the data.

4.2 Baseline linear model

The baseline model is taken from Kilian (2009) and Jo (2014). It employs three-variable VAR model consisting of global crude oil production (Δpro), real global economic activity (Δip) and real oil price (Δrpo); this model has been widely used to examine the effects of demand and supply shocks in the crude oil market. Each of the variables is expressed in percentage changes by taking the log differences.[10]

Let $\mathbf{z}_t = (\Delta pro_t, \Delta ip_t, \Delta rpo_t)'$. The structural representation of our benchmark VAR(p) model can be expressed as

$$\mathbf{B}\mathbf{z}_t = \boldsymbol{\gamma} + \sum_{i=1}^{p} \boldsymbol{\Gamma}_i \mathbf{z}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{5}$$

where $\boldsymbol{\varepsilon}_t$ is assumed to independently follow a standard multivariate normal distribution. Following Jo (2014), we set the number of lags, p, at four to allow for sufficient dynamics of the system, as well as to keep the estimation's plausibility. We also assume that $\mathbf{B}$ is a lower triangular matrix with 1 along the diagonal elements, as Kilian (2009). The reduced form of VAR is obtained by premultiplying $\mathbf{B^{-1}}$ to both sides of (5) as

$$\mathbf{z}_t = \boldsymbol{\alpha} + \sum_{i=1}^{p} \mathbf{A_i z_{t-i}} + \mathbf{e_t}, \tag{6}$$

[9]See Hamilton (2018) for a justification on the alternative proxies for global economic activity.

[10]Note that Kilian (2009) uses the real oil price in level, while other variables are in log difference. A discussion about what specification of oil variables we should consistently use in modelling the oil market can be found, for example, in Kilian (2009), Kilian and Park (2009), Kilian and Murphy (2014), Lütkepohl and Netšunajev (2014) and Jadidzadeh and Serletis (2017). According to these empirical studies, it is not clear whether the real price of crude oil should be modelled in log levels or log differences. The current paper prefers the log differences because it makes our results directly comparable with Jo (2014).

where $\boldsymbol{\alpha} = \mathbf{B^{-1}}\boldsymbol{\gamma}$, $\mathbf{A_i} = \mathbf{B^{-1}}\boldsymbol{\Gamma}_\mathbf{i}$, and $\mathbf{e_t} = \mathbf{B^{-1}}\boldsymbol{\varepsilon}_\mathbf{t}$. The reduced form can be easily estimated by the equation-by-equation ordinary least squares (OLS), which is equivalent to the maximum likelihood estimation (MLE) under the normality assumption of $\boldsymbol{\varepsilon}_t$.

It is worth noting that by relying on the recursive structure of $\mathbf{B}$, we identify the structural oil market shocks with respect to the global oil production, global economic activity and oil prices in a recursive manner, ordered as in vector $\mathbf{z}_t$. In other words, we postulate a vertical short-run supply curve of crude oil, which is plausible for monthly data. Accordingly, the first type of shock is *supply shocks*. These shocks represent an exogenous disruption of global oil production that may be caused by, for example, geopolitical turmoil. Under our identification scheme, the supply shocks simultaneously impact global activity and the real price of oil. The second type of shock arises from the fact that increases in aggregate global economic activity contemporaneously affect the price of oil but has no contemporaneous effect on global oil production. These shocks are therefore called *global (aggregate) demand shocks*. The third type of shocks originates from a specific factor generated demand and are therefore called *oil-specific demand shocks*.[11] This idea comes from Kilian (2009), who finds that increases in precautionary demand for crude oil, which are associated with changes in market expectations about the availability of future oil supply relative to demand, are an important factor causing oil price shocks. The recursive identification assumes that these shocks impact global oil production and global activity from one month after the shocks. This identification strategy is also applied to uncover the structural oil market shocks derived from the STVAR model, which is described in detail in the following subsection.

4.3 STVAR model

In addition to the baseline analysis, we also estimate a STVAR model to examine the possible regime-dependent effects of the oil market shocks, depending on the state of oil price uncertainty.

The smooth-transition autoregressive (STAR) model was developed by, among others, Chan and Tong (1986) and Granger and Teräsvirta (1993), and its statistical inference was established by Teräsvirta (1994). Since then, many types of smooth-transition models have been considered. In particular, the STVAR model is an extension of the STAR model to a multivariate system of equations that can analyse the dynamic relations among several variables with taking a possible regime change into account (Weise, 1999; Gefang and Strachan, 2010; Auerbach and Gorodnichenko, 2012). Similar to these studies, we adopt a STVAR model to examine the regime-dependent relationship among the prices

[11]We note that, as the oil-specific demand shock is identified by controlling shocks to oil production and demand for oil, therefore the shock often purely reflects sudden changes in the price of oil.

of crude oil, as well as global economic activity, depending on the degree of oil price uncertainty.

Following Weise (1999) and Gefang and Strachan (2010), we accommodate the smooth transition into the reduced form equation (6) as

$$\begin{aligned}\mathbf{z}_t &= (1 - F(s_{t-1}; c, \gamma)) \left(\boldsymbol{\alpha}^{(1)} + \sum_{i=1}^{p} \mathbf{A}_{\mathbf{i}}^{(\mathbf{1})} \mathbf{z}_{\mathbf{t-i}} \right) \\ &\quad + F(s_{t-1}; c, \gamma) \left(\boldsymbol{\alpha}^{(2)} + \sum_{i=1}^{p} \mathbf{A}_{\mathbf{i}}^{(\mathbf{2})} \mathbf{z}_{\mathbf{t-i}} \right) + \mathbf{e}_{\mathbf{t}}, \qquad (7)\end{aligned}$$

where $\boldsymbol{\alpha}^{(j)}$ and $\mathbf{A}_{\mathbf{i}}^{(\mathbf{j})}$ are the reduced form parameters for regime j, $F(\cdot; c, \gamma)$ is a transition function taking the values between 0 and 1 with a transition variable s_t, and c and γ are the parameters to determine the threshold between two regimes and the smoothness of the regime transition, respectively.

The transition function and transition variable are determined according to the purpose of the analysis. For example, to identify the differences in the size of the fiscal spending multiplier in the U.S. economy over the business cycle, Auerbach and Gorodnichenko (2012) use a logistic transition function with a seven-quarter moving average of the output growth rate as a transition variable. Following a similar idea, we use a logistic transition function given as

$$F(s_{t-1}; c, \gamma) = \frac{1}{1 + \exp\big(-\gamma(s_{t-1} - c)\big)}, \quad \gamma > 0, \qquad (8)$$

and an average oil price uncertainty over the last p-months as a transition variable s_t.[12]

Adopting the convention, we date the index s by $t-1$ to avoid contemporaneous feedback. With this choice of transition function and variable, we can interpret regime 1, which is characterised by $\boldsymbol{\alpha}^{(1)}$ and $\mathbf{A}_{\mathbf{i}}^{(\mathbf{1})}$, as the low-oil-price-uncertainty regime with $F(s_{t-1}) \approx 0$ and regime 2, which is characterised by $\boldsymbol{\alpha}^{(2)}$ and $\mathbf{A}_{\mathbf{i}}^{(\mathbf{2})}$, as the high-oil-price-uncertainty regime with $F(s_{t-1}) \approx 1$. The location parameter c determines the threshold between the low- and high-uncertainty regimes. More specifically, if s_t is smaller (larger) than c, the VAR dynamics become closer to those in the low- (high-) uncertainty regime, or regime 1 (regime 2). The smoothness parameter γ determines the speed of the transition from regime 1 to regime 2 as the past p-month oil price uncertainty increases. More specifically, when γ takes a large value, the transition is abrupt, whereas the transition is gradual for small values of γ.

One of the advantages of the logistic transition function (8) is that it can express various forms of transitions, depending on the values of c and γ. Additionally, c and

[12] We set the length of a period to define the past oil price uncertainty as equal to the lag length for the VAR model. We also normalised s_t so that it has a mean of 0 and a standard deviation of 1.

γ can be estimated from the data, enabling the selection of the best regime-dependent interdependence patterns among the oil market, global economic activity and the level of oil price uncertainty based on the data, which is very attractive for the purposes of the current paper.

In principle, we can estimate the parameters of the STVAR model (7) simultaneously by using the MLE. However, it is challenging, if not impossible, to maximise the likelihood function with respect to all the parameters because of the large number of parameters and the highly nonlinear structure of the STVAR model. For example, Weise (1999) fixes c at a predetermined value and estimates γ by the grid search, while Auerbach and Gorodnichenko (2012) assume $c = 0$ and calibrate γ without any estimation. In contrast to these studies, we estimate both c and γ by using the grid search.[13] Given the fixed values of c and γ, the STVAR model becomes a seemingly unrelated regression (SUR) model with the same set of regressors. In this case, we can maximise the likelihood with the equation-by-equation OLS. Therefore, using a grid search, we can find the maximum likelihood estimates of c and γ relatively easily.

5 Empirical results

The aim of the current paper is to explore if the reactions of the oil market and global economic activity to oil market shocks change when uncertainty about oil prices is taken into account. More precisely, we investigate the dynamic responses of the global oil production, real price of oil and global economic activity to the structural oil market shocks that are conditional on the state of oil price uncertainty. To facilitate the analysis, first, we report the cumulative impulse response functions derived from the benchmark linear VAR model in Section 4.2. Second, we utilise the oil price uncertainty index presented in Section 3 as a transition variable in the STVAR model; this setting allows the oil price uncertainty to affect how oil shocks propagate. These shocks include the oil supply shock, oil demand shock and oil-specific demand shock, as having been discussed and identified in Section 4. The cumulative impulse responses obtained from the STVAR model are discussed in detail in Section 5.2. In Section 5.3, we then assess the quantitative importance of the positive and negative shocks to oil supply and oil-specific demand on global economic activity. This is motivated by the fact that oil price innovations may have asymmetric effects on economic activity, as suggested by, among others, Mork (1989) and

[13] One cost of estimating c and γ with a grid search is that the standard errors are not able to be evaluated for c and γ. Therefore, the standard errors for the impulse responses calculated below do not consider the effects of the estimation of c and γ. However, judging from the estimation results, this should not be a serious problem because the rest of parameter estimates seem to be insensitive to the small changes in the estimates of c and γ.

Hamilton (2003, 2011). Following Kilian (2009), our impulse response analysis is based on a recursive-design wild bootstrap with 2,000 replications. For the details of the method, see Gonçalves and Kilian (2004).

5.1 Baseline results and linearity tests

We begin our analysis with a discussion of the cumulative impulse responses estimated from the linear VAR, which are illustrated with dashed lines along with the confidence intervals (dotted lines) in Figures 5–7. For comparison purposes, the figures also report the corresponding impulse responses derived from the STVAR model. We find that the negative supply shock generates a sharp decline in global oil production, a permanent reduction of real economic activity and a small increase in the price of oil. The aggregate demand and oil-specific demand shocks both cause increases in the oil prices, but the impact of the specific demand shock is found to be relatively larger. These findings are generally in line with those found in Kilian (2009). Having said that, in all cases, the impulse responses obtained from the linear model are likely to present the average composition of the two regimes of oil price uncertainty over the sample period. This is because under the linear setting, shifts in uncertainty about oil prices are muted. As a result, ignoring the degree of oil price uncertainty would mislead the behaviour of the oil market and the responses of global economic activity to oil market shocks.

As mentioned, the main objective of the present paper is to examine the possible regime-dependent effects of structural oil price shocks, depending on the oil price uncertainty. To this end, we employ the STVAR model, but it is useful to look at whether there is some evidence of regime dependency before estimating it. Specifically, we conduct systemwide linearity tests, as proposed by Weise (1999) and Teräsvirta and Yang (2014), to motivate our use of the STVAR model.[14] A test of linearity is a test of the null hypothesis $H_0 : \gamma = 0$ against the alternative $H_1 : \gamma > 0$ in (7). However, this test is not standard because the parameters $\boldsymbol{\alpha}^{(j)}$ and $\mathbf{A}_i^{(j)}$, $j = 1, 2$ cannot be identified under the H_0. To deal with this identification problem for a univariate system, Luukkonen et al. (1988) suggest using the auxiliary regressions by approximating the logistic transition function with the Taylor approximation around $\gamma = 0$ to test the linearity against the STAR model.[15] Weise (1999) extends their test to a STVAR framework based on the log-likelihood ratio-type test statistic, while Teräsvirta and Yang (2014) consider a generalisation using the Lagrange-multiplier-type test statistic. Both tests are applied to our VAR system (6) to test against the STVAR model (7) and strongly reject the linear

[14] A nice summary of these tests can be found in Hubrich and Teräsvirta (2013).

[15] In the current paper, we use the first-order Taylor approximation because the employed tests seem to have enough power to detect the possible regime dependency in our data.

VAR model with P-values of 0.012 and 0.000, respectively. Thus, there seems to be a solid reason to estimate the STVAR model (7) with oil price uncertainty as a transition variable.

Having discovered that the STVAR model provides a better description for our data, we now discuss the regimes that are detected by our model. As mentioned in Section 4.3, we estimate c and γ using the grid search, and their estimates are given by 0.711 and 300, respectively.[16] This means that if the average oil price uncertainty over the last four months is 0.711 standard deviations higher than the average, the regime would become closer to the high-oil-price-uncertainty regime. Assuming the normality of oil price uncertainty, this corresponds to about a 24% event over the sample period, meaning that the economy spends nearly a quarter of its time in the high-uncertainty regime. In addition, the large estimate of γ indicates that the transition from the low uncertainty regime to a high-uncertainty regime is very rapid. These can be also confirmed from Figure 4, plotting the estimated dynamics of transition function (8) or the weight on the high-oil-price-uncertainty regime along with the U.S. recessions identified by the NBER. The estimated regime dynamics indicate that the regime tends to be of a high uncertainty around the periods of U.S. recessions. In addition, the recent volatile oil price period between April 2015 and October 2016 is identified as a high-uncertainty regime. In the following section, we examine the regime-dependent impulse responses of the oil market and global activity to the structural oil market shocks.

5.2 Oil price uncertainty matters

Our estimation result of the transition function (8) strongly indicates that there are two distinct regimes depending on the level of oil price uncertainty. To see the different effects of oil market shocks in each regime, Figure 5 displays the global oil production cumulative responses to a one-standard-deviation oil market shock. The oil supply shock, which is defined as an unexpected oil supply disruption, contemporaneously causes a sharp decline in the world oil production, followed by a slight recovery after a year. This pattern is in line with results in Kilian (2009). An additional insight from our nonlinear model is that the recovery of global oil production after the shock is found to differ in periods of high and low uncertainty. When uncertainty is high, the recovery seems to disappear quickly; however, recovery largely remains in place when uncertainty is low. The reaction of oil producers to the degree of uncertainty about oil prices is in line with previous findings in the literature. Kellogg (2014), for example, finds that in the face of higher

[16] If the transition function looks like a step function, the estimate of γ becomes very large and is not well determined because the log-likelihood becomes insensitive with γ. For this reason, we set an upper bound of γ at 300.

uncertainty, Texas oil producers tend to reduce their investments. This is because firms optimally make their decisions by taking the presence of time-varying uncertainty into consideration, which is aligned with what predicted by real options theory discussed in Introduction. That is, when uncertainty about the future price of oil is high, drilling activity decreases because variations in oil price can reduce the value of drilling.

Oil price uncertainty also matters to the response of oil global production to the global demand shock. Oil production responds positively to an unexpected increase in global economic activity when uncertainty is low. In contrast, when oil price uncertainty is high, the response is quite small and insignificant. This could be because when oil price uncertainty is high, the oil producers would cut down their production, and this effect offsets the positive responses of oil production to solid contemporaneous demand.

We also observe that positive shocks in oil-specific demand have a negligible effect on global oil production in a low-uncertainty regime. This evidence is again consistent with the results in Kilian (2009). If oil market uncertainty is high, then an oil-specific demand shock causes a persistent increase in oil production; this indicates that a sudden increase in the price of oil that reflects fluctuations in precautionary demand arriving at times of high oil price uncertainty has a significant positive effect on oil production. This reaction reflects the view that producers would increase oil production in anticipation of higher oil prices in the future. Indeed, we find that the price of oil increases significantly in response to the oil-specific demand shock during the periods of high uncertainty. This is different from the findings in Kilian (2009), who claims that increases in oil-specific demand do not cause an increase in global oil production. Part of the explanation could be the state-dependent impulse responses based on high and low uncertainty, and Kilian (2009)'s sample seems to contain more low-oil-price-uncertainty periods.

Turning to the responses of the oil price, Figure 6 provides little evidence that the reactions of oil prices to structural oil market shocks differ, depending on the state of oil market uncertainty. When uncertainty is low, we find that the oil supply shock triggers a small increase in the price of crude oil, and the effect is negligible after about four months. Similarly, when uncertainty is relatively high, we find that the real price of oil increases slightly upon the impact of a negative supply shock, but its effect becomes insignificant after this.

The real price of oil reacts persistently and positively to the oil demand shock, regardless of the uncertainty regimes. Consistent with the empirical evidence found in the oil literature, we see that an unexpected expansion of global real economic activity causes an immediate and positive response in the oil price. Furthermore, our evidence indicates that under a low-uncertainty environment, the impact of the global demand shock is relatively larger than that of the same shock hitting in times of high oil price uncertainty.

This shows that oil prices react strongly during normal times when uncertainty about oil prices is relatively low, but when oil price uncertainty is high, the price would respond moderately because global economic activity is also dampened by oil price uncertainty. Indeed, Jo (2014) find that an oil price uncertainty shock has negative effects on world industrial production. In contrast, the oil-specific demand shock, which reflects the fluctuations in precautionary demand for oil, is found to have a relatively stronger effect on oil prices in periods of high uncertainty. Despite this, in both regimes, the shock has a large, persistent and positive effect on the price of oil.

The responses of global real economic activity to structural oil market shocks are also nonlinear. As shown in Figure 7, these responses depend not only on the underlying structural shocks but also on the state of oil market uncertainty. In periods of low uncertainty, we find that global real economic activity is not very sensitive to an oil supply shock. However, this shock produces a sharp decline in global economic activity during periods of high uncertainty. In other words, when oil price uncertainty is high, the recessionary effects of the unfavourable oil supply shock are amplified. An unanticipated increase in the demand for oil, which is associated with an expansion in real economic activity, triggers an increase in global economic activity, and the effect is state independent. We also observe that the oil-specific demand shock only affects global economic activity when the shock hits in times of high uncertainty. In contrast, during periods of low uncertainty, the oil-specific demand shock has no significant effect on economic real activity.

5.3 Sign matters

Having discovered that oil price uncertainty matters to the international oil markets in the way that it can propagate the effects of oil price shocks, we now evaluate whether the relationship between oil prices and economic activity is asymmetric in addition to uncertainty dependent. More precisely, we examine whether positive and negative oil market shocks have the same (mirror image) effects on global economic activity between a high- and low-oil-price-uncertainty environments.

We investigate the response of global economic activity to both positive and negative oil supply and oil-specific demand shocks, explicitly taking oil price uncertainty into account. To this end, we re-estimate the model proposed in Section 4.3 by replacing Δpro_t by $\Delta ppro_t = \max(\Delta pro_t, 0)$ and $\Delta npro_t = \min(\Delta pro_t, 0)$. More specifically, we estimate the STVAR model consisting of four variables, $\tilde{\mathbf{z}}_t = (\Delta ppro_t, \Delta npro_t, \Delta ip_t, \Delta rpo_t)'$. Then, we calculate the impulse responses of global economic activity to a negative supply shock defined as a negative one-standard-deviation shock to $\Delta npro_t$ and a positive supply shock, which is defined as a positive one-standard-deviation shock to $\Delta ppro_t$. This approach is somewhat similar to the common nonlinear transformation of oil prices proposed in the literature, as in Mork (1989), Hamilton (1996, 2003) and Herrera et al. (2011). Similarly, using $\hat{\mathbf{z}}_t = (\Delta pro_t, \Delta ip_t, \Delta prpo_t, \Delta nrpo_t,)'$ where $\Delta prpo_t = \max(\Delta rpo_t, 0)$ and $\Delta nrpo_t = \min(\Delta rpo_t, 0)$, we also evaluate the responses of global economic activity to the positive and negative oil price shocks driven by other factors generated demand for oil, such as preference shocks, speculative demand or politically motivated changes.

Figure 8 plots the cumulative impulse responses of global economic activity to the positive and negative oil supply shock that is conditional on the state of oil price uncertainty. As can be seen from the figure, the sign of the shocks matters. An unexpected increase in oil production that causes the price of oil to fall has a negligible impact on global economic activity in periods of low oil price uncertainty. In contrast, the negative supply shock in a low-uncertainty regime that leads to an increase in the price of oil is found to have a significant contractionary impact on global activity. In times of high oil price uncertainty, the impacts of the supply shock are amplified, which is consistent with our finding in the previous subsection. In addition, we find that the positive shock to oil production has a stronger and more persistent effect on global activity compared with a negative shock. Altogether, these results indicate that the effects of oil supply shocks on global economic activity are asymmetric and regime dependent. Thus, the effects of negative supply shocks are significant only for the low-uncertainty regime, while the effects of positive supply shocks are more pronounced with much larger effects when oil price uncertainty is relatively high. These findings are consistent with our expectations based on the real options theory. These results are also in line with those of Elder and Serletis (2010) and Pinno and Serletis (2013), who find that increased oil price uncertainty amplifies the negative relationship between oil supply shocks and economic activity. Our results are not only in line with these previous results, but also provide richer insights by distinguishing the positive and negative supply shocks.

Regarding the oil-specific demand shocks, Figure 9 presents the impulse responses of global economic activity to the positive and negative shocks. When oil price uncertainty is low, we find that global economic activity slightly drops in the short run in response to a negative shock, but the global economy is not sensitive to a positive shock. More interestingly, in periods of high oil price uncertainty, the impacts of oil-specific demand shock are magnified but turn out to be symmetric. We find that an increase in the oil-specific demand has the almost same (mirror image) effect as a decrease in the oil-specific demand. In this regard, our results may be in line with Kilian and Vigfusson (2011) and Herrera et al. (2011), who also find weak evidence for the asymmetries between oil price shocks and U.S. aggregate data.

Taken together, our results indicate that the degree of asymmetric responses of global economic activity to oil price increases or decreases depending on the underlying structural shocks and the level of uncertainty about the price of oil in the market.

6 Additional results and robustness analysis

In this section, we extend the analysis by examining the regime-dependent reactions of the oil market to its fundamental shocks under another different uncertainty environment: financial uncertainty. This exercise solidifies our conclusion. We also report a sensitivity analysis showing that our results are robust to different oil price merits: RAC and WTI.

6.1 Additional results

Because uncertainty is unobservable, there have been several proxies proposed in the recent literature that measure uncertainty about different perspectives, such as financial uncertainty or policy uncertainty. Given the objective of the current paper, the proxy presented in the present paper is designed to capture uncertain events that typically generate uncertainty about the price of crude oil. We have provided clear evidence that there is a weak correlation between our oil uncertainty measure and other proxies existing in the literature. A natural question, however, is whether the oil market reacts in a distinguishable way under different uncertainty environments, other than the uncertainty stemming from the oil market that we have investigated. We address this issue in this section. We examine the sensitivity of our findings by considering two other well-known uncertainty proxies: the VIX and U.S. Equity Market Uncertainty Index from EPU (WLEMUINDXD). These indexes are widely accepted as reasonable measures for financial uncertainty.

We find strong evidence that the responses of global economic activity to oil price shocks, inducing shocks originating from the sudden changes in global oil production and specific factors driving the price of oil, are sign dependent, regardless of the uncertainty measures. However, the results indicate little regime dependence between the high- and low-uncertainty regimes when we use VIX or WLEMUINDXD as a measure of uncertainty. Thus, we conclude that uncertainty-dependent responses only emerge when uncertainty about oil prices is taken into account, solidifying our main results.

Appendix C reports these exercises in detail. Not surprisingly, we find that the results estimated with VIX are somewhat similar to those achieved with WLEMUINDXD. Thus, the following comparisons between the results based on the oil price uncertainty and VIX also hold for WLEMUINDXD. First, we observe that the responses of global economic activity to the oil supply shock and the oil-specific demand shock under financial uncertainty regimes differ from those under the oil uncertainty regimes found in our main analysis. The differences are more obvious in periods where financial uncertainty and oil price uncertainty are relatively low. This is partly because the times where financial uncertainty is low are not necessarily related to the times where uncertainty about oil prices is also low. However, in periods of high financial uncertainty, these responses are found to be very similar. This implies that when financial uncertainty is considerably high, it is likely that uncertainty about oil price is also high but not vice versa.

Next, we also observe that the responses of global economic activity are different when considering the positive and negative supply shocks. These differences can be seen clearly when comparing the responses to the positive supply shock between the periods where both financial uncertainty and oil price uncertainty are relatively high. This is, when oil price uncertainty is high, the world economy benefits from lower oil prices following the unanticipated increases in global oil production. In contrast, when financial uncertainty is high, cheaper oil prices have negligible effects on the economy. This indicates that the recessionary effects of high uncertainty generated from financial markets would offset the expansionary effects of decreased oil prices.

Finally, regarding the oil-specific demand shocks, the different effects between financial uncertain and oil price uncertainty regimes only emerge under low uncertainty times. We find that when financial uncertainty is low, the effects of the shocks on global economic activity are large, but when oil price uncertainty is low, the effects of the corresponding shocks are very negligible.

6.2 Robustness

We also examine the robustness of our results using the different measures of oil prices commonly used in the literature. Instead of using the average price of oil as discussed in Section 4.1, we alternately use RAC and WTI. We report the detailed results obtained from these robustness exercises in Appendix C. We find that our main results are robust to these changes.

7 Conclusion

We investigated the oil market reaction to its fundamental shocks, namely supply, aggregate demand and oil-specific demand shocks, in times of low and high uncertainty. To this end, we offered a novel measure of oil price uncertainty. In contrast to the existing results in the literature, our approach can include additional information that is important in explaining oil price fluctuations; these include the exchange rate, oil production, global economic activity and comovement in the fuel market. As a result, we demonstrated that the index can pick up uncertainty events that are highly specific to the oil market. We then utilised this new index in a nonlinear model that allows for the propagation of oil market shocks to be different between high- and low-uncertainty regimes, exploring the interaction between the oil market and its structural shocks by explicitly taking the state of oil price uncertainty into account.

Using a nonlinear model, we found that the oil market reactions to its fundamental shocks are different from those obtained from a linear setting that mutes the role of oil price uncertainty. In particular, shocks to the demand for crude oil arising from sudden increases in global economic activity have persistent impacts on global oil production and oil price only in times of low uncertainty. When oil price uncertainty is relatively high, shocks to oil-specific demand have a magnified impact on the price of oil. In relation to real economic activity, we find that both supply shocks and oil-specific demand shocks have negligible impacts in periods of low oil price uncertainty but sizeable effects in periods of high oil price uncertainty.

We also evaluated the hypothesis that real economic activity responds asymmetrically to unexpected increases and decreases in oil prices. Although the existing evidence that real economic activity responds (a)symmetrically is often derived from a linear environment, we show that relaxing this assumption by allowing the oil market reaction to be uncertainty dependent is important. Indeed, we find that the effects of oil supply shocks on global economic activity are asymmetric and regime dependent; however, oil-specific demand shocks are only regime dependent. More specifically, the effects of negative supply shocks are significant only for the low-uncertainty regime, while the effects of positive shocks are more pronounced and have much larger effects when oil price uncertainty is relatively high. The impacts of oil-specific demand shocks are insignificant when the oil price uncertainty is low but symmetrically magnified in the periods of high uncertainty. Thus, our results demonstrated that the degree of asymmetric responses of global economic activity to unexpected oil price increases and decreases depends on the underlying structural shocks and the level of uncertainty about the price of oil in the market. Taken together, our findings offer new explanations for the contrasting results found in the literature.

References

Aastveit, K. A., Bjørnland, H. C., and Thorsrud, L. A. (2015). What drives oil prices? Emerging versus developed economies. *Journal of Applied Econometrics*, 30(7):1013–1028.

Auerbach, A. J. and Gorodnichenko, Y. (2012). Measuring the output responses to fiscal policy. *American Economic Journal: Economic Policy*, 4(2):1–27.

Bai, J. and Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica*, 70(1):191–221.

Bai, J. and Ng, S. (2008). Forecasting economic time series using targeted predictors. *Journal of Econometrics*, 146(2):304–317.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

Baumeister, C. and Hamilton, J. D. (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *American Economic Review*, 109(5):1873–1910.

Baumeister, C. and Peersman, G. (2013). Time-varying effects of oil supply shocks on the US economy. *American Economic Journal: Macroeconomics*, 5(4):1–28.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, 98(1):85–106.

Bjørnland, H. C. and Zhulanova, J. (2018). The Shale Oil Boom and the US Economy: Spillovers and Time-Varying Effects. *CAMP Working Paper Series*, (No 7/2018).

Bjørnland, H. C., Larsen, V. H., and Maih, J. (2018). Oil and macroeconomic (in)stability. *American Economic Journal: Macroeconomics*, 10(4):128–51.

Bloom, N., Bond, S., and Van Reenen, J. (2007). Uncertainty and investment dynamics. *The Review of Economic Studies*, 74(2):391–415.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., and Terry, S. J. (2018). Really uncertain business cycles. *Econometrica*, 86(3):1031–1065.

Bredin, D., Elder, J., and Fountas, S. (2011). Oil volatility and the option value of waiting: An analysis of the G-7. *Journal of Futures Markets*, 31(7):679–702.

Brennan, M. J. and Schwartz, E. S. (1985). Determinants of GNMA mortgage prices. *Real Estate Economics*, 13(3):209–228.

Bresnahan, T. F. and Ramey, V. A. (1993). Segment shifts and capacity utilization in the US automobile industry. *The American Economic Review*, 83(2):213–218.

Chan, K. S. and Tong, H. (1986). On estimating thresholds in autoregressive models. *Journal of Time Series Analysis*, 7(3):179–190.

Chen, Y.-C., Rogoff, K. S., and Rossi, B. (2010). Can exchange rates forecast commodity prices? *The Quarterly Journal of Economics*, 125(3):1145–1194.

Cross, J. and Nguyen, B. H. (2017). The relationship between global oil price shocks and China's output: A time-varying analysis. *Energy Economics*, 62:79–91.

Datta, D., Johannsen, B. K., Kwon, H., and Vigfusson, R. J. (2018). Oil, equities, and the zero lower bound. *BIS Working Papers*, No. 617.

Dixit, A. (1989). Entry and exit decisions under uncertainty. *Journal of Political Economy*, 97(3):620–638.

Elder, J. and Serletis, A. (2009). Oil price uncertainty in Canada. *Energy Economics*, 31(6):852–856.

Elder, J. and Serletis, A. (2010). Oil price uncertainty. *Journal of Money, Credit and Banking*, 42(6):1137–1159.

Elder, J. and Serletis, A. (2011). Volatility in oil prices and manufacturing activity: An investigation of real options. *Macroeconomic Dynamics*, 15(S3):379–395.

Ferderer, J. P. (1996). Oil price volatility and the macroeconomy. *Journal of Macroeconomics*, 18(1):1–26.

Gefang, D. and Strachan, R. (2010). Nonlinear impacts of international business cycles on the UK—A Bayesian smooth transition VAR approach. *Studies in Nonlinear Dynamics and Econometrics*, 14(1):1–33.

Gonçalves, S. and Kilian, L. (2004). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics*, 123(1):89–120.

Granger, C. and Teräsvirta, T. (1993). Modelling Nonlinear Economic Relationships, New York: Oxford University Press.

Hamilton, J. D. (1988). A neoclassical model of unemployment and the business cycle. *Journal of Political Economy*, 96(3):593–617.

Hamilton, J. D. (1996). This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics*, 38(2):215–220.

Hamilton, J. D. (2003). What is an oil shock? *Journal of Econometrics*, 113(2):363–398.

Hamilton, J. D. (2011). Nonlinearities and the macroeconomic effects of oil prices. *Macroeconomic Dynamics*, 15(S3):364–378.

Hamilton, J. D. (2018). Measuring global economic activity. *Manuscript, University of California at San Diego.*

Herrera, A. M. (2018). Oil price shocks, inventories, and macroeconomic dynamics. *Macroeconomic Dynamics*, 22(3):620–639.

Herrera, A. M., Lagalo, L. G., and Wada, T. (2011). Oil price shocks and industrial production: Is the relationship linear? *Macroeconomic Dynamics*, 15(S3):472–497.

Holm-Hadulla, F. and Hubrich, K. (2017). Macroeconomic implications of oil price fluctuations: a regime-switching framework for the Euro area. Working Paper Series 2119, European Central Bank.

Hou, C. and Nguyen, B. (2018). Understanding the US natural gas market: A Markov switching VAR approach. *Energy Economics*, 75:42–53.

Hubrich, K. and Teräsvirta, T. (2013). Thresholds and smooth transitions in vector autoregressive models. In *VAR Models in Macroeconomics–New Developments and Applications: Essays in Honor of Christopher A. Sims*, volume 32 of Advances in Econometrics, pages 273–326. Emerald Group Publishing Limited.

Jadidzadeh, A. and Serletis, A. (2017). How does the US natural gas market react to demand and supply shocks in the crude oil market? *Energy Economics*, 63:66–74.

Jo, S. (2014). The effects of oil price uncertainty on global real economic activity. *Journal of Money, Credit and Banking*, 46(6):1113–1135.

Joëts, M., Mignon, V., and Razafindrabe, T. (2017). Does the volatility of commodity prices reflect macroeconomic uncertainty? *Energy Economics*, 68:313–326.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3):1177–1216.

Kellogg, R. (2014). The effect of uncertainty on investment: Evidence from Texas oil drilling. *American Economic Review*, 104(6):1698–1734.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3):1053–69.

Kilian, L. and Murphy, D. P. (2012). Why agnostic sign restrictions are not enough: understanding the dynamics of oil market var models. *Journal of the European Economic Association*, 10(5):1166–1188.

Kilian, L. and Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics*, 29(3):454–478.

Kilian, L. and Park, C. (2009). The impact of oil price shocks on the US stock market. *International Economic Review*, 50(4):1267–1287.

Kilian, L. and Vigfusson, R. J. (2011). Are the responses of the us economy asymmetric in energy price increases and decreases? *Quantitative Economics*, 2(3):419–453.

Lee, K., Ni, S., and Ratti, R. A. (1995). Oil shocks and the macroeconomy: the role of price variability. *The Energy Journal*, pages 39–56.

Lippi, F. and Nobili, A. (2012). Oil and the macroeconomy: a quantitative structural analysis. *Journal of the European Economic Association*, 10(5):1059–1083.

Lütkepohl, H. and Netšunajev, A. (2014). Disentangling demand and supply shocks in the crude oil market: How to check sign restrictions in structural VARs. *Journal of Applied Econometrics*, 29(3):479–496.

Luukkonen, R., Saikkonen, P., and Teräsvirta, T. (1988). Testing linearity against smooth transition autoregressive models. *Biometrika*, 75:491–499.

Majd, S. and Pindyck, R. S. (1987). Time to build, option value, and investment decisions. *Journal of Financial Economics*, 18(1):7–27.

Mork, K. A. (1989). Oil and the macroeconomy when prices go up and down: an extension of Hamilton's results. *Journal of Political Economy*, 97(3):740–744.

Nguyen, B. and Okimoto, T. (2019). Asymmetric reactions of the us natural gas market and economic activity. *Energy Economics*, 80.

Ohashi, K. and Okimoto, T. (2016). Increasing trends in the excess comovement of commodity prices. *Journal of Commodity Markets*, 1(0):48–64.

Pindyck, R. S. (1991). Irreversibility, uncertainty, and investment. *Journal of Economics Literature*, 29(3):1110–48.

Pindyck, R. S. and Rotemberg, J. J. (1990). The excess co-movement of commodity prices. *The Economic Journal*, 100(403):1173–1189.

Pinno, K. and Serletis, A. (2013). Oil price uncertainty and industrial production. *The Energy Journal*, pages 191–216.

Rahman, S. and Serletis, A. (2011). The asymmetric effects of oil price shocks. *Macroeconomic Dynamics*, 15(S3):437–471.

Teräsvirta, T. (1994). Specification, estimation, and evaluation of smooth transition autoregressive models. *Journal of the American Statistical Association*, 89(425):208–218.

Teräsvirta, T. and Yang, Y. (2014). Linearity and misspecification tests for vector smooth transition regression models. *Research Paper 2014-4*, CREATES, Aarhus University.

Weise, C. L. (1999). The asymmetric effects of monetary policy: A nonlinear vector autoregression approach. *Journal of Money, Credit and Banking*, 31(1):85–108.

Figures

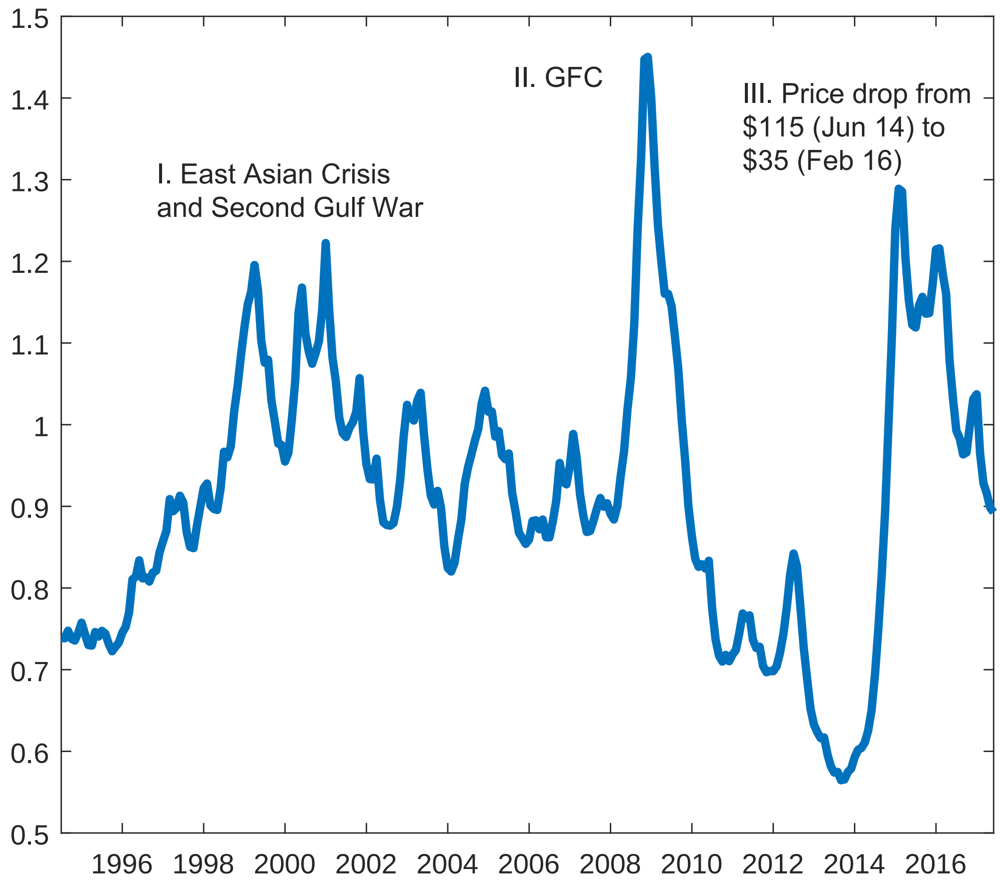


Figure 1: Oil price uncertainty index

Notes: The figure plots the oil price uncertainty index (OPU) constructed in Section 3 from 1994M07 to 2017M06.

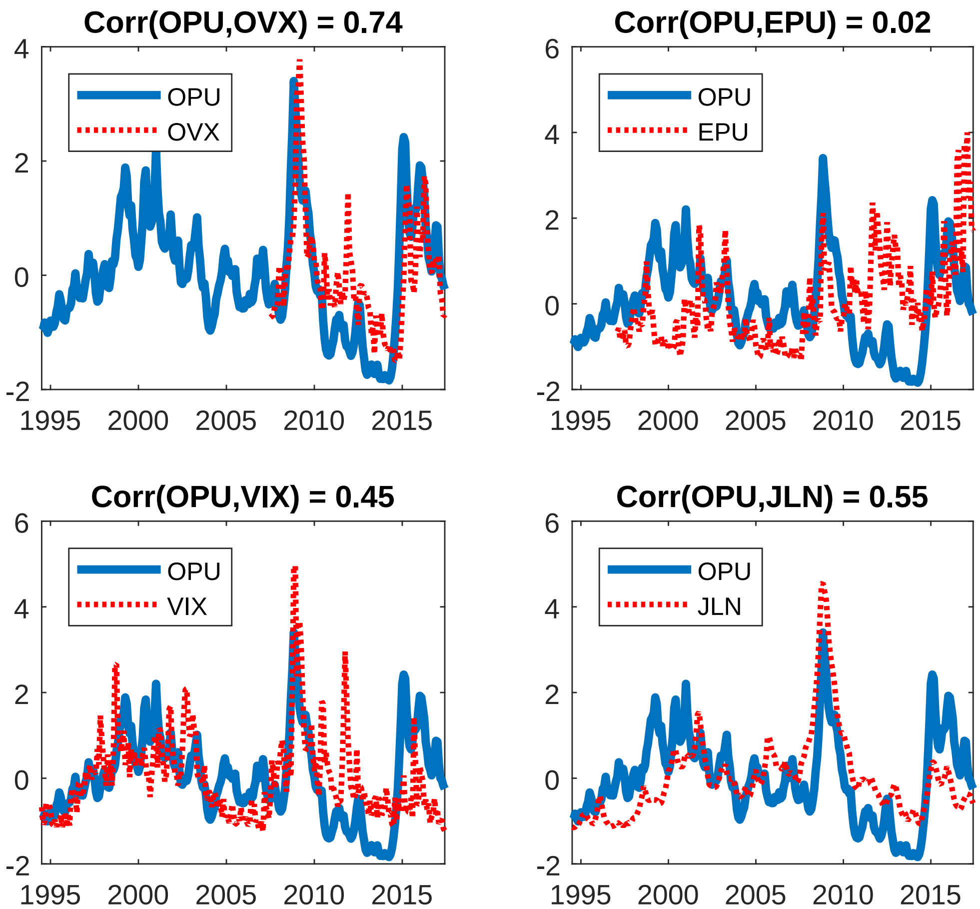


Figure 2: Oil price uncertainty index: comparison with other uncertainty indices

Notes: The figure compares the oil price uncertainty index (OPU) constructed in Section 3 from 1994M07 to 2017M06 to: (i) The CBOE Oil Price Volatility Index (OVX) from 2007M05 to 2017M06 (ii) The Global Economic Policy Uncertainty index (EPU) by Baker et al. (2016) from 1997M01 to 2017M06, (iii) The CBOE volatility index (VIX) from 1994M07 to 2017M06 and (iv) The uncertainty index (JLN) for the U.S by Jurado et al. (2015) from 1994M07 to 2017M06. All series are normalised to have means of 0 and standard deviations of 1.

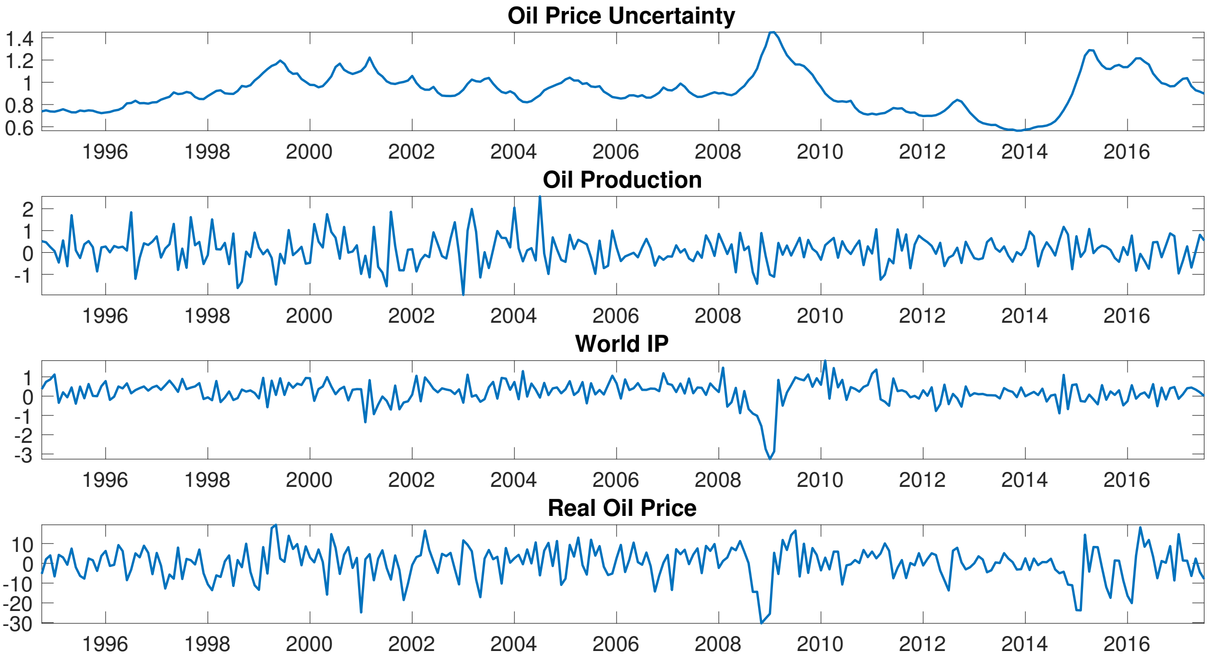


Figure 3: Historical evolution of the series (1994M7-2017M6)

Notes: The oil price uncertainty (OPU) index constructed in Section 3. The monthly raw data of crude oil prices and global oil production collected from EIA. World IP is the global industrial production index for OECD+ 6 as in Baumeister and Hamilton (2019). While OPU remaining series are in levels, oil production, World IP and real oil prices are in percent changes.

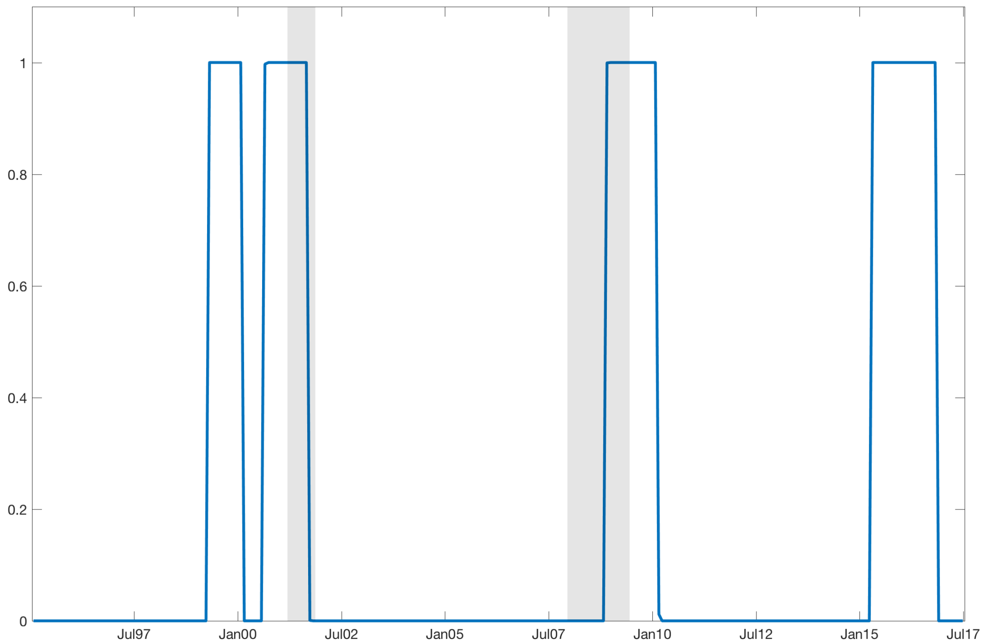
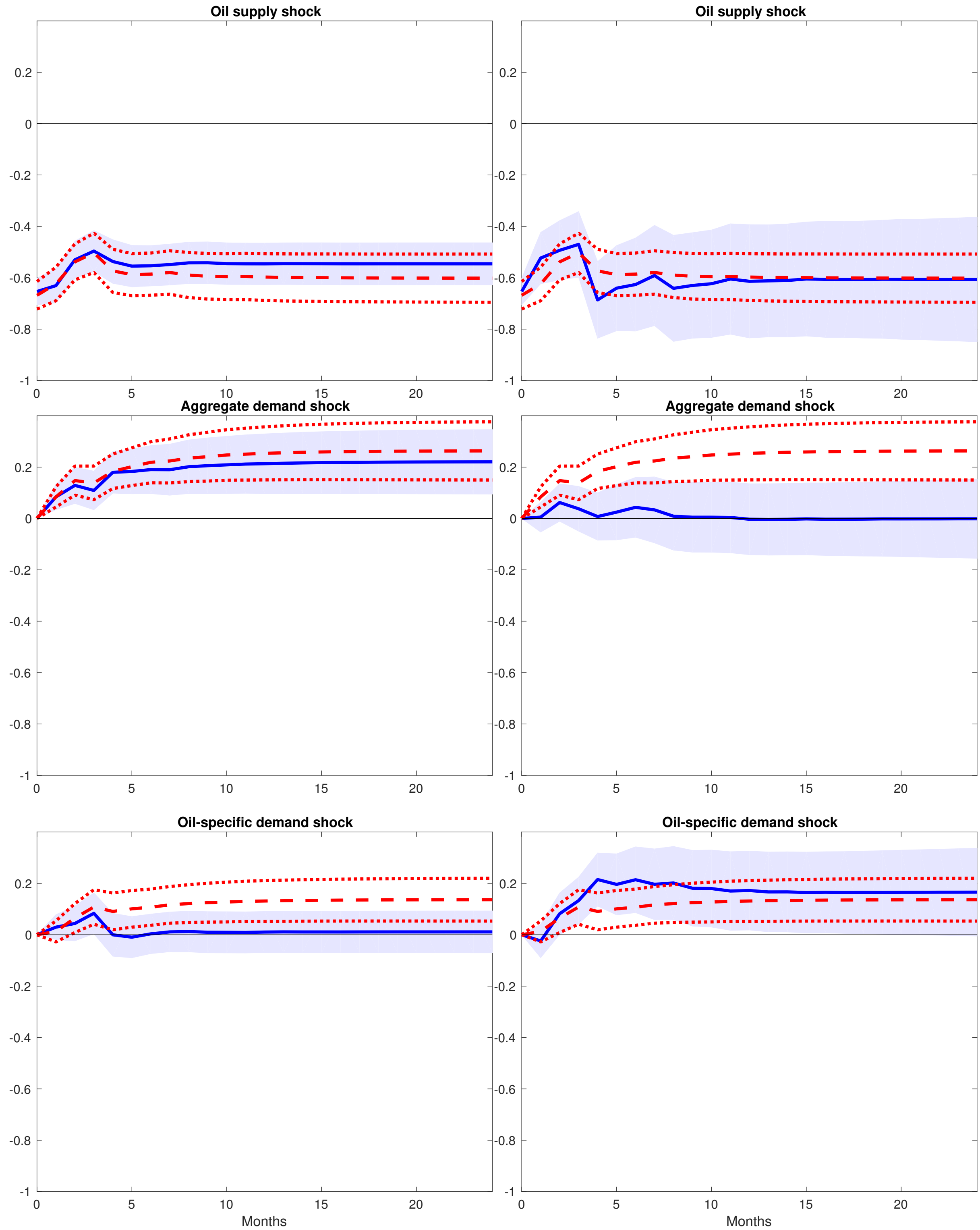


Figure 4: NBER dates and weight on low oil price uncertainty regime $F(s_t)$

Notes: The shaded region shows recessions as defined by the NBER. The solid line shows the weight on recession regime $F(s_t)$.

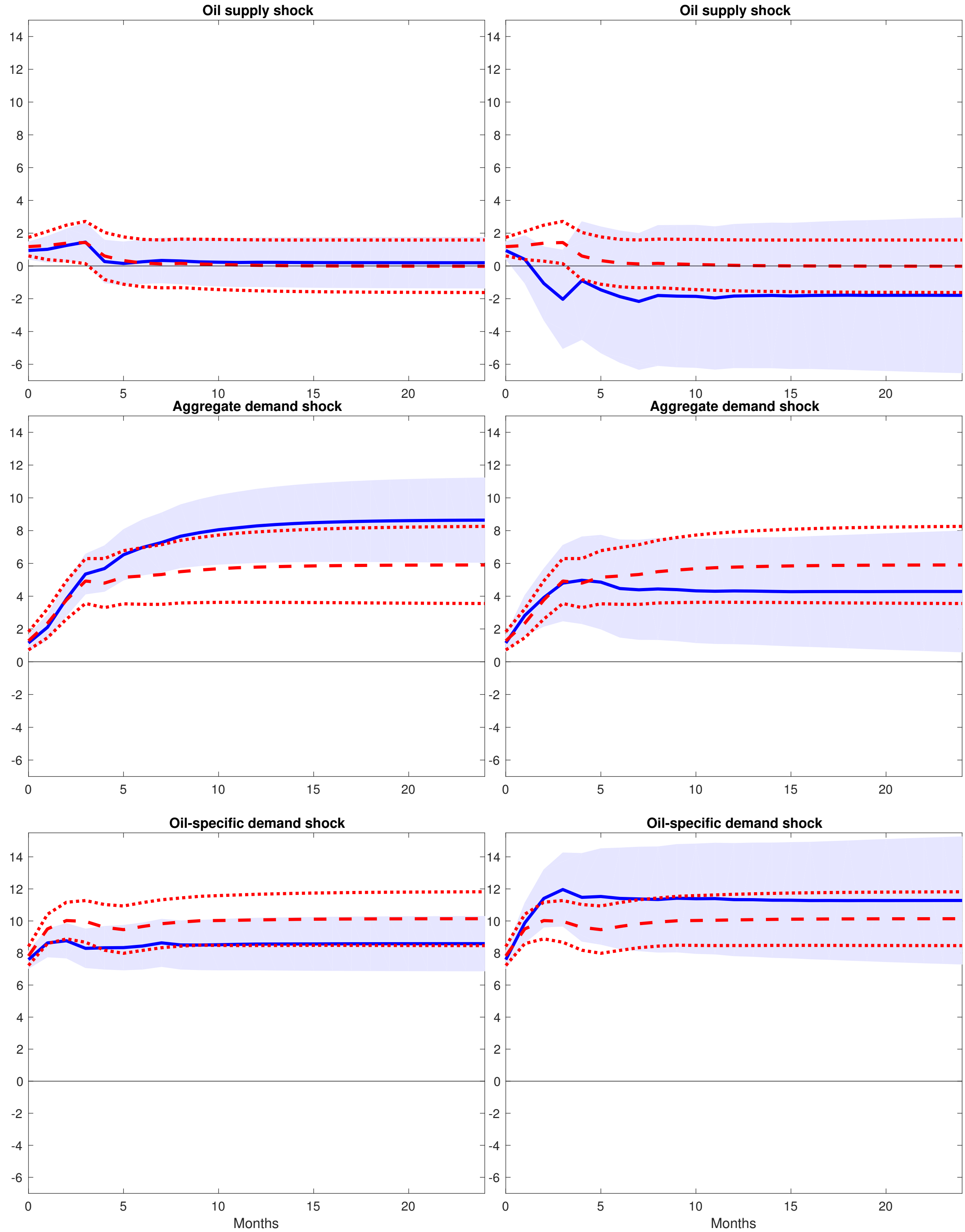


(a) Low oil price uncertainty

(b) High oil price uncertainty

Figure 5: Oil production responses to one-standard-deviation structural shocks

Notes: Red dashed lines show regime-independent impulse responses based on the linear model along with the confidence intervals (dotted lines). Blue solid lines show uncertainty-regime-dependent impulse responses based on the nonlinear model and shaded areas are the corresponding confidence intervals constructed using a recursive-design wild bootstrap. The oil supply shock is normalized to disrupt oil production.

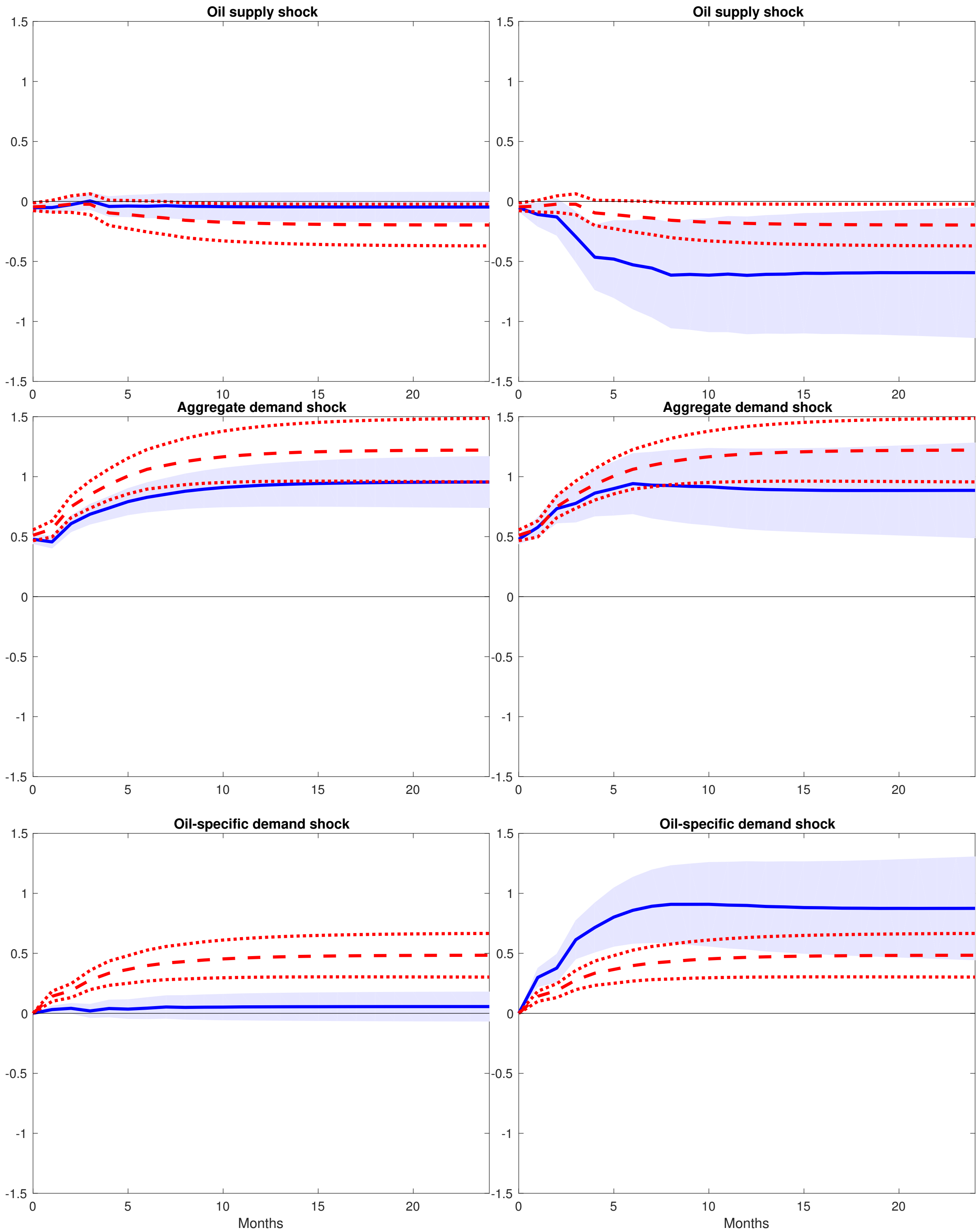


(a) Low oil price uncertainty

(b) High oil price uncertainty

Figure 6: Responses of the price of oil to one-standard-deviation structural shocks

Notes: See Figure 5



(a) Low oil price uncertainty

(b) High oil price uncertainty

Figure 7: Global economic activity responses to one-standard-deviation structural shocks

Notes: See Figure 5

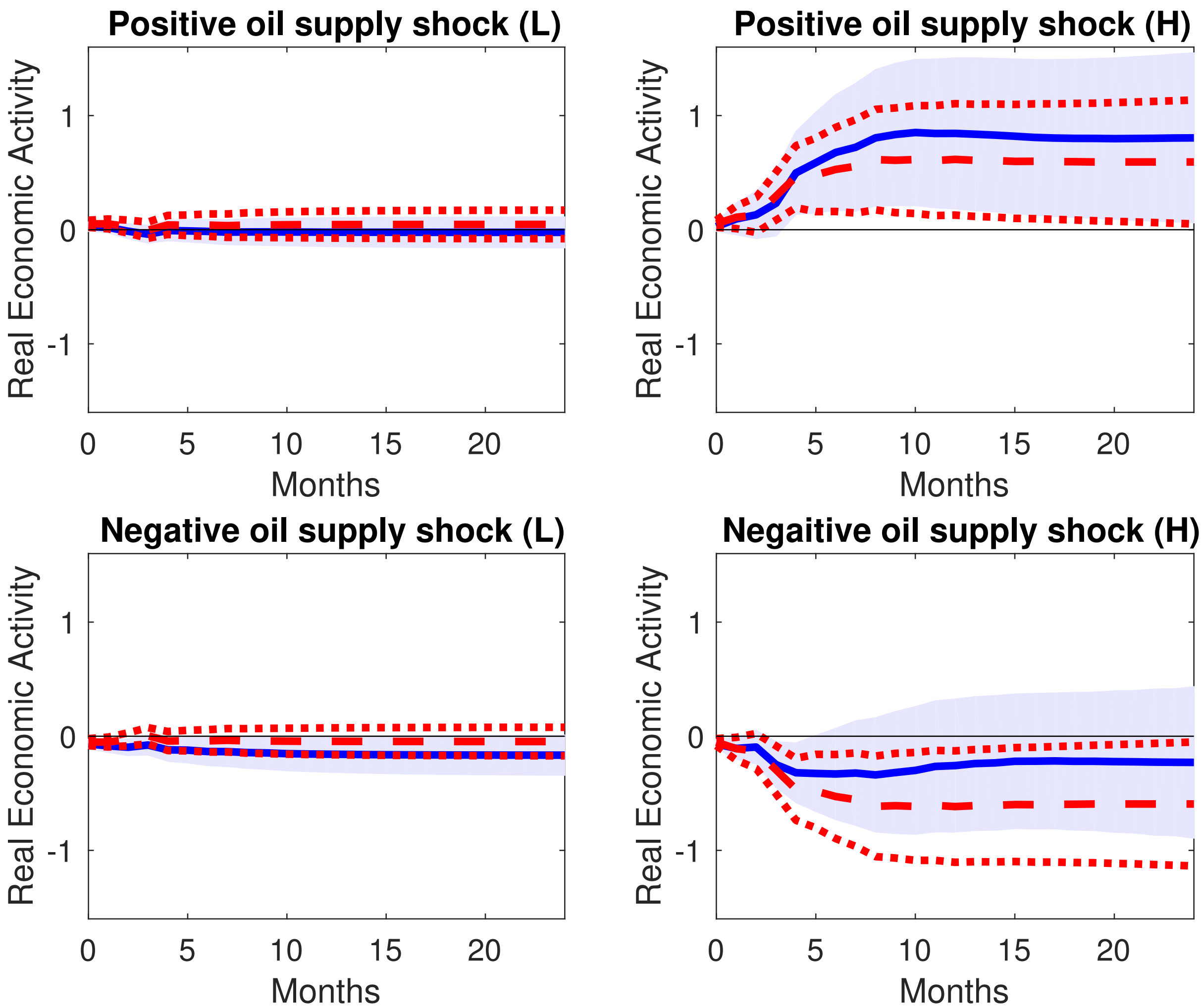


Figure 8: Responses of global economic activity to positive and negative oil supply shocks

Notes: Red dashed lines show uncertainty-regime-dependent impulse responses along with the confidence intervals (dotted lines). Blue solid lines show uncertainty-regime- and sign-dependent impulse responses and shaded areas are the corresponding confidence intervals constructed using a recursive-design wild bootstrap.

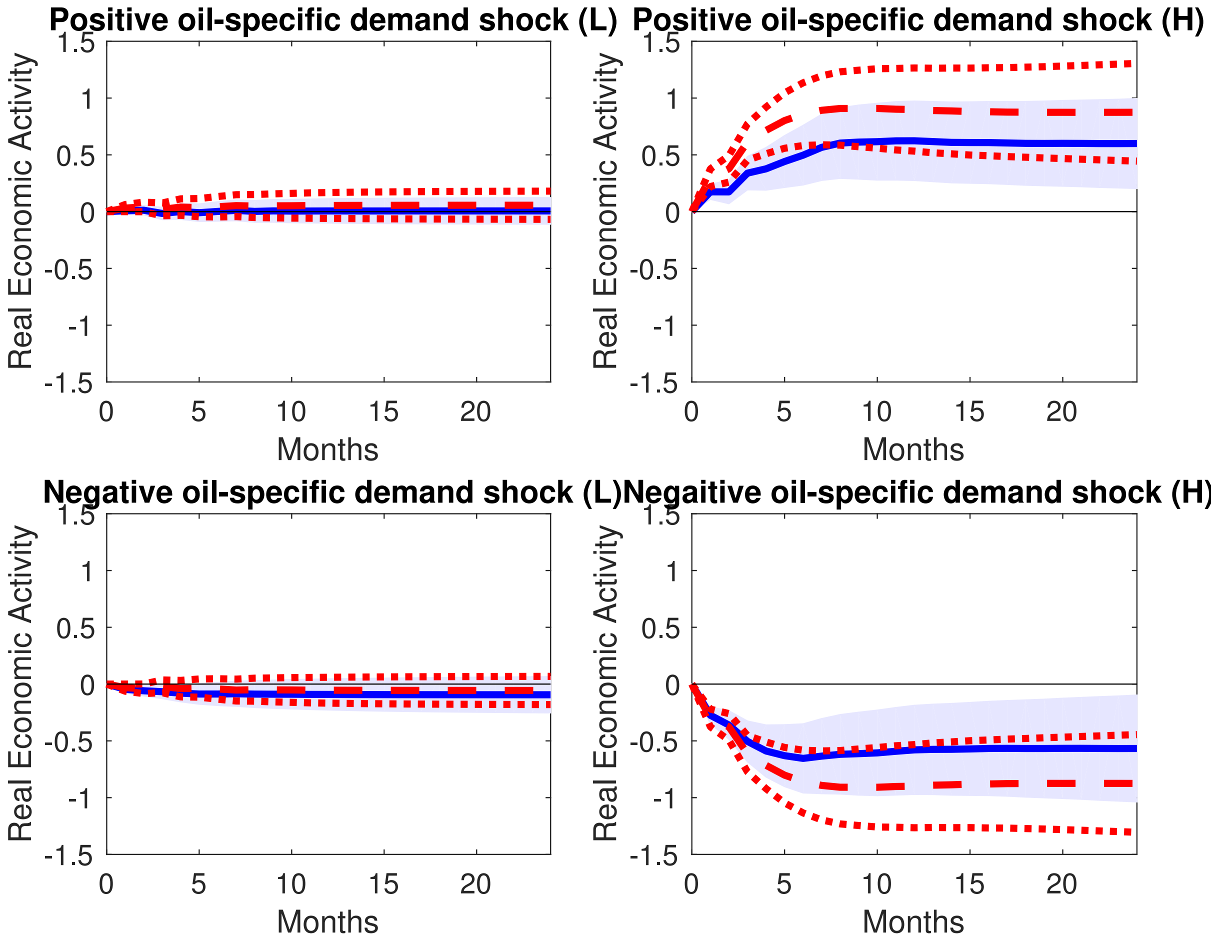


Figure 9: Responses of global economic activity to positive and negative oil-specific demand shocks

Notes: See Figure 8

Appendix A The role of predictors

The construction of the uncertainty index underscores the importance of extracting an unpredictable component in order to capture true uncertainty. Figure A1 compares the uncertainty index with two counter-factual estimate of uncertainty. First, the forecast regression does not include any information. That is when Equation (2) becomes: $y_{j,t+1} = \upsilon_{j,t+1}$. Second, the forecast regression only includes the AR(4) terms. In this case, Equation (2) becomes: $y_{j,t+1} = \phi_{jt} y_{jt} + \upsilon_{j,t+1}$. As we mention in the main text, the baseline estimate of uncertainty and the AR(4) estimate of uncertainty are identical as a result of additional predictors do not pass the hard threshold test.

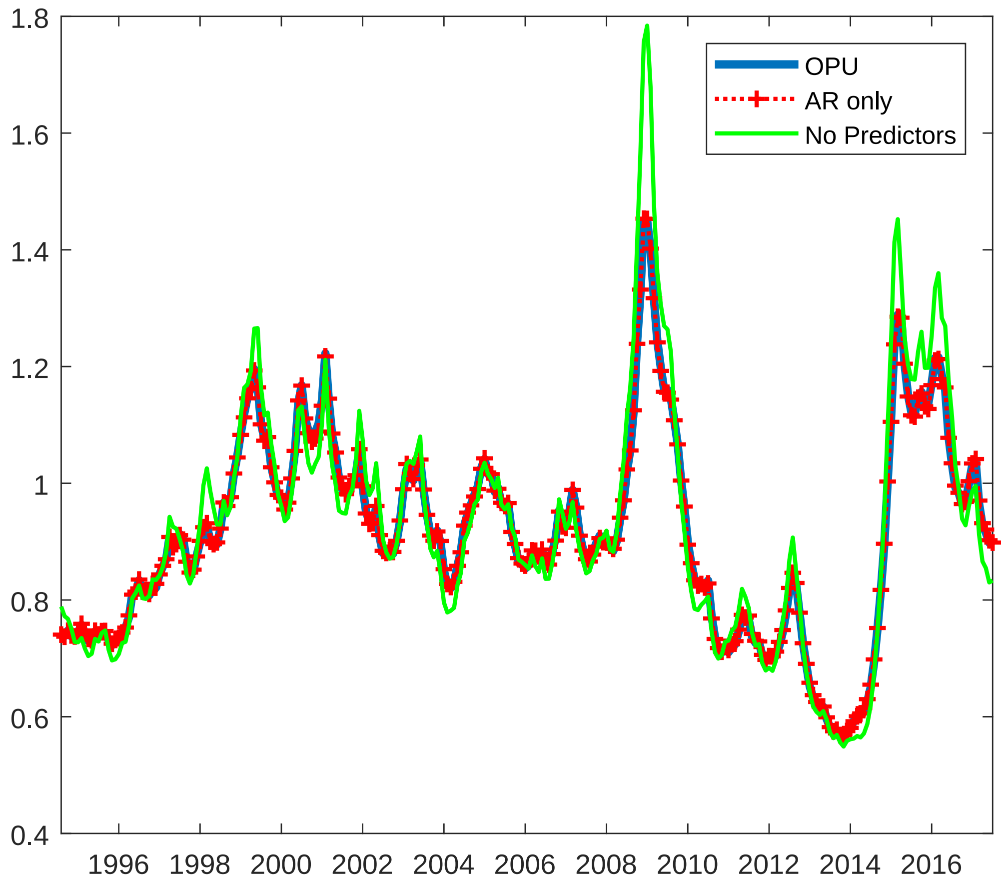


Figure A1: Oil Price Uncertainty index: Role of predictors

Notes: The figure compares different estimates of uncertainty according to Appendix A.

Appendix B Different predictive equation specification

The choice of the predictive Equation (2) is due to the advantage of its having direct interpretation from each of the predictors. Instead of doing that, we could postulate two other predictive equations.

1. The set of predictors by estimating an optimal number of principle components for all predictors according to the Bai and Ng (2002) criterion as in Jurado et al. (2015).

2. One principle component for each of group of predictors: exchange rate, world activity, fuel-group prices)

We find that the results are consistent across different equation specifications. It is because of the hard-threshold rule that rule out the contribution of additional predictors to extract an unpredictable component in oil prices.

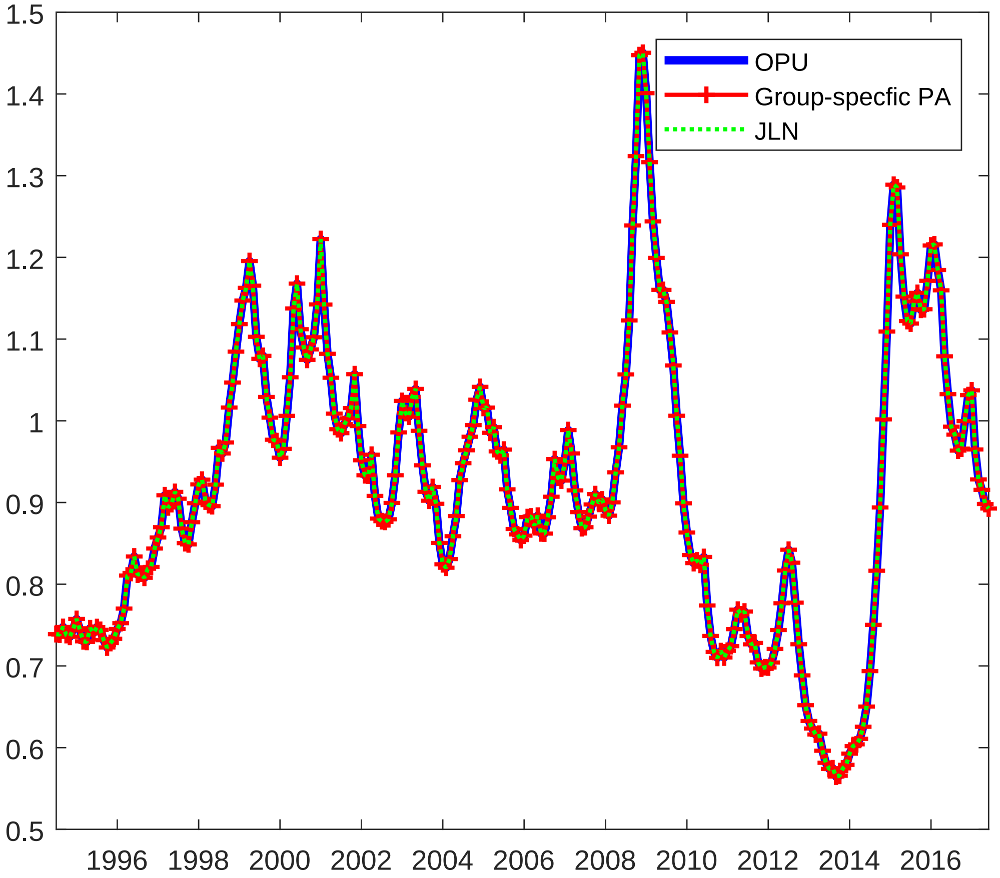


Figure B1: Oil Price Uncertainty index: Different equation specification

Notes: The figure plots compare different estimates of oil price uncertainty according to Appendix B.

Appendix C Additional results

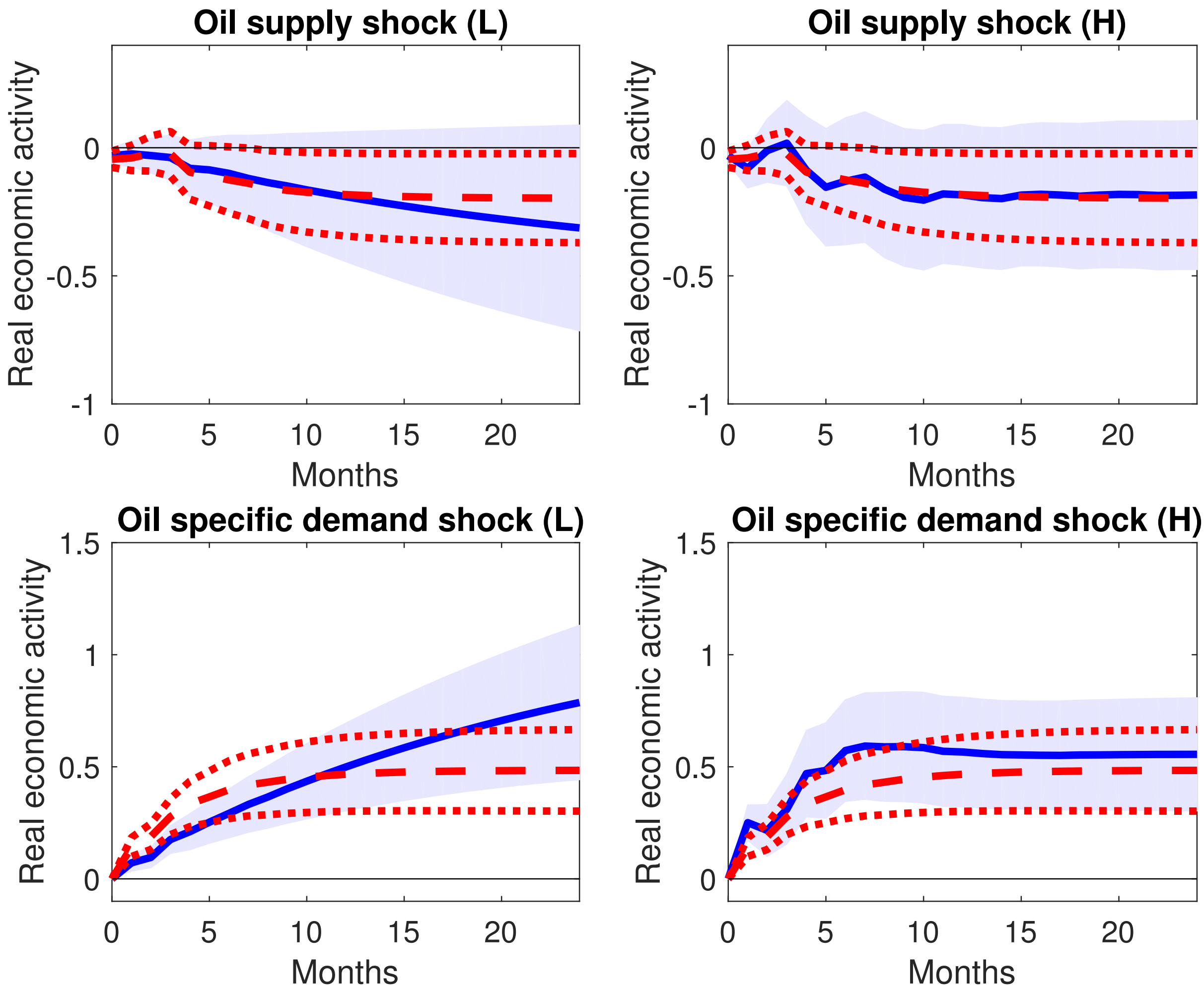


Figure C1: Responses of global economic activity to oil shocks under low (left column) and high (right column) financial uncertainty (VIX) regimes

Notes: Red dashed lines show regime-independent impulse responses based on the linear model along with the confidence intervals (dotted lines). Blue solid lines show regime-dependent impulse responses based on the nonlinear model and shaded areas are the corresponding confidence intervals constructed using a recursive-design wild bootstrap. The oil supply shock is normalized to disrupt oil production.

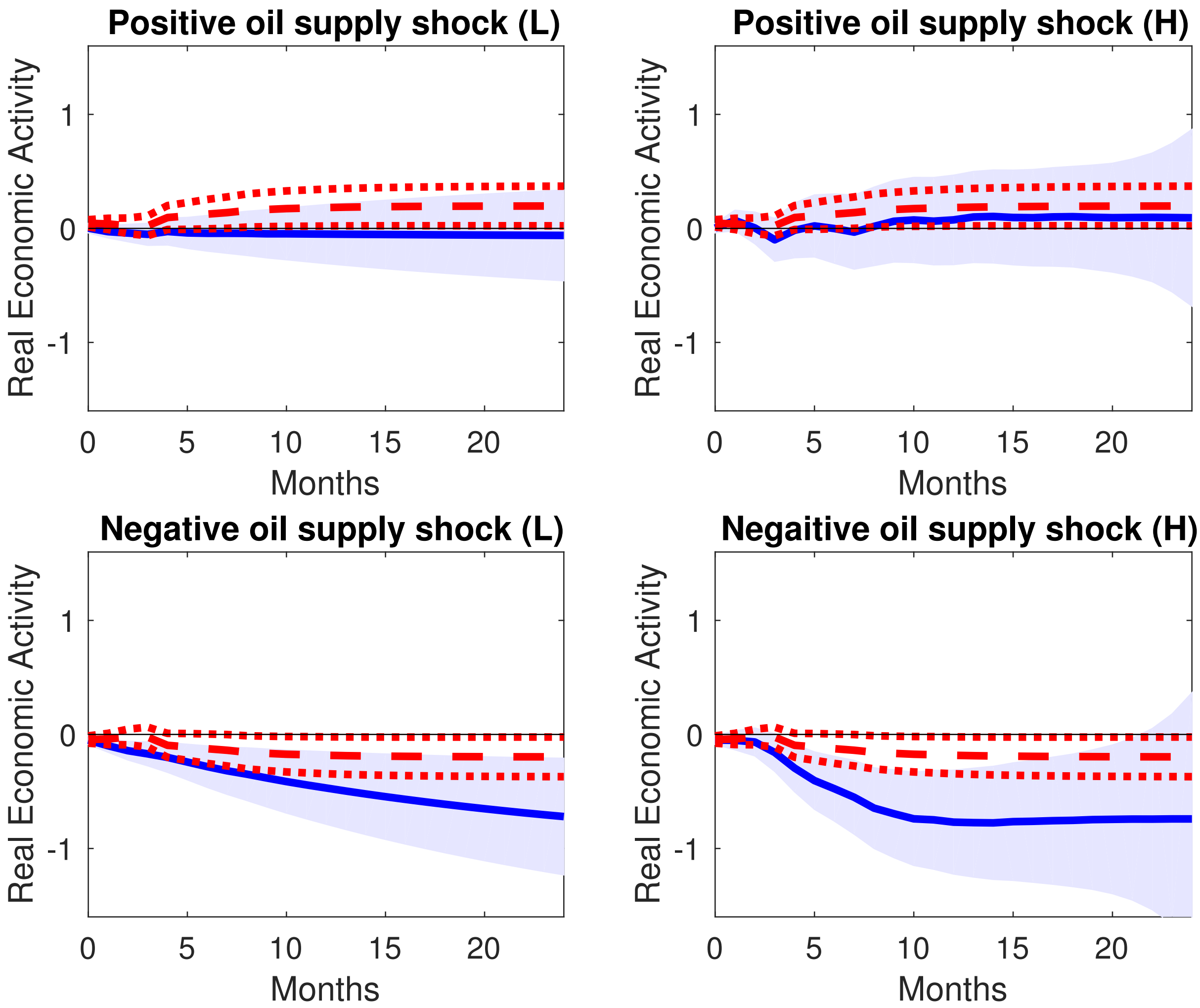


Figure C2: Responses of global economic activity to a positive and negative oil supply shock under low (left column) and high (right column) financial uncertainty (VIX) regimes.

Notes: Red dashed lines show regime-independent impulse responses based on the linear model along with the confidence intervals (dotted lines). Solid blue lines show regime-dependent impulse responses based on the nonlinear model and shaded areas are the corresponding confidence intervals were constructed using a recursive-design wild bootstrap.

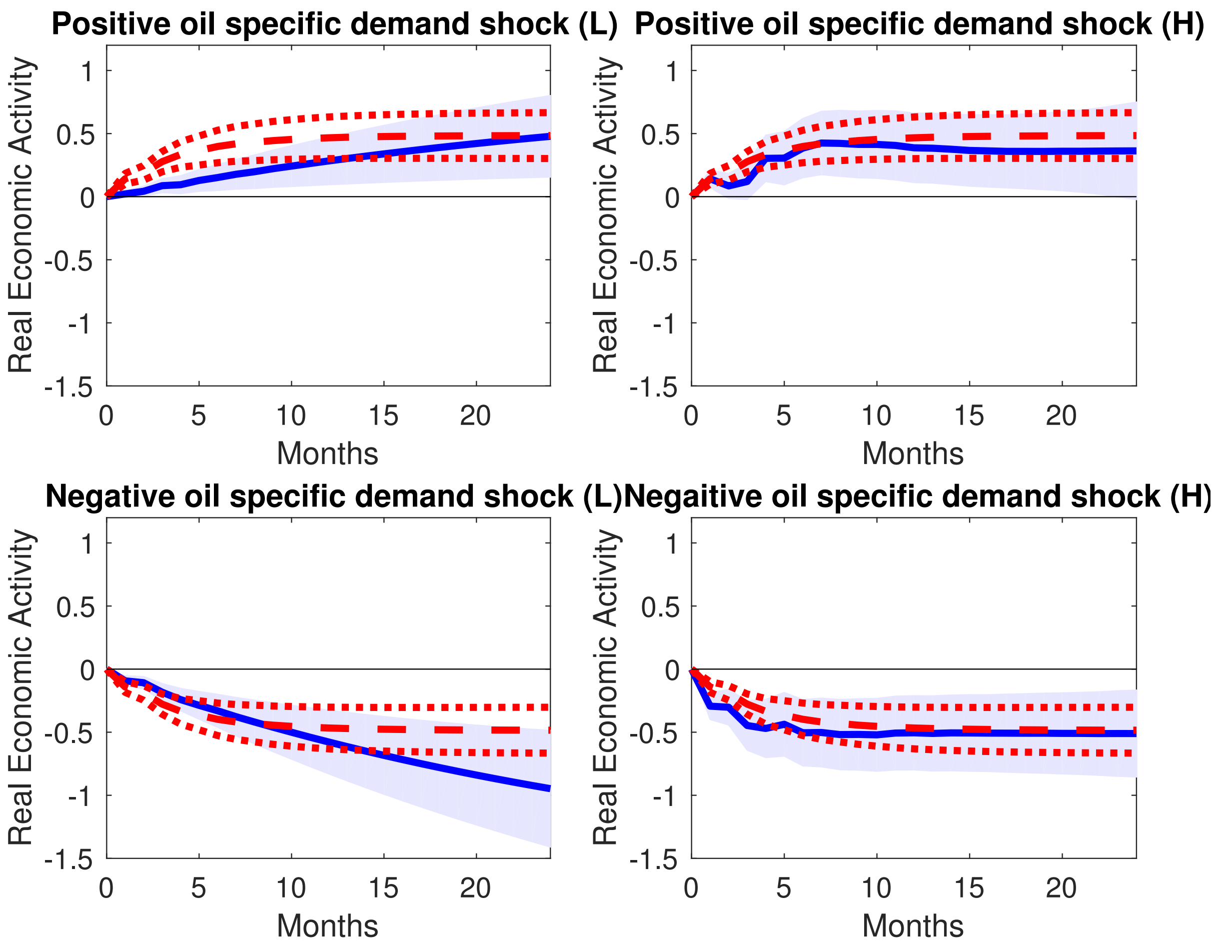


Figure C3: Responses of global economic activity to a positive and negative oil-specific demand shock under low (left column) and high (right column) financial uncertainty (VIX) regimes.

Notes: See Figure C2

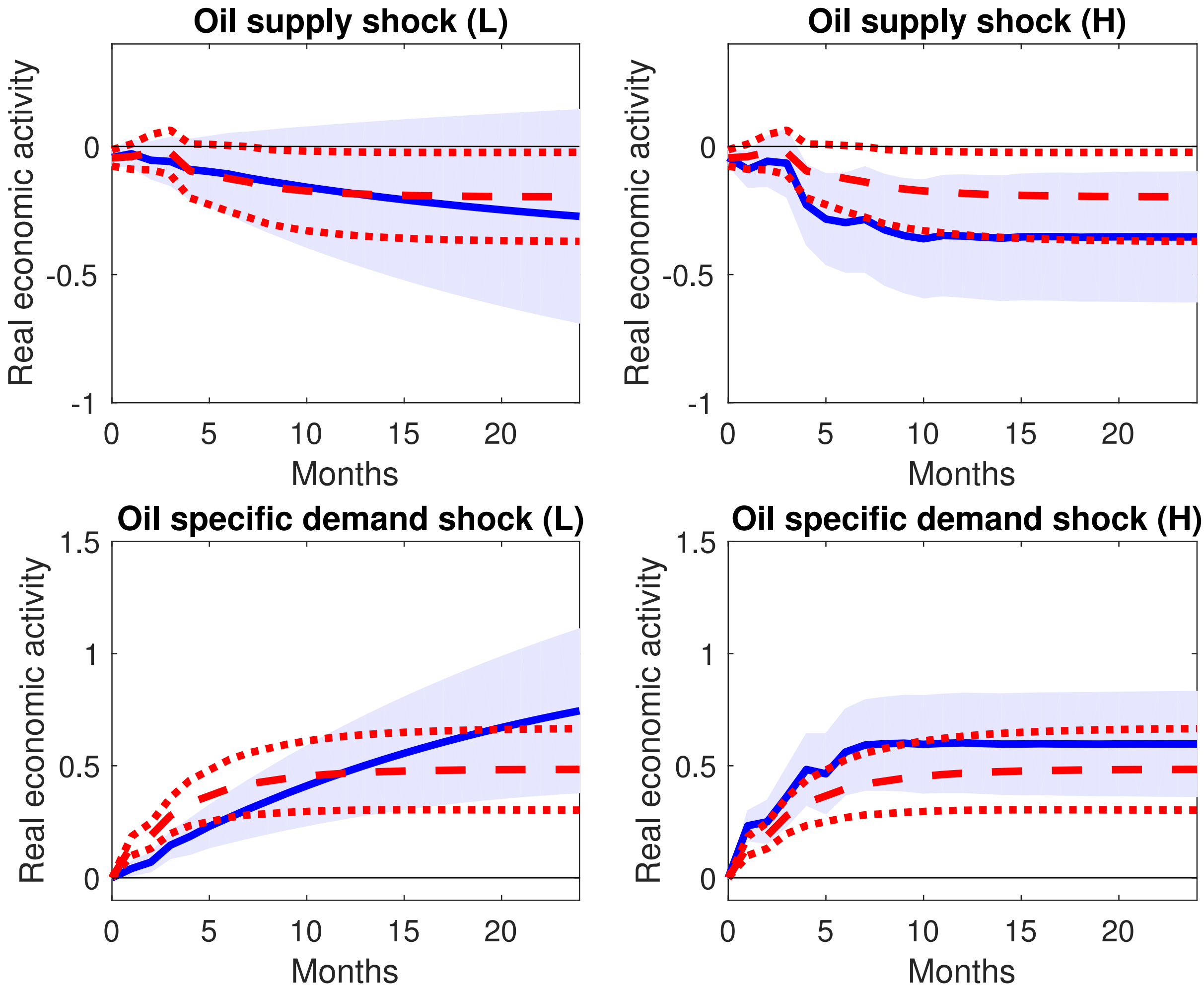


Figure C4: Responses of global economic activity to oil shocks under low (left column) and high (right column) financial uncertainty (WLEMUINDXD) regimes

Notes: See Figure C1.

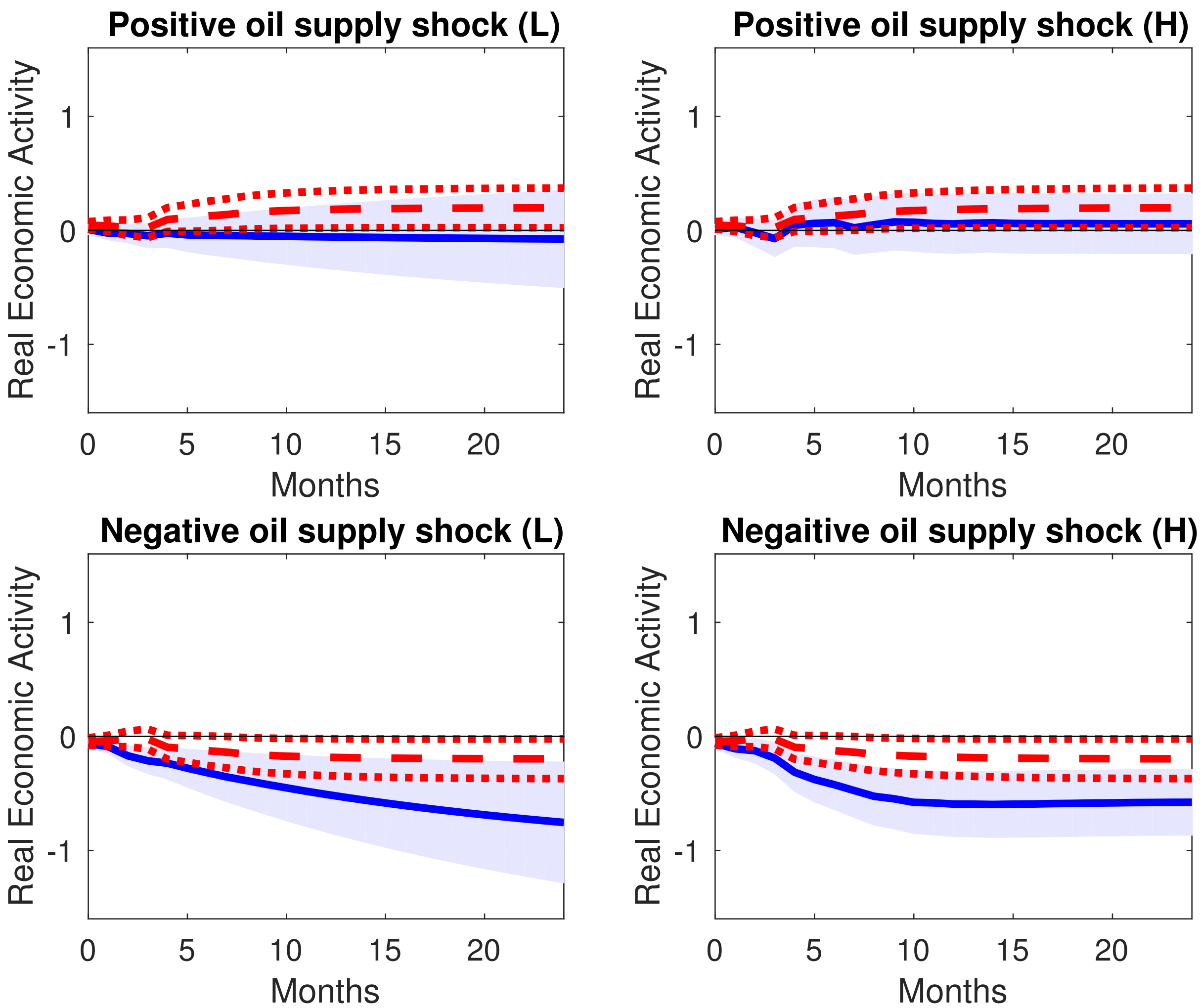


Figure C5: Responses of global economic activity to a positive and negative oil supply shock under low (left column) and high (right column) financial uncertainty (WLEMUINDXD) regimes.

Notes: See Figure C2

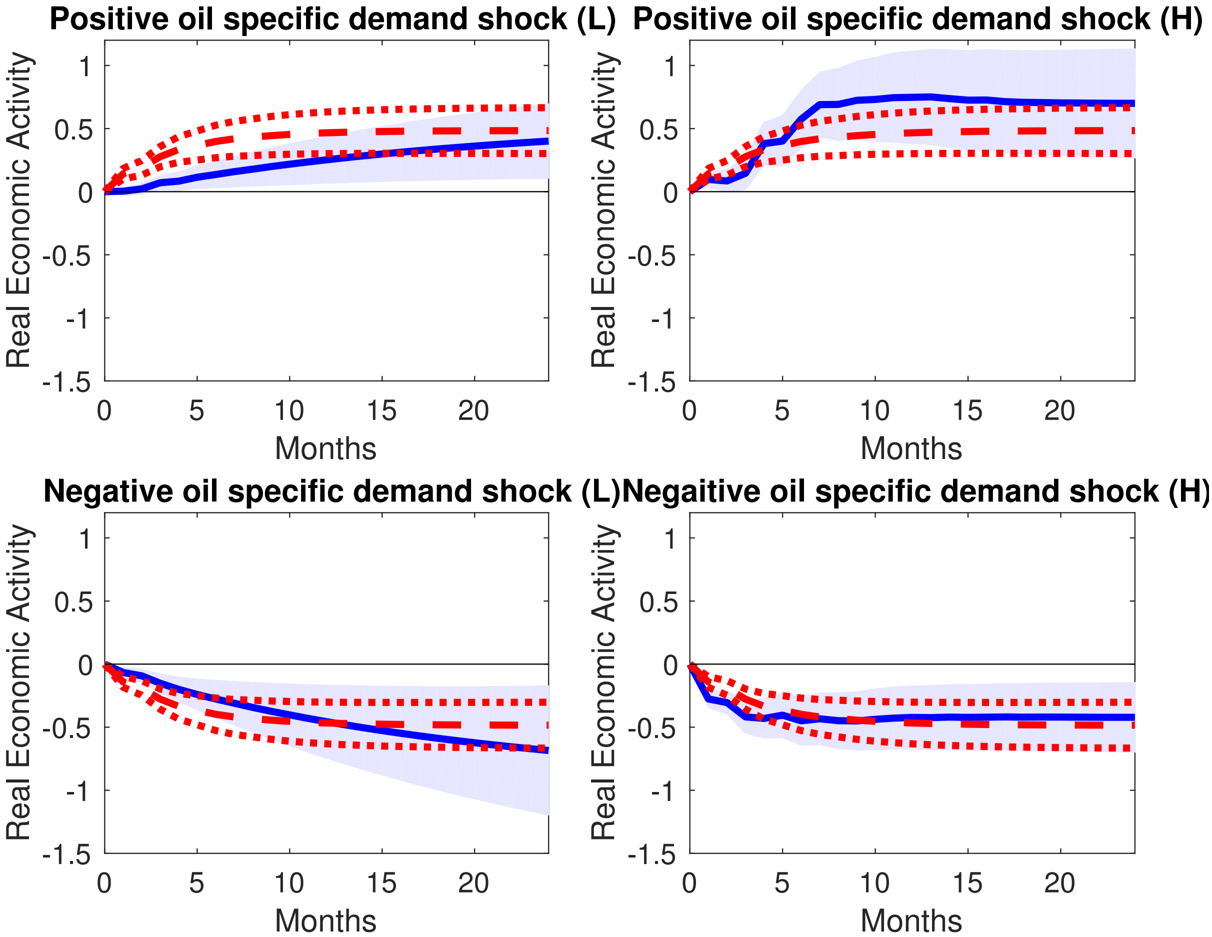


Figure C6: Responses of global economic activity to a positive and negative oil-specific demand shock under low (left column) and high (right column) financial uncertainty (WLEMUINDXD) regimes.

Notes: See Figure C2

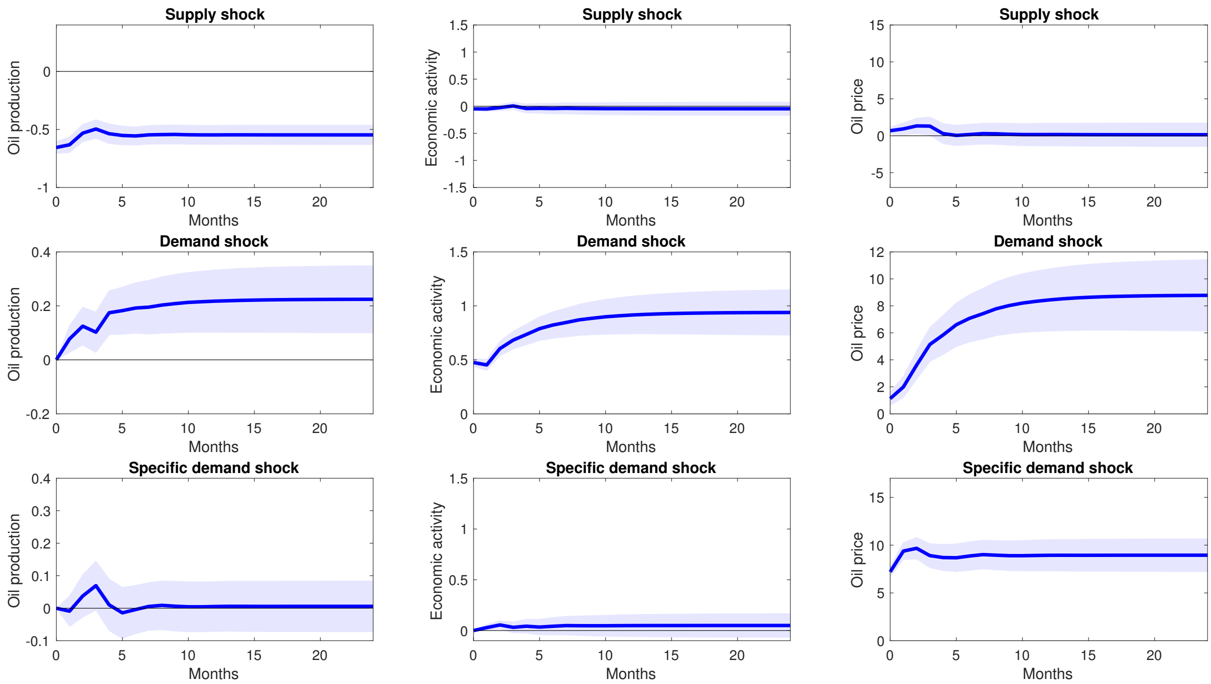


Figure C7: Impulse response functions to the choice of RAC in times of low oil uncertainty

Notes: See Figure C1. Note that, while Figure C1–C6 only report the impulse responses of global economic activity to supply and oil price shocks under different uncertainty environments, this figure reports the responses of global oil production, oil price as well as global economic activity to the structural shocks obtained with different oil price merits that is specifically conditional on oil price uncertainty.

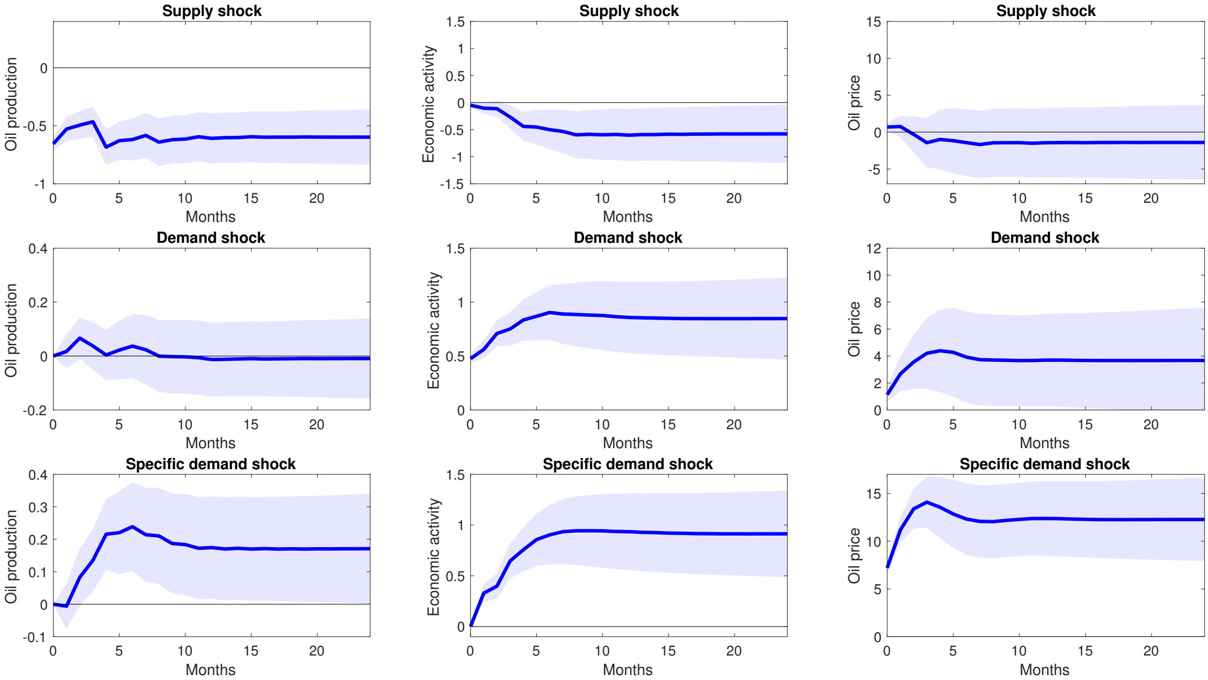


Figure C8: Impulse response functions to the choice of RAC in times of high oil uncertainty

Notes: See Figure C7

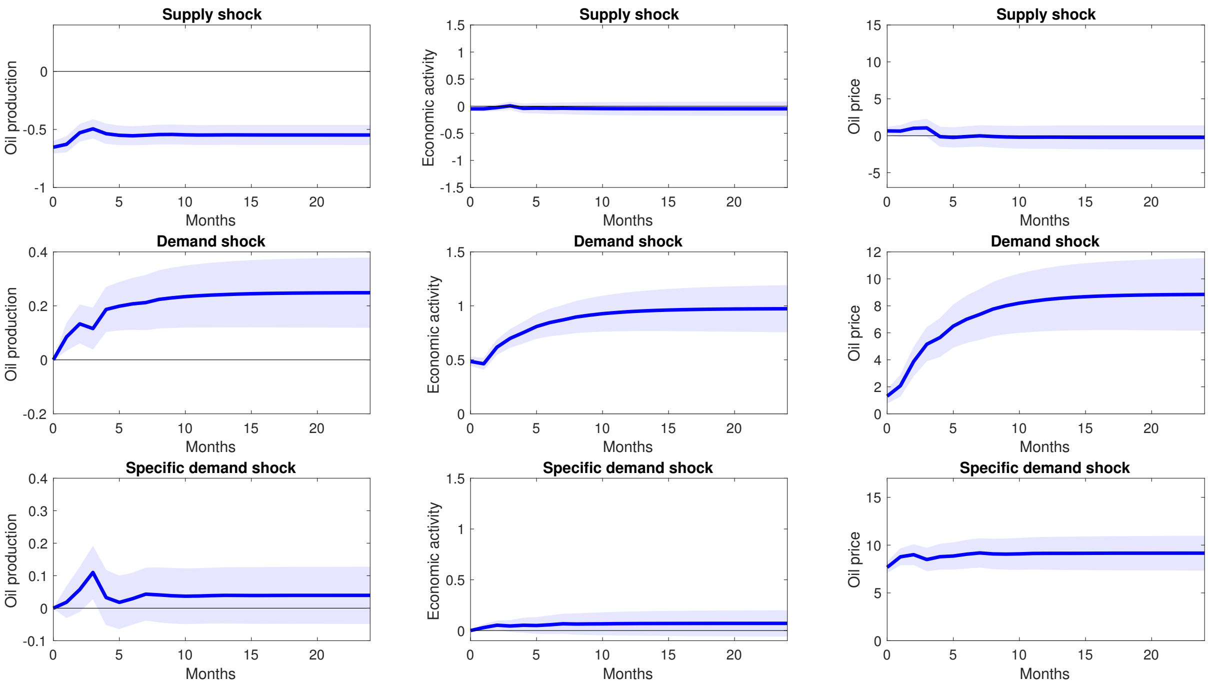


Figure C9: Impulse response functions to the choice of WTI in times of low oil uncertainty

Notes: See Figure C7

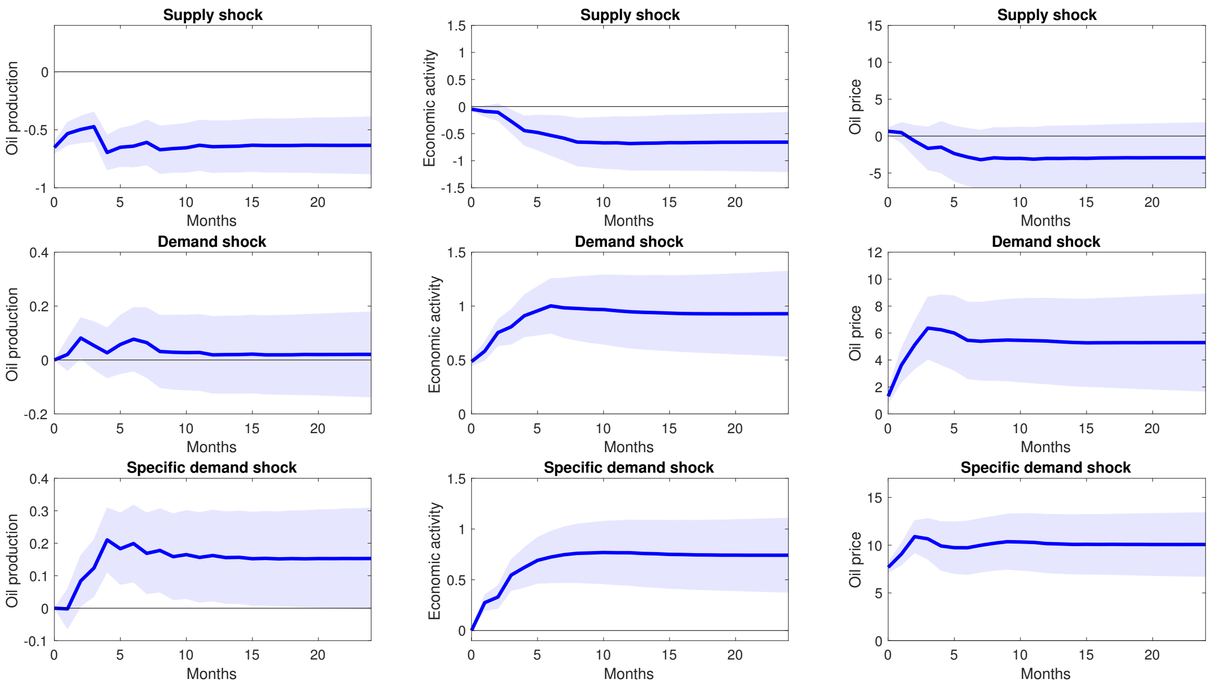


Figure C10: Impulse response functions to the choice of WTI in times of high oil uncertainty

Notes: See Figure C7