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# Uncertainty and sign-dependent effects of oil market shocks

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**Bao H. Nguyen**
Crawford School of Public Policy, ANU
School of Economics, University of Economics Ho Chi Minh City (UEH), Vietnam
Centre for Applied Macroeconomic Analysis, ANU

**Tatsuyoshi Okimoto**
Crawford School of Public Policy, ANU
Research Institute of Economy, Trade, and Industry (RIETI), Japan
Centre for Applied Macroeconomic Analysis, ANU

**Trung Duc Tran**
University of Melbourne



## Abstract

This paper investigates the oil market reaction to its fundamental shocks: supply, aggregate demand and oil-specific demand in different regimes characterised by high versus low uncertainty in the market. We do so by first proposing a novel oil uncertainty index that is measured by the conditional volatility of the unpredictable component of oil prices. Then, we employ a nonlinear model to show that the structural oil market shocks have asymmetric effects. For instance, 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. Our model also enables us to evaluate the hypothesis that real economic activity responds asymmetrically to unexpected increases and decreases in oil prices driven by supply and specific demand shocks. We find that the effects of oil supply shocks are asymmetric but oil specific demand shocks are not, which indicates that the (a)symmetric oil market reaction depends on the underlying market shocks.

**Keywords**

oil price uncertainty, STVAR model, asymmetric effect

**JEL Classification**

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**Address for correspondence:**

(E) cama.admin@anu.edu.au

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# Uncertainty and sign-dependent effects of oil market shocks*

Bao H. Nguyen† Tatsuyoshi Okimoto‡ Trung Duc Tran§

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**Abstract**

This paper investigates the oil market reaction to its fundamental shocks: supply, aggregate demand and oil-specific demand in different regimes charactertised by high versus low uncertainty in the market. We do so by first proposing a novel oil uncertainty index that is measured by the conditional volatility of the unpredictable component of oil prices. Then, we employ a nonlinear model to show that the structural oil market shocks have asymmetric effects. For instance, 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. Our model also enables us to evaluate the hypothesis that real economic activity responds asymmetrically to unexpected increases and decreases in oil prices driven by supply and specific demand shocks. We find that the effects of oil supply shocks are asymmetric but oil specific demand shocks are not, which indicates that the (a)symmetric oil market reaction depends on the underlying market shocks.

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

‡Crawford School of Public Policy, Australian National University, Australia, and Research Institute of Economy, Trade, and Industry (RIETI), Japan. Email: tatsuyoshi.okimoto@anu.edu.au

§University of Melbourne, Australia. Email: brian.tran@unimelb.edu.au

# 1 Introduction

It is well-known that not all oil price shocks are alike (Kilian, 2009). 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. 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). However, there is surprisingly little research investigating the reactions of the oil market and global economic activity to the shocks when uncertainty about oil prices takes into account. This is motivated by the fact that recent studies have established evidence that uncertainty matters to real economic activity, see Dixit (1989); Bloom et al. (2007); Jurado et al. (2015); Bloom et al. (2018), among others. In this paper, we address this shortcoming. In particular, we question whether (i) the oil market reacts differently depending on the level of oil price uncertainty; and (ii) uncertainty about the oil price amplifies the effects of unexpected increases and decreases in oil prices to global real economic activity.

Our paper is closely related to two strands of literature on modeling the oil market and oil price uncertainty. The first strand acknowledges that the movement of oil prices could be driven by underlying shocks which are 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, 2017). For instance, Kilian (2009) uses a linear vector autoregressive (VAR) model and finds that a combination of global aggregate demand shocks and precautionary demand shocks is the main factor driving the price of oil, rather than supply shocks. The key difference of our work relative to these contributions is that we explicitly study the oil market under a nonlinear environment, in which we allow the market to react distinguishably between a high and low oil price uncertainty regime. This is motivated by recent findings that international oil markets and the relationship between oil shocks and the macroeconomy behave in asymmetrical manner (Bodenstein et al., 2013; Nguyen and Okimoto, 2019; Holm-Hadulla and Hubrich, 2017; Hou and Nguyen, 2018; Hou et al., 2018; Datta et al., 2018). For instance, Bodenstein et al. (2013) and Nguyen and Okimoto (2019), independently highlight that the effect of an adverse oil price shock occurring in times of recession tends to be much larger than that of the same shock happening in normal times.

The second strand of the literature relates to the works that measure and study the effect of oil price uncertainty. Early theoretical discussions, for example Pindyck (1991) and Bernanke (1983), show that firms may delay their investments in response to higher oil price uncertainty.[1] On empirical side, the works by Lee et al. (1995) and Ferderer

[1]Their findings are later supported by Kellogg (2014) who use data on oil producers in Texas and

(1996) highlighting the importance of taking into account the second moment 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 allow for generalized autoregressive conditional heteroskedasticity (GARCH) in mean errors, or GARCH-in-Mean VAR for short (Bredin et al. (2011), Elder and Serletis (2009, 2010, 2011) and 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. They find that uncertainty about the oil price has a negative effect on real economic activity, measured by GDP, investment, consumption in the US and different countries. Although the GARCH in-Mean VAR framework has become popular in such analysis, Jo (2014) argues that oil price uncertainty 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 utilizing a stochastic volatility in mean VAR model. In this framework, oil price uncertainty is modeled as time-varying stochastic volatility of the second moment changes and thus it evolves independently of any change in the oil price level. The paper 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 those found in previous studies. Our paper differs Jo (2014) in three dimensions: (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) it explores the asymmetric reaction of global economic activity to positive and negative oil price shocks that generated separately by typical supply and demand drivers.

With regard to the construction of the oil uncertainty index, in the spirit of Jurado et al. (2015), we construct oil price uncertainty as the one-period ahead forecast error variance of a forecasting regression with stochastic volatility in the residual terms. The novelty of this construction approach lies in its flexibility in including a large number 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 is able to capture uncertainty in oil price rather than

find that increases in the expected volatility of future price of oil are associated with decreases in drilling activity.

volatility as measured by both GARCH and SV in mean models.[2] The index is then employed in a smooth transition VAR model as a transition variable and the oil market is modelled as in Kilian (2009) and Jo (2014). To further explore the asymmetric relationship between the global economic activity and oil price shocks, the model is also estimated with the identified set of positive and negative changes in oil supply and demand. The method of nonlinear tranformation used in our analysis is somewhat similar to Mork (1989) and Hamilton (2003), who evaluate the asymmetric impact of oil price increases and decreases.

Our analysis yields several intriguing results. First, we find that the propagation of the structural oil market shocks is uncertainty dependent. In particular, shocks to the demand for crude oil arise from sudden increases in global economic activity have persistent impacts on global oil production and oil price only in times of low uncertainty. When uncertainty is high, shocks to specific factor generated demand have a magnified impact on oil prices. 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 also find that the asymmetric effect of oil price increases or decreases depend on the underlying oil market shocks. This is, the effects of oil supply shocks are asymmetric but oil specific demand shocks are not. Taken together our findings offer new explanations for contrasting results found in the literature.

The remainder of the paper is organized as follows: First, Section 2 describes the method that we construct the index of oil price uncertainty. Next, Section 3 presents the data that we use to model the oil market. Section 4 outlines the econometric methodology, including the model specification and estimation of the models. Identification strategy is also discussed in this section. Section 5 then presents our results. In this section, we first analyse the regime dependent impulse responses obtained from the linear and nonlinear model and then we evaluate the asymmetric effects of positive and negative oil shocks to global economic activity. Section 6 reports additional results and the robustness check. Finally, Section 7 concludes the paper.

## 2 Construction of the oil price uncertainty index

In the spirit of Jurado et al. (2015), our oil price uncertainty index (OPU) is defined as the one-period ahead forecast error variance of a forecasting regression with stochastic

[2]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."

volatility in the residual terms. By definition, the h-period ahead uncertainty, $U_t(h)$, of an oil price series, $y_t$ is the conditional volatility of the un-forecastable component. That is:

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

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

We consider uncertainty in the crude oil (petroleum) price index from the IMF which is a simple average of three spot prices: Dated Brent, West Texas Intermediate, and Dubai Fateh from 1994M01-2017M06. To construct the one-period ahead commodity price uncertainty index ($h = 1$), the conditional expectation in Equation (1) is replaced by

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

This step is critical as in 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 prices in the literature, such as 'commodity currency' exchange rate, oil production and global economic activity, U.S uncertainty and the comovement in the fuel market.[3] The reason for using these variables is that they have been shown to be important drivers of the price of oil. For instance, Chen et al. (2010) shows that commodity currency exchange rates including the Australian, Canadian, and New Zealand dollars, as well 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. 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), comovement in the fuel-market is captured by including the first principle component and the quadratic terms of the principle component of oil prices and natural gas prices.[4]

Following Bai and Ng (2008), the predictors ultimately used in the predictive equation (2) only include those that have significant predictive power (t-stat $> 2.575$). We however find that additional predictors do not improve the predictability of oil prices on top of the AR(4) terms.[5] We then calculate the stochastic components of the forecast error

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

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

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

variance according to Equation (3) and (4). Let $\upsilon_{t+1} = \sigma_{t+1}\epsilon_{t+1}$, following Jurado et al. (2015) the parametric stochastic process is defined as[6]

$$\log[(\sigma_{t+1})]^2 = \alpha + \beta \log[(\sigma_t)^2] + \tau_j \eta_{t+1} \tag{3}$$

where $\epsilon_{t+1}$ and $\eta_{t+1}$ are *iid* $N(0,1)$ disturbances. Using its definition, the one-period ahead uncertainty is equal to stochastic volatility in residual terms:[7]

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

Figure 1 plots the OPU. 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 that we observe distinct peaks in oil price uncertainty. The first peak during 2000-2002 seems to coincide with the East Asian Crisis and the Second Gulf War in Iraq. The second peak in 2009 happened during the Global Financial Crisis and the last peak during 2015-2016 was due to the sharp drop in oil price, 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 dynamic of OPU to other major uncertainty proxies commonly used in the literature, namely the Oil Price Volatility (OVX) index, the Economic Policy Uncertainty (EPU) index proposed by Baker et al. (2016), the financial uncertainty (VIX) index and the U.S uncertainty (JLN) index constructed by Jurado et al. (2015). The dynamics of the OPU are 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 is that the OPU does not report any heightened uncertainty around 2011. Next, oil uncertainty is highly different to economic policy uncertainty, as seen by the lack of correlation with the EPU index. Last, although oil price uncertainty correlates moderately with financial 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 that are otherwise detected by the VIX since those events are more relevant to the stock exchange. In addition, neither the VIX nor the JLN macro uncertainty index detect any surge in oil uncertainty during 2000-2002 and during 2015-2016. Taken together, this suggests that the OPU index picks up uncertainty events that are highly specific to the oil market.

[6]The stochastic volatility parameters are estimated by using the STOCHVOL package in R.

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

# 3 Data

Along with the realized uncertainty oil price 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, a measure of global economic activity. With regard to 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, existing literature also considers two other alternative measures of oil prices: the US 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 Herrera (2018) and Bjørnland and Zhulanova (2018), among many others. The real oil price is obtained by deflating the nominal price by the US 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 US Energy Information Administration. Finally, we measure global economic activity using the global industrial production index for OECD plus 6 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 (2017).[8] 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 natural logarithms multiplied by 100. Figure 3 plot the evolution of the data. To further evaluate our newly-oil price uncertainty index, we also use other uncertainty indexes to extend the analysis: CBOE Volatility Index (VIX), CBOE Crude Oil Volatility Index (OVX) obtained from Yahoo! Finance and Economic Policy Uncertainty Index (EPU) and macro, financial uncertainty (JLN) as in Baker et al. (2016) and Jurado et al. (2015), respectively.

# 4 Empirical methodology

This section begins by describing the baseline model, taken to be the recursive VAR in Kilian (2009). The linear setting enables us to understand the behavior of the oil market, under the assumption that the effects of uncertainty about oil prices remains time-invariant. A key contribution of our paper is that we relax the assumption by considering a nonlinear specification, namely a smooth transition vector autoregressive (STVAR) model. This model allows us to capture any regime changes and is well suited to our research questions.

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

## 4.1 Baseline linear model

The baseline model is taken from Kilian (2009) and Jo (2014). It employs three-variables: global crude oil production ($\Delta pro$), real global economic activity ($\Delta ip$), and real oil price ($\Delta rpo$), and has been widely used to examine the effects of demand and supply shocks in the crude oil market. Each of the variables are expressed in percentage changes.[9]

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 keep the estimation 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

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

where $\boldsymbol{\alpha} = \mathbf{B^{-1}}\boldsymbol{\gamma}$, $\mathbf{A_i} = \mathbf{B^{-1}\Gamma_i}$, and $\mathbf{e_t} = \mathbf{B^{-1}}\boldsymbol{\varepsilon}_t$. 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 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 with monthly data. Accordingly, the first type of shock is *supply shocks*. Such 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 on global activity and the real price of oil. The second type of shock arises from the fact that increases in aggregate global economic activity that contemporaneously affects the price of oil but has no effect on global oil production on impact. Such shocks are therefore called *global oil demand shocks*. The third type of shocks originates from specific factor

[9] Note that, Kilian (2009) use the real oil price in level while other variables are in log difference. A discussion on 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 modeled in log levels or log differences. This paper prefer to log differences as it makes our results directly comparable with Jo (2014).

generated demand and are therefore called *oil specific demand shocks*. 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 is an important factor causing oil price shocks. The recursive identification suggests that such shocks only impact on the global oil production and global activity is delayed after a month. This identification strategy is also applied to uncover the structure shocks derived from the STVAR model, which is described in details in the following section.

## 4.2 STVAR model

In addition to the baseline analysis, we also estimate a STVAR model to examine the possible regime-dependent asymmetric reactions of the oil market to its market fundamental 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 the smooth-transition model have been considered. In particular, the STVAR model is an extension of the STAR model to a multivariate system of equations that can analyze the dynamic relations among several variables with taking a possible regime change into account (e.g., Weise (1999), Gefang and Strachan (2010), and Auerbach and Gorodnichenko (2012)). The same as these studies, we adopt a STVAR model to examine the regime-dependent relationship among the prices 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

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

where $\boldsymbol{\alpha}^{(j)}$ and $\mathbf{A}_{\mathbf{i}}^{(\mathbf{j})}$ are 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 $s_t$, $c$ and $\gamma$ are 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

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

and an average oil price uncertainty over the last $p$-months as a transition variable $s_t$.[10]

Adopting the convention, we date the index $s$ by $t-1$ to avoid contemporaneous feedbacks. With this choice of transition function and variable, we can interpret regime 1, characterized 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, characterized 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) regime or regime 1 (regime 2). The smoothness parameter $\gamma$ determines the speed of the transition from regime 1 to regime 2 as the past $p$-month oil price uncertainty increases. More specifically, when $\gamma$ takes a large value, the transition is abrupt, whereas the transition is gradual for small values of $\gamma$.

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 $\gamma$. Additionally, $c$ and $\gamma$ 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 uncertainty based on data, which is very attractive for the purposes of this paper.

In principle, we can estimate the parameters of the STVAR model (7) simultaneously by MLE. However, it is challenging, if not impossible, to maximize the likelihood function with respect to all parameters because of a 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 $\gamma$ by the grid search while Auerbach and Gorodnichenko (2012) assume $c = 0$ and calibrate $\gamma$ without any estimation. In contrast to these studies, we estimate both $c$ and $\gamma$ by the grid search.[11] Given the fixed values of $c$ and $\gamma$, the STVAR model becomes a seemingly unrelated regression (SUR) model with the same set

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

[11] One cost to estimate $c$ and $\gamma$ with a grid search is that standard errors are not able to be evaluated for $c$ and $\gamma$. Therefore, the standard errors for the impulse responses calculated below do not consider the effects of the estimation of $c$ and $\gamma$. 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 $\gamma$.

of regressors. In this case, we can maximize the likelihood with the equation-by-equation OLS. Therefore, using the grid search we can find the ML estimates of $c$ and $\gamma$ relatively easily.

# 5 Empirical results

The aim of this paper is to explore if the reactions of oil market and global economic activity to oil market shocks change when uncertainty about oil prices takes into account. More precisely, we investigate the dynamic responses of global oil production, the real price of oil and global economic activity to the structural oil market shocks that are conditional on the state of oil market uncertainty. To facilitate the analysis, first, we report the cumulative linear impulse response functions derived from the benchmark VAR model in Section 4.1. Second, we utilize the oil price uncertainty index presented in Section 2 as a transition variable in the STVAR model. This setting allows for oil price uncertainty can affect how oil shocks propagate. These shocks include the oil supply shock, oil demand shock and oil-specific demand shock as have 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 real economic activity. This is motivated by the fact that, oil price innovations may have asymmetric effects on economic activity. 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 cumulative impulse response estimates obtained from the linear VAR, see Figures 5–7. For the 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 triggers a small increase in the price of oil. The aggregate demand and specific demand shock both cause increases in oil prices but the impact of the specific demand shock found to be relatively larger. These findings are 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 uncertainty over the sample period. This is because, under linear setting, shifts in uncertainty about oil prices are muted. As a result, ignoring the degree of oil price uncertainty would lead to misleading the behavior of the oil market and the responses of global economic activity to oil shocks.

As mentioned, the main objective of the paper is to examine the possible regime-dependent effects of oil price structural shocks, depending on the oil price uncertainty. To this end, we employ the STVAR model, but it is instructive to see whether there is some evidence of regime dependency before estimating it. Specifically, we conduct systemwise linearity tests proposed by Weise (1999) and Teräsvirta and Yang (2014) to motivate our use of STVAR model.[12] 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 since 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 nonlinearity against the STAR model.[13] 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 generalization using the Lagrange-multiplier-type test statistic. Both tests are applied to our VAR system (6) to test against the STVAR model and strongly reject the linear 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 the better description for our data, we now discuss the estimation and the regimes that are detected by our model. As mentioned in Section 4.2, we estimate $c$ and $\gamma$ by the grid search, and their estimates are given by 0.711 and 300, respectively.[14] This means that if the average oil price uncertainty over the last four months is 0.711 standard deviation 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 24% event over the sample period, meaning that the economy spends nearly quarter of time in the high uncertainty regime. In addition, the large estimate of $\gamma$ indicates that the transition from the low uncertainty regime to 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 US recessions identified by the NBER. The estimated regime dynamics indicate that the regime tend to be the high uncertainty

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

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

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

regime around the US recessions. In addition, the recent volatile oil price period between April, 2015 and October, 2016 are 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 shocks.

## 5.2 Oil price uncertainty matters

Our estimation result of 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 price shocks in each regime, Figure 5 displays global oil production cumulative responses to a one-standard-deviation structural innovations. The oil supply shock, which is defined as an unexpected oil supply disruption, causes a sharp decline in world oil production on the impact, 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 be sluggish, however recovery is fast 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 uncertainty, Texas oil producers tend to reduce their investment. That is because, align with what predicted by real options theory discussed in detail in the next section, firms optimally make decision in the present of time-varying uncertainty. That is, when uncertainty about future price of oil increases, drilling activity decreases as variations in oil price volatility can reduce the value of a drilling.

Oil price uncertainty also matters to the response of oil global production to the market 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 are quite small and insignificant. This could be because, as oil price uncertainty increases the oil producers would cut down their production and this effect offsets the positive responses of oil production to a solid contemporaneous demand.

We also observe that, without concerning uncertainty about oil prices, positive shocks in oil market-specific demand have negligible effect on global oil production. This evidence is again consistent with results in Kilian (2009). If oil market uncertainty is high, then oil-specific demand shock causes a persistently increase in the oil production. This suggests that, a sudden increase in the price of oil that reflects fluctuations in precautionary demand arriving at times that oil price uncertainty is high has a significant effect on oil production. 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 response functions based on high and low uncertainty. Indeed, the results obtained by our benchmark VAR model, which does not incorporate oil price uncertainty, show that the reaction of global oil production to a positive shock in specific demand is less significant.

Turning to the responses of the oil price, Figure 6 provides little evidence that the reactions of oil price to structural 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 4 months. Similarly, when uncertainty is relatively high, we find that the real price of oil increases slightly upon impact of a negative supply shock, but its effect becomes insignificant after that.

The real price of oil reacts persistently to the oil demand shock. Consistent with empirical evidence found in the oil literature, we see that an unexpected expansion on global real economic activity causes an immediate and positive response of the oil price. Furthermore, our evidence indicates that under 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 suggests 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 as 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, the shock that reflects fluctuations in precautionary demand for oil, is found to have a relatively stronger effect on oil prices in periods of high uncertainty. Despite this fact, in both regimes, the shock has a large, persistent and positive effects on the price of oil.

The responses of global real economic activity to the structural oil market shocks are also nonlinear. As shown in Figure 7, they 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 the oil supply shock. However, this shock produces a sharp decline in real economic activity during periods of high uncertainty. In other words, when oil price uncertainty is high, it amplifies the recessionary effects of the unfavourable oil supply shock. An unanticipated increase 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 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 shocks, we now evaluate whether the relationship between oil prices and economic activity is asymmetric. More precisely, we examine whether a positive and negative oil market shocks have the same (mirror image) effects on global economic activity between a low and high oil price uncertainty environment. This is motivated by the fact that, theoretical prediction seems to agree that economic activity contracts when oil prices increase but does not expand when oil prices fall. One of plausible explanations for the asymmetric relationship between the movement of oil prices and economic activity is known as *real options theory*, detailed in Bernanke (1983); Brennan and Schwartz (1985) and Majd and Pindyck (1987).[15] The real options theory explains the possibility of non-linear effects of oil price shocks on economic activity from the perspective of uncertainty. It argues that a decline in the price of oil produces the expansionary effect on real output but at the same time, it also generates an increase in uncertainty about the future oil price, holding back consumption and investment spending. As a result, the contractionary effect of uncertainty offsets the stimulating effect of the favourable oil price shock.

In this section, we report new evidence in support of the predictions of the real options theory. It is worth noting that while our objective is similar to those in existing studies looking for empirical evidence of the asymmetric effect of oil price shocks on economic activity, our approach is different from theirs along a number of important dimensions. These studies either focus solely on quantifying the magnitude of outputs response to a positive and negative oil price shock or examine the direct effects of oil price uncertainty on real economic activity. For instance, Kilian and Vigfusson (2011) and Herrera et al. (2011) independently test the hypothesis of nonlinear feedback from the oil price increases and decreases to US aggregate and disaggregate industrial production, while Elder and Serletis (2010) and Pinno and Serletis (2013) explore the asymmetric effects of oil price uncertainty. A key contribution of our paper is that we put them together.

We investigate how global economic activity responds to a positive and negative oil market shock that explicitly take oil price uncertainty into account. We also study the response of economic activity to both positive and negative oil price shocks and changes in oil production. To this end, we re-estimate the model proposed in Section 4.2 with

[15] Another explanation is that lower oil prices would increase expenditure on energy-intensive durables and thus cause a reallocation of capital and labour toward 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).

replacing $\Delta pro_t$ by $\Delta npro_t = \min(\Delta pro_t, 0)$ or $\Delta ppro_t = \max(\Delta pro_t, 0)$. Then, we calculate the impulse responses from the set of identified negative and positive changes in the series of oil quantity. 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, with the same approach, we also evaluate the responses of global economic activity to the positive and negative oil price shock driving by other factors generated demand for oil, such as preference shocks, speculative demand or politically motivated changes.

Figure 8 plots the impulse responses of global economic activity to the positive and negative oil supply shock that are conditional on the state of oil price uncertainty. As can be seen clearly from the figure, the sign of the shocks matters. Unexpected increase in the 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 low uncertainty regime that leads to 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 the global activity compared with the negative shock. All together, these results indicate that the effects of oil supply shocks on economic activity are asymmetric as well as regime dependent. The effects of negative shocks are significant only for the low uncertainty regime, while those of positive shocks are more pronounced with much larger effects when oil price uncertainty is relatively high. These findings are consistent with our expectations suggested by 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.

With respect to 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 falls in the short run in response to the negative shock, but the global economy is not sensitive to the positive shock. More interesting, 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 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 asymmetries between oil price shocks and US aggregate data.

Taken together, our results suggest that the degree of asymmetric responses of global economic activity to oil price increases and decreases depend 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 other 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

As uncertainty is unobservable, there have been several proxies proposed in the recent literature measuring uncertainty about different perspectives, such as financial uncertainty or policy uncertainty. Given the objective of the paper, the proxy presented in this 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, whether the oil market reacts distinguishably under different uncertainty environments, other than uncertainty stemming from the oil market that we have investigated. We address that concern in this section. We examine the sensitivity of our findings by considering two other well-known uncertainty proxies: VIX and US 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 originated by sudden changes in global oil production and specific factors driving the price of oil, are different, depending the uncertainty environment that the shocks arrive. We do find evidence of asymmetry with respect to the negative and positive shocks regardless of the uncertainty environment. However, the results indicate little asymmetry between the high and low uncertainty regimes when we consider VIX and WLEMUINDXD. Thus, we conclude that asymmetric responses only emerge when uncertainty about oil prices taking into account, solidifying our main results. Appendix C reports these exercises in details. Interestingly, we find that the results estimated with VIX are somewhat similar to those with WLEMUINDXD. Thus, the following analysis based on the results obtained by VIX but still 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 the responses of the corresponding shocks under oil uncertainty regimes found in our main analysis. The differences are more obvious in periods that financial uncertainty and oil price uncertainty are relatively low. This is partly because in times that financial uncertainty is low are not necessarily related to the times that uncertainty about oil prices are 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 shock. These differences can be seen clearly when comparing the responses to the positive supply shock between the periods that 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 followed unanticipated increases in global oil production. In contrast, when financial uncertainty is high, cheaper oil prices have negligible effects on the economy. This suggests that the recessionary effects of high uncertainty generated from financial markets would offset the expansionary effects of decreased oil prices.

Finally, with respect to the oil specific demand shocks, the different effects between financial uncertain and oil price uncertainty regime 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 with different measures of oil prices commonly used in the literature. Instead of using the average price of oil as discussed in Section 3, we alternately use RAC and WTI. We report 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: supply, aggregate demand and oil-specific demand, in times of low and high uncertainty. To this end, we offered a novel measure of oil price uncertainty. In contrast to existing results in the literature, our approach is able to capture 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 is able to pick up uncertainty events that are highly specific to the oil market. We then utilize this new index in a nonlinear model that allows the propagation of oil shocks to be different between low and high uncertainty regimes. This is the first paper that explores the interaction between the oil market and its structural shocks 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 shifts. In particular, shocks to the demand for crude oil that arise 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 specific factor generated 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.

Our model specification also enabled us to evaluate the hypothesis that real economic activity responds asymmetrically to unexpected increases and decreases in oil prices. While 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 under a nonlinear environment is important. Indeed, we find that the effects of oil supply shocks are asymmetric but oil specific demand shocks are not. The findings indicate that the asymmetric manner depends on the underlying market shocks. Taken together our findings offer new explanations for contrasting results found in the literature.

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# Figures

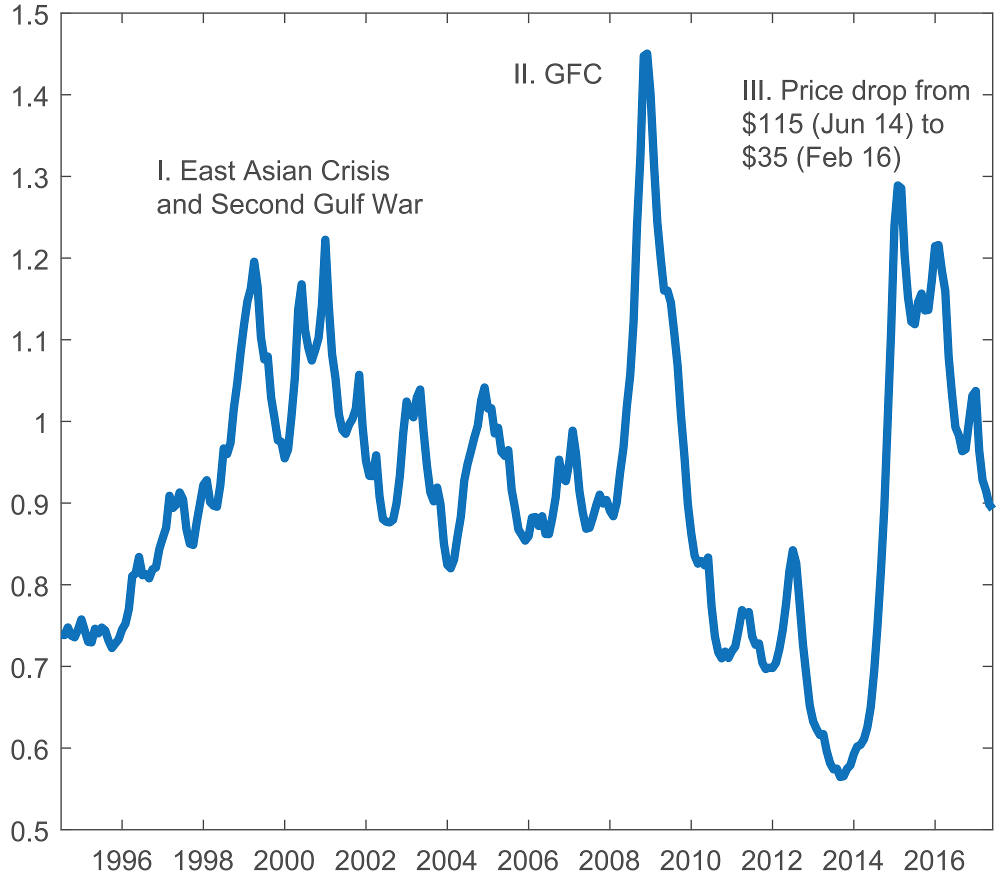



Figure 1: Oil price uncertainty index

*Notes:* The figure plots the oil price uncertainty index (OPU) constructed in Section 2 from 1994M07 to 2017M06.

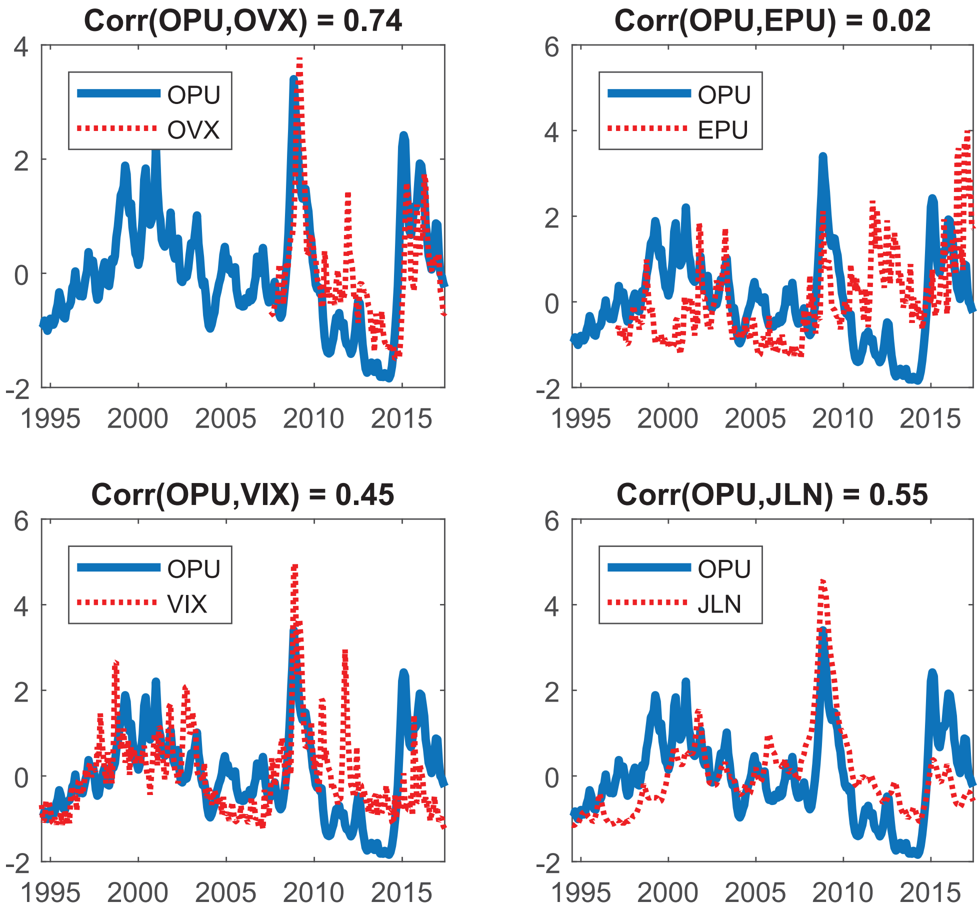



Figure 2: Oil price uncertainty index: comparison with other uncertainty indices

*Notes:* The figure compares the oil price uncertainty index (OPU) constructed in Section 2 from 1994M07 to 2017M06 to: (i) The CBOE Oil Price Volatility Index (OVX) from 2007M05 to 2017M06 (ii) The Global Economic Policy Uncertainty index by Baker et al. (2016) from 1997M01 to 2017M06, (iii) The CBOE volatility index (VIX) from 1994M07 to 2017M06 and (iv) The uncertainty index for the U.S by Jurado et al. (2015). All series are normalised to have means of 0 and standard deviations of 1.

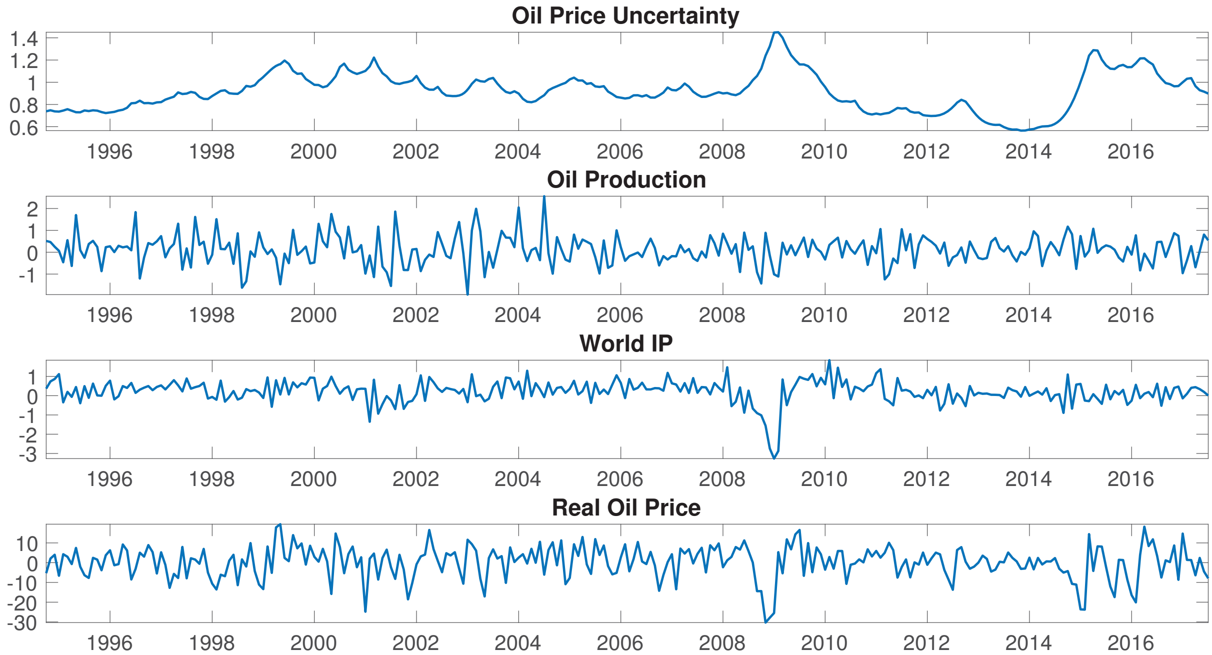



Figure 3: Historical evolution of the series (1994M7-2017M6)

*Notes:* The oil price uncertainty (OPU) index constructed in Section 2. 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 (2017). While OPU remaining series are in levels, oil production, World IP and real oil prices are in percent changes.

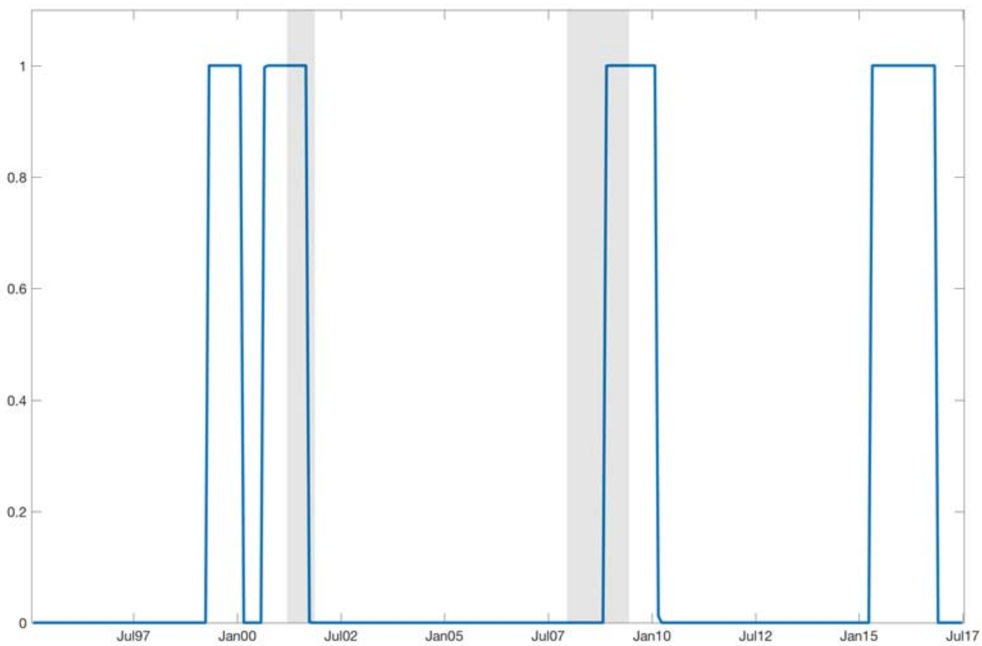
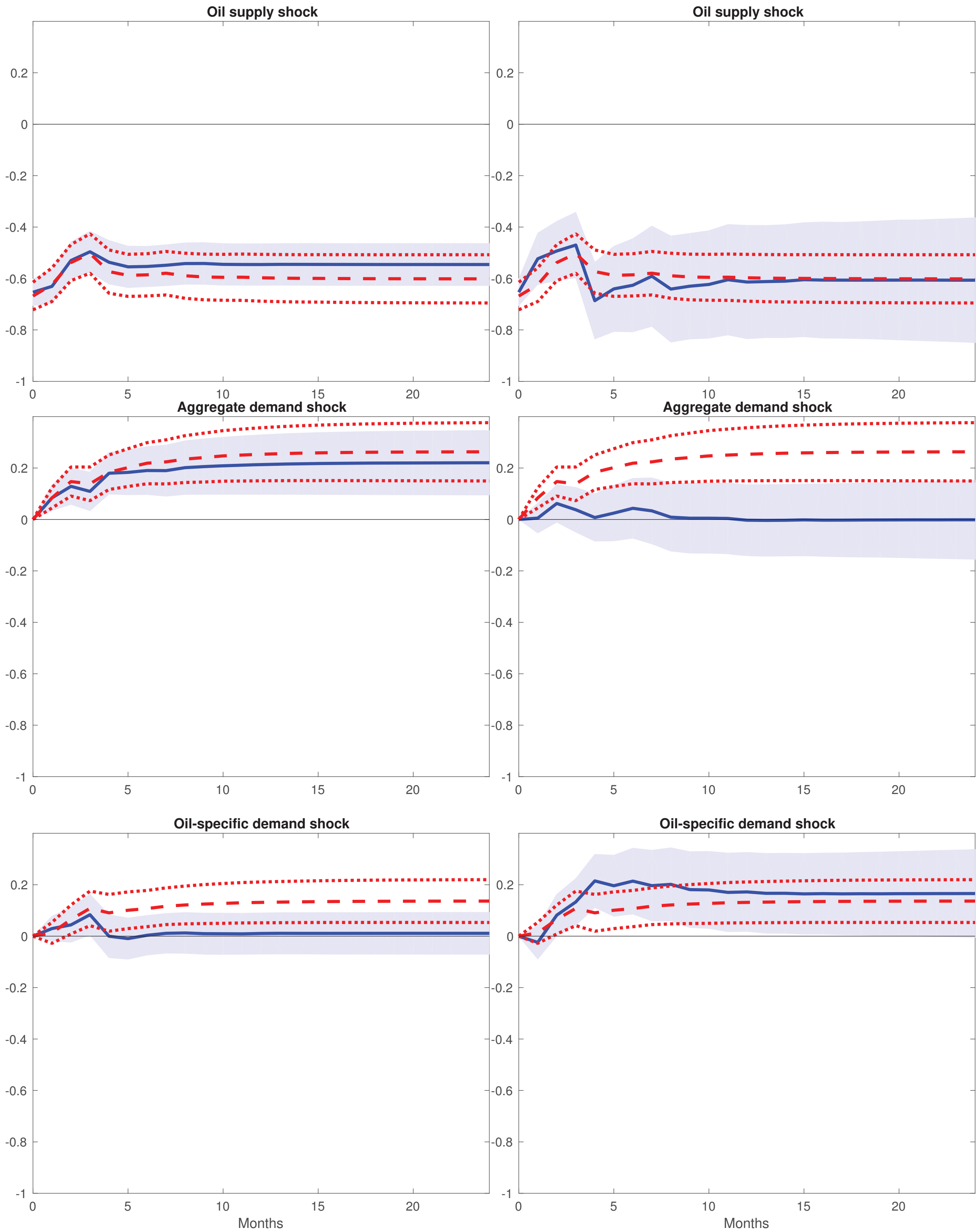



Figure 4: NBER dates and weight on low oil price uncertainty regime $F(s_t)$

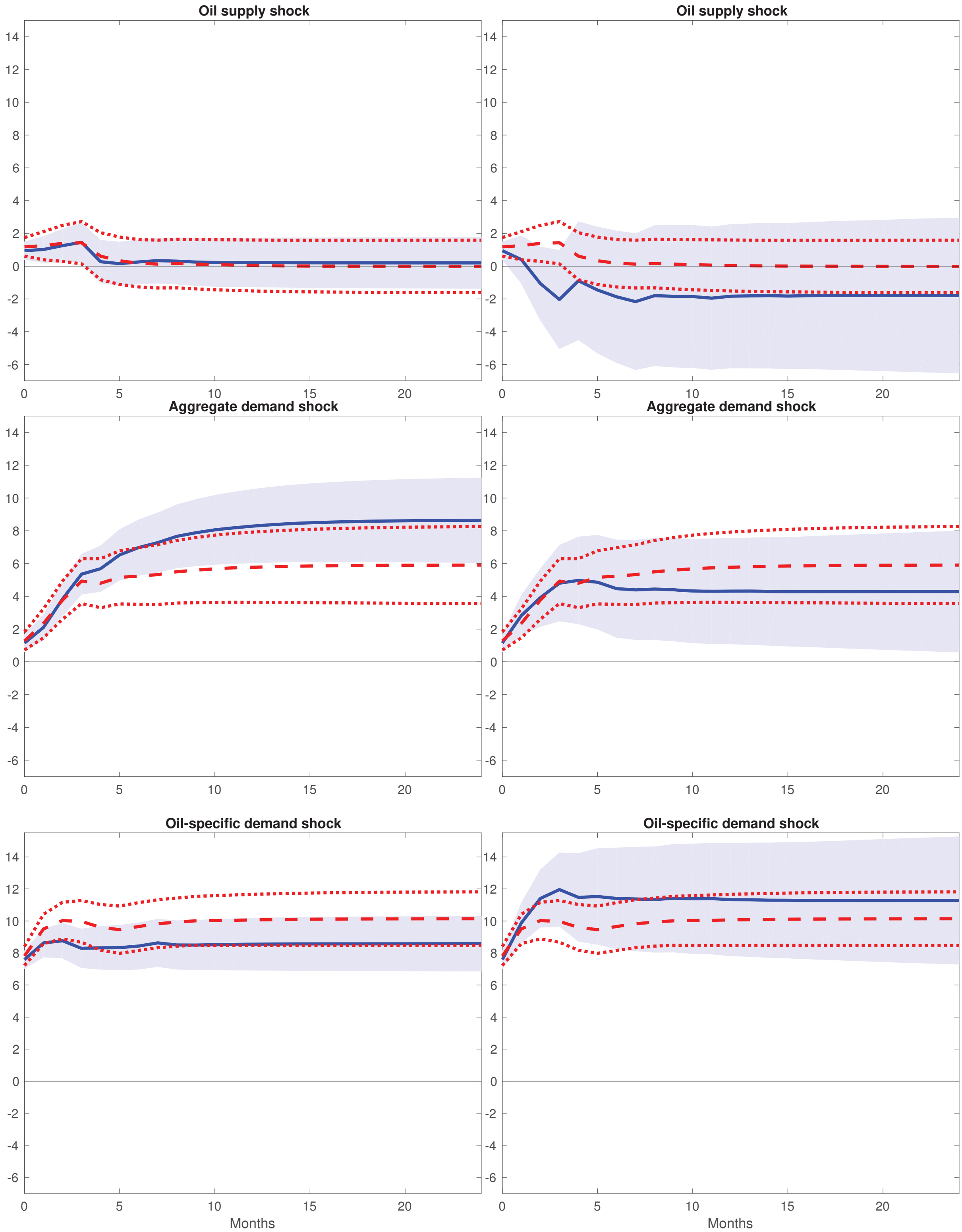
*Notes:* The shaded region shows recessions as defined by the NBER. The solid line shows the weight on recession regime $F(s_t)$.




(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 impulse responses based on linear model along with the confidence intervals (dotted lines). Blue solid lines show 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.

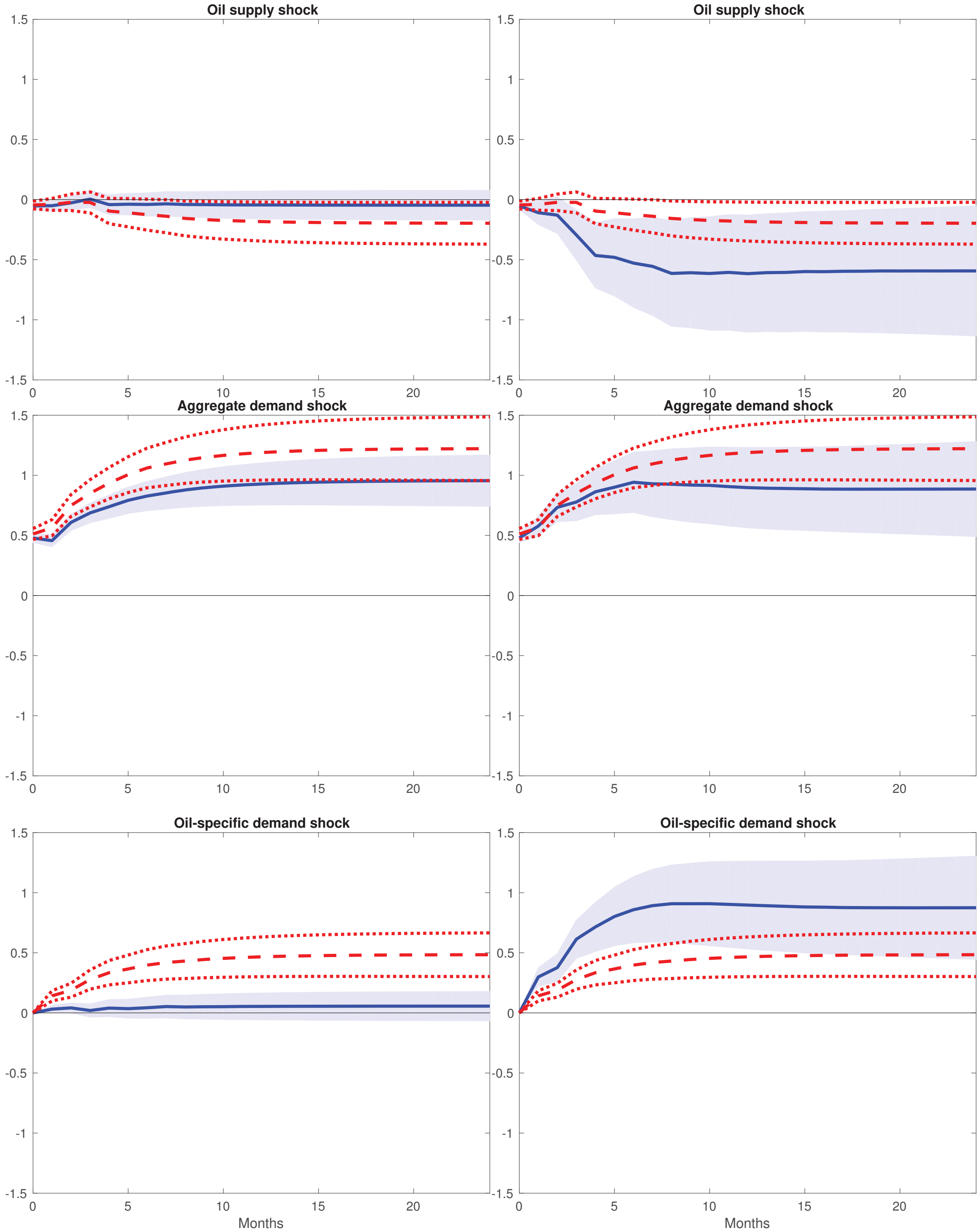



(a) Low oil price uncertainty

(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

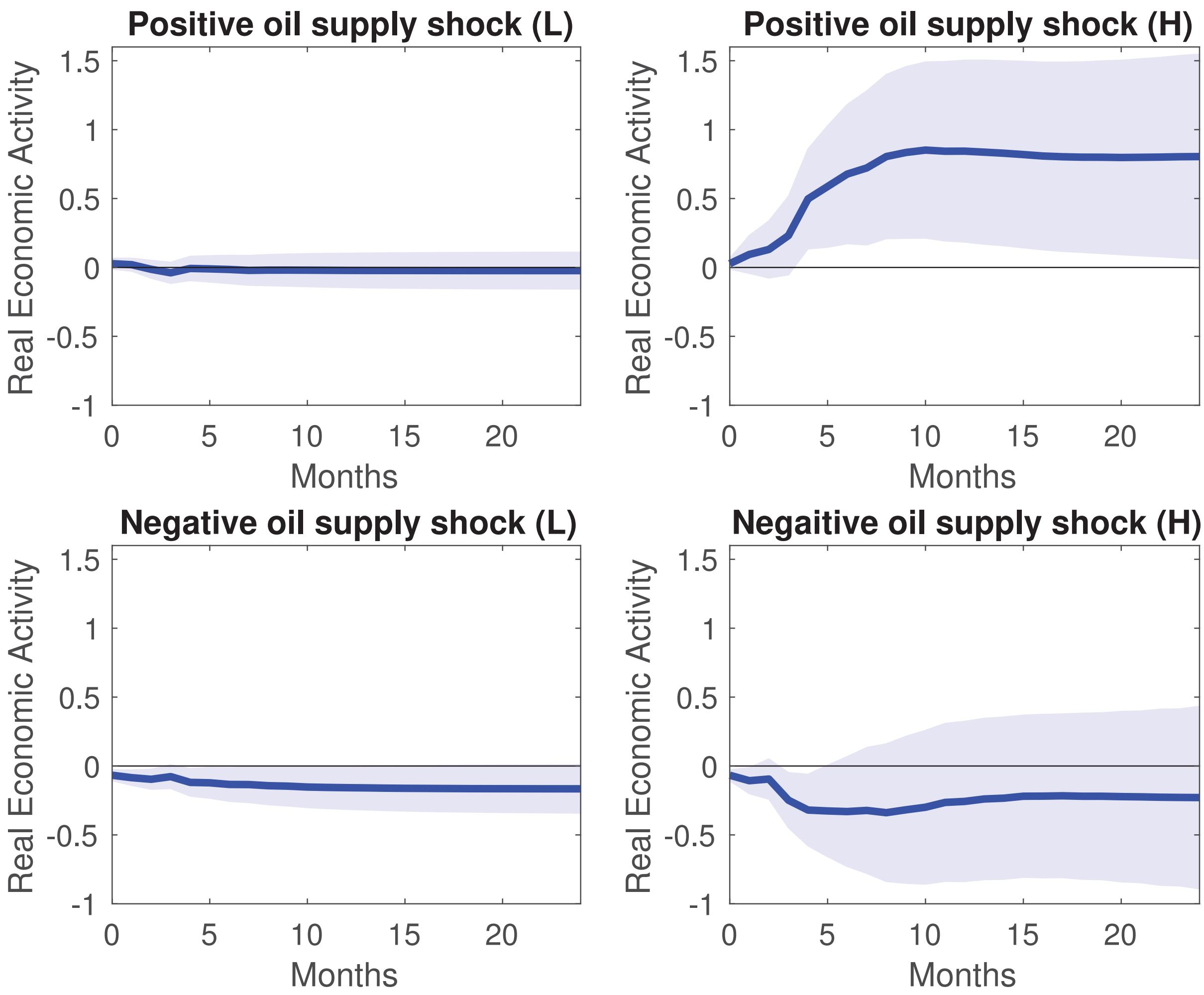



Figure 8: Responses of global economic activity to positive and negative oil supply shocks

*Notes:* Blue solid lines show impulse responses based on the nonlinear model and shaded areas are the corresponding confidence intervals constructed using a recursive-design wild bootstrap.

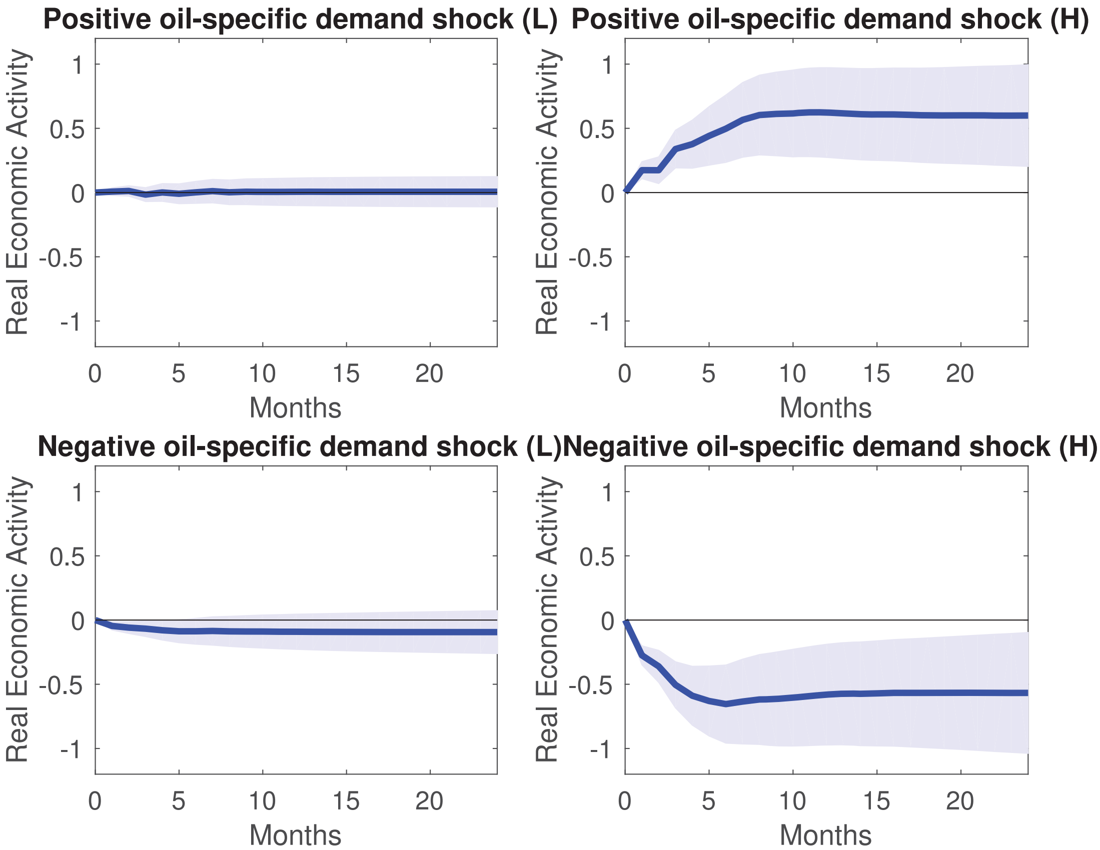



Figure 9: Responses of global economic activity to positive and negative oil-specific demand shocks

*Notes:* See Figure 8

# Appendix A The role of predictors

The construction of the uncertainty index underscores the importance of removing 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: $y_{j,t+1} = v_{j,t+1}$. Second, the forecast regression only includes the AR(4) terms. In this case, Equation (2) becomes: $y_{j,t+1} = \phi_{jt} y_{jt} + v_{j,t+1}$. 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.

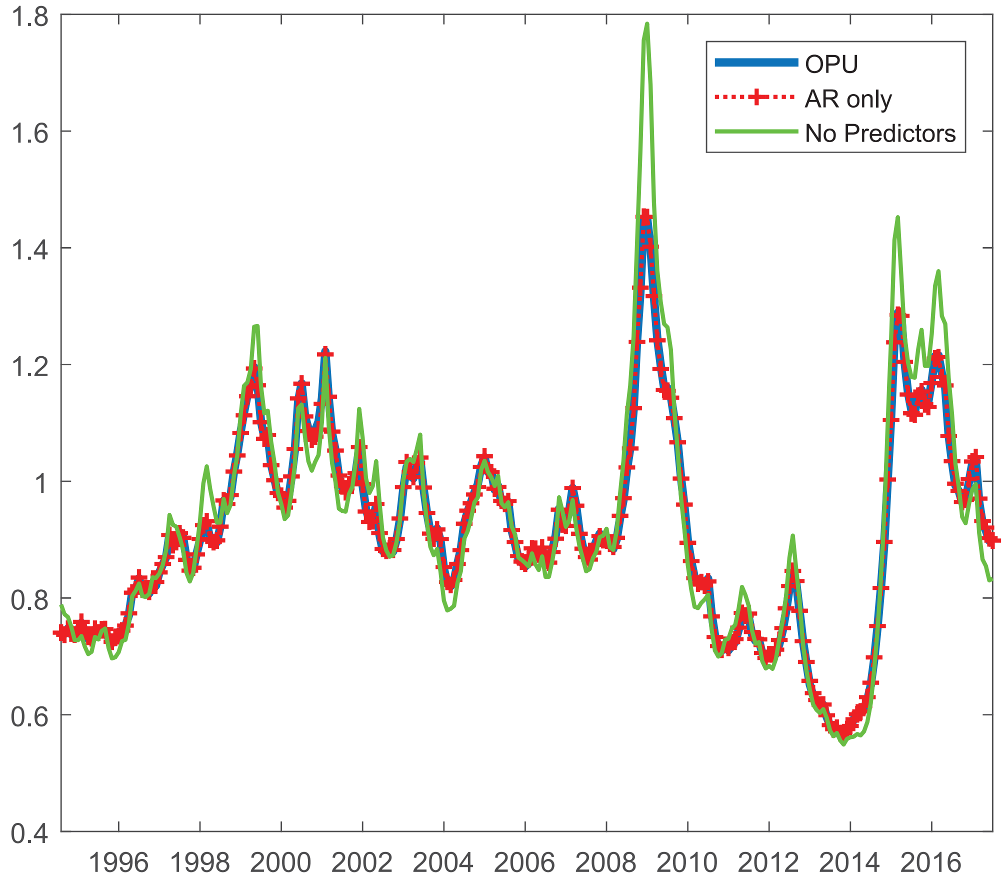



Figure A1: Oil Price Uncertainty index: Role of predictors

*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 predictor 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 remove unpredictability in oil prices.

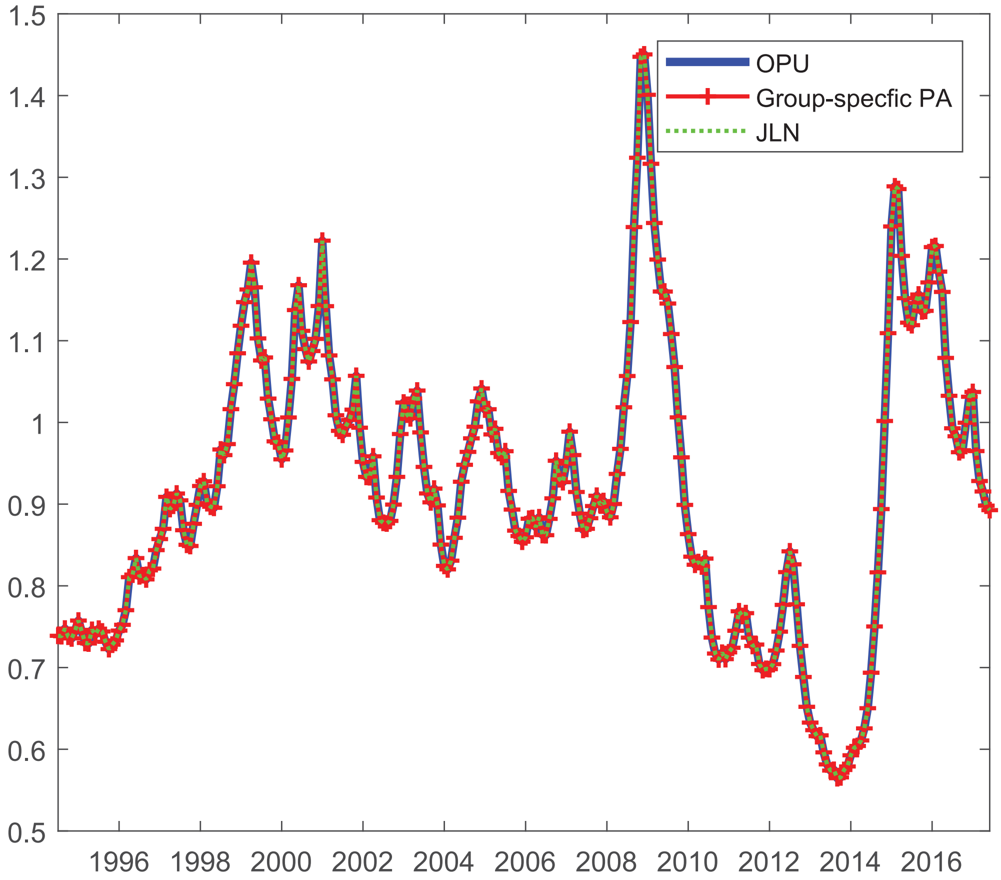



Figure B1: Oil Price Uncertainty index: Different equation specification

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

# Appendix C  Additional results

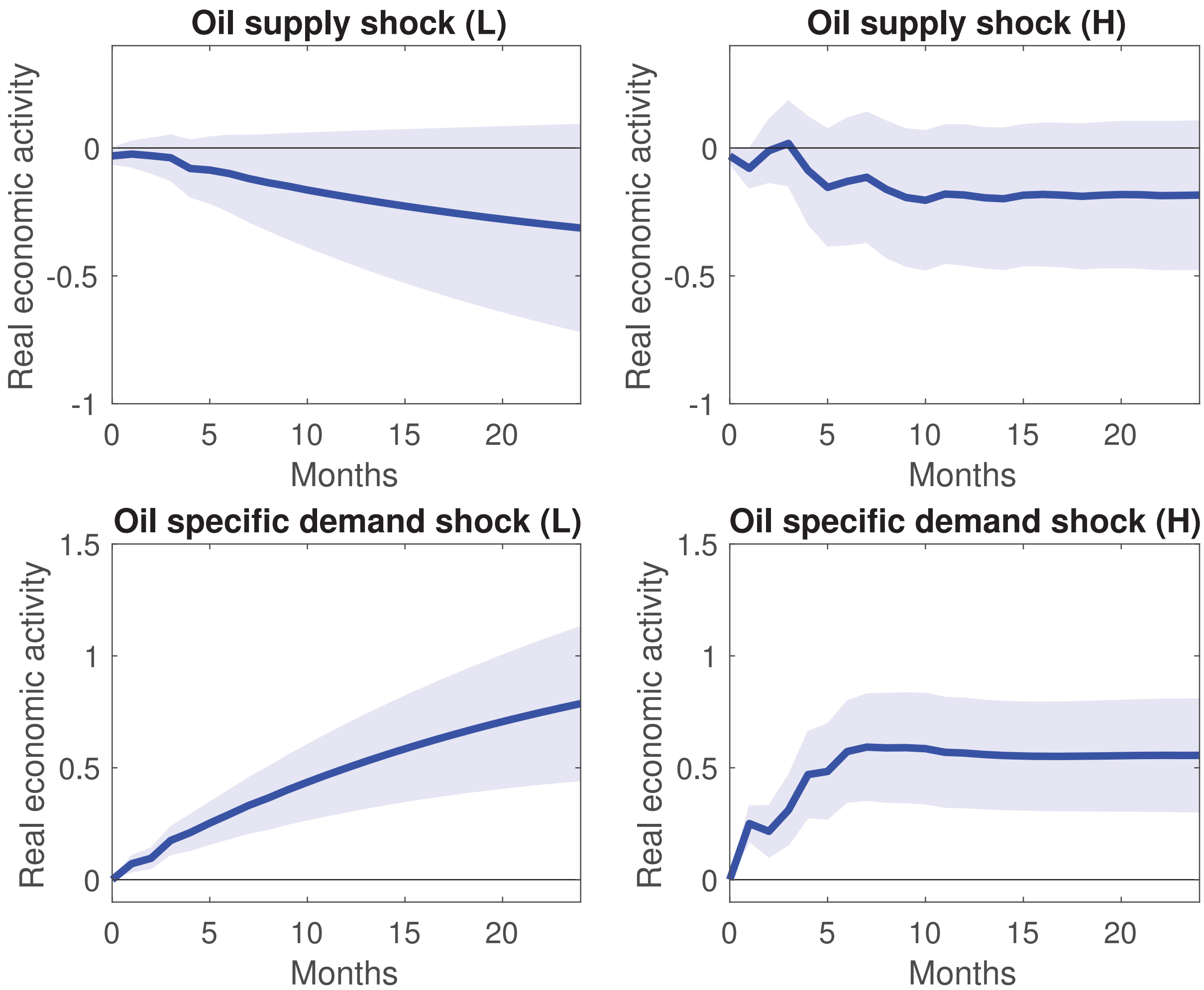



Figure C1: Responses of global economic activity to oil shocks under low (left column) and high (right column) financial uncertainty (VIX) regimes

*Notes:* Blue solid lines show 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.

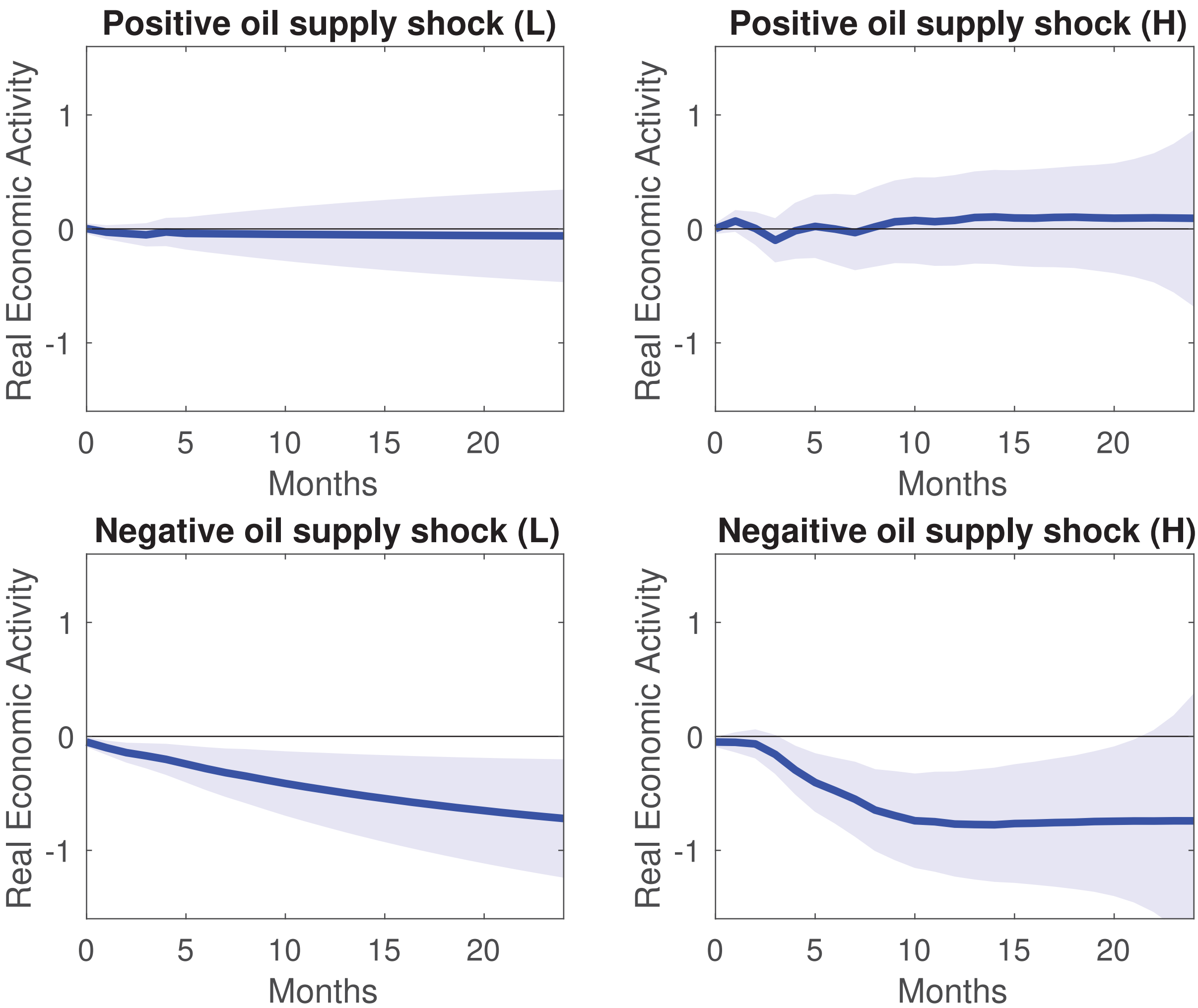



Figure C2: Responses of global economic activity to a positive and negative oil supply shock under low (left column) and high (right column) financial uncertainty (VIX) regimes.

*Notes:* Solid blue lines show impulse responses based on the nonlinear model and shaded areas are the corresponding confidence intervals were constructed using a recursive-design wild bootstrap.

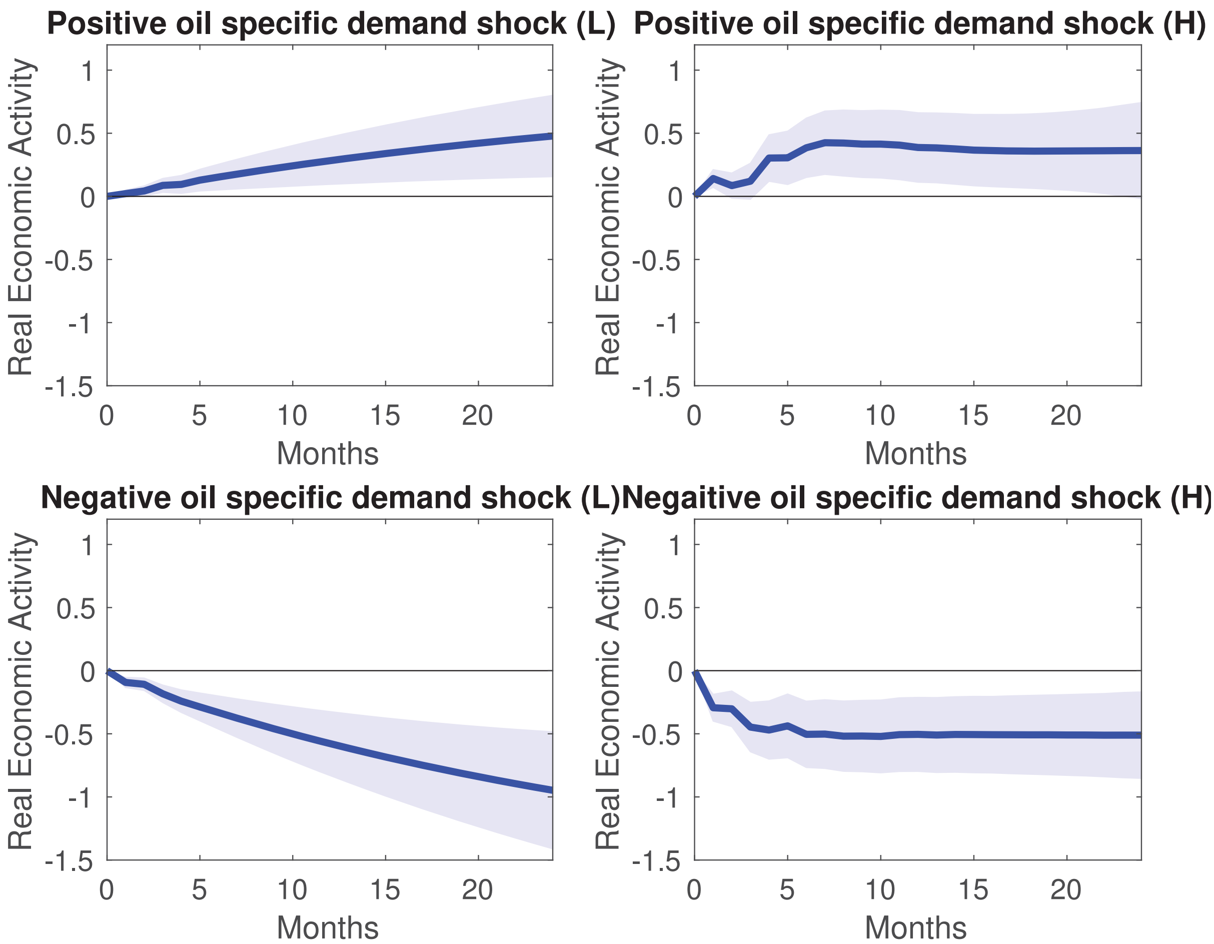



Figure C3: Responses of global economic activity to a positive and negative oil demand shock under low (left column) and high (right column) financial uncertainty (VIX) regimes.

*Notes:* See Figure C2

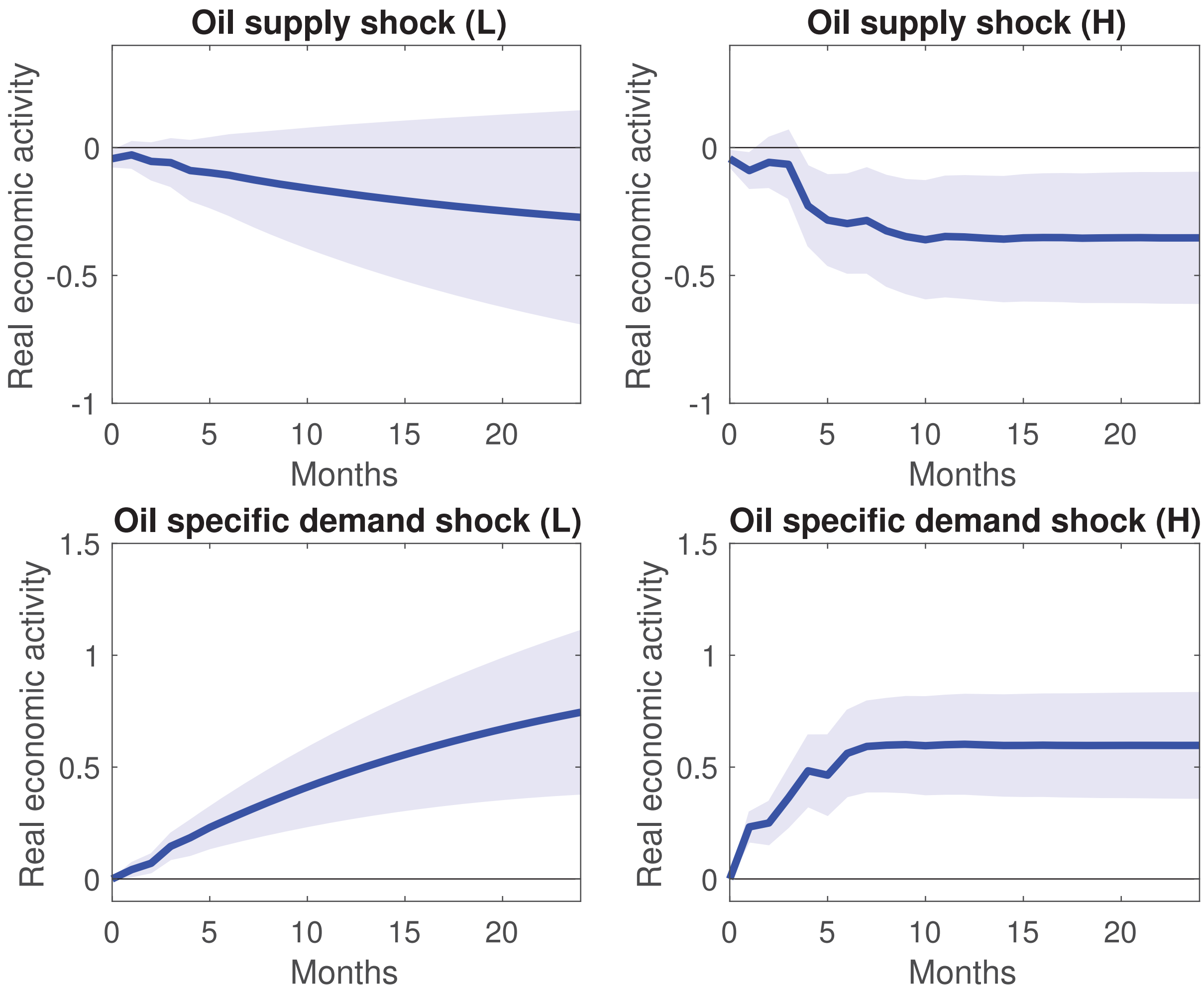



Figure C4: Responses of global economic activity to oil shocks under low (left column) and high (right column) financial uncertainty (WLEMUINDXD) regimes

*Notes:* See Figure C1.

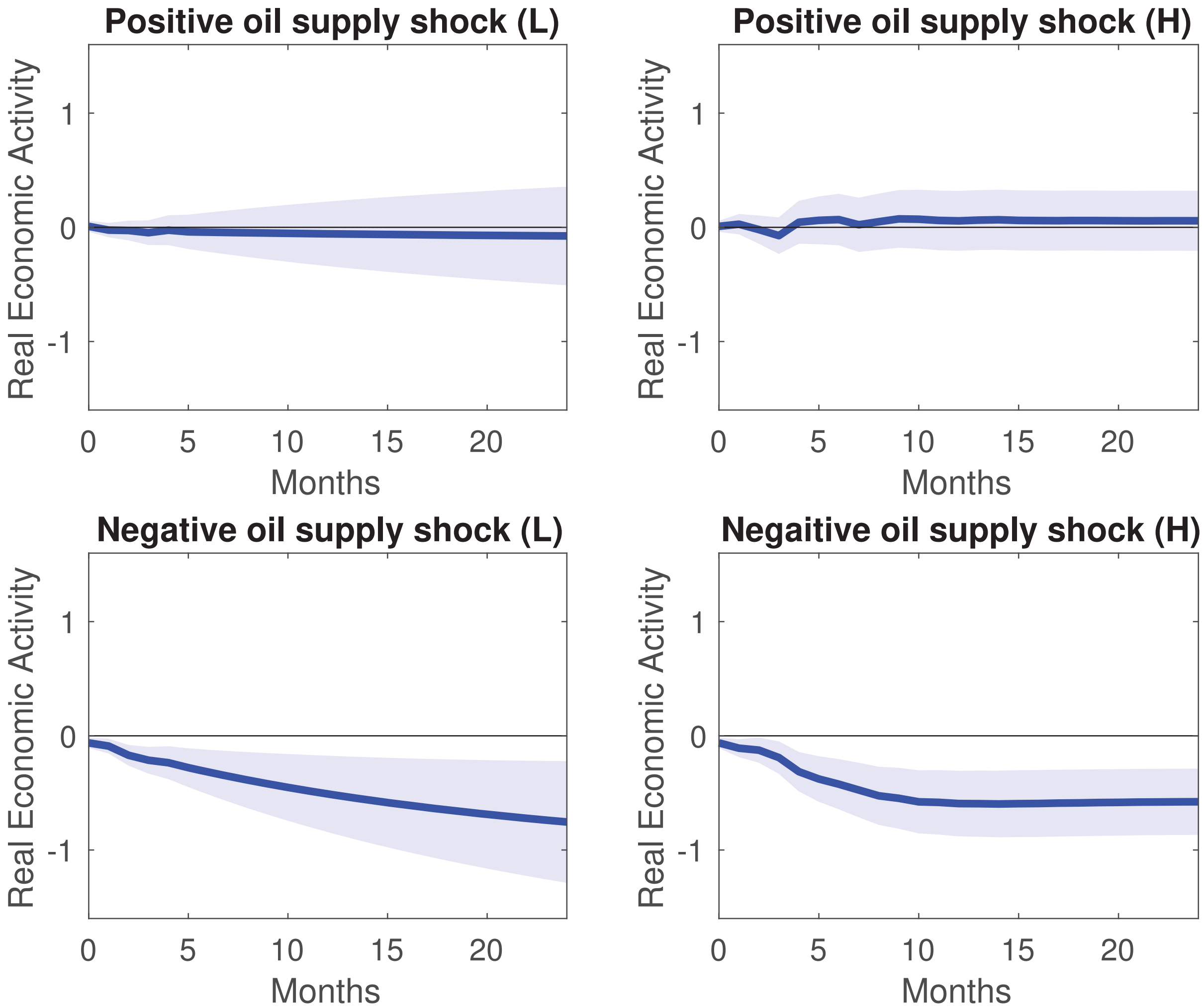



Figure C5: Responses of global economic activity to a positive and negative oil supply shock under low (left column) and high (right column) financial uncertainty (WLEMUINDXD) regimes.

*Notes:* See Figure C2

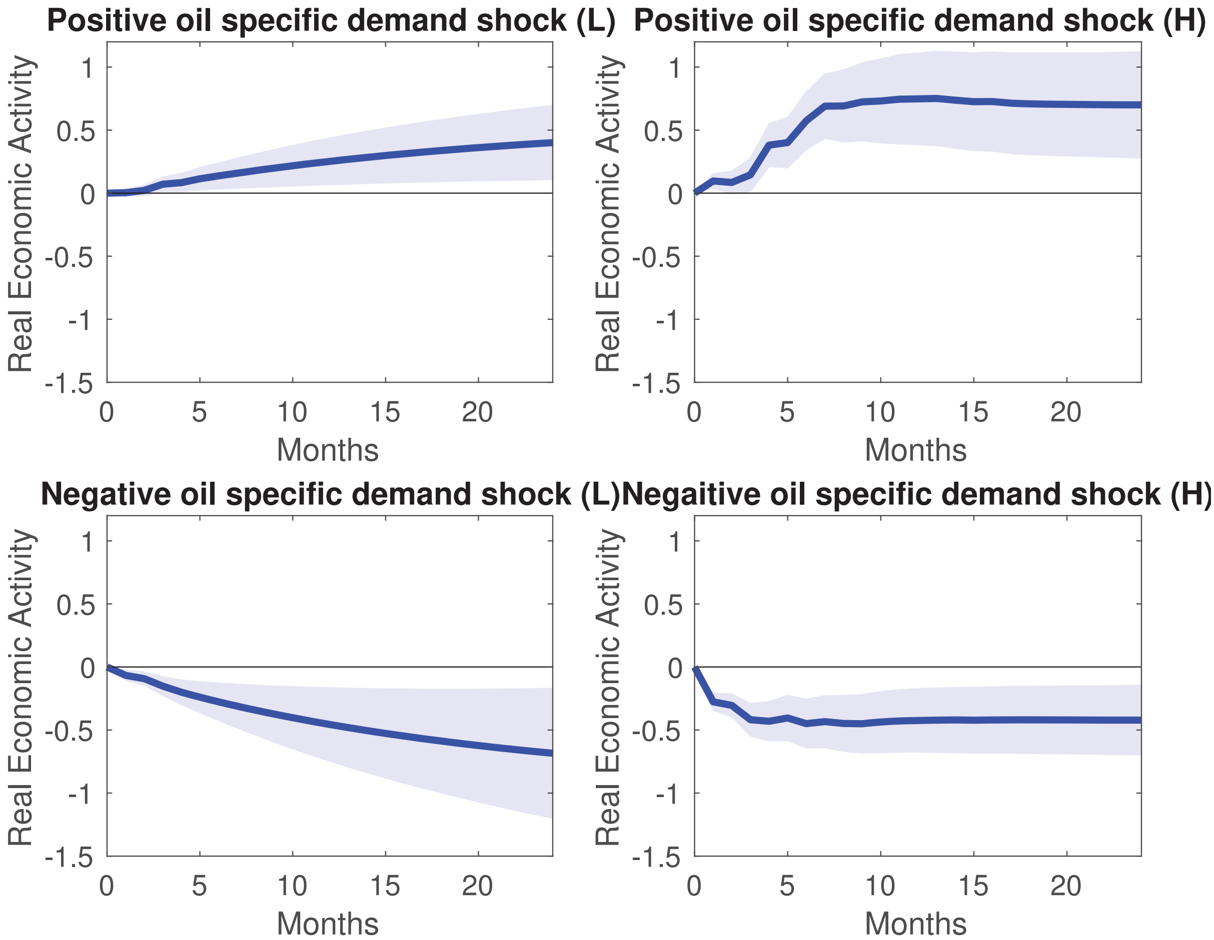



Figure C6: Responses of global economic activity to a positive and negative oil demand shock under low (left column) and high (right column) financial uncertainty (WLEMUINDXD) regimes.

*Notes:* See Figure C2

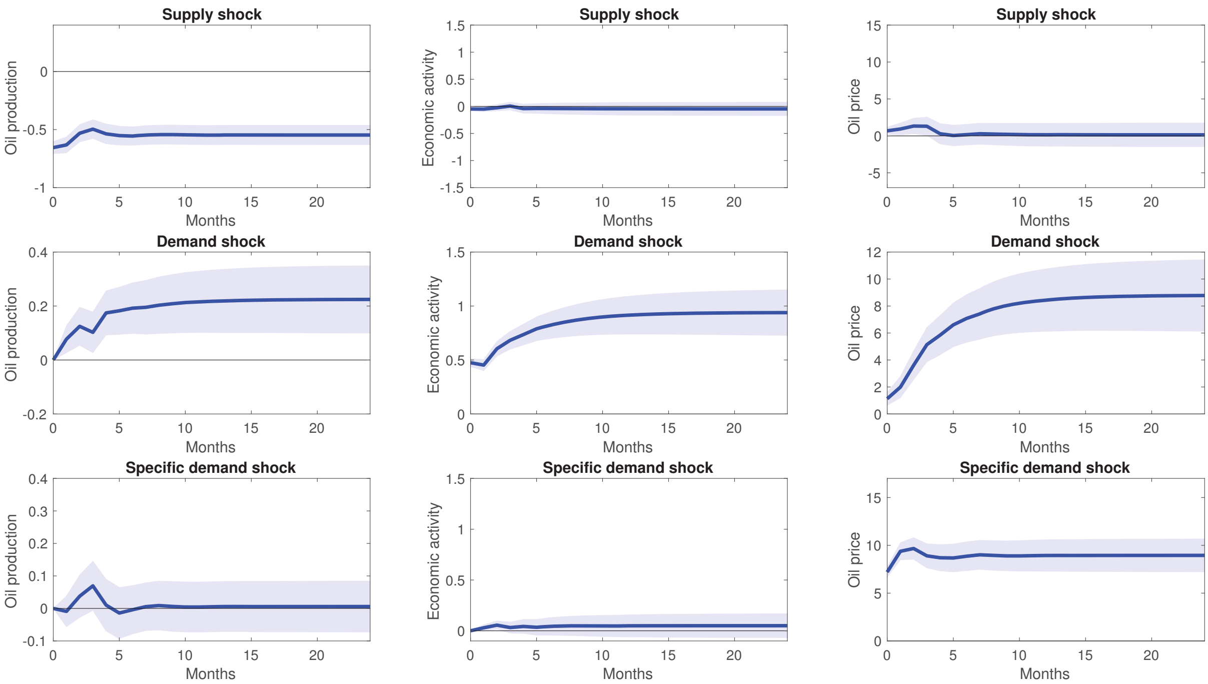



Figure C7: Impulse response functions to the choice of RAC in times of low oil uncertainty

*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.

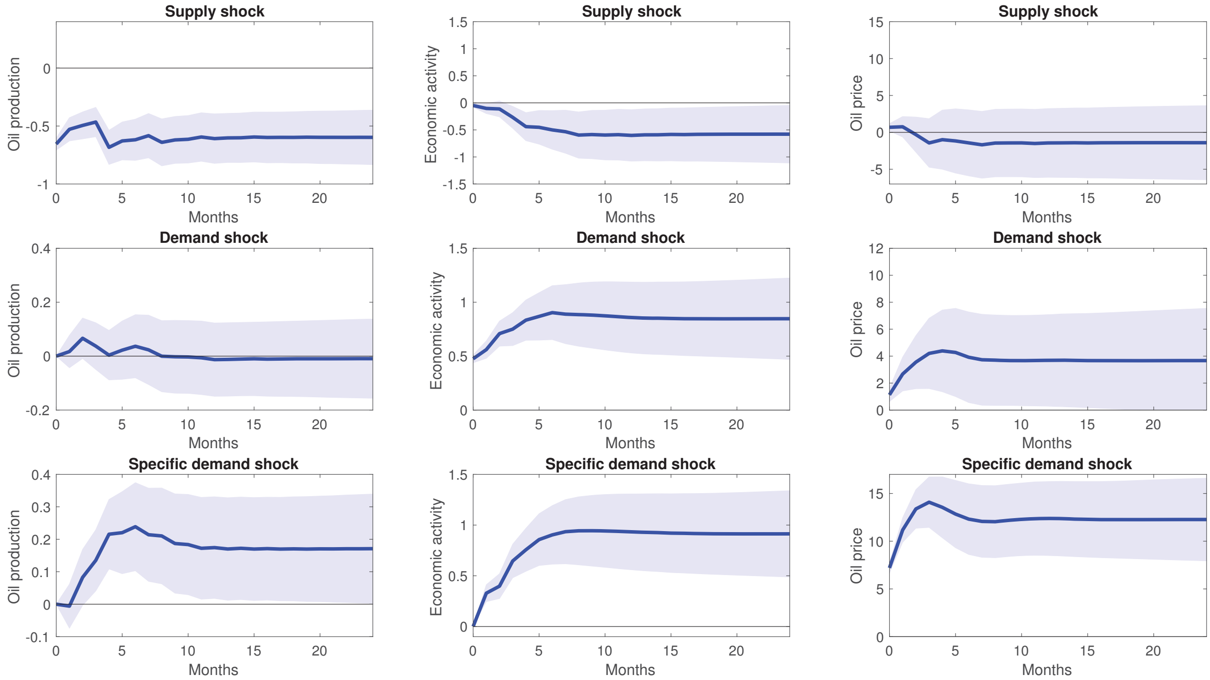



Figure C8: Impulse response functions to the choice of RAC in times of high oil uncertainty

*Notes:* See Figure C7

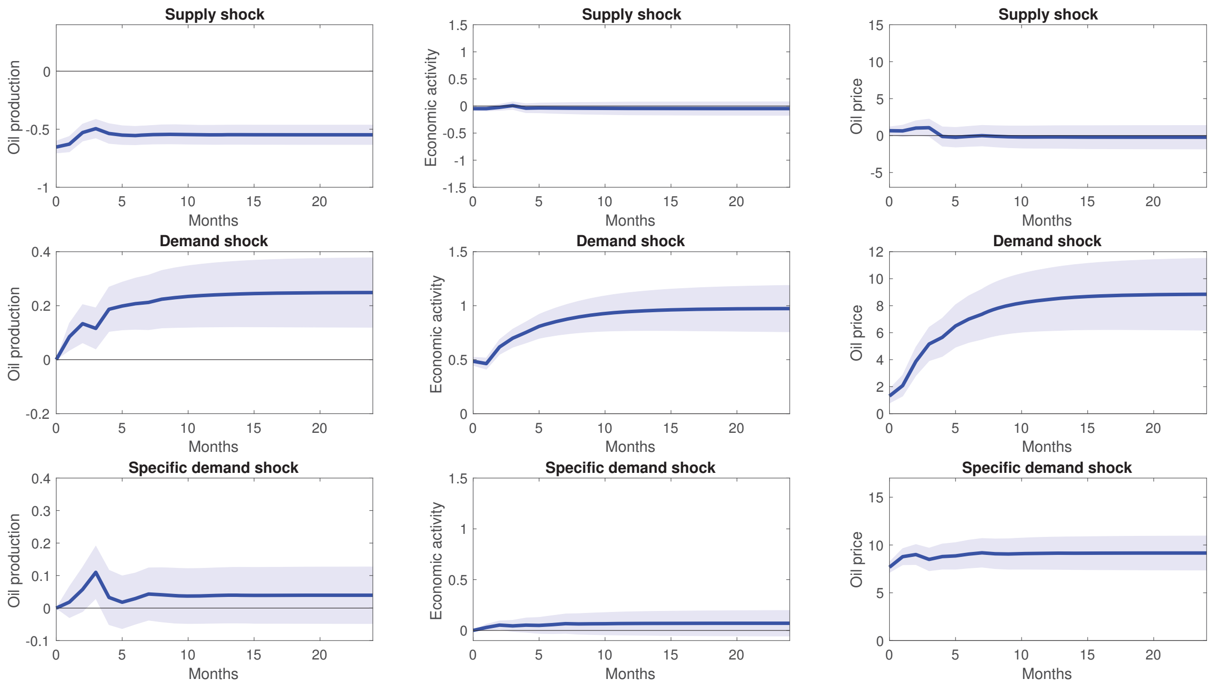



Figure C9: Impulse response functions to the choice of WTI in times of low oil uncertainty

*Notes:* See Figure C7

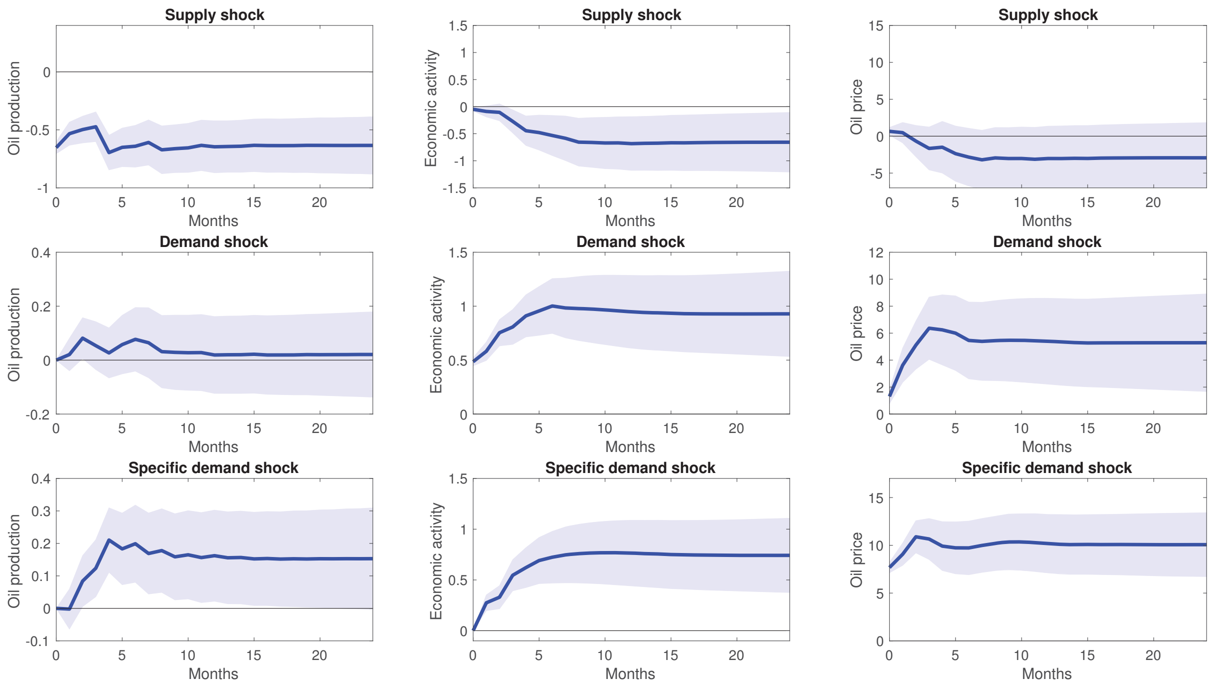



Figure C10: Impulse response functions to the choice of WTI in times of high oil uncertainty

*Notes:* See Figure C7