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Abstract

This paper evaluates whether macroeconomic uncertainty changes the impact of oil shocks on the oil price. Using a structural threshold VAR model, we endogenously identify different regimes of uncertainty in which we estimate the effects of oil demand and supply shocks. The results show that higher macroeconomic uncertainty, as measured by higher world industrial production volatility, significantly increases the responsiveness of oil prices to oil shocks. This implies a lower price elasticity of oil demand and supply in the uncertain regime, or in other words, that both oil curves become steeper when uncertainty is high. The difference in oil demand elasticities is both statistically and economically meaningful. Accordingly, varying uncertainty about the macroeconomy can explain time variation in the oil price elasticity and hence in oil price volatility. Also the impact of oil shocks on economic activity appears to be significantly stronger in uncertain times.

JEL-Code: E310, E320, Q410, Q430.

Keywords: oil prices, uncertainty, price elasticity, threshold VAR, sign restrictions.

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1 Introduction

The remarkable increase in oil price volatility over the past decade sparked an intensive debate about its driving factors. Many studies argue that the stronger oil price fluctuations can be explained by sharp movements in fundamental oil supply and demand-side factors (Baumeister and Peersman 2008, 2012; Hamilton 2009, Kilian and Murphy 2010). Others claim that changes in fundamentals are not sufficient to explain the full extent of the oil price fluctuations, and argue that also financial speculation played a role (Lombardi and Van Robays 2011, Tang and Xiong 2011, Singleton 2012). A factor which has been overlooked in this debate is that in periods of strong oil price volatility, uncertainty about the macroeconomy was typically very high. It is well documented that increased uncertainty can influence the decision behavior of economic agents (Bernanke 1983, Pindyck 1991, Litzenberger and Rabinowitz 1995, Bloom et al. 2007). Higher uncertainty causes a delay in the production or consumption decision, thereby lowering the quantity response and increasing the price impact of shocks. Analogously, uncertainty could affect the responsiveness of oil prices to fundamental oil shocks, and thereby change oil price volatility.

In this paper, we evaluate whether the impact of fundamental oil shocks differs in times of increased uncertainty. We define macroeconomic uncertainty as volatility in world industrial production growth. Using a monthly threshold vector autoregressive (TVAR) model that we estimate over the period 1986:01-2011:07, we endogenously identify high and low uncertainty regimes based on our measure of macroeconomic volatility crossing an estimated threshold. Conditional on being in a particular regime, we quantify the impact of different types of oil shocks on oil prices, oil production and economic activity. We identify three types of oil shocks using sign restrictions; oil supply shocks, oil demand shocks driven by economic activity, and oil-specific demand shocks, similar to Peersman and Van Robays (2009, 2012), Baumeister, Peersman and Van Robays (2010), Baumeister and Peersman (2012) and Kilian and Murphy (2012). The aim of this paper is to establish some stylized facts on the interaction between uncertainty and oil price volatility that seem worthwhile exploring further in general equilibrium models.

Our results show that the impact of oil demand and supply shocks tends to differ substantially when macroeconomic uncertainty is high. Oil shocks have a significantly stronger effect on oil prices for a given response of oil production, implying that the price elasticity of oil demand and supply is lower in the high uncertainty regime. In other words, the oil demand and oil supply curve become steeper in uncertain times. We estimate the impact oil demand elasticity to decline from a range of -0.52 to -0.15 when uncertainty is low, to -0.36 to -0.11 when uncertainty is high. The oil supply elasticity drops from a range of 0.21 to 0.03, to a number in between 0.15 and 0.02 conditional on a highly uncertain environment. Although there is some overlap across the regimes, the difference in estimated elasticity across regimes is statistically significant. The difference is also economically significant, as the price impact of a similar oil shock might double when it hits the economy in uncertain times. Hence, we show that different levels of macroeconomic uncertainty over time can explain time variation in the price elasticity of oil, and therefore in oil price volatility. Hamilton (2009) and Kahn (2009) argue that a lower price elasticity could explain why fundamental oil supply and demand shocks impacted more strongly on oil prices over the last decade, and we empirically demonstrate that this could have been the case because of higher uncertainty. Moreover, not only oil prices and oil production react differently, but also economic activity reacts more aggressively to oil shocks when macroeconomic volatility is already high.

As far as we are aware, this is the first paper which estimates the impact of macroeconomic uncertainty on the effects of oil shocks, and manages to endogenously explain time variation in the price elasticity of oil. On the one hand, several studies have touched upon the relationship between uncertainty and oil prices. However, mostly they focus on uncertainty with respect to the oil price itself, i.e. oil price volatility instead of macroeconomic volatility more generally (Bredin et al. 2011, Elder and Serletis 2010, Ferderer 1996, Kellogg 2010, Lee, Ni and Ratti 1995, Pindyck 2004).[1] On the other hand, numerous studies have documented an increase in the volatility of oil prices over time, and explained this by varying elasticities of oil demand and supply (Lee, Ni and Ratti 1995, Ferderer 1996, Regnier 2007, Baumeister and Peersman 2008, 2012). We link these two strands in the oil literature by showing that time variation in the oil price elasticity, and hence in oil price volatility, can be explained by variation in the level of macroeconomic uncertainty.

The remainder of this paper is organized as follows. In the next section, we provide some intuition and evidence on why uncertainty could matter for the impact of oil shocks. In Section 3, we describe the threshold VAR model and its specification, test for thresh-

[1] Two exceptions to this are Pindyck (1980) and Litzenberger and Rabinowitz (1995), although their focus is different. Pindyck (1980) concentrates on the theoretical effect of demand and oil reserves uncertainty on expected oil price behavior, and Litzenberger and Rabinowitz (1995) focus on explaining backwardation in oil futures markets.

old effects and explain the identification strategy. The empirical results are discussed in Section 4 and Section 5 briefly evaluates the robustness of the results. Section 6 concludes.

2 How Can Uncertainty Affect the Oil Market?

A lower price elasticity of oil demand and supply during uncertain economic times means that shocks hitting the oil market generate larger responses in prices but smaller responses in quantities compared to more certain times. In this section, we discuss several possible ways in which macroeconomic uncertainty can negatively impact on the price elasticity of oil demand and supply. These explanations are not mutually exclusive and mainly serve to provide intuition behind the results and possible avenues for further research.

First, both oil demand and oil supply could be less responsive because of an *option value to wait*. Under the condition that the action to be decided on is irreversible, uncertainty creates an option value to wait through which investors are willing to forego current returns in order to gain from more information in the future. In other words, uncertainty over future demand reduces current investment. There exists a large literature providing both theoretical and empirical evidence on this link. Bernanke (1983) relies on this concept to explain cyclical fluctuations in investment, and in more recent work, Bloom et al. (2007) and Bloom (2009) confirm that firms delay investment and hiring decisions because of higher uncertainty about future demand.[2] Accordingly, in the oil market, following an oil demand shock that occurs when macroeconomic volatility is already high, crude oil producers could decide to wait with changing their production until more information is available on the persistence of the oil shock as well as on its impact on the already fragile economy. This option value to wait would then lower the elasticity of oil supply. Using an econometrical model of firm‘s optimal drilling investment under time-varying uncertainty, Kelogg (2010) indeed shows that higher uncertainty about future revenues causes drilling firms to delay their investments in oil wells. Guiso and Parigi (1999) find the effect of demand uncertainty on the responsiveness of investment to be stronger if it is harder to reverse investment decisions and if the firm has more market power, which is characteristic to oil firms. Similarly, the elasticity of oil demand could be lower as oil consumers prefer to wait with reducing their demand following an oil supply shock that pushes oil prices

[2] Other examples are Arrow (1968), Henry (1974a,b), Pindyck (1991), Brennan and Schwartz (1985), Majd and Pindyck (1987), Elder and Serletis (2010) and Bredin et al. (2011).

upwards. In addition, uncertainty could reduce the tendency of oil consumers to substitute oil for other energy products, or at least delay substitution until there is more certainty about the effect of the oil shock.

Second, *futures markets* might also play a role in explaining why oil demand and supply elasticities vary over time. Baumeister and Peersman (2012) note that hedging against oil price movements could weaken the responsiveness of oil demand and supply. Accordingly, if higher macroeconomic uncertainty leads to an increased use of futures contracts, which is plausible given that futures markets exist to transfer risks, it could cause the oil price elasticity of demand and supply to decline.

Third, the oil supply elasticity could decline during uncertain periods because oil producers prefer to *leave oil reserves below the ground* when uncertainty rises. In a two period equilibrium model, Litzenberger and Rabinowitz (1995) show that uncertainty increases the value of oil reserves below the ground for any level of the extraction cost. As oil producers will not extract oil as long as the net value of oil below the ground is higher than that above the ground, an increase in uncertainty will lower the extraction of oil. Litzenberger and Rabinowitz (1995) also find empirical support for this.

Finally, uncertainty could also affect price setting in the oil spot and futures markets without the need for immediate oil demand and supply adjustments. Singleton (2012) shows that *heterogeneous beliefs* about public information concerning the future course of economic events can induce higher price volatility, price drifts and even booms and busts in prices. The release of new information about oil supply and demand can have a large effect on prices as investors learn about the economic environment. Although Singleton (2012) uses these arguments to explain the role of financial flows on oil prices, they could also help in understanding why in times of higher macroeconomic uncertainty, when investors' beliefs typically diverge more than in normal times, shocks to oil demand and supply have a larger impact response on prices.

3 Model and Identification

3.1 Threshold VAR model

To evaluate the role of macroeconomic uncertainty on the oil market, we rely on a structural threshold vector autoregressive (TVAR) model. The threshold model is attributed to

Tong (1978) and has been extensively used afterwards, see Hansen (2011) for an overview. The TVAR model enables us to endogenously identify different regimes with respect to one endogenous transition variable, which is called the threshold variable. In our case, this is a function of macroeconomic uncertainty. The different regimes are determined by the value of this threshold variable with respect to a certain threshold which is estimated within the model. Once the different regimes are identified, we generate the impulse response functions conditional upon the regime to compare the estimated effects. In Markov-Switching models, in contrast, the transition variable is typically not observed, which makes the TVAR model particularly attractive for addressing our research question. We estimate a two-regime TVAR model of the following form:

$$Y_t = \mu_1 + A^1 Y_t + B^1(L)\, Y_{t-1} + \left(\mu_2 + A^2 Y_t + B^2(L)\, Y_{t-1}\right) I_t(c_{t-d} \geq \gamma) + u_t$$

The vector of endogenous variables Y_t captures the global dynamics in the oil spot market, i.e. world oil production (Q_{oil}), the price of crude oil expressed in US dollars (P_{oil}), a measure of world economic activity (Y_w) and oil inventories (I_{oil}). To model different uncertainty regimes, we also add a measure of macroeconomic uncertainty denoted by U. The variable c_{t-d} is the threshold variable and $I_t(.)$ is an indicator function that takes value one when the d-lagged value of the threshold variable is higher or equal to the estimated threshold γ, and zero otherwise. This indicator function thus determines the regimes based on the value of c_{t-d} relative to γ. As the threshold variable c_{t-d} is a function of macroeconomic uncertainty and subsequently an endogenous variable in the TVAR model, shocks to the oil market as well as to macroeconomic uncertainty are allowed to determine whether the economy is in a high or low uncertainty regime.[3] μ is a vector of constants, $B(L)$ is a matrix polynomial in the lag operator L and A is the contemporaneous impact matrix of the vector of orthogonalized error terms u_t. The TVAR model allows for non-linearity in the effects across regimes as each regime has different autoregressive matrices. If $I_t = 0$, the dynamics of the system are given by μ_1, A^1 and $B^1(L)$, and if $I_t = 1$, the relevant coefficients are $\mu_1 + \mu_2$, $A^1 + A^2$ and $B^1(L) + B^2(L)$. Note that the contemporaneous impact of the shocks is allowed to vary, which is crucial for our analysis of the price elasticities on impact.

The TVAR model is estimated using monthly data over the period 1986:01-2011:07. We choose 1986 as our starting point for two reasons. First, Baumeister and Peersman

[3] We discuss possible endogeneity issues later in this section.

(2008, 2012) document an exogenous structural break in the oil price elasticities around the mid-1980s, after which both the oil demand and oil supply elasticity became substantially smaller. This decline is typically explained by a reduction in spare capacity which reduces the responsiveness of oil supply, and a more limited scope for substitution away from oil which reduces the responsiveness of oil demand. Second, the Great Moderation in the mid-1980s caused a downward shift in the level of uncertainty as macroeconomic volatility declined, which implies a downward shift of the threshold in our model. Including these two events in our sample period could therefore significantly bias the identification of the regimes and the estimation results.[4]

The oil price is the nominal refiner acquisition cost of imported crude oil, which has extensively been used in the literature as the best proxy for the free market global price of imported crude oil.[5] We proxy global economic activity by the OECD measure of global industrial production, which covers the OECD countries and the six major non-OECD economies, including e.g. China and India. Following Kilian and Murphy (2010), we proxy global crude oil inventories as total US crude oil inventories scaled by the ratio of OECD petroleum stocks over US petroleum stocks. Global macroeconomic uncertainty is proxied by the volatility of world industrial production growth, which is modelled as a GARCH(1,1) process.[6] To ensure robustness of our findings, we construct two additional measures of uncertainty. Following Baum and Wan (2010), the first alternative measure is the conditional variance of US GDP production growth. We generate a monthly GDP series by interpolating quarterly GDP using industrial production based on the Chow-Lin procedure, after which we model the conditional variance as a GARCH(1,1) process. As a second alternative, we consider the Chicago Board of Exchange VXO stock market volatility measure. The VXO index is based on a hypothetical at the money S&P100 option,

[4] The fact that macroeconomic uncertainty decreased around the same time that the price elasticity of oil declined does not contradict our results, i.e. increased uncertainty lowers the price elasticity of oil. This is because the break in the oil price elastcicity around the mid-1980s is found to be *exogenous*, see Baumeister and Peersman (2008, 2012).

[5] We use the nominal price oil because this should allow for a better identification of the different types of oil shocks. For example, when we would deflate the nominal price of oil by US CPI, it could be that a domestic positive demand shock to the US could wrongly be identified as a negative oil supply shock because real oil prices fall, and oil production and economic activity do not decline (see Section 3.3 for more details on the shock identification). The results are robust to using the real price of oil.

[6] The GARCH(1,1) gives the best specification for modelling the conditional variance according to various information criteria. We estimated the conditional variance over the period 1985-2011 to avoid a possible bias due to the Great Moderation.

and is the measure of uncertainty used by Bloom (2009). We constructed a monthly series of the VXO index by taking monthly averages of the daily closing price. As noted by Baum and Wan (2010), these different measures capture different types of uncertainty. The measure based on GDP growth is designed to reflect the overall uncertainty of the macroeconomic environment, whereas the measure based on industrial production disregards uncertainty about the service sector. The VXO stock market volatility measure is more closely related to financial market uncertainty. Note that the first two measures of uncertainty are backward looking as these are based on GARCH models, whereas the measure based on the VXO index is essentially forward looking.[7] As data on world GDP growth is not available, we have a trade-off between modeling volatility on a global scale using industrial production (and hence excluding the service sector), or using the volatility of total economic activity but then on the level of the US. Given that oil prices are set at a global level, we choose the global industrial production measure as our preferred indicator of macroeconomic uncertainty. The results indicate that the conclusions hold for the other measures of uncertainty as well.

We include four lags of the endogenous variables based on the conventional lag length criteria. Except for macroeconomic uncertainty, all the variables are transformed to monthly growth rates by taking the first difference of the natural logarithm. In general, the results are robust to different specifications of the variables and the structural TVAR model, see Section 5 for a more detailed discussion.

3.2 Test for Threshold Effects and Identification of Regimes

Before testing whether the model is indeed non-linear, and the dynamics between the variables are described by different regimes, we have to decide on the exact specification of the threshold variable. First, the threshold variable is typically assumed to have a certain delay in determining the regimes, which prevents potential problems of endogeneity between the identified shocks and the regimes. As we model uncertainty as a GARCH process, however, shocks can by construction only affect uncertainty with a delay. Hence, we assume no additional delay in the TVAR model. Second, the threshold variable is typically modeled as a moving average process depending on the persistence of the series (Balke 2000). As the measures of uncertainty that we employ are highly volatile, we

[7] More specifically, a GARCH(1,1) model specifies the variance as a function of a lagged squared error term and the lagged variance: $\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$.

model the threshold variable as a moving average process of order three to allow for some persistence in the uncertainty regimes, which corresponds to the average volatility of the past quarter.

To test for the significance of threshold effects, we use the approach described in Balke (2000). If the threshold value γ was known, the test of linearity under the null hypothesis against the presence of threshold behavior would simply come down to testing whether $\mu_2 = A^2 = B^2(L) = 0$. As this is not the case, we have to rely on non-standard inference. A commonly used approach is to estimate the model for each possible value of the threshold variable using least squares. The range of possible thresholds is trimmed by a certain percentage to allow for sufficient observations in each regime. As suggested by Hansen (1999), we choose a trimming parameter of 10 percent. Conditional on each threshold, we calculate the Wald statistic that evaluates the hypothesis of equality between the regimes. Three different summary test statistics are generated: the maximum Wald statistic (sup-Wald), the average Wald statistic (avg-Wald) and a statistic calculated as a function of the sum of the exponential Wald statistics for all possible thresholds (exp-Wald). For the reason that the distribution of these test statistics is non-standard, we rely on the bootstrap technique proposed by Hansen (1996) to simulate the unknown asymptotic distributions. This enables us to derive the p-values associated with the test statistics and hence to evaluate the significance of the threshold effects. The estimated threshold value is the one that maximizes the log determinant of the variance-covariance matrix of residuals.

Table 1 shows the threshold test results for the different measures of uncertainty and some summary statistics on the identified regimes. There is strong evidence for significant threshold effects for all measures of uncertainty according to the three Wald test statistics. The threshold based on the preferred measure of macroeconomic uncertainty using world industrial production growth is estimated to be 0.3512, which splits the sample into high and low uncertainty regimes that represent respectively 17 and 83 percent of all observations. To put this into perspective, Panel A of Figure 1 illustrates the threshold variable, the estimated threshold and the identified regimes for this measure of uncertainty. The shaded areas correspond to the high uncertainty states, when the threshold variable surpasses the threshold. Using world industrial production growth volatility, the main periods of higher global uncertainty are identified to be the slowdown in GDP growth across most industrialized countries in 2001, the 9/11 Terrorist Attacks at the end of 2001, and the financial crisis that hit the global economy in 2008. Global uncertainty was already elevated before the financial crisis hit due to a recession in the US and a decline in economic growth in other major industrialized countries. More recently, concerns about the sovereign debt crisis in the euro area might explain why uncertainty is again higher. When comparing Panel A with Panel B and C in Figure 1, it is clear that the different measures of uncertainty correspond to somewhat different definitions of uncertainty. The US GDP volatility measure is more closely related to US economic downturns in addition to global uncertainty. In general, it succeeds well in capturing the periods that are typically regarded as uncertain, see e.g. Bloom (2009).[8] The periods identified to be highly uncertain, which are not captured by the global measure, are Black Monday at the end of 1987, the US recession in the early 1990s, the Russian financial crisis in 1998, and the US recession of the early 2000s. On the other hand, the VXO measure captures financial market uncertainty more closely.[9]

It is well known that oil shocks can lower economic activity and cause recessions (e.g. Hamilton 1983, 2009; Bjørnland 2000; Peersman and Van Robays 2009, 2012). Accordingly, as higher oil price movements might also cause higher uncertainty, the results might be subject to an endogeneity bias. Assuming that macroeconomic uncertainty is strictly exogenous with respect to oil shocks might not be realistic. For that reason, the TVAR model allows macroeconomic uncertainty to endogenously respond to oil shocks when identifying the uncertain periods. There are several reasons, however, to believe that an endogeneity bias is negligible if not non-existent. First, the threshold variable is defined as a moving average process of macroeconomic uncertainty and is assumed to only switch regimes with a delay of one period.[10] Hence, oil shocks will not cause a regime shift in the same month that the shock hits. By modelling the threshold variable as a three-month moving average process, there should also be some persistence in the increase of macroeconomic uncertainty before it can trigger a regime switch. Second, most of the high uncertainty events identified are not directly linked to oil shocks, and the results are

[8] Bloom (2009) identifies 17 volatility shock events that substantially increased uncertainty, which he uses as 'arguably exogenous' shocks to empirically evaluate the effect of uncertainty shocks. Most of these shocks are caused by economic events, war or terrorism.

[9] Using the VXO index, high uncertainty is concentrated around the Black Monday event, the Russian and Long-Term Capital Management (LTCM) default, 9/11 Terrorist attack, the Enron and Worldcom accounting scandals, Gulf War II and the financial crisis. The working paper version of Bloom (2009) provides more details on these events.

[10] As mentioned before, this delay is imposed by the GARCH structure of the uncertainty measure.

robust to using financial uncertainty instead of macroeconomic uncertainty. Third, the correlation between oil price changes and macroeconomic uncertainty is negative, and when we estimate the model over the total sample, the different types of structural oil shocks do not significantly affect uncertainty on impact. In addition, the conditional variance decompositions show that the contribution of the oil shocks in explaining variability in macroeconomic uncertainty is small.[11]

3.3 Identifying Oil Shocks using Sign Restrictions

In our VAR model, we face the problem that the contemporaneous errors could be correlated. In order to make the shocks orthogonal and thereby econometrically interpretable, we need to impose structure on the model to identify the different shocks. Given that we only want to evaluate whether uncertainty acts as a reinforcer of oil shocks, we are only interested in identifying the oil shocks.

The oil literature has increasingly recognized that different factors can drive oil price movements, and that the economic effects of those shocks crucially depend on the underlying source of the oil price change (e.g. Kilian 2009, Peersman and Van Robays 2009, 2012). Not accounting for the driving force behind the oil price increase could therefore significantly bias the results. It is also crucial to separate oil demand from supply shocks when evaluating the role of uncertainty, as uncertainty can affect the behavior of oil producers and consumers differently, which implies a different impact on the price elasticity of oil supply and demand. We will identify three different types of oil shocks using sign restrictions: oil supply shocks, oil demand shocks driven by global economic activity and oil-specific demand shocks, similar to Peersman and Van Robays (2009, 2012), Baumeister and Peersman (2012) and Kilian and Murphy (2012). Sign restriction identification is particularly useful as we do not have to rely on zero impact restrictions to separate oil demand and supply shocks. Calculating the short-run oil demand elasticity is for example not possible if we assume that oil supply does not respond to oil demand shocks on impact, see the assumptions made by Kilian (2009) for example. We identify the oil shocks by relying on the following set of sign restrictions:[12]

[11] The contribution of the different types of oil shocks to the contemporaneous median variance decomposition of macroeconomic uncertainty is around 4%.

[12] The sign restrictions are shown for oil shocks that increase the oil price. We choose not to impose the elasticity bounds proposed by Kilian and Murphy (2010) as they base their oil demand and supply

STRUCTURAL SHOCKS	Q_{oil}	P_{oil}	Y_w	I_{oil}
Oil supply	≤ 0	≥ 0	≤ 0	
Oil demand driven by economic activity	≥ 0	≥ 0	≥ 0	
Oil-specific demand	≥ 0	≥ 0	≤ 0	

The sign restrictions are derived from a simple supply-demand scheme of the oil market. An oil supply shock is an exogenous shift of the oil supply curve to the left and therefore moves oil prices and production in opposite directions. Production disruptions caused by military conflicts in the Middle-East are natural examples. As oil prices are higher, global industrial production will not increase following this supply shock. In contrast, shocks on the demand side of the oil market will result in a shift of oil production and oil prices in the same direction. On the one hand, demand for oil can endogenously increase because of changes in macroeconomic activity. A change in the demand for commodities from emerging economies like China or India for example, will shift world economic activity, oil prices and oil production in the same direction. We define such a shock as an oil demand shock driven by economic activity. On the other hand, oil demand can also vary for reasons not related to economic activity. We label these shocks as oil-specific demand shocks. Shocks to expected net oil demand in the future, which increases oil inventory demand as a precaution, and oil-gas substitution shocks are two examples. In contrast to demand shocks driven by economic activity, oil-specific demand shocks do not have a positive effect on global economic activity as oil prices are higher.

We conduct estimation and inference in the TVAR model in the following way. The estimated threshold value splits the sample period into two subsamples, corresponding to high and low uncertainty states. Conditional upon these two subsamples, we generate two sets of impulse response functions, one estimating the effects in the high uncertainty state and the other in the low uncertainty state. We do this by following the sign restriction procedure of Peersman (2005) and Peersman and Van Robays (2009, 2012), which we apply to both subsamples. More specifically, we use a Bayesian approach for estimation and inference. Our prior and posterior distributions of the reduced form VAR belong to the Normal-Wishart family. To draw the 'candidate truths' from the posterior, we take a

restrictions on sample estimates obtained from linear models. The focus in this paper is exactely to evaluate whether these elasticities vary over time, and whether we can endogenously explain this variation by time-variation in uncertainty.

joint draw from the unrestricted Normal-Wishart posterior for the VAR parameters as well as a random possible decomposition of the variance-covariance matrix, which allows us to construct impulse response functions. If the impulse response functions from a particular draw satisfy the imposed sign conditions, the draw is kept. Otherwise, the draw is rejected by giving it a zero prior weight. We simultaneously rotate the model conditional upon high and low uncertainty, and restrict both of them to satisfy the sign restrictions of all three shocks simultaneously. To improve identification of the shocks, we impose the sign conditions to hold for the first three months, see Paustian (2007). A total of 1000 'successful' draws from the posterior are then used to construct the 68 percent probability range of possible impulse responses. For each rotation, we also generate the difference in estimated impulse response functions across regimes, which allows us to also calculate the 68 percent posterior probability range of the difference in estimated effects. This enables us to evaluate the significance of the difference in effects across regimes.

Hence, we analyze the change in impact of oil shocks on the oil price elasticity under different regimes of uncertainty by constructing *conditional* impulse response functions, i.e. conditional upon a specific uncertainty regime. In most of the TVAR literature, the effects of shocks are evaluated using so-called 'generalized impulse response functions', which allow shocks to cause a switch in regime over the duration of the response.[13] By estimating the responses conditional upon the regimes, we assume that the impact is linear within a regime, but the size and persistence of the responses to similar oil shocks can differ. We make this assumption for two main reasons. First, there is an important inconsistency between the non-linear and deterministic character of the GARCH process used to construct the uncertainty measure and the linear structural VAR model, through which including the uncertainty measure in the structural model is not desirable.[14] Constructing generalized impulse response functions is not possible when excluding uncertainty from the structural model, as this uncertainty variable is needed to model the regime transitions after shocks. Therefore, we identify the structural oil shocks in a model that only includes oil prices, oil production, world economic activity and oil inventories. Remember

[13] See for example the working paper version of Calza and Sousa (2006) for more details, as they construct both the conditional and the generalized impulse response functions.

[14] More specifically, we model macroeconomic uncertainty as a GARCH(1,1) model which has the following representation: $\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$, with ε_{t-1}^2 the lagged squared error term. This squared term causes the impact of shocks on uncertainty to be non-linear, e.g. both positive and negative shocks will increase uncertainty. This non-linearity is not allowed for in the structural linear model that we use to generate the conditional impulse response functions.

that when identifying the uncertainty regimes, we do allow for feedback effects between oil prices and uncertainty, see Section 3.2. Second, constructing generalized impulse response functions when using sign restrictions instead of recursive identification proves to be quite difficult.[15] A drawback of not allowing the shocks to cause switches in regimes during the response might be that the conditional impulse response functions are only informative in the short run. Concerning the estimation of the impact price elasticities of oil demand and supply, however, this assumption does not make any difference.

4 Effects of Oil Shocks in Different Uncertainty Regimes

Figure 2 shows the estimated effects of the variables in the TVAR model to different types of oil shocks in the two regimes. In order to make the effects comparable across regimes, we normalized the contemporaneous response of oil production to a one percent change. The conditional impulse responses are accumulated and shown in levels over the first two years after the shock. The shaded responses in the figure represent the 68 percent posterior probability range of the estimated effects in the high uncertainty regime and the dotted ones represent those conditional on low uncertainty.[16] In Figure 2, the posterior probability range represents the uncertainty concerning the model specification. An overlap between the estimated responses across regimes could thus partly be due to the fact that we are comparing different model specifications. In Figure 3, we evaluate the significance of the difference in estimated responses across regime per model specification.

The first two rows of Figure 2 show the effects of the different types of shocks on oil prices and oil production. It is clear that for all three oil shocks, a similar impact change in oil production has a much stronger impact effect on the oil price in the high uncertainty regime.[17] This indicates that when macroeconomic conditions are highly uncertain, oil

[15] In order to model the transition between the regimes following a structural shock, it is necessary that the shocks come from the same model. This assumption is satisfied for e.g. the Cholesky decomposition, but not when using sign restrictions. Up to our knowledge, only Candelon and Lieb (2011) have used TVAR models in combination with sign restrictions, and they make the same assumption as we do here.

[16] Note that as we report the posterior *range* of possible outcomes, the results are not subject to the Fry and Pagan (2011) critique, which only applies when some kind of summary measure such as the median is used.

[17] During some periods of high uncertainty, small changes in oil demand were associated with enormous variation in the oil price, which might explain why the estimation uncertainty surrounding the oil price response following the oil demand shock driven by economic activity is so high. For example, in the fourth

shocks have larger effects on oil prices compared to more normal times. The production response relative to the price response following a shock gives an estimate of the price elasticity. Accordingly, we can estimate the elasticity of oil demand and supply as the ratio of the impact response in oil production and the oil price following oil supply and oil demand shocks respectively. These estimated elasticities are given in the third row of Figure 2. As expected, the elasticity of both oil demand and supply falls considerably when uncertainty is high. In other words, the oil demand and supply curve become steeper in uncertain times.

Following the oil supply shock, we estimate the oil demand elasticity to decrease from within a range of -0.52 to -0.15 in the low uncertainty regime, to a value within the range of -0.36 to -0.11 in the high uncertainty regime. As there is quite some overlap in estimated elasticities across the regimes, we calculated the significance of the difference in order to evaluate the relevance of the uncertainty effect. Figure 3 displays the 68 percent posterior probability range of the estimated difference in responses between the high and the low uncertainty regime. These estimations show that the difference in estimated oil demand elasticities across regimes is statistically significant. Given that the oil price elasticity in the high uncertainty regime might be less than half its value of the low uncertainty regime, the effect is also economically very significant. The estimated oil demand elasticities are broadly in line with those estimated in the literature. Hamilton (2009), Dahl (1993) and Cooper (2003) report oil demand elasticities between -0.05 and -0.07, whereas Baumeister and Peersman (2010), Bodenstein and Guerrieri (2011) and Kilian and Murphy (2010) arrive at estimates ranging from -0.26 to -0.44, which is at the higher end of our estimation range. Kilian and Murphy (2010) argue that allowing for endogeneity of oil price could be a reason for why they find relatively high oil demand elasticities. Our model however, while modelling oil prices endogenously, also generates low elasticities once we allow for endogenous non-linearity in the price elasticity depending on the economic regime. Interestingly, using a time-varying VAR model and thereby allowing for non-linearity, Baumeister and Peersman (2012) estimate the median price elasticity of oil demand to fluctuate within a range of -0.05 to -0.25 since 1986, with 68 percent posterior credible sets reaching up to -0.40, which comes close to our estimation range over the two regimes. Therefore, the variation of the oil demand elasticity within their sample could be explained by varying levels of macroeconomic uncertainty.

quarter of 2008, oil demand felt by 0.6 percent whereas oil prices plummeted by more than 111 percent.

For the reason that we have two types of oil demand shocks, we can estimate the curvature of the oil supply curve following the oil demand shock driven by economic activity and following the oil-specific demand shock. Figure 2 shows that also the elasticity of oil supply, as proxied by both types of oil demand shocks, tends to be lower when uncertainty is higher. Following the oil demand shock driven by economic activity, the estimated oil supply elasticity drops from a maximum value of 0.21 in the low uncertainty regime to a maximum of 0.15 when uncertainty is high. The minimum estimated elasticity of oil supply reduces from 0.03 to 0.02. Again, these estimates correspond well with the estimates in the literature. Baumeister and Peersman (2012), for example, estimate the median oil supply elasticity to lie in between 0.02 and 0.25. When the oil supply elasticity is generated through a shift in the oil-specific demand curve, the results also show a reduction in the oil supply elasticity conditional on high uncertainty, although the magnitudes differ slightly. These differences could be due to the fact that the oil-specific demand shock captures a broad set of shocks, i.e. all demand shocks that are not driven by global economic activity. Shocks to expected net oil demand and oil-gas substitution shocks are two examples, and also speculation shocks are thought to be part of it.[18] For the reason that these shocks could trigger diverging responses in oil demand and supply, the estimation of the oil price elasticities could be subject to significant noise. As noted by Baumeister and Peersman (2012), the differences in the estimated elasticities could also be explained by a different reaction of oil supply to both shocks in oil demand. Although there again is some overlap between the estimated elasticities, Figure 3 shows that differences are significantly different from zero.

Not only the oil price elasticity, but also the real economic effects of oil shocks appear to differ considerably when uncertainty is high. The fourth row of Figure 2 shows that economic activity appears to react more strongly following oil shocks in the high regime. The difference in real impact effects across regimes is statistically significant for all three shocks, see Figure 3. Again, the uncertainty effect is also economically relevant as the impact response in the high uncertainty regime might be twice as large than when uncertainty is low, which could be explained by increased sensitivity of the oil price. At first sight, there is no apparent difference between the reaction of oil inventories across regimes. Nevertheless, Figure 3 indicates that following the oil demand shocks on impact, the reaction of inventories is stronger when uncertainty is high, which corresponds well with

[18] See for example Kilian and Murphy (2010) and Lombardi and Van Robays (2011).

increased precautionary inventory building motivated by increased uncertainty (Pirrong 2009).

A simple back-on-the-envelope calculation illustrates the economic relevance of the difference in estimated elasticities. In the aftermath of the financial crisis that hit the global economy in summer 2008, oil demand dropped considerably. Global oil demand declined with about two percent between 2008Q3-2009Q2 and oil prices decreased from about USD 112 to USD 58 per barrel. Based on our estimates, uncertainty concerning the macroeconomy was already high before the financial crisis hit (see Figure 1). If we assume the price elasticities of oil supply in the different regimes to be equal their average value, the part of the oil price decline that could be attributed to the uncertainty effect would be about six percent.[19] This strengthens the view that oil supply and demand-side fundamentals may have been responsible for most part of the sharp movements in oil prices, as high uncertainty about the macroeconomic outlook reinforced the price impact of these fundamental oil shocks, independent of any speculative activity in the oil futures market. The finding that the oil demand elasticity and the oil supply elasticity tends to be smaller when uncertainty is higher is robust to using the other measures of uncertainty that we constructed, see Panel B and C of Figure 4 in comparison with Panel A.

5 Robustness of the Results

The main results on the lower price elasticity of oil demand and supply in times of higher uncertainty, and the stronger real economic impact of oil shocks, hold for various specifications of the model used. First, our conclusions hold for the real oil price, reasonable variation in the number of lags given our data sample (2, 3 and 5 lags), only imposing the sign restrictions on impact and for different measures of uncertainty as described in the main text. Second, if we identify regimes of negative growth instead of regimes of higher uncertainty, the overall results remain the same although the significance of the difference across regimes disappears. This indicates that our findings concerning the uncertainty effect can not be solely explained by a different effect of oil shocks on oil prices in recessions versus expansions. These results are available upon request.

[19] For simplicity, we made the assumption that the two percent drop in global oil demand is entirely caused by an oil demand shock driven by economic activity, and that the drop in production is equal to the drop in demand. These and the other assumptions made could be restrictive, and therefore these results should be interpreted with caution.

6 Conclusions

This paper analyzes whether the impact of oil shocks differs in times of high and low macroeconomic uncertainty. As it is well documented that uncertainty can affect the decision behavior of economic agents, it could equally impact on the strength at which shocks to oil fundamentals affect oil prices, oil production and economic activity. Several important insights emerge from our analysis. First, a test for the significance of threshold effects indicates that the oil model is non-linear and behaves differently in regimes of high uncertainty which are mostly associated with periods of slowing economic growth, recessions and financial crises. Second, higher macroeconomic uncertainty causes oil prices to respond more strongly given a certain change in oil production, implying that the price elasticity of oil demand and supply decreases when uncertainty is higher. The reduction in the oil price elasticity in the high uncertainty regime is both statistically and economically significant. A third, possibly related finding is that the effect of all types of oil shocks on economic activity is more aggressive in times when macroeconomic volatility is already high. These findings are robust to variations in the specification of the model, identification of the shocks and the measure of uncertainty.

As far as we are aware, this is the first paper considering a role for macroeconomic uncertainty in explaining changes in the impact of oil shocks, and that endogenously explains variations in the elasticity of oil demand and supply over time. We provide empirical evidence for the arguments made by Hamilton (2009) and Kahn (2009) that fundamental shocks in oil demand and supply impacted more strongly on oil prices over the past decade, and managed to explain why oil price volatility varies over time, as documented by e.g. Baumeister and Peersman (2012). In the discussion on the driving factors behind the recent rollercoaster ride in oil prices, our findings imply that the contribution of oil demand and supply shocks to the oil price could be larger than previously estimated, once the non-linearity of the price elasticity of oil demand and supply is taken into account. We leave the analysis of the channels of transmission through which higher macroeconomic uncertainty affects the price elasticity of oil demand and supply as an interesting avenue for future research.

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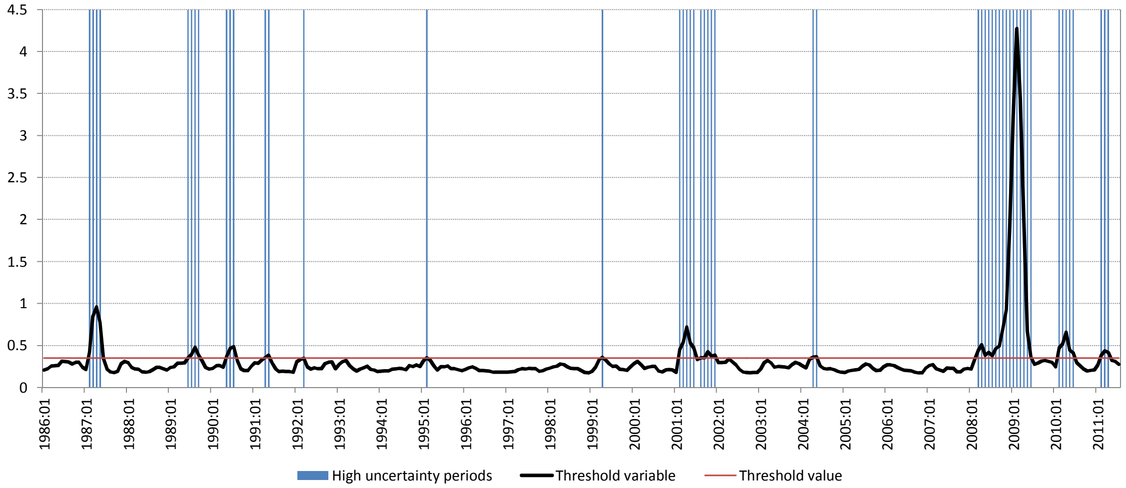
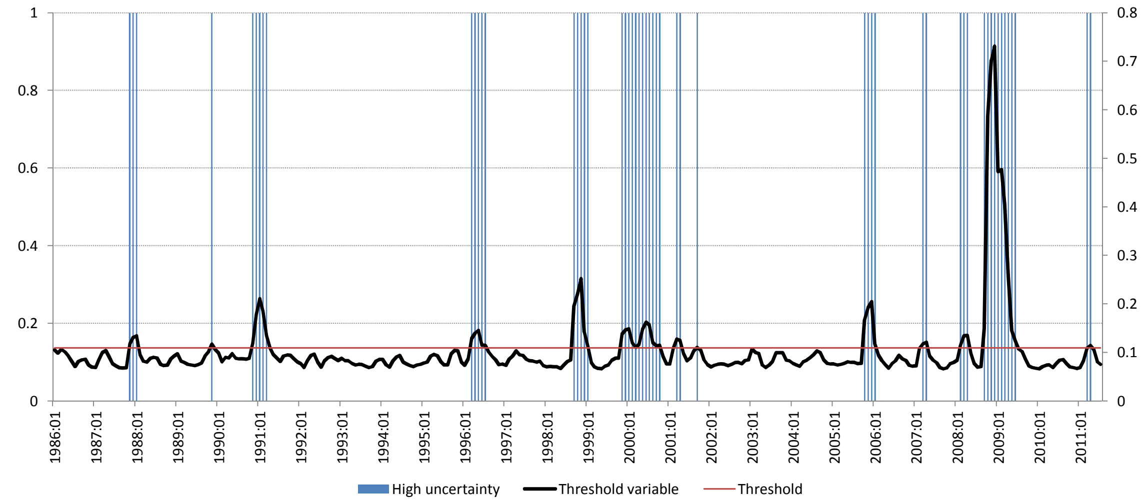
PANEL A. Macroeconomic uncertainty based on conditional variance world industrial production growth



PANEL B. Macroeconomic uncertainty based on conditional variance US GDP growth



PANEL C. Macroeconomic uncertainty based on CBOE VXO stock market volatility

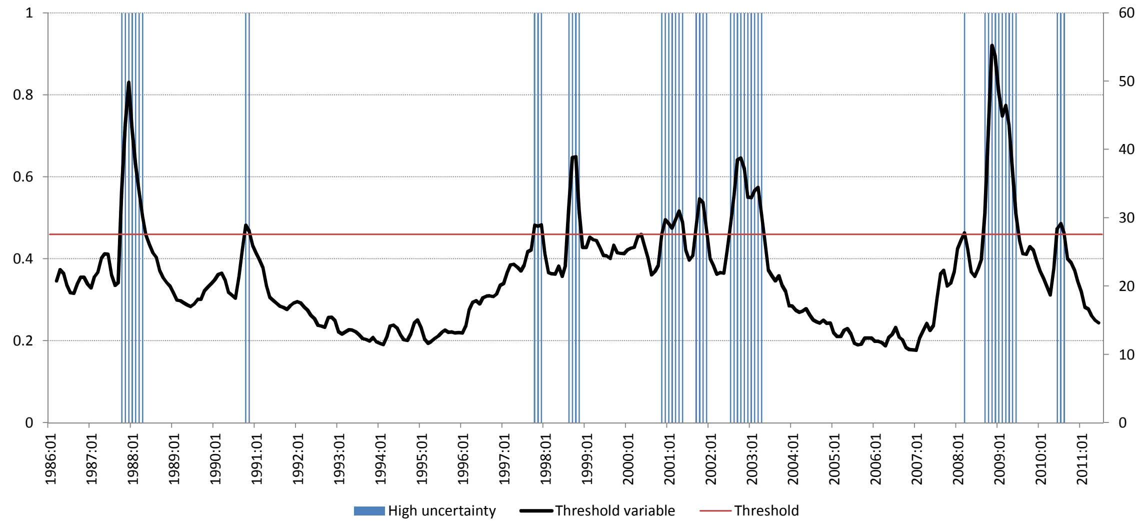


Figure 1. Threshold variable related to uncertainty, estimated threshold and identified periods of high uncertainty

Notes: the threshold variable is constructed as a three-period moving average of the respective measure of uncertainty.

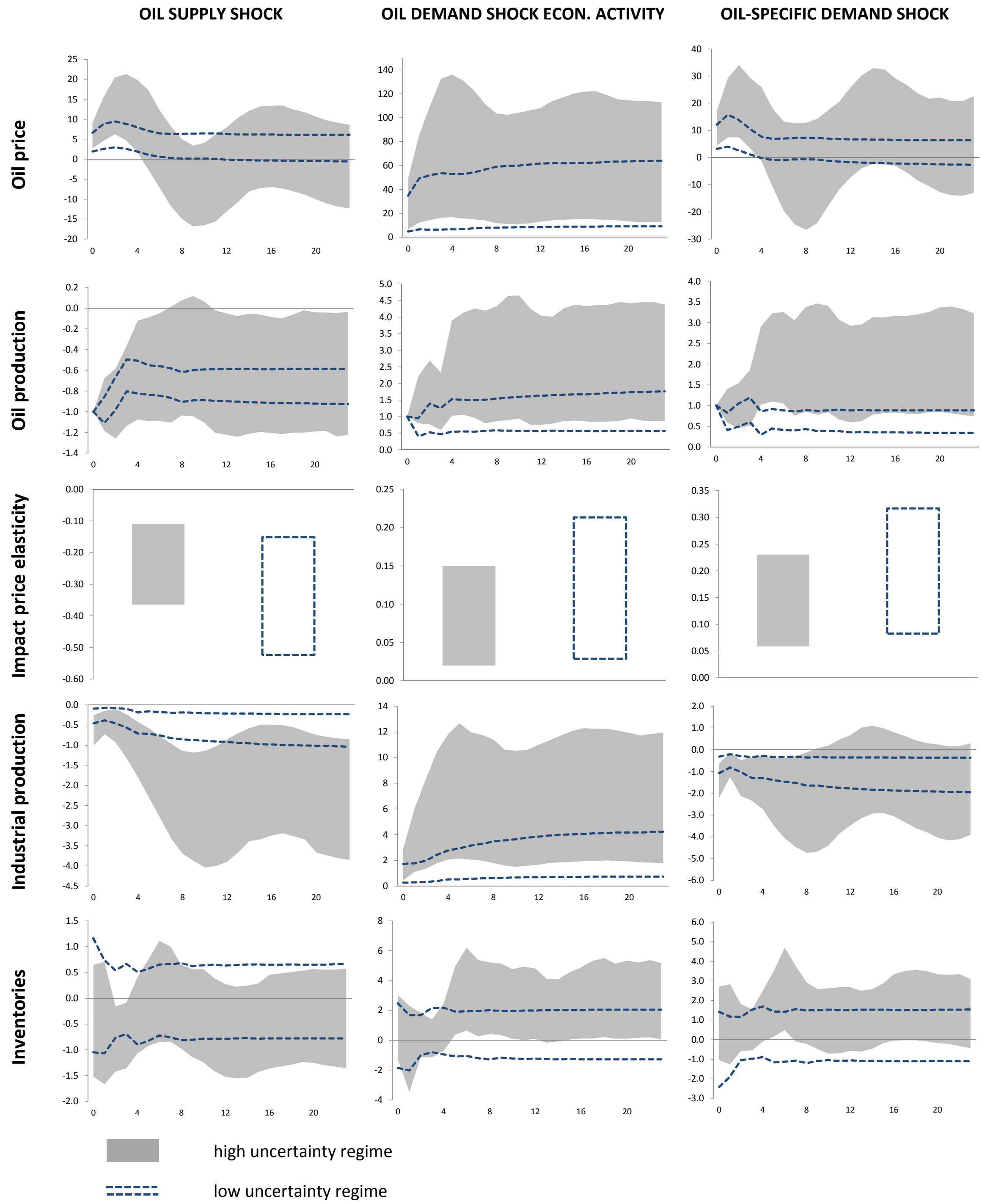


Figure 2. Impact of different types of oil shocks in different regimes of macroeconomic uncertainty

Notes: Figures are 68 percent posterior probability regions of the estimated conditional impulse response functions normalized on a 1 percent change in oil production, horizon is monthly and the measure of uncertainty is the conditional variance of world industrial production growth.

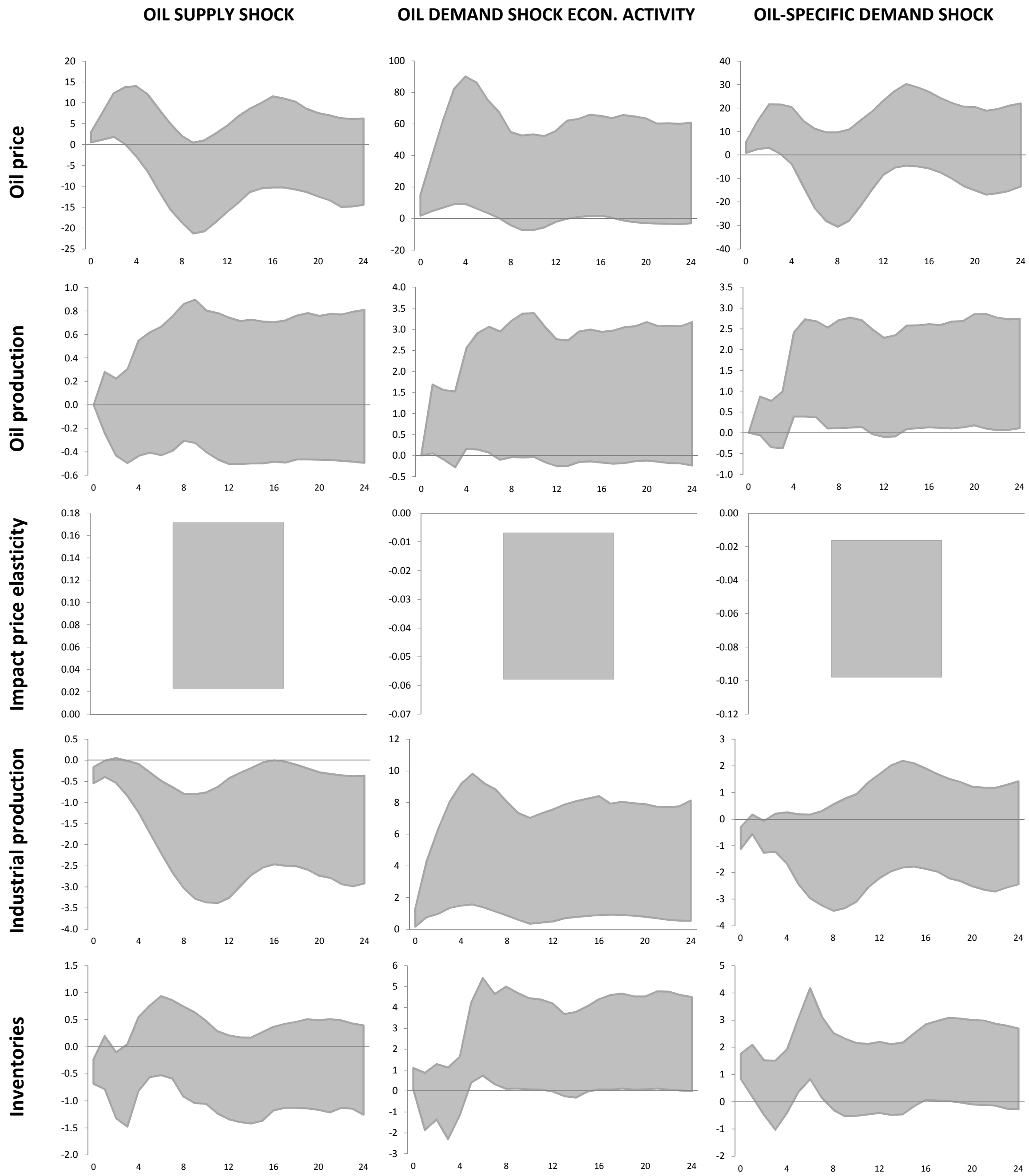
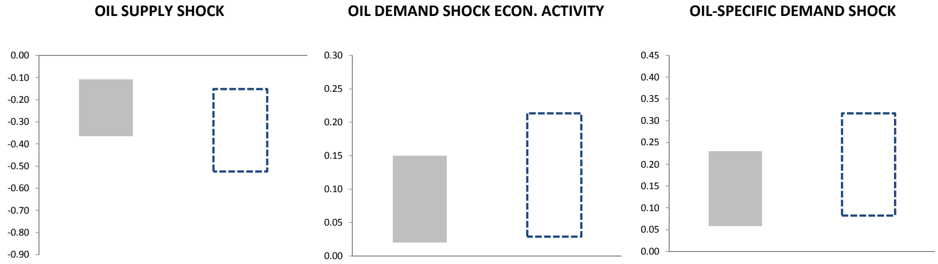


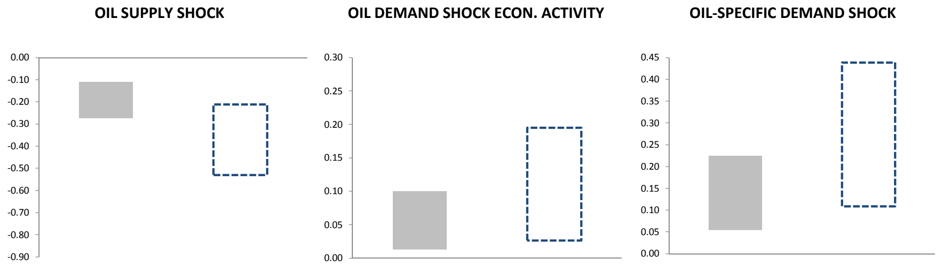
Figure 3. Signifcance of the difference in impact between high uncertainty and low uncertainty regime

Notes: Figures are 68 percent posterior probability regions of the difference in estimated conditional impulse response functions in the high uncertainty regime minus the low uncertainty regime. The impulse response functions normalized on a 1 percent change in oil production, horizon is monthly and the measure of uncertainty is the conditional variance of world industrial production growth.

PANEL A. Estimated impact elasticities using uncertainty proxied by conditional variance world industrial production growth



PANEL B. Estimated impact elasticities using uncertainty proxied by conditional variance US GDP growth



PANEL C. Estimated impact elasticities using uncertainty proxied by CBOE VXO stock market volatility

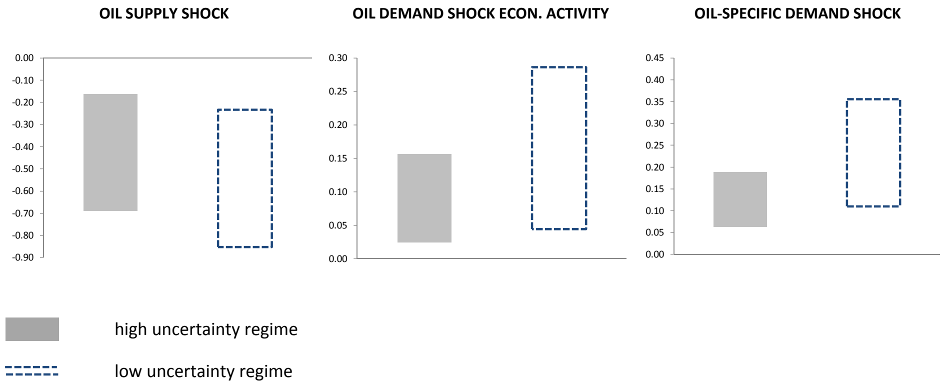


Figure 4. Robustness impact elasticities of oil demand and supply to various uncertainty measures

Notes: estimated impact elasticities estimated conditional on high or low uncertainty regimes identified based on threshold values shown in Table 1

Threshold Variable	Estimated threshold	Wald Statistics			% observations in high uncertainty regime	Duration of the high uncertainty regimes in months (min; max; mean)
		Sup-Wald	Avg-Wald	Exp-Wald		
World industrial production growth GARCH(1,1)	**0.3512**	431.45 (0.00)	211.88 (0.00)	210.43 (0.00)	17%	(1; 16; 8.5)
US GDP growth GARCH(1,1)	**0.1095**	435.40 (0.00)	179.62 (0.00)	212.86 (0.00)	18%	(1; 12; 6.5)
CBOE VXO monthly average of daily closing price	**27.5467**	389.15 (0.00)	176.60 (0.00)	189.35 (0.00)	17%	(1; 10; 5.5)

Table 1. Test for threshold effects

Notes: Tests are performed for the reduced form of the 5-variable TVAR model described in equation (1) with four lags of the endogenous variables, no delay parameter and three moving average terms for the threshold variable. The p-values based on the simulation technique of Hansen (1996) for 500 replications are in parenthesis. GDP and CBOE VXO stand respectively for gross domestic product and the Chicago Board of Option Exchange VXO US stock market volatility measure. The sample period is 1986:01-2011:07.