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Abstract

This paper accounts for informational frictions when modelling the time-varying relationship between crude oil prices, traditional fundamentals and expectations. Informational frictions force a wedge between oil prices and supply and/or demand shocks, especially during periods of elevated risk aversion and uncertainty. In such a context expectations can be a key driver of oil price movements. We utilize a variety of proxies for forward-looking expectations, including business confidence, consumer confidence and leading indicators. In addition, our paper implements a time-varying parameter approach to account empirically for time-varying informational frictions. Our results illustrate firstly that oil supply shocks played an important role in both the 1970's and coinciding with the recent shale oil boom. Secondly, demand had a positive impact upon oil prices, especially from the mid-2000's. Finally, we provide evidence that oil prices respond strongly to expectations but the source of the shock matter: business leaders' expectations are positively related, while markets' expectations are not strongly linked to oil prices.

Keywords: Crude Oil Prices; Informational Frictions; Fundamentals; Expectations; Time-Varying Parameters.
JEL classification: C30, E30, F00, Q43.

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1 Introduction

Oil is a core source of energy for the global economy and essential for economic activity. Analysts and academics alike have sought to better understand the implications and causes of the dramatic fluctuations in oil prices since the 1970's. Traditionally, oil price fluctuations were thought to reflect unexpected changes in oil supply, such as production disruptions due to conflicts, co-ordinated supply constraints in producing nations, see Hamilton (2003) and Jones et al. (2004). Subsequent research has argued that supply factors were only one among many explanations and less important than previously believed (see the literature from Lippi and Nobili, 2012; Baumeister and Peersman, 2013a; Abhyankar et al., 2013; Kilian and Murphy, 2014). Kilian (2009) has sought to disentangle the relative contribution of supply and demand shocks underlying the evolution of the real price of oil. He found that since 1973 major changes in oil prices were primarily driven by demand factors. These factors included shifts in global demand for industrial commodities and unanticipated increases in precautionary demand for crude oil. Traditional supply and demand fundamentals are clearly important; however recent papers have considered whether market participants directly observe these fundamentals (see Singleton, 2014; Sockin and Xiong, 2015). In particular, Sockin and Xiong (2015) highlight that the presence of severe informational frictions could lead to confusion among market participants about the strength of the global economy and oil demand relative to supply. Therefore, it may be unrealistic to assume that producers and consumers can directly and contemporaneously observe whether oil prices are fully consistent with actual fundamentals. Without a contemporaneous link between oil prices and fundamentals, the role of expectations becomes crucial.

Our paper extends the literature on identifying the determinants of oil prices by incorporating economic agents' expectations on the state of the global economy. This issue relates specifically to informational frictions but more generally to research in behavioural finance and psychology, which argues that moods and emotions affect individuals' behaviour and aggregate prices and quantities (see for example Akerlof and Shiller, 2009; Gino et al., 2012; Garcia, 2013). However, this topic has not been extensively investigated in relation to oil prices. To carry out our investigation, we account for a range of confidence and leading indicators which provide a broader perspective of the global economic outlook. Widely used survey-based confidence indicators shall therefore be adopted in this study as a gauge the state of the global economy in the presence of informational frictions.[1]

There are several important reasons why it is important to investigate the role of expectations in the oil market. First, although supply and demand factors may be the fundamental cause of oil price fluctuations, expectations may be the proximate cause of their movements. Second, expectations account for informational frictions and departures from the oil price suggested by fundamentals Sockin and Xiong (2015). Third, expectations also account for the idea that oil prices exhibit forward looking behaviour, which can augment measured demand especially at turning points in the economic cycle. Furthermore, expectations are frequently emphasized in economics research, see for example the New Keynesian Phillips curve literature, which considers the importance of fundamentals and forward-looking behaviour in a goods price setting (see Gali and Gertler, 1999; Byrne et al., 2013). Finally, expectations encompass the idea that there has been increased financialization of oil, since investors shall seek to maximise expected returns based upon asset prices (see Cheng and Xiong, 2014).

Our paper adopts an empirical framework which considers whether the source of expectations matters for oil prices. We have three different expectational proxies: business confidence, consumer confidence and market leading indicators of OECD countries. Respectively they capture the expectations on future global economic outcomes from business leaders', consumers' and aggregate markets' prospects. Even though these expectations may be interrelated and contemporaneous, business leaders, consumers and markets can act on a specific set of (imperfect) information that emanates from the state

[1] See, for example, Carroll et al. (1994); Bram and Ludvigson (1998); Ludvigson (2004); Bachmann and Sims (2012); Christiansen et al. (2014); Caglayan and Xu (2016).

of the economy, rational inattention, or the agent's own asymmetric goals and strategies. Figure 1 illustrates that while there are similarities between these sources of expectations they do evolve differently over time. Therefore, it is important to find out how oil prices would respond to variations in different economic agents' expectations on the state of the economy.

Moreover, this paper takes account of the potentially time-varying impact of fundamentals on expectations. There are reasons to believe that over time there may be an unstable relationship between oil price shocks and the underlying drivers. For example, China has significantly increased its market shares of global commodities following its rapid development and this may have demand effects (Kilian, 2009; Frankel, 2014). Financial investors' risk-bearing appetite and the risk premium can vary over time (e.g., Acharya et al., 2013; Cheng and Xiong, 2014). There is also time-dependent volatility in both world oil production and oil prices (e.g., Kilian, 2009; Baumeister and Peersman, 2013b). Importantly informational frictions may themselves change over time, also leading to a decoupling of oil prices and fundamentals in periods of acute uncertainty about the global economy. These characteristics imply a time-varying relationship between the underlying drivers and oil prices.[2] To carry out our investigation, therefore we use a time-varying vector autoregression (TVP-VAR) model with stochastic volatility model to simultaneously model the evolving roles of both oil market fundamentals and expectation shocks on oil prices for the period between 1974 and 2016.

Our investigation extends the existing literature by providing evidence that oil prices respond to both traditional fundamentals and heterogeneous economic agents' expectations over time. In contrast to prior research, we firstly find that supply shocks arising from unexpected changes in oil production played an important role in explaining changes in oil prices. For instance, the negative effects of oil supply shocks have intensified due to the recent US shale oil boom (Kilian, 2016). Second, we find that since the middle of the 2000's oil prices responded positively and strongly to unexpected increases in demand,

[2]For example, Peersman and Van Robays (2012); Millard and Shakir (2013); Baumeister and Peersman (2013a,b).

possibly due to increased demand for industrial commodities from many emerging market economies. Furthermore, we find that real price of oil responds differently to expectations that arise from business leaders, consumers and aggregate markets. We also identify that increases in business leaders' expectations have a strong and positive impact upon the real price of oil. On contrary, we find that unexpected increases in consumers' expectation negatively affect the real price of oil. Our results suggest that there may be greater complementarity between oil prices and firm production than household consumption.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 formally presents our econometric methodology and Section 4 discusses the data. Section 5 reports the empirical results and robustness checks. Section 6 offers some concluding remarks.

2 Brief Literature Review

Changes in oil prices can be rapid, and large price swings severely impact commodity importers, exporters and speculators. For example, higher oil prices may lead to lower aggregate demand and production outputs, induce inflationary tendencies and higher interest rates for importing countries; whereas a sustained decline in oil prices supports the so-called "resource curse" hypothesis for commodity abundant emerging economies (see among the others, Lu and Neftci, 2008; Frankel, 2014; Baumeister and Kilian, 2016). Thus, a better understanding of the nature of oil prices and their determinants are crucial for policymakers and the private sector and may lead to better decision making in areas such as macroeconomic policy, risk and portfolio management.

The recent economic literature has contributed substantially to a better understanding of the causes of oil price fluctuations (see, among others, Lorusso and Pieroni, 2015). In an innovative paper, Kilian (2009) disentangles the effects of demand and supply side shocks underlying the evolution of the real price of oil. He found that an increase in demand for crude oil causes a large increase in the real price of oil, whereas crude oil production disruptions only cause a small and transitory increase in the real price of oil. A large number of authors have also reported findings consistent with this global growth arguments (e.g., Kilian and Park, 2009; Lippi and Nobili, 2012; Baumeister and Peersman, 2013a; Abhyankar et al., 2013; Kilian and Murphy, 2014; Baumeister and Kilian, 2016). They argue that the unusually widespread growth in global economic activity after 2000 caused a substantial increase in demand for commodities, especially from China and other emerging economies. This strong demand coupled with stagnant supply led to a persistent increase in the real price of oil.

Another strand of literature focused on the role of expectations, as the extent to which oil price fluctuations are unexpected depends on how these expectations are formed. One common approach to modelling oil price expectations is to consider the role of speculative trading. In particular, a number of authors have highlighted the financialization of commodity markets and growth in positions of index speculators had significant positive impacts on the drifts and high volatilities of commodity prices between 2005 and 2008 (e.g., Cheng and Xiong, 2014).[3] An alternative empirical strategy to detect speculative effects is through the level of inventory. According to the theory of storage, speculative purchases arise in the physical market with the intention of storing it for future use in anticipation of rising prices accelerate the futures price of a commodity, which in turn would drive up the spot price as less of the commodity is made available for current consumption. Hence, if momentum trading in financial markets is a primary driver of price trends in physical markets, one would expect to observe an upswing in speculative holdings of inventories. Yet, there is lack of consensus as to the effects of speculation on oil prices. For example, a number of authors found no persuasive evidence in supporting this financial speculation hypothesis as the level of inventories did not surge before the July 2008 peak in oil price (e.g., Fattouh et al., 2013; Kilian and Murphy, 2012). On

[3]The composition of participants in commodity futures markets changed dramatically over the past decade. Traditionally, two major categories of investors are commercial hedgers (e.g., famers, producers, and consumers) and non-commercial traders (e.g., hedge funds). However, since 2000's there has been a large inflow of investment capital from non-user speculators and passive investors in commodity futures markets.

the other hand, Kilian and Murphy (2014) found that speculative demand raised the price of oil in the mid-2008, but there was no evidence of speculative demand pressures between early 2003 and early 2008. Juvenal and Petrella (2015) found that both global demand shocks and speculative shocks played an important role in explaining oil price fluctuations.

However, in a recent paper, Sockin and Xiong (2015) argued that the standard approach to modelling oil prices ignore important informational frictions faced by economic agents. For example, the inventory-based detection strategy assumed that oil consumers can observe global economic fundamentals and are able to recognize whether current oil prices are too high relative to fundamentals. They highlighted that this assumption can be unrealistic during periods of considerable economic uncertainty (e.g., the global financial crisis in 2008), when firms and consumers faced severe informational frictions in inferring the strength of the global economy. They also argued that by ignoring informational frictions we are likely to understate the effect of supply shocks and overstate the effect of demand shocks, speculation can drive up commodity prices without necessarily reducing commodity consumption and increasing inventory. Their work echoes the findings of Singleton (2014) who highlighted the importance of accounting for agents' expectations in explaining the commodity market boom-bust cycles.

In contrast to the existing literature, we link economic agents' expectations on future economic conditions to the crude oil market. Our paper also relates to the extensive literature on behavioural finance. When we survey the literature, we come across an expanding research area that examines the effects of economic agents' confidence on the behaviour of decision-making, institutions and markets. In their studies, researchers use various sentiment or confidence proxies including survey-based measures, market-based measures and text-based measures. Survey-based indicators have long been scrutinized for the information they contain on the state of the economy which is not already covered in other well-used economic indicators.[4] For example, Batchelor and Dua (1998) showed

[4]Note that the words of "sentiment" and "confidence" can be used interchangeably.

that Michigan's Index of Consumer Sentiment is very useful in forecasting GDP. Ludvigson (2004) suggested that measures of consumer sentiment contained information about consumers' future spending. Christiansen et al. (2014) found strong evidence that both Michigan's Index of Consumer Sentiment and Purchasing Manager's Index hold significant predictive power in capturing recessions in the US in excess of standard recession predictors and common factors.

Furthermore, there is a large and growing literature which uses market-based measures and text-based measures to study its effects on stock market. For example, Baker and Wurgler (2006) constructed a composite investor sentiment index by using the first principal component of six sentiment proxies suggested in prior research and showed that this composite index significantly predicted the future stock returns.[5] Schmeling (2009); Bathia and Bredin (2013) both found that sentiment has a significant influence on stock market returns across many industrialised countries. In addition, several authors constructed text-based measures of investment confidence through sources such as media or news. For example, Garcia (2013) found that news-based investor sentiment helps to predict stock returns at the daily frequency, especially during recessions.

However, only handful of studies considers the effect of sentiment upon the oil market. Deeney et al. (2015) followed methods applied by Baker and Wurgler (2006) and built a composite investor sentiment index in oil market using the trading volume of oil futures, the historical volatility of the oil price, the put-call ratio of oil options, the ratio of speculative traders to oil demand and stock index volatility. They found that sentiment played an important role in explaining WTI and Brent prices using data from January 2002 to December 2013 based on a regression analysis. One of the main drawbacks for this approach is that it treats oil prices as exogenous with respect to the global economy and it is now generally accepted that crude oil prices are endogenous with respect to the global macroeconomic conditions (see, for example, Barsky and Kilian, 2004). Han

[5] They used close-end fund discount, market turnover, number of IPOs, average first day return on IPOs, equity share of new issuances, and log difference in book-to-market ratios between dividend payers and dividend non-payers.

et al. (2017) constructed an investor attention index using the Google search volume index based on a set of words related to oil-related variables and terms that are directly linked to real economy to measure investor attention. They found that investor attention provide significant in-sample and out-of-sample forecasting power to forecast oil prices.

Given the earlier literature, our study extends the literature on the determinants of oil prices for the following reasons. While previous studies focused on the traditional fundamentals of supply and demand or the role of speculation, we account for economic agents' expectations of future economic conditions from business leaders, consumers and markets' points of view, respectively. Therefore, our empirical approach is able to account for informational frictions faced by heterogeneous economic agents. Moreover, we use a TVP-VAR model with stochastic volatility that allows us to examine determinants of shocks to oil market fundamentals and expectations over time and across economic agents. We now turn to formally laying out our econometric methodology.

3 Empirical Methodology

In this section, we demonstrate how a standard Bayesian VAR model can be extended to account for time-varying parameters (TVP) and used to examine the determinants of oil prices. The TVP-VAR model with stochastic volatility allows us to understand how changes in macroeconomic fundamentals and expectations affect real oil prices over time.

3.1 Bayesian VAR Model

Our basic VAR model can be written as follows:

$$AY_t = \Sigma_{i=1}^{p} + \Gamma_i Y_{t-i} + u_t, \ t = p+1, ..., T \tag{1}$$

where Y_t is a $K \times 1$ vector of endogenous variables includes the changes in the global oil production ($\Delta prod_t$), an index of global real economic activity (rea_t), the changes of economic agents' expectations (Δexp_t), and the real price of oil (rpo_t). Γ_i is a $K \times K$ matrix of coefficients, A is a $K \times K$ matrix of contemporaneous coefficient of Y_t, and u_t captures the structural shocks in the commodity market and macroeconomic conditions. We assume u_t to be *i.i.d.* $N(0, \Sigma\Sigma)$. The lag length is two (i.e. $p = 2$)[6] where Σ is the diagonal matrix:

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sigma_k \end{pmatrix}$$

To specify the simultaneous relations of the structural shock, we employ its reduced-form representation by multiplying both sides by A^{-1}, resulting in:

$$Y_t = \Sigma_{i=1}^{p} B_i Y_{t-1} + A^{-1}\Sigma\varepsilon_t, \ \varepsilon_t \sim (0, I_k) \tag{2}$$

where $B_i = A^{-1}\Gamma_i$ for $i = 1, ..., p$. We can stack all the VAR coefficients (B_i) into a $K^2p \times 1$ vector to form B and define $X_t = I_k \otimes (Y'_{t-1}, ..., Y'_{t-p})$, where $\otimes$ denotes the Kronecker product. We rewrite equation (2) as:

$$Y_t = X_t B + A^{-1}\Sigma\varepsilon_t \tag{3}$$

Note that the reduced-form residuals ε_t are correlated between each equation and can be viewed as a weighted average of the structural shocks u_t in equation (2). In order to orthogonalize the shocks, we impose a recursive structure on the contemporaneous terms

[6]Most lag length specification tests (e.g., Final Prediction Error; Akaike Information Criterion; and Hannan-Quinn Information Criterion) suggest that four lags should be included for our model with quarterly data.

and assuming that A is lower-triangular:

$$A = \begin{pmatrix} 1 & \dots & \dots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \dots & a_{k1,k-1} & 1 \end{pmatrix}$$

The ordering of the variables is as follows: $Y_t = [\Delta prod_t, rea_t, \Delta exp_t, rpo_t]$. The structural shocks u_t are identified by decomposing the reduced-form errors ε_t as follows:

$$\varepsilon = \begin{pmatrix} \varepsilon^{\Delta prod_t} \\ \varepsilon^{rea_t} \\ \varepsilon^{\Delta exp_t} \\ \varepsilon^{rpo_t} \end{pmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21,t} & 1 & 0 & 0 \\ a_{31,t} & a_{32,t} & 1 & 0 \\ a_{41,t} & a_{42,t} & a_{43,t} & 1 \end{bmatrix} \begin{pmatrix} u_t^{supply} \\ u_t^{demand} \\ u_t^{exp} \\ u_t^{res} \end{pmatrix}$$

We disentangle four structural shocks that drive the real price of oil. Firstly, u_t^{supply} reflects an unexpected shift of global oil supply. These are not driven by changes in the macroeconomic environment, but due to exogenous production disruptions due to political instabilities, wars or changes in production quotas set by the OPEC members. Secondly, u_t^{demand} captures the shift in the demand for all industrial commodities including crude oil that is associated with unexpected fluctuations in the global business cycle, such as the unexpected strong demand from emerging economies. Next, u_t^{exp} reflects the variations of specific economic agent's (i.e., consumers, business leaders, and markets) expectations about future economic conditions. These expectations include sentiment from different agents about future economic trends. Sentiment may vary based upon elevated risk or uncertainty in financial markets, as in the global financial crisis. Finally, u_t^{res} denotes the residual shock that captures idiosyncratic oil demand shocks not otherwise accounted for. In Appendix A, we describe in detail the restrictions on A_t^{-1} that are based on economic intuitions.

Note that, we estimate the VAR model with Bayesian methods and adopt the independent Normal-Wishart prior, which is more flexible than the natural conjugate prior. The prior distributions are described as:

$$B \sim N(\underline{B}, \underline{V_B})$$
$$\Sigma^{-1} \sim W(\underline{S}^{-1}, \underline{v})$$

where $\underline{B} = 0$, $\underline{V_B} = 10I_4$, $\underline{S} = I_4$, and $\underline{v} = 5$ are as in Koop and Korobilis (2010). The conditional posterior distributions $p(B \mid Y, \Sigma^{-1})$ and $p(\Sigma^{-1} \mid Y, B)$ are computed by the MCMC method. Following Primiceri (2005), we use a training sample prior to obtain the initial Σ^{-1}. The training sample is the first 40 observations (1974:Q4 to 1984:Q3). Using the MCMC method, 100,000 samples are obtained after the initial 30,000 samples are used as burn-in and discarded.

3.2 Time-varying Parameter VAR with Stochastic Volatility

Note that all parameters in equation (2) are time-invariant. Next, we adjust the model by allowing these parameters to vary over time:

$$Y_t = X_t B_t + A_t^{-1} \Sigma_t \varepsilon_t \tag{4}$$

where the coefficients B_t, and the parameters A_t^{-1}, and Σ_t are all time-varying. Time-varying parameters allow the relationship between oil market fundamentals, expectations and oil prices to evolve over time. Stochastic volatility allows for varying shock intensity and improves estimation precision (see Nakajima et al., 2011). We follow Primiceri (2005) and let $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, a_{42}, a_{43})'$ be a stacked vector of the lower-triangular elements in A_t and $h_t = (h_{1,t}, ..., h_{k,t})'$ with $h_{j,t} = \log \sigma_{j,t}^2$, for $j = 1, ..., k$ and $\sigma_{j,t}$ is the diagonal element of Σ_t. We assume that the parameters in (4) follow a driftless random walk process, thus allowing both temporary and permanent shift in the parameters:

$$\begin{aligned} B_t &= B_{t-1} + u_{B,t}, \\ a_t &= a_{t-1} + u_{a,t}, \\ h_t &= h_{t-1} + u_{h,t}, \end{aligned} \quad \begin{pmatrix} \varepsilon_t \\ u_{B,t} \\ u_{a,t} \\ u_{h,t} \end{pmatrix} \sim N \left(0, \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \Sigma_B & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix} \right), t = 1, ..., T$$

The shocks to the innovations of the time-varying parameters are assumed uncorrelated among the parameters B_t, a_t and h_t. We further assume for simplicity that Σ_B, Σ_a and Σ_h are all diagonal matrices. Our dynamic specification permits the parameters to vary and the shock log variance follows a random walk process to capture possible gradual or sudden structural changes, as discussed by Primiceri (2005).

For estimation, we employ a training sample prior, as shown in previous section and the prior distributions are set as follows:

$$\begin{aligned} B_0 &\sim N(B_{OLS}, 4 \cdot V(B_{OLS})) \\ A_0 &\sim N(A_{OLS}, 4 \cdot V(A_{OLS})) \\ h_0 &\sim N(h_{OLS}, 4 \cdot I_k) \end{aligned}$$

where B_{OLS}, A_{OLS}, and h_{OLS} denote the OLS point estimates and $V(\cdot)$ denotes the variance. We also need to set the hyper-parameters Σ_B, Σ_a, and Σ_h and we postulate the following inverse-Wishart prior distributions:

$$\begin{aligned} \Sigma_B &\sim IW(k_B^2 \cdot 40 \cdot V(B_{OLS}), 40) \\ \Sigma_a &\sim IW(k_a^2, 2) \\ \Sigma_{1,h} &\sim IW(k_h^2 \cdot 2 \cdot V(A_{1,OLS}), 2) \\ \Sigma_{2,h} &\sim IW(k_h^2 \cdot 3 \cdot V(A_{1,OLS}), 3) \\ \Sigma_{3,h} &\sim IW(k_h^2 \cdot 3 \cdot V(A_{1,OLS}), 4) \end{aligned}$$

where $k_B = 0.01$, $k_\alpha = 0.1$, and $k_h = 1$. $\Sigma_{1,h}$, $\Sigma_{2,h}$, and $\Sigma_{3,h}$ denote the three blocks of Σ_h

and $A_{j,OLS}$ for $j = 1, ..., 3$, denotes the three corresponding blocks of A_{OLS}. Again the estimation procedure is the MCMC method and the first 30,000 samples are discarded and 100,000 samples are obtained for the inference. The details of the MCMC procedure for TVP-VAR are explained by Primiceri (2005), Koop and Korobilis (2010) and Nakajima et al. (2011).

4 Data

To carry out our investigation we use quarterly data and our sample period begins in 1974:Q4 and ends in 2016:Q1. As is well known, quarterly data are preferred when estimating time-varying parameter models to keep estimation tractable. Indeed, TVP-VAR estimation at a monthly frequency would require many lags to capture data dynamics, and hence would be computationally intensive (see, among the others, Nakajima et al., 2011).

In Table 1, we present the sources and definitions of the data used in this study. First of all, we use the percentage change of global crude oil production ($\Delta prod_t$) obtained by the log differences of world crude oil production in millions per barrels pumped per day (averaged by month). This data is obtained from the Energy Information Administration (EIA). Secondly, as a proxy for global economic activity (rea_t), following Kilian (2009)[7] we use a measure constructed from an equal-weighted index of the percent growth rates of a panel of single voyage bulk dry cargo ocean shipping freight rates measured in dollars per metric ton. The rationale behind using this proxy is that increases in shipping rates reflects changes in the global demand for industrial commodities, including that of emerging countries such as China and India, given that supply of ocean-going vessels is likely to be inelastic in the short-run.

Regarding our measures of economic agents' expectations (Δexp_t), we extract standardized and amplitude adjusted business confidence indicators, consumer confidence

[7]Data used in Kilian (2009) is available from Lutz Kilian's homepage. The reader is referred to Kilian (2009) for details on the construction of this index.

indicators, and composite leading indicators for all OECD countries from the "OECD Main Economic Indicators" database. The main advantage of obtaining these composite indicators from the OECD is that they apply the same criteria to construct these indicators across countries so that they are consistent and comparable. Firstly, we use the OECD's Business Confidence Index (BCI) as a proxy for business leaders' expectations. This indicator combines a set of business tendency survey variables (e.g., the current and immediate future expectations on production, orders and stocks) into a single composite indicator that summarizes managers' assessment and expectation of the general economic situation. To capture consumers' expectations, we make use of the OECD's Consumer Confidence Index (CCI). Similar to BCI, CCI is based on information collected from consumer opinion surveys regarding the households' intensions for major purchases, their current economic state as compared to the recent past and their expectations for the immediate future (i.e., three months). The main characteristic of the business and consumer surveys is that they ask for the direction of change by referencing to a normal state. In translating these qualitative results into a time series, only the balance is shown by taking the difference between percentages of respondents giving favourable and unfavourable answers. Both BCI and CCI are expressed as an index (long-term average = 100) and they are seasonally adjusted. In addition, we use the Composite Leading Indicator (CLI) to capture the aggregate perception of the business leaders and consumers on the economic outlook. CLI is an aggregate time series which comprises a set of component series selected from a wide range of key short-term economic indicators. Although the underlying component series can be different for different countries depending on their economic significance, cyclical behaviour, data quality, timeliness and availability for the specific country, the CLI is designed to capture turning points and moves in the same directions as the business cycle.[8]

Our measure of the real oil price (rpo_t) is based on the Europe Brent spot price

[8]For detailed component series for each country, the reader is referred to the OECD Leading Indicators webpage. For example, the component series used to construct the CLI for the UK are: business climate indicator, new car registrations, consumer confidence indicators, Sterling 3 month interbank lending rate, production future tendency, FTSE-100 share price index.

FOB which is expressed in US dollars per barrel. We use this series as the relevant crude oil price for the world economy.[9] The monthly series of the Brent crude oil price obtained from the Datastream database is aggregated in quarterly terms and deflated using the US consumer price index. Figure 2 depicts the behaviour and dynamics of the price of Brent crude for the sample period 1985-2016. The graph shows that the oil price seems sensitive to different shocks, including changes in global crude oil production due to political instabilities, changes in quotas or production policies, the discovery of new oil fields, and the recent shale oil boom; and unexpected changes in the global macroeconomic conditions such as the Asian crisis, unexpected strong demand for oil from emerging markets from 2003 to 2008 and the global financial crisis (e.g., Abhyankar et al., 2013; Kilian, 2008; Kilian, 2016).

5 Empirical Discussion

In this section, we examine the relationships between oil price shocks, oil market fundamentals and economic agents' expectations. Firstly, we present the impulse response functions of oil prices based upon a standard Bayesian VAR (BVAR) model. Thereafter, we investigate whether the VAR model is robust to time variation based upon findings from our TVP-VAR model.

5.1 Impulse Responses from a BVAR Model

Figures 3 to 5 depict the impulse responses of oil prices to oil supply, aggregate demand and expectations shocks over the full sample and two sub-sample periods corresponding to 1974:Q4-1998:Q4 (S1) and 1999:Q1-2016:Q1 (S2), respectively. Our sample split relates to the pattern of oil prices showing a moderate volatility of this series in S1 whereas, evidently, during the period 1999:Q1-2016:Q1 sharp changes to oil prices have occurred (see for example, Baumeister and Peersman, 2013a). We present our results for a ten

[9] In the robustness checks section, we present the estimated results of our model using the US refiner acquisition cost of imported crude oil; this does not qualitatively change our main conclusions.

quarter response horizon. Our responses include the posterior median as the solid line, while the dashed lines are the 16^{th} and 84^{th} percentiles of the posterior distribution.[10]

We start by discussing the impulse responses functions (IRFs) of oil prices to oil market fundamentals and business leaders' expectation shocks (see Figure 3). The estimated results for the full sample period are shown in the first row. As we can see, an increase in oil production does not affect oil prices much since the zero axis is within the error bands. This response can be interpreted as statistically insignificant within a frequentist methodology. On the other hand, we find that the demand shocks have larger and more persistent effects. To be more specific, aggregate demand shocks caused by unexpected increases in global demand for all industrial commodities lead to a persistent and significant increase in the real price of oil. The response reaches its peak after two quarters and stabilizes soon after that. Our findings are consistent with previous studies such as Kilian (2009) and Abhyankar et al. (2013) who also find that supply played a less important role on average in explaining the price movement in oil as compared to aggregate demand.

Furthermore, as we can see from the top right graph in Figure 3, a positive expectation shock from business leaders' expectations about the future economic conditions causes an immediate increase in the real price of oil. Our findings are consistent with previous literature showing that survey-based sentiment indicators contain additional information on the state of economy which is not already available in other standard economic indicators (e.g., Ludvigson, 2004; Christiansen et al., 2014). In addition, Deeney et al. (2015), and Han et al. (2017) found that market-based and text-based sentiment proxies played an important role in modelling and forecasting the price of oil, respectively. The second and third rows of Figure 3 display the median impulse responses of oil prices to oil supply, aggregate demand and expectations shocks for subsamples S1 and S2. In general, we observe an evolving relationship between the real price of oil, oil market fundamentals and managers' expectations. For example, we find that the aggregate demand shocks and expectation shocks played more important roles during the second sub-sample period as

[10] Under normality, the 16^{th} and 84^{th} percentiles correspond to the bounds of one-standard deviation (Primiceri, 2005).

compared to the first subsample period.

Given that we are interested in finding out whether oil prices respond differently to several economic agents' expectations, now we replace the series of business confidence indicator in our BVAR model with the series of consumer confidence indicator and composite leading indicator over the full sample and the two subsamples S1 and S2 (see Figures 4 and 5). As we can observe from the first and second columns of Figures 4 and 5, the responses of oil prices to supply and demand shocks are similar to those in Figure 3. However, changes in consumers' expectations with regards to future economic conditions play a less important role as compared to business leaders' expectations. This may be explained by the fact that business leaders are generally better informed about the prospects of the economy than consumers, because they focus on investment prospects and future profitability which are affected by a large number of factors. Hence, managers have better access to information and possibly a better understanding of economic news and analyses (e.g., Bachmann and Sims, 2012; Delis et al., 2014; Caglayan and Xu, 2016). The top right graph of Figure 5 gives the impact of aggregate markets expectations from our OECD composite leading indicator (CLI). Raised expectations of the state of the economy induce a positive rise in oil prices. In addition, when we split our samples into two sub-periods, our estimated results indicate that the relationship between the real price of oil, oil markets' fundamentals and economic agents' expectations have evolved over time (see the second and third rows of Figures 4 and 5). This motivates the use of a TVP-VAR which firstly does not assume the impact of fundamentals and expectations are constant over time, and secondly, does not require us to exogenously fix subsamples.

5.2 TVP-VAR Model with Stochastic Volatility

In this section, we focus upon the time evolution of the relationship between the real price of oil, global oil production, aggregate real economic activity and expectations using a TVP-VAR model with stochastic volatility. Such an approach allows us to consider the evolving impact of oil market fundamentals, as well as expectations which may be important when there are heightened informational frictions.

Figure 6 shows the contemporaneous time-varying impulse responses of oil prices to positive shocks in oil supply, aggregate demand and expectations. In this figure the posterior median is the solid line and the dashed lines are the 16^{th} and 84^{th} percentiles of the posterior distribution. First, we find that positive innovations to global oil supply have a consistently negative impact on the real price of oil (see top panel of Figure 6). The response of commodities to demand is consistently out-with the zero axis and hence can be considered to be statistically significant from a frequentist perspective. The effect of oil supply shocks on the real price of oil is evidently time-varying as we observe a smaller response during the 1990's and 2000's as compared to the early years of our sample. Only recently, with the beginning of the US oil shale revolution, the negative effect of oil supply shocks on the real price of oil has intensified again (Kilian, 2016). Our estimated results are in contrast with the time-invariant studies, which have argued that oil supply shocks have played a minor role in explaining oil price fluctuations (e.g., Kilian, 2009; Abhyankar et al., 2013; Kilian and Murphy, 2014).

Secondly, we find that the real price of oil has responded positively to aggregate demand shocks over the entire sample period based on upon the 16^{th} and 84^{th} percentiles (see the middle panel of Figure 6). Our estimated results are in line with previous studies showing that an expansion in the global economy increases demand for industrial commodities and drives up oil prices (e.g., Kilian, 2008; Frankel, 2014). We also find that the effect of real economic activity on oil prices is time-varying. In this regard, we confirm the findings by Kilian (2009) and Abhyankar et al. (2013) indicating that the relationship between aggregate demand and the real price of oil was weaker during the 1980's and the 1990's whereas it has intensified in the mid-2000's in correspondence with the unexpected increase in demand from many emerging economies. The peak impact of demand was around the global financial crisis, but softened afterwards possibly due to heightened risk and/or uncertainty about the global economy.

Using our more flexible time-varying parameter methodology, the third shock to oil prices that we consider is that of business leaders' expectations. Our estimated results show that revised expectations regarding to the status of the economy from business leaders have a substantial and positive impact upon oil prices, see the bottom panel of Figure 6. The effect is also very time-dependent, which is less evident from the constant parameter results in Figure 3. The acutely time-varying impact is closely associated with the Global Financial Crisis, during which uncertainty rose to the levels that have rarely been seen since the Wall Street Crash. This led in 2008 to a full-blown banking crisis following the failures of Lehman Brothers, and government takeovers of Fannie Mae, Freddie Mac, and AIG (Ivashina and Scharfstein, 2010). During the periods of severe informational frictions led to confusion among market participants about the strength of economies. In particular, from 2007 until the beginning of 2008 commodity price surged due to the combination of strong demand from emerging economies and stagnant supply by oil producers. However, oil prices continued to increase over 40% from January to July 2008 when many economies were showing signs of weaknesses. Therefore, our findings suggest that expectations are useful to help to gauge global economic activity while markets growth and hence global demand was difficult to measure during the period of heightened uncertainty of the global financial crisis (see, Singleton, 2014; Sockin and Xiong, 2015).

Next, we investigate to what extent oil price change in response to variations in different economic agents' expectation on the state of the economy. In Figure 7, we report the responses of the real price of oil to oil supply shocks, aggregate demand shocks and unexpected changes in consumers' expectations. The solid line in the figures is the posterior median and the dashed lines are the 16^{th} and 84^{th} percentiles. We immediately observe the same responses of oil prices to supply and aggregate demand shocks as in Figure 6, in which negative innovations to production and positive innovations to global economic activity drive up the oil prices. However, we find that positive shocks to consumers' expectations on the economic outlook have a negative impact on oil prices. This result can be explained by the fact that the consumer confidence index is based on households' current and future economic conditions including their plans for major purchases (Ludvigson, 2004). Our findings are consistent with the literature on the cost channel that is associated with higher oil prices (Kilian, 2008; Edelstein and Kilian, 2009). For example, consumers may increase their precautionary savings and smooth their consumptions in response to positive oil price shocks as they perceive a greater chance of future unemployment; large oil price volatility can also raise uncertainties about future energy market conditions and affect consumers' consumption and investment behaviour, often resulting in reduced or postponed investments and purchases on goods and services. Our estimated results suggest that an increase (deterioration, respectively) in consumers' expectations affect the price of oil negatively (positively, respectively).

Figure 8 shows the estimated IRFs of oil prices in response to oil supply, aggregate demand and market aggregate expectation shocks. We find that the responses of the real price of oil to both supply and aggregate demand shocks are similar to those in Figures 6 and 7. However, increases in market expectations affect oil prices to a lesser extent than before. This result can be explained by the nature of composite leading indicators combining the expectations of business leaders and consumers. As we have seen in Figures 6 and 7 these shocks have opposite effects on oil prices. As a consequence, the response of the real oil price to changes in aggregate expectation played a less important role.

In sum, our empirical findings highlight the importance for allowing heterogeneous expectations across economic agents (Baumeister and Kilian, 2016). Our results also consistent with the arguments from Morris and Shin (2002) and Sockin and Xiong (2015) that there may be greater complementarity between oil prices and firms' productions than households' consumptions, when the oil price increases in the presence of informational frictions represents a rise in global demand. Hence, firms benefit more from news about positive global demand, rather than the cost effects of increased oil prices. For example, good producers continued to increase their demand for commodities despite the high commodity prices from January to July 2008. On the other hand, consumers may have less complementarity between oil prices and consumption, since households' individual consumption decisions are less affected by global demand and more impacted by the cost channel of increased oil prices.

5.3 Robustness Checks

We now report some robustness checks for our TVP-VAR model, and report most of the results in Appendix B. First, we focus on the series of the oil price. In particular, many previous studies analysing the determinants of oil price fluctuations have used the series US refiner acquisition cost of imported crude oil (see, for example, Barsky and Kilian, 2004; Kilian, 2009; Kilian and Murphy, 2012). Therefore, we re-estimate our models by replacing the series of the Europe Brent spot price with this series. Figure B1 suggests that the responses of oil prices to oil supply, aggregate demand and expectations shocks are in line with those reported in Figures 6-8. Second, we show that our assumptions about the identification order do not influence the main empirical findings. Figure B2 shows that the directions of the responses to the structural shocks are qualitatively similar when we placed the economic agents' expectations first in equation ((4)). Finally, we replace the economic agents' expectations emanated from all OECD countries to the US market only. The estimated impulse response functions of oil prices to oil market fundamentals and expectations shocks are shown in online Appendix Figure B3. Again, this does not qualitatively change our main findings.

6 Conclusion

Modelling oil price movements is important to many decision makers in macroeconomic policy, capital investment/production decisions, consumption, risk and portfolio management. The oil price is considered as an important barometer for the global economy (Sockin and Xiong, 2015; Ravazzolo and Philip, 2016). For example, changes in oil prices help to predict GDP fluctuations, and often central banks take explicit account of the volatility of oil price in setting monetary policy. Morris and Shin (2002) set out why noise in public information has an amplified effect on agents' actions. Oil prices can play an important role in feeding back news to, and affecting the investment decisions of, a wide range of agents and industries. Oil prices can also affect the design of regulatory policies such as the imposition of automotive fuel standards or gasoline taxes, environmental policies in reducing carbon emissions and climate change. For instance, energy companies decision to expand oil and gas exploration, or invest in renewable energy technologies. It also has important implications for the economic viability of the production of shale oil and biofuels, which directly affects the energy security of the oil-importing countries.

Our paper extends the topical literature on identifying the determinants of oil prices, by emphasising the role of informational frictions and expectations. Our research relates to work in behavioural finance and psychology, which argues that human behaviour and financial markets respond differently in times of heightened fear and uncertainty. Our investigation focuses upon expectations from three sources: business leaders, consumers and markets. Oil price may not fully reflect fundamentals since agents can have severe informational frictions. In this context expectations impact oil prices, although the source of these expectations matters. Another innovation in this paper is the application of a TVP-VAR model with stochastic volatility to flexibly delineate the impact of fundamentals and economic agents' expectations. This approach allows all parameters to evolve continuously, informing us when, and to what extent, there is a change over time in the impact of oil price determinants. This is rather than imposing an arbitrary sample split to account for changing price dynamics. Our model also allows for time-varying heteroskedasticity in the VAR innovations to account for changes in the magnitude of shocks. This feature is especially important given abrupt changes in volatility between the Great Moderation and Global Financial Crisis (Primiceri, 2005; Baumeister and Peersman, 2013a).

Our results show that supply shocks arising from unexpected global oil production changes negatively affect the real price of oil. We find that the effect of production on oil prices is time-varying. For instance, the negative effects of oil supply shocks have intensified recently, which may account for the US shale oil boom. We identify that since the middle of the 2000's, oil prices respond positively to unexpected increases in demand, for example from emerging economies since the mid-2000's. Furthermore, we discover that the real price of oil responds differently to expectations that arise from business leaders, consumers and aggregate markets. Increases in business leaders' expectations have a more positive impact upon the real price of oil than due to aggregate markets' expectations. Additionally, unexpected increases in consumers' expectation negatively affect the real price of oil, if at all.

In sum, our empirical evidence is consistent with the idea that there is non-constant relationship between oil prices and global demand, partly because this link is masked by informational frictions. This implies that the oil price itself may be a useful signal of global economic activity for policy makers and market participants. Regulators might consider how their policies (e.g., capital and asset allocation, taxes, and environmental policies) might be perceived by mangers and households. For market participants, our results suggest that one need to take account of heterogeneous beliefs from economic agents' perception on the future economic conditions, and their impact on oil prices to set up their decision (e.g., capital investment, productions, consumptions, risk management, and trading strategies). Moreover, informational frictions and expectations may be important for other commodity prices, such as metals and agricultural price. We shall leave these issues for future work.

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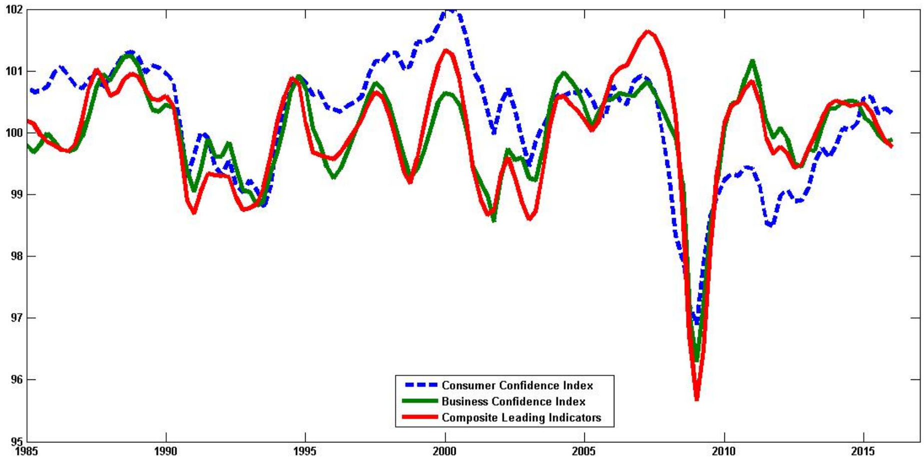
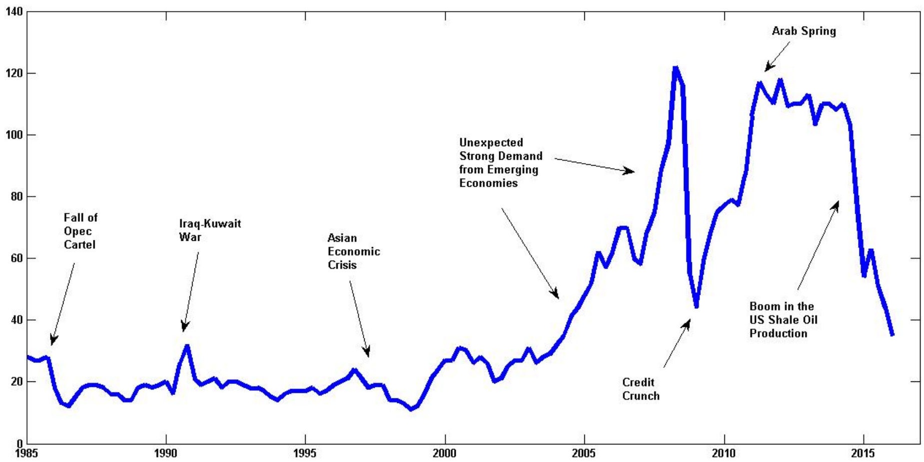
Figure 1: Time Series proxies Economic Agents Expectations



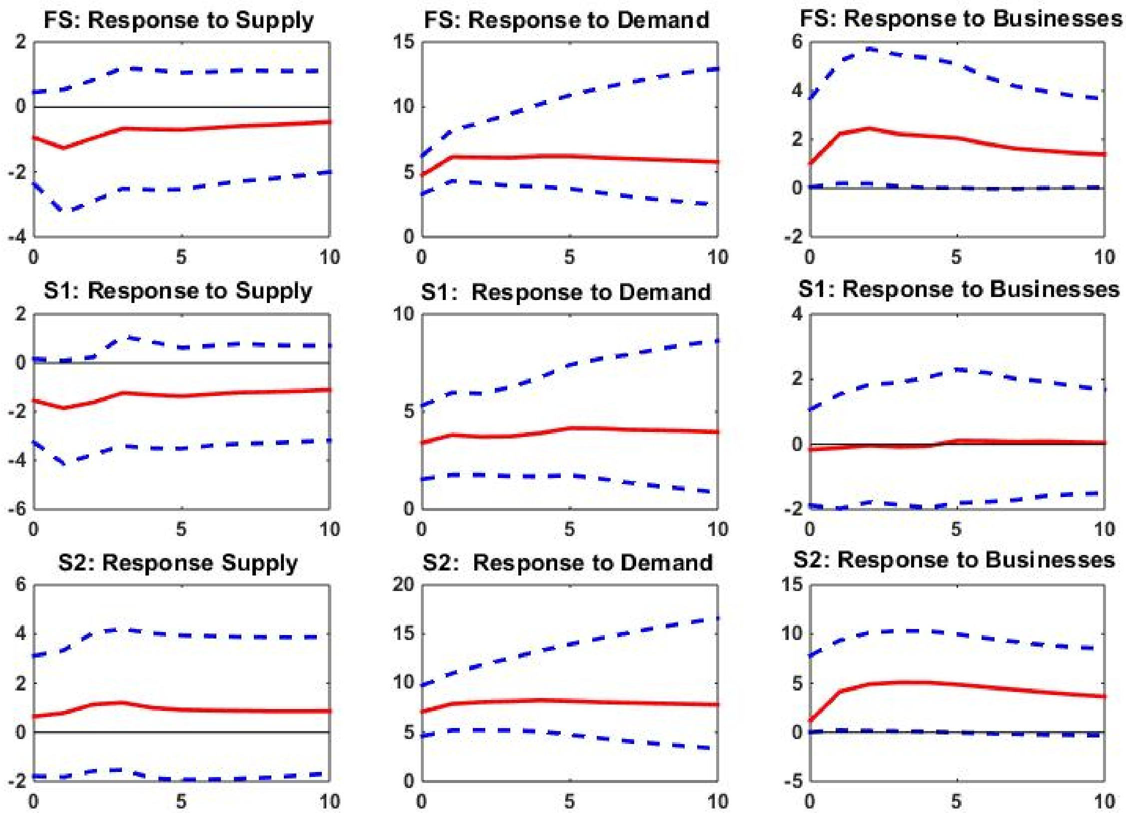
Notes: This figure contains time series data including business expectations as proxied by OECD Business Confidence Index (BCI). Consumer expectations are proxied by Consumer Confidence Index (CCI). Finally we proxy market analysts expectations using Composite Leading Indicators (CLI).
Source: OECD Monthly Main Economic Indicators Database.

Figure 2: Europe Brent Spot Crude Price FOB



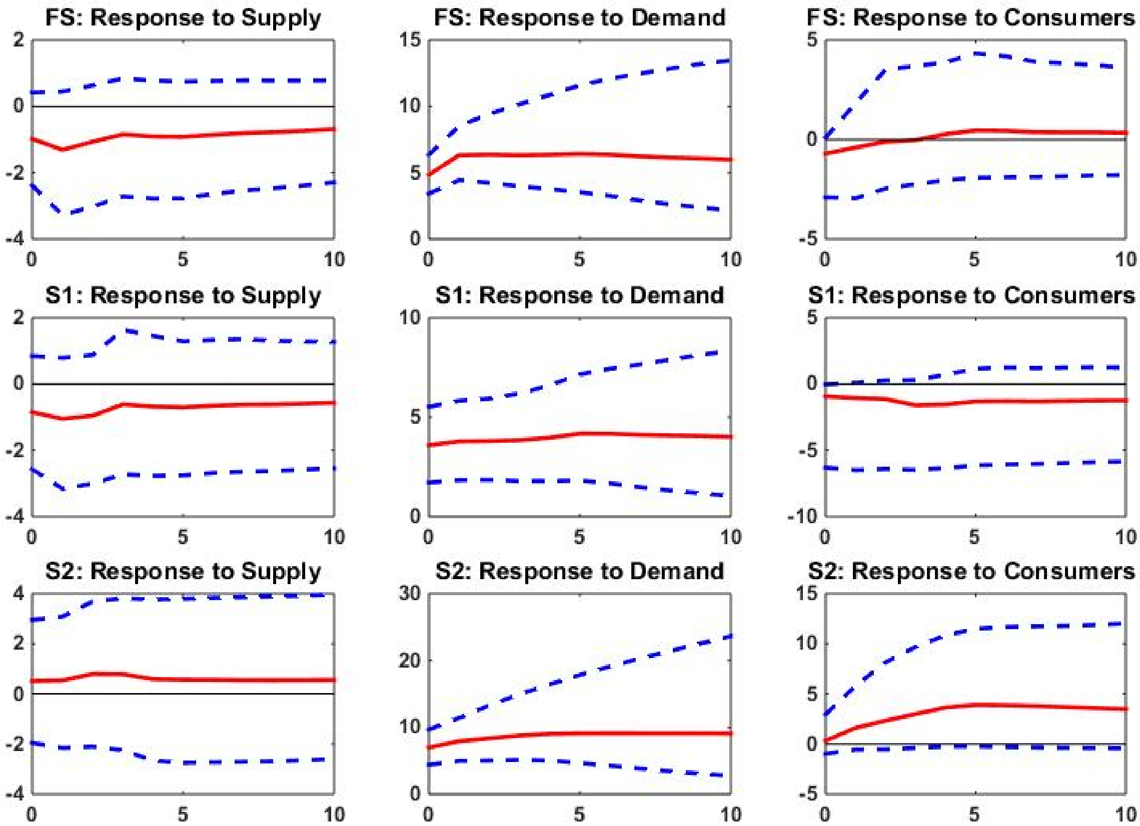
Notes: Europe Brent Spot Price FOB (US dollars per barrel) and major oil price episodes.
Source: Datastream database.

Figure 3: BVAR Impulse Responses of Real Price of Oil under Business Leaders Expectations



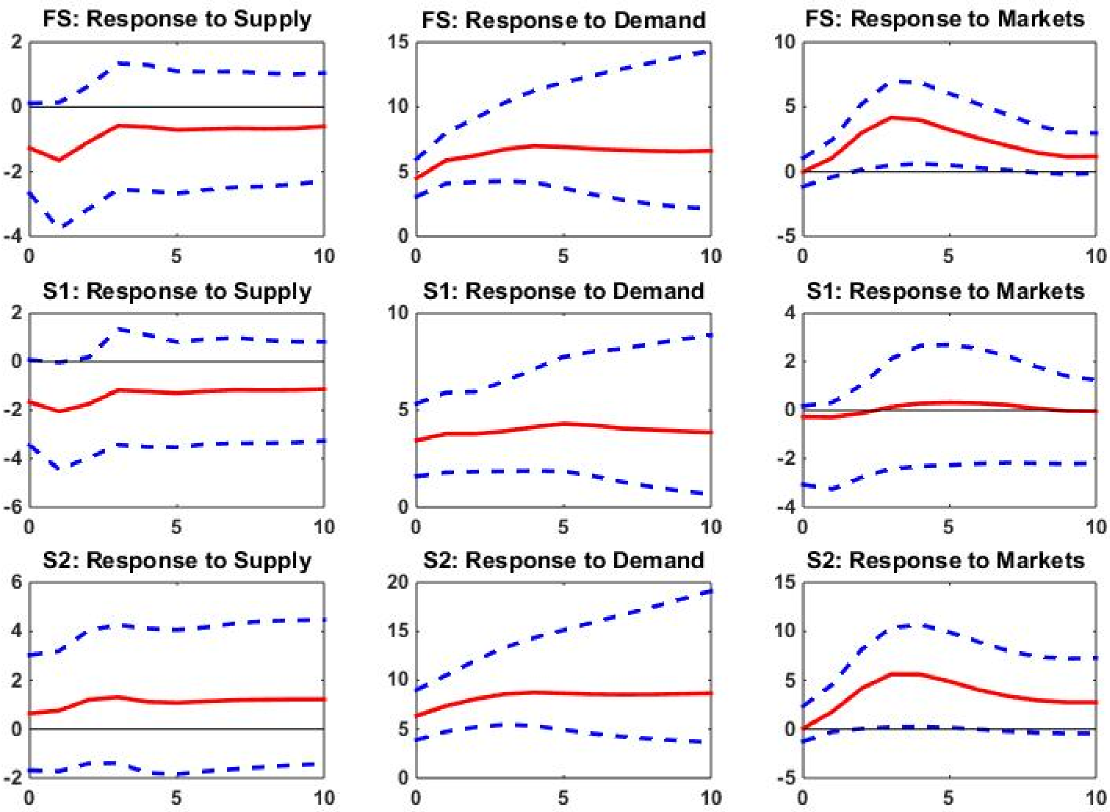
Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16th and 84th percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and business confidence indicator (BCI). The first row reports the IRFs for the full sample period (1974:Q4-2016:Q1) whereas, the second and third rows report the IRFs for two sub-samples 1974:Q4-1998:Q4 (S1), and 1999:Q1-2016:Q1 (S2), respectively.

Figure 4: BVAR Impulse Responses of the Real Price of Oil under Consumers Expectations



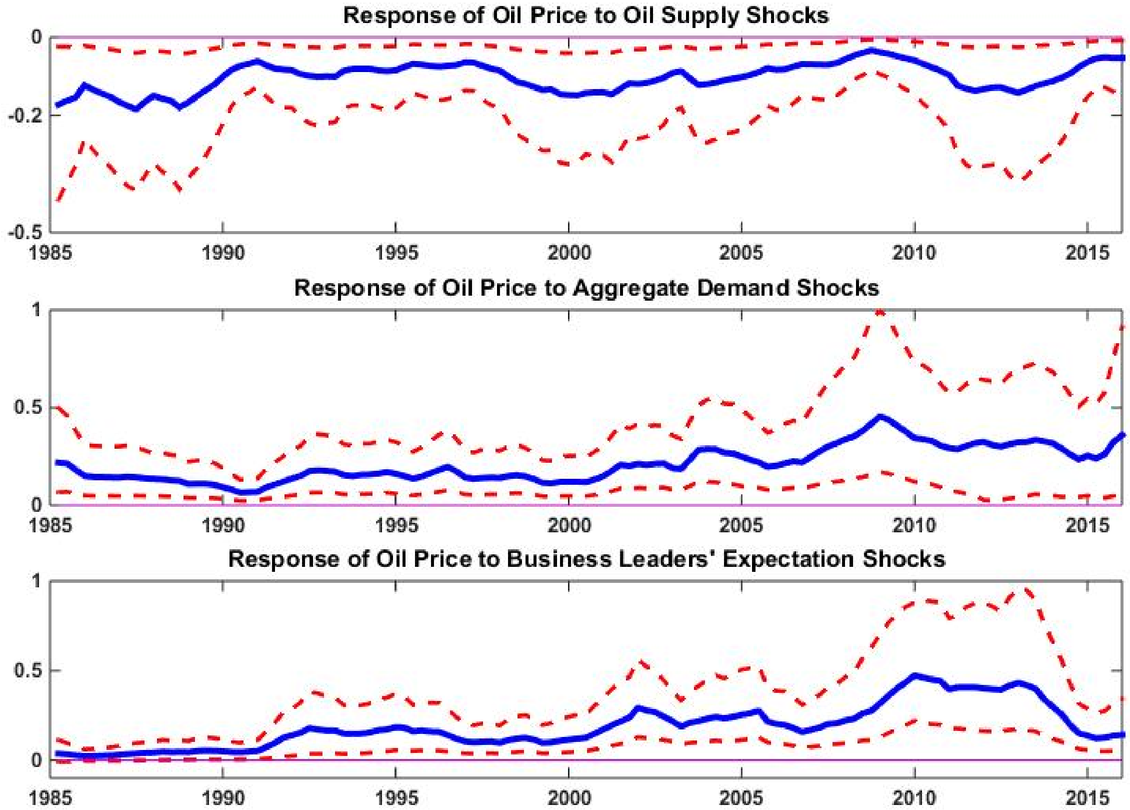
Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16th and 84th percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and consumer confidence indicator (CCI). The first row reports the IRFs for the full sample period (1974:Q4-2016:Q1) whereas, the second and third rows report the IRFs for two sub-samples 1974:Q4-1998:Q4 (S1), and 1999:Q1-2016:Q1 (S2), respectively.

Figure 5: BVAR Impulse Responses of the Real Price of Oil under Markets Expectations



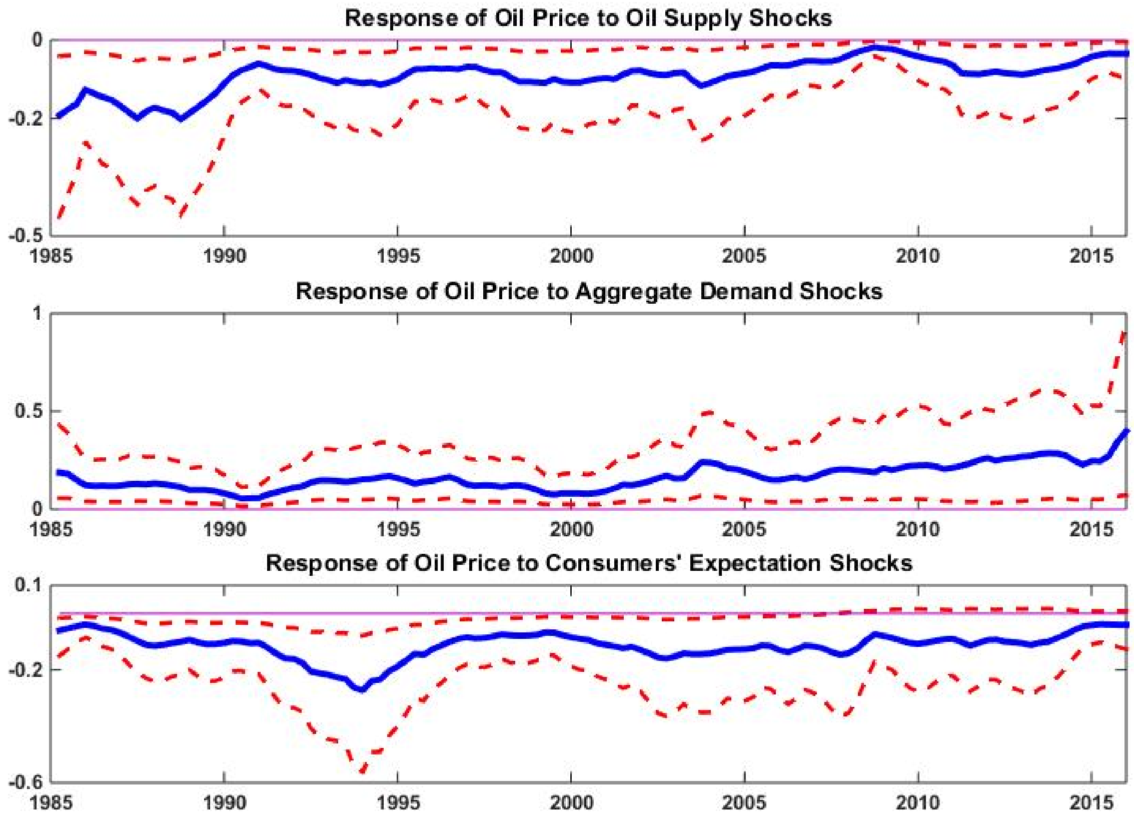
Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16th and 84th percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and composite leading indicator (CLI). The first row reports the IRFs for the full sample period (1974:Q4-2016:Q1) whereas, the second and third rows report the IRFs for two sub-samples 1974:Q4-1998:Q4 (S1), and 1999:Q1-2016:Q1 (S2), respectively.

Figure 6: TVP-VAR Impulse Responses of Real Price of Oil under Business Leaders Expectations



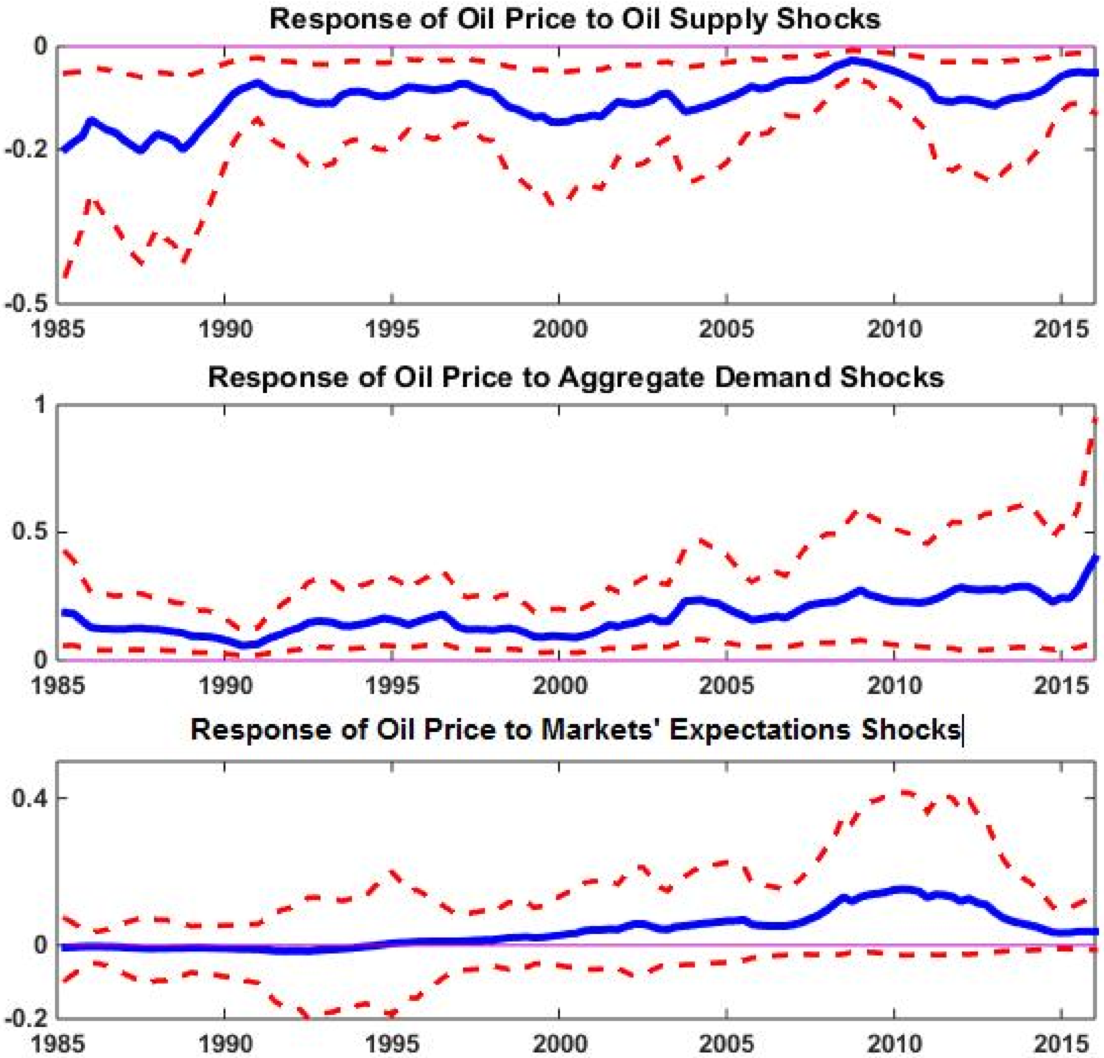
Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16th and 84th percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and business confidence indicator (BCI). The estimates are based on the TVP-VAR model in equation (4). Each panel measures how a unit impulse of several shocks impacts the oil price over the full sample period.

Figure 7: TVP-VAR Impulse Responses of Real Price of Oil under Consumers Expectations



Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16th and 84th percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and consumer confidence indicator (CCI). The estimates are based on the TVP-VAR model in equation (4). Each panel measures how a unit impulse of several shocks impacts the oil price over the full sample period.

Figure 8: TVP-VAR Impulse Responses of Real Price of Oil under Markets Expectations



Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16th and 84th percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and composite leading indicator (CLI). The estimates are based on the TVP-VAR model in equation (4). Each panel measures how a unit impulse of several shocks impacts the oil price over the full sample period.

Table 1: Data Sources and Definitions

Variable	Data Series	Definition	Sources of Data
Percentage change in global oil production	Global Oil Production	World crude oil production in millions per barrels pumped per day (averaged by month).	Energy Information Administration, Monthly Energy Review
Global real economic activity	Single-voyage freight rates	See Kilian (2009) for detailed information on how to construct this series.	Lutz Kilians homepage: http://www-personal.umich.edu/ lkilian/reaupdate.txt.
Economic Agents Expectations	Business Confidence Indicator (BCI)	BCI is a composite indicator that summarizes managers' assessments and expectations of the general economic situation.	OECD Monthly Main Economic Indicators database.
	Consumer Confidence Indicator (CCI)	CCI include indicators on consumer confidence, expected economic situation and price expectations.	
	Composite Leading Indicator (CLI)	CLI is an aggregate time series displaying a reasonably consistent leading relationship with the reference series (e.g., industrial production up to March 2012 and GDP afterwards) for the macroeconomic cycle in a country. CLI is designed to provide early signals of turning points between expansions and slowdowns of economic activity.	
Real oil Price	Europe Brent spot price FOB	The original series is aggregated in quarterly terms and deflated using the US CPI.	DataStream

Appendix A: Identification Assumptions

Our restrictions on A_t^{-1} are based on the following assumptions and economic intuitions. The first assumption is that global crude oil supply does not respond to the demand shocks in the crude oil market immediately, but does so with a delay of at least a quarter. This is plausible since making changes in oil production are costly in the short-run and oil producers therefore base their production plans on expectations of medium-term demand (see e.g., Hamilton, 2009; Kilian and Murphy, 2012).

The second assumption is that increases in the real price of oil driven by expectation demand shocks and oil-market specific demand shocks do not affect global economic activity immediately. This assumption is based upon Stock and Watson (2005), who have classified the series into slow-moving variables, such as real output; and fast-moving variables such as stock prices, money and credit. Global real economic activity is considered slow-moving: it is plausible that consumers and firms slowly revise their spending plans after financial market shocks or expectation shocks.

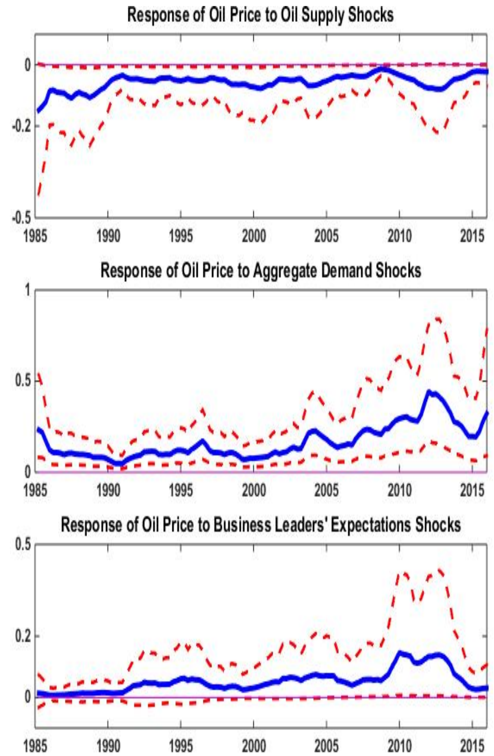
Our third restriction implies that changes to economic agents' expectations are predetermined with respect to oil prices. This assumption is related to informational frictions that in our empirical framework are captured by agents expectations. The best example to explain our argument relates to the commodity price boom of 2007 to 2008. In particular, from 2007 until the beginning of 2008 commodity prices skyrocketed due to the combination of strong demand from emerging economies and stagnant supply by oil producers. However, oil prices continued to increase from January to July 2008 at a time when the US had already entered a recession in November 2017 and many developing economies were showing signs of weakness. At the same time a large investment flow led goods producers to believe that developing economies were stronger than they actually were. Therefore, goods producers continued to increase their demand for commodities despite the high commodity prices. We believe that this episode allows us to rule out the instantaneous feedback from real oil prices to global economic agents' expectations without loss of generality.

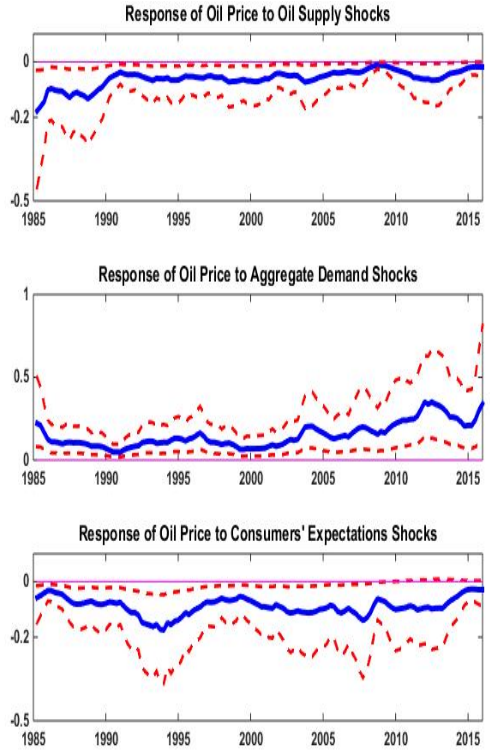
Finally, shocks to the real oil price that are not explained by oil supply shocks or aggregate demand shocks by construction reflect changes in the demand for oil in contrast to changes in the demand for all industrial commodities. We define these shocks as oil market-specific demand shocks. In particular, these shocks represent the fluctuations in precautionary demand for oil due to uncertain future oil supply.

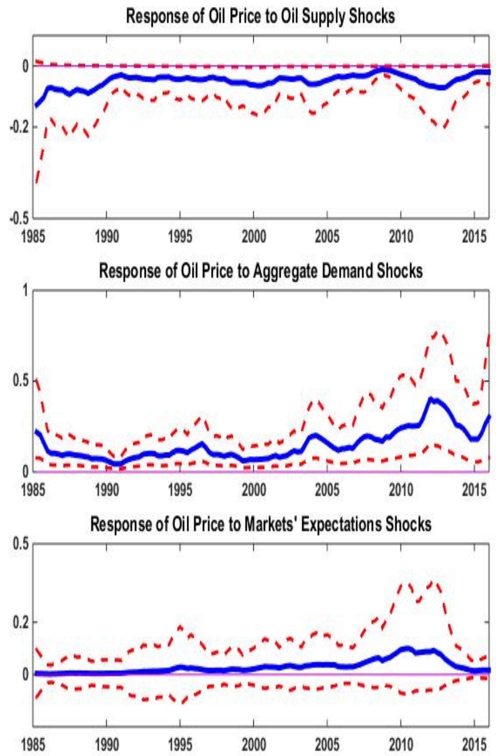
Appendix B: Robustness Check

Table B1: Replacing Brent Crude to US Refiner Acquisition Cost of Imported Crude Oil

Panel A: Responses of oil prices to fundamentals and business leaders expectations shocks	**Panel B:** Responses of oil prices to fundamentals and Consumers expectations shocks	**Panel C:** Responses of oil prices to fundamentals and Markets expectation shocks



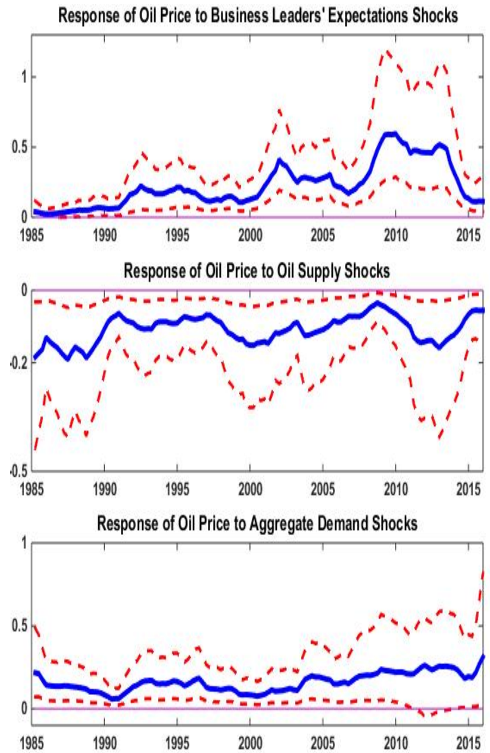


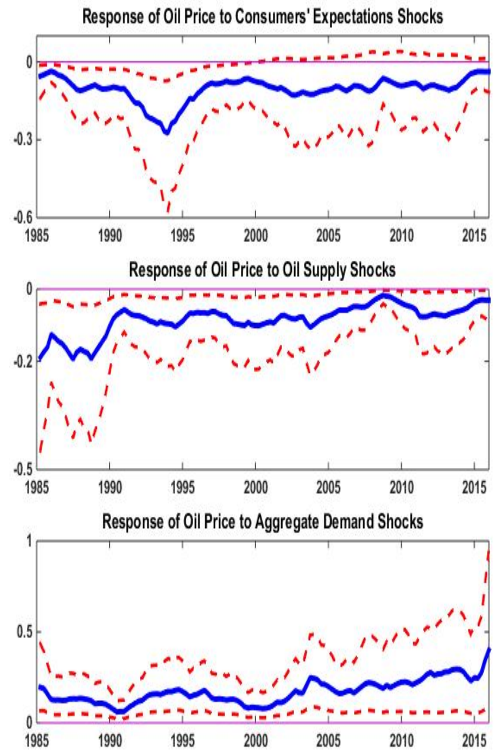


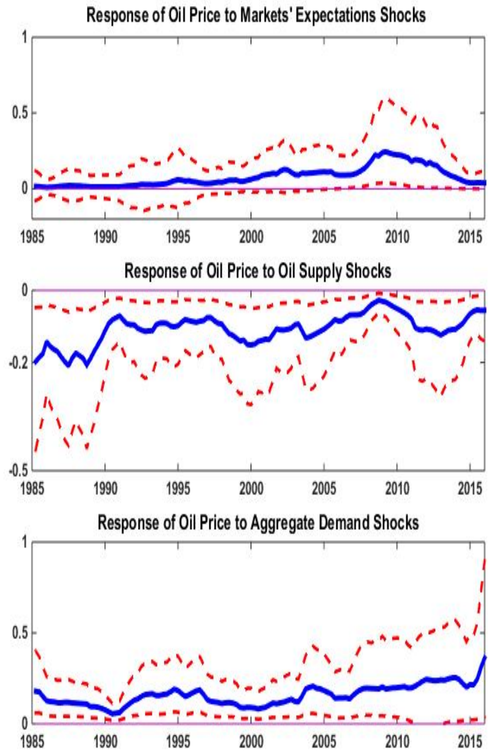
Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16th and 84th percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and expectations. Each figure measures how a unit impulse of several shocks impacts the oil price over the full sample period.

Table B2: Impulse Responses of Oil Price with Different Ordering of the Variables

Panel A: Responses of oil prices to fundamentals and business leaders expectations shocks	**Panel B:** Responses of oil prices to fundamentals and Consumers expectations shocks	**Panel C:** Responses of oil prices to fundamentals and Markets expectation shocks



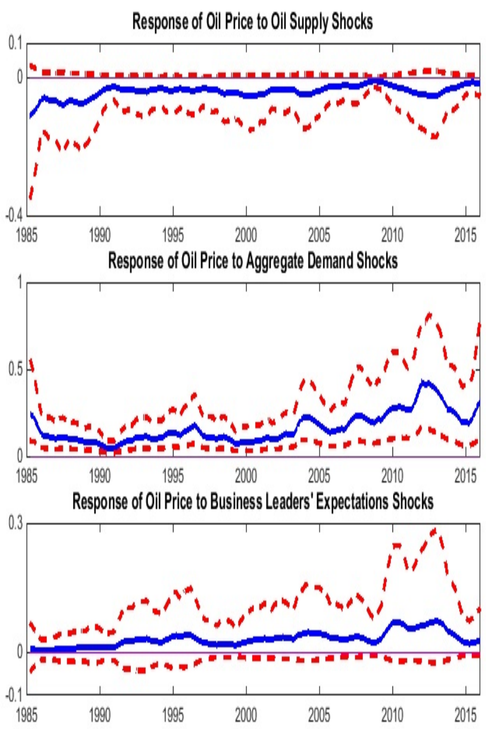


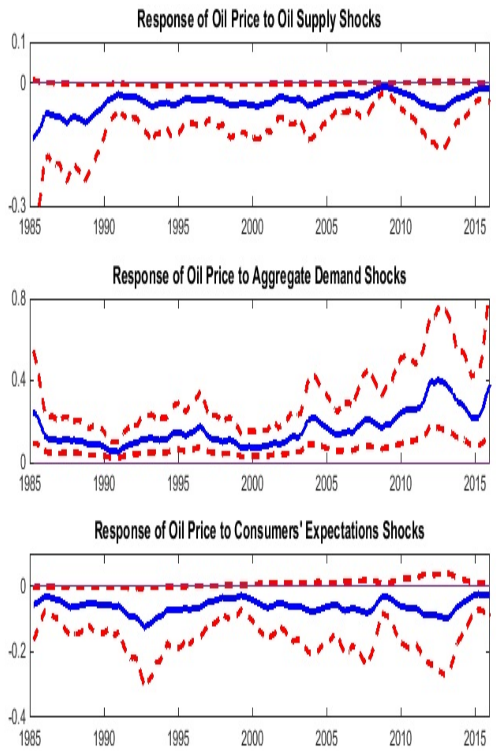


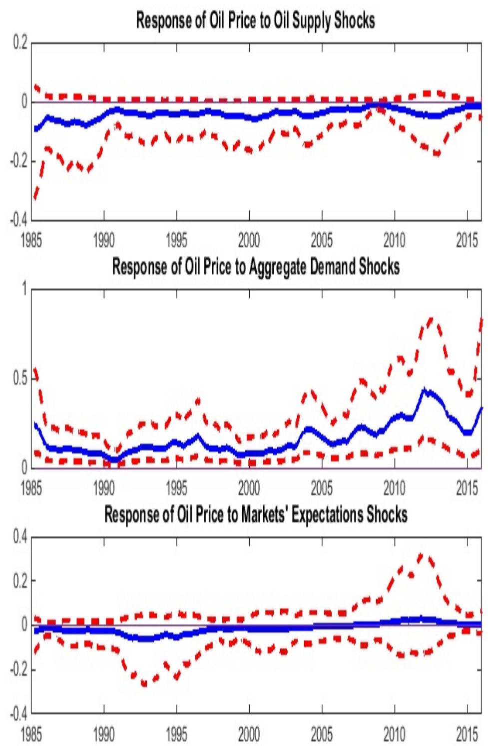
Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16th and 84th percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and expectations. Each figure measures how a unit impulse of several shocks impacts the oil price over the full sample period.

Table B3: TVP-VAR Robustness Analysis Using US Expectation Indicators

Panel A: Responses of oil prices to fundamentals and business leaders expectations shocks	**Panel B:** Responses of oil prices to fundamentals and Consumers expectations shocks	**Panel C:** Responses of oil prices to fundamentals and Markets expectation shocks







Notes: In each graph solid lines represent the median responses whereas dashed lines indicate the 16th and 84th percentiles error bands. We consider three different shocks to oil prices: oil supply, aggregate demand and expectations. Each figure measures how a unit impulse of several shocks impacts the oil price over the full sample period.