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Joseph P. Byrne and Erkal Ersoy

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EH14 4AS
ceerp.hw.ac.uk

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Joseph P. Byrne* and Erkal Ersoy†

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Abstract

There continues to be considerable interest in the relationship between oil market fundamentals, oil prices, and uncertainty. This paper examines the impact of oil market uncertainty shocks upon oil fundamentals and prices. We utilise a Bayesian stochastic volatility-in-mean VAR approach, which endogenously models oil market uncertainty and allows the data to dynamically impact uncertainty. We find evidence that supply uncertainty shocks are linked to demand uncertainty, and that supply shocks are associated with a fairly pronounced increase in oil price uncertainty.

Keywords: Oil Prices; Endogenous Uncertainty; Bayesian VAR; Stochastic Volatility-in-Mean.

JEL Classification Codes: C32; E32; Q43.

*Address: Edinburgh Business School (Economics), Heriot-Watt University, Edinburgh, Scotland, UK. Email: <j.p.byrne@hw.ac.uk>.

†Corresponding author. Address: Edinburgh Business School (Economics) and Centre for Energy Economics Research and Policy (CEERP), Heriot-Watt University, Edinburgh, Scotland, UK. Email: <e.ersoy@hw.ac.uk>.

1 Introduction

The oil market and oil prices are of perennial importance to consumers and producers, and therefore to academic researchers and policy makers. A host of important issues pertaining to the oil market have been considered by the academic literature, including the measurement and relative importance of supply and demand shocks for oil prices (see Kilian, 2009; Kilian and Murphy, 2013; Baumeister and Hamilton, 2019) and the impact of oil prices upon macro- and microeconomic activity (see *inter alia* Hamilton, 2005; Blanchard and Riggi, 2013; and Baumeister and Hamilton, 2019).

We add to the oil market literature by considering the relevance of time varying endogenous uncertainty for the oil market itself and for economic activity more broadly. Existing work examining oil and uncertainty include research by Elder and Serletis (2010) and Jo (2014). The former considers whether oil price uncertainty depresses investment using GARCH-in-mean methods, while the latter uses an exogenous stochastic volatility model to examine the role of oil price shocks for demand. However, oil market fundamentals may reasonably be expected to impact stochastic volatility endogenously, and uncertainty may not only arise with respect to oil prices but also regarding the impact of supply or demand shocks on the oil market.

In an econometric innovation particularly useful for our application, Mumtaz (2018) and Mumtaz and Theodoridis (2019) extend Bayesian VAR model estimation to accommodate the role of endogenous variables in driving uncertainty shocks. In their approach, like Jo (2014), uncertainty is proxied by stochastic volatility, although there are deeper dynamics within Mumtaz's (2018) volatility-in-mean model. This facilitates the possibility of feedback between level and volatility shocks in the oil market.

Our contribution to the oil uncertainty literature is therefore as follows. First, we endogenously examine the impact of oil market uncertainty within the Bayesian VAR with stochastic volatility-in-mean model of Mumtaz (2018). This allows the data to dynamically impact time varying uncertainty, as measured by stochastic volatility. Second, we utilise the global demand indicator recently developed by Baumeister and Hamilton (2019), when examining the oil market. Third, within this context, we consider a fuller set of oil fundamental shocks, with different identification schemes. To preview our results, we find evidence that oil price uncertainty shocks impact demand uncertainty. Further, we observe that supply shocks are linked to oil price uncertainty, although we find less evidence that supply *uncertainty* impacts price uncertainty. This paper is structured as follows. Section 2 provides a brief introduction to the literature, Section 3 provides an overview of econometric model and data used in our study, Section 4 presents our results and then Section 5 concludes.

2 Literature Review

Oil has the largest market share in global primary energy consumption compared to other fuels, accounting for over a third of global consumption in 2019 (BP, 2020). Much effort has been dedicated to understanding how oil prices relate to economic activity and growth. A negative relationship between oil prices and country GDP has consistently been identified, irrespective of whether countries are industrialised or net importers (Mork, 1989, 1994; Papapetrou, 2001).[1] There is also extensive evidence considering whether oil prices are impacted by demand, see Hamilton (1996), Kilian (2008), Baumeister and Peersman (2013) and Blanchard and Riggi (2013).[2]

[1]Early contributions to this literature are from Nordhaus, Houthakker, and Sachs (1980) and Hamilton (1983).

[2]See also Allan (2009) and Stern and Kander (2012).

The impact of economic uncertainty upon investment and wider macroeconomic activity has frequently been highlighted, see Dixit and Pindyck (1994). For example, irreversibility justifies a delay in investment in periods of uncertainty (Bernanke, 1983; Pindyck, 1991). Hamilton (2005), Kilian and Vigfusson (2011) point out that this observation holds for durable good purchases, especially those that use oil as an input. The oil industry is particularly susceptible to uncertainty given large investment chains and capital-intensive production processes. Pindyck (2004) argue that volatility affects total marginal cost of production and persistent changes in volatility can alter investment decisions, including those in production facilities and transportation. Further, these studies conclude that volatility has implications for derivative valuation, hedging decisions, and investment decisions in physical capital tied to production and consumption of oil.

These make oil market volatility a critical component of modelling. The existing literature has considered several facets of oil volatility. Sadorsky (2006) focused on forecasting volatility; Yang, Hwang, and Huang (2002), Chen and Chen (2007) and Elder and Serletis (2010) investigated the relationship between oil price volatility and the economy; Regnier (2007) studied the relative price volatility of crude oil, refined petroleum products, and natural gas. Jo (2014) examines the impact of oil price uncertainty on world industrial production, which covers global industrial activities in key sectors. The author defines a time-varying measure for oil price uncertainty, which is the standard deviation of one-quarter-ahead oil price forecasting error, and uses a stochastic volatility-in-mean approach to model oil market uncertainty. Based on a quarterly vector autoregressive model, the author concludes that a shock to stochastic volatility negatively impacts global real economic activity and demand for oil, measured in the form of global industrial production. See also Byrne, Lorusso, and Xu (2019) for an empirical oil model with exogenous volatility.

There is a lively debate in the literature about how to accurately measure global oil demand. Kilian (2009) measures global demand using a shipping index. This has been criticised since it can vary for logistical reasons, making the demand measure noisy. Baumeister and Hamilton (2019) construct a measure of industrial production based on OECD and large non-OECD countries. Using this measure, the authors find robust evidence of the impact upon global economic activity of oil supply shocks, but little evidence of an impact of shocks to oil demand. The authors also concluded that supply disruptions play a larger role in historical oil price fluctuations than other factors, including inventory accumulation (Baumeister & Hamilton, 2019).

3 Empirical Methods

3.1 Stochastic Volatility-in-Mean VAR

In this section, we introduce Mumtaz's (2018) state space model with stochastic volatility in mean, which we use to investigate the oil market. The key advantage of this empirical approach over potential alternatives is that it allows the data to dynamically affect stochastic volatility, and the covariance between level shocks and volatility is not restricted to zero.[3]

$$h_t = \alpha + \theta h_{t-1} + \sum_{j=1}^{Q} d_j Z_{t-j} + S^{1/2}\eta_t \tag{1}$$

$$Z_t = \gamma + \sum_{j=1}^{P} \beta_j Z_{t-j} + \sum_{k=1}^{K} b_k h_{t-k} + H_t^{1/2} e_t \tag{2}$$

Transition equation (1) represents the stochastic volatility (h_t) element of our model, and the measurement equation (2) gives the dynamics for the core data,

[3] See also Koopman and Hol Uspensky (2002) for a more restrictive stochastic volatility in mean model.

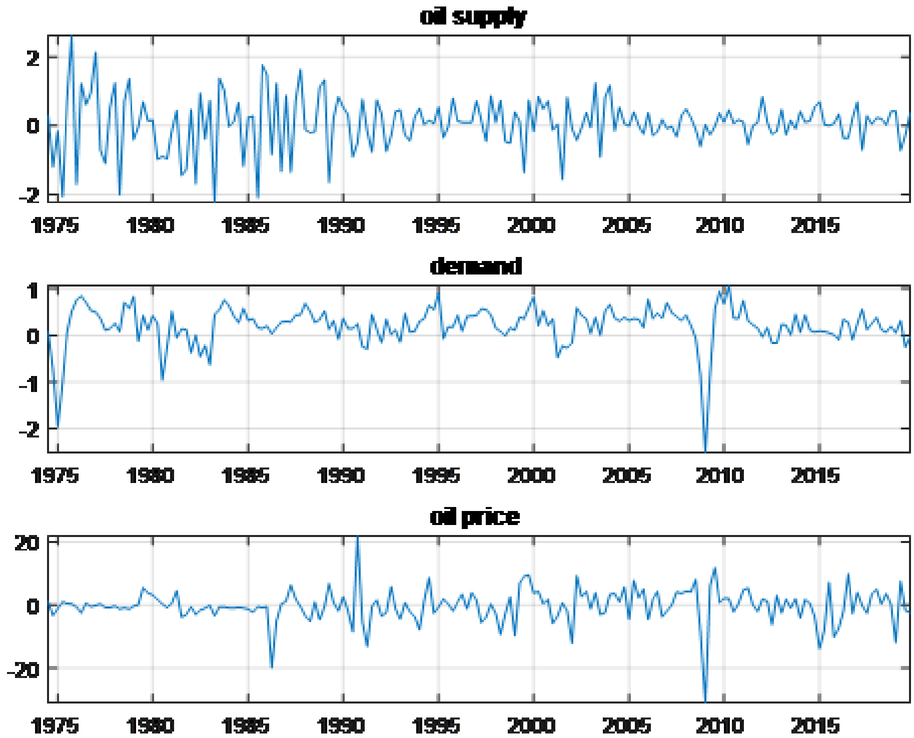
Z_t. In the former equation, stochastic volatility, $h_t = (h_{1t}, h_{2t}, h_{3t})$, is a function of lagged h_t. Data dynamics are provided by $Z_t = (dq_t, dy_t, dp_t)$ which is an $(N \times 1)$ vector, and consists of supply (dq_t), demand (dy_t) and real oil prices (dp_t). $S^{1/2}$ and $H_t^{1/2}$ are the shocks in the transition and measurement equations. Transition and measurement equation residuals η_t and e_t are 3×1 disturbance vectors (i.e. η_t, $e_t \sim \mathcal{N}(0, \Sigma)$ and the model allows these error terms to be correlated. Parameters of interest are α, θ, d_j, γ, β_j and b_k.

The model is estimated using a Gibbs sampling algorithm. We use 30,000 repetitions and 25,000 burn-in, with priors estimated over a pre-sample of 40 observations. The VAR lag lengths Q, P and K are equal to 2, based upon a basic VAR Bayesian Information Criteria (BIC) and in the interest of model parsimony.

3.2 Data

This section outlines the data used in our study. For oil prices, we use US Refiners Acquisition Cost (RAC) of Imported Crude Oil, as in Ersoy (2020). We deflate oil prices using US CPI from the Bureau of Labor Statistics. We capture demand in our model as measured by global industrial production from Baumeister and Hamilton (2019). This includes industrial production in OECD and large non-OECD countries from OECD Main Economic Indicators (MEI). Supply is global oil production from the US Energy Information Administration and Thomson Reuters Datastream (Code: WDPCOBD.P). The data span the period from January 1974 to August 2019 at monthly frequency. Figure 1 presents the growth rates (i.e. $100 * ln(X_t/X_{t-1})$) for oil supply, demand, and oil prices, which are the core data used in our analysis.

Figure 1: **Oil Supply, Demand, and Prices**

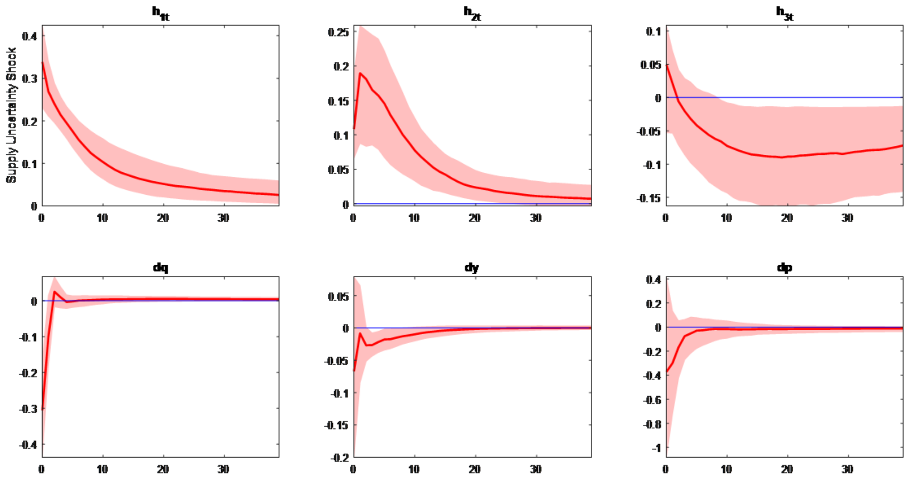


Notes: This figure shows growth rates of each of the key variables in our analysis as a percentage change over the sample period (January 1974 through August 2019).

4 Results and Discussion

We now turn to the impulse response functions based on a series of shocks to uncertainty measures and fundamentals within our empirical model. As a reminder, in our approach, uncertainty is represented by endogenous stochastic volatility. In this context, we consider the impact of uncertainty both within and outwith the oil market. We start by focusing on the impact of supply shocks. Examining the impact of supply uncertainty is of interest itself but particularly valuable, since it can contribute to the debate about the relative importance of supply versus demand shocks for the oil market. Due to stock-building or inventory withdrawals in some cases, supply can have limited impact on oil prices, but it may still affect supply uncertainty and, by extension, the parameters of our model.

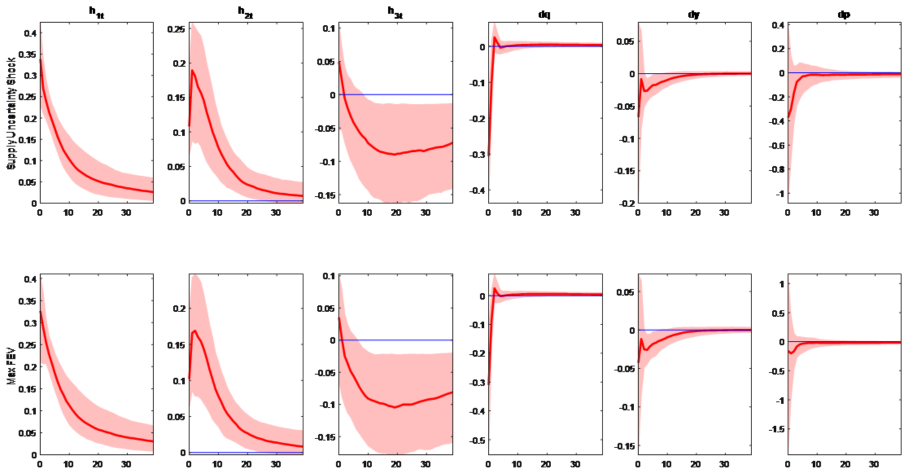
Figure 2: **Oil Market Supply Uncertainty Shock**



Notes: This figure gives the impulse response functions to a shock to oil supply uncertainty. Estimation is by a Bayesian SV-in-Mean VAR. Each panel shows the magnitude of the response on the y-axis and a 40-month response horizon on the x-axis. The top row shows the uncertainty responses of, respectively, supply (h_{1t}), demand (h_{2t}), and oil prices (h_{3t}). The bottom panel has the responses of supply (dq), demand (dy), and oil prices (dp) themselves. Shaded posterior response intervals are 32% and 68%.

Figure 2 provides impulse response functions with 40-month response horizons for a shock to oil supply volatility (h_{1t}) and its impact on stochastic volatility of oil demand (h_{2t}), stochastic volatility of oil prices (h_{3t}) as well as oil supply (dq), oil demand (dy), and oil prices (dp). We identify the supply shock using a Cholesky decomposition, and we order the data in the VAR(2) as supply, demand, and oil price. We therefore shock the first series in our VAR. From Figure 2, we see that a positive shock to supply uncertainty is associated with a similar positive impact on demand volatility. In contrast, oil price volatility is impacted to a lesser extent. While the relationship between supply and demand is intuitively appealing (i.e. shocks to supply are associated qualitatively with shocks to demand), the notion that positive supply shocks are associated with a fall in oil price uncertainty is more challenging to conceptualise. Visual inspection of Figure 1 helps rationalise that while supply shocks predominated in the 1970s, oil price volatility, based upon our measure of RAC, increased later in the sample period.[4]

Figure 3: **Supply Uncertainty Shock with Additional Shock Identification**



Notes: This figure gives the impulse response functions to a shock to oil supply. The top row shows the responses based on Cholesky identification. The bottom row shows the responses based on Uhlig (2004) identification. Posterior response intervals are 32% and 68%.

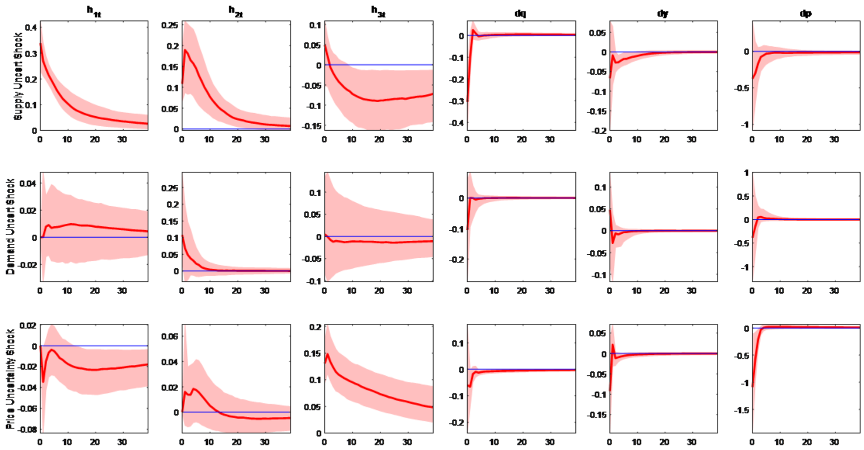
A natural way to consider whether our results are robust to different identification schemes is to use the approach of Uhlig (2004). This places restrictions on the forecast error contribution of the shocks and can be applied to the first, and only the first, variable in the VAR. In Figure 3, the two sets of impulse response functions from Cholesky and Uhlig identification are broadly consistent: supply and demand uncertainty shocks are positively correlated.

Next, we consider the impact of demand and oil price uncertainty shocks. Figure 4 provides evidence that demand uncertainty is less important for the oil market than other variables we have studied. In contrast, oil price uncertainty

[4]Results based upon the post-1990 period indicate that the negative supply-price nexus does not survive beyond the 1980s.

is expected to reduce oil prices. Finally, we consider the impact of shocks to the growth rates, rather than uncertainty, of oil supply, demand, and oil price. These impulse response functions are shown in Figure 5, and the key result is that demand growth raises oil prices consistent with previous evidence. A further observation is that although supply shocks do not impact oil prices directly, they raise oil price uncertainty.

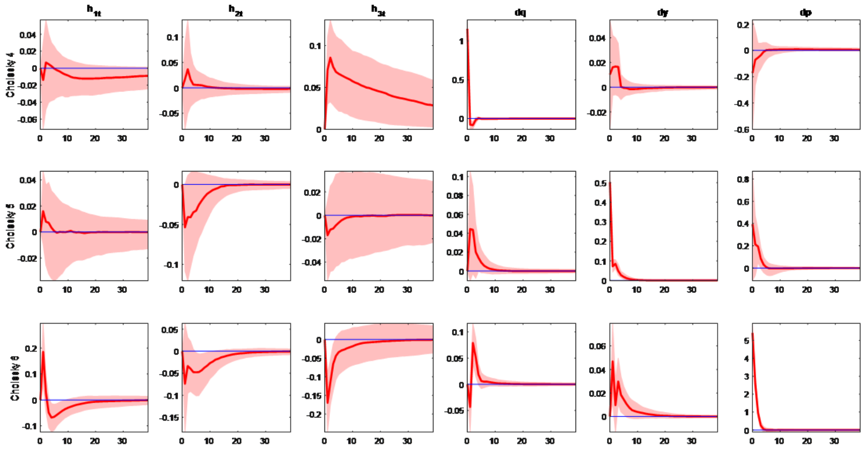
Figure 4: **Supply, Demand and Price Uncertainty Shocks**



Notes: This figure gives the impulse response functions to three different uncertainties shocks to supply (top row), demand (middle row), and price (bottom row). Each row (shock) has six responses: supply uncertainty (h_{1t}), demand uncertainty (h_{2t}), and oil price uncertainty (h_{3t}), followed by supply growth (dq), demand growth (dy), and oil price growth (dp) rates themselves. Shaded posterior response intervals are 32% and 68%.

Comparing our results to those in Jo (2014), we identify a few key differences: first, our results show that the impact of oil supply shocks are transmitted through an uncertainty channel. Second, we find evidence that demand and oil price growth are linked positively. Third, controlling for the endogeneity of oil price uncertainty weakens the observed negative relationship between increases in oil price uncertainty and demand, as suggested by Jo (2014).

Figure 5: **Supply, Demand and Price Shocks**



Notes: This figure gives the impulse response functions to three different growth rate shocks supply (top row), demand (middle row), and price (bottom row). Each row (shock) has six responses: supply uncertainty (h_{1t}), demand uncertainty (h_{2t}) and oil price uncertainty (h_{3t}), followed by supply growth (d_q), demand growth (d_y), and oil price growth (d_p) rates themselves. Shaded posterior response intervals are 32% and 68%.

5 Conclusion

This paper presents an empirical study of the impact and response of oil price uncertainty shocks. We utilise recently developed Bayesian VAR methods with stochastic volatility in mean. We find evidence that supply uncertainty shocks are linked to demand uncertainty, and that supply shocks are associated with a fairly pronounced increase in oil price uncertainty. We also contrast our results with Jo (2014). In particular, we find that the impact of oil supply shocks primarily operate through an uncertainty channel. Further, we observe that demand and price growth are strongly and positively linked to one another. While increases in oil price uncertainty have a negative impact on demand as suggested by Jo (2014), we do not find that this evidence is especially strong once we account for the endogeneity of uncertainty.

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