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Jamie L. Cross
BI Norwegian Business School, Norway

Bao H. Nguyen
University of Tasmania, Australia

Trung Duc Tran
University of Sydney, Australia

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The Role of Precautionary and Speculative Demand in the Global Market for Crude Oil*

Jamie L. Cross[†] Bao H. Nguyen[‡] Trung Duc Tran[§]

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Abstract

Contemporary structural models of the global market for crude oil treat storage demand as a composite of precautionary responses to uncertainty and speculative behavior, due to difficulties in jointly identifying these distinct demand components. This difficulty arises because the underlying expectation shifts are latent and operate through similar transmission mechanisms. In this paper, we extend the workhorse oil market model by jointly identifying these distinct demand components. Our main insight is that precautionary demand is the primary driver of the real price of crude oil, previously associate with storage demand shocks. Historically, precautionary demand shifts associated with adverse sociopolitical conditions in the Middle-East, can explain the oil price spikes during the 1979 oil crisis and the Wars of 1980 and 1990, while speculative demand was a more important driver during the disbandment of OPEC. Finally, we find that these newly identified shocks have distinct consequences for the U.S. economy: precautionary demand shocks reduce real GDP, while speculative demand shocks cause inflation.

JEL-codes: C32, C52, Q41, Q43

Keywords: Oil price uncertainty, Oil market, SVAR, Narrative sign restrictions

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[†]BI Norwegian Business School, Centre of Applied Macroeconomics and Commodity Prices (CAMP).

[‡]University of Tasmania and Centre for Applied Macroeconomic Analysis (CAMA).

[§]University of Sydney.

1 Introduction

Over the past decade, numerous studies have shown that identifying the underlying drivers of the global market for crude oil is important not only for explaining real price of oil dynamics, but also for understanding the macroeconomic consequences of oil price shocks.[1] Central to these insights has been the application of a structural vector autoregressive (VAR) model proposed in Kilian and Murphy (2014), which jointly identifies three such drivers: (i) *flow supply shocks*—unanticipated variation in the quantity of oil being extracted from the ground; (ii) *flow demand shocks*—unanticipated demand for commodities associated with the business cycle; and (iii) *storage demand shocks*—unanticipated demand for above-ground oil inventories arising from *expectations* about the level of supply relative to demand.[2] While the identification of flow demand and supply shocks stems from earlier work by Kilian (2009), storage demand shocks are identified by noting that unobservable shifts in expectations about future oil demand and supply conditions are reflected in observable shifts of the demand for above-ground crude oil inventories. Underlying these shifts, however, are two very different types of economic behavior (Kilian and Murphy, 2014, p.455). First, *speculative demand* for oil occurs as buyers anticipate future market conditions. Second, *precautionary demand* for oil occurs in response to heightened uncertainty about the price of oil.[3] Thus, while storage demand shocks are known to be an important driver in the global market for crude oil, the relative effects of the underlying precautionary and speculative demand shocks remains unknown. This calls for a more general structural model that is capable of simultaneously capturing these distinct demand components.

In this paper, we jointly identify the precautionary and speculative demand for oil that underlie storage demand shocks, and for the first time examine their relative effects in the global market for crude oil and on US macroeconomic aggregates. The difficulty in jointly identifying these two demand shocks arises because the expectation shifts are latent and operate through similar transmission mechanisms. On the one hand, an unanticipated increase in uncertainty about future market conditions causes agents to insure against possible shortfalls by increasing their holdings of above-ground oil inventories. This precautionary demand for oil results in an immediate increase in the real spot price of crude oil, followed by a gradual decline (Alquist and

[1]See e.g. Herrera and Rangaraju (2019) for a recent survey of the empirical literature.

[2]An overview of the methodological developments of oil market models is provided by Kilian and Zhou (2020).

[3]The notion of precautionary demand shocks stems from earlier papers by Kilian (2009) and Alquist and Kilian (2010).

Kilian, 2010). On the other hand, when speculators purchase a large quantity of oil inventories, they send a signal to oil producers that they expect higher prices in the future. This speculative demand results in producers increasing their holdings of inventories in order to sell it at the higher future price (Kilian and Murphy, 2014).

To overcome this identification problem, we build on the workhorse structural VAR model of the global oil market developed in Kilian and Murphy (2014), as recently refined in Zhou (2019), by jointly identifying both precautionary and speculative behavior. This is done by first proposing an observable monthly measure of real oil price uncertainty, and then utilizing a set of theoretically consistent sign restrictions, along with the fact that precautionary motives are associated with high uncertainty, to identify these two distinct shocks.

To measure oil price uncertainty (OPU) we construct an observable monthly OPU index. In the spirit of Diebold and Kilian (2001) and Jurado et al. (2015), we define OPU as the conditional volatility of the unpredictable component from a forecasting model of the real price of oil. Unlike commonly used volatility indicators, such as the Chicago Board Options Exchange's (CBOEs) Oil Price Volatility Index (OVX) or model based measures, e.g. generalized autoregressive heteroscedasticity (GARCH) and stochastic volatility (SV), this definition captures the fact what matters for economic decision making is not whether the real price of oil has become more or less variable, but rather whether it has become more or less predictable, i.e. less or more uncertain. In this sense, the index also differs from alternative OPU indexes that are based on OPEC announcements (Plante and Traum, 2012) or media coverage (Bonaparte, 2015), but is similar that in Nguyen et al. (2019), who construct a similar index to examine the macroeconomic effects of flow demand and supply shocks in states of high and low uncertainty. While both our index and that in Nguyen et al. (2019) are premised on the same idea, the present index differs from theirs in four ways that are each important to examining the effects on the real price of oil. First, the real price of oil is measured by the conventional US refiners' acquisition cost for imported crude oil (IRAC), as compared to the International Monetary Fund's (IMFs) crude oil price index. Second, our index starts at 1973 instead of 1994. Third, we use a state of the art oil price forecasting model as opposed to a simple auto regressive model. Fourth we specify a sufficient lag structure to capture long cycles in the real price of oil as suggested in Kilian and Lütkepohl (2017).

Our results provide new insights on the relative roles of precautionary and speculative demand in driving the real price of oil since the 1970s. Overall, we find that uncertainty driven precautionary demand for crude oil is, on average, the primary driver of fluctuations in the real price of oil that have previously been associated with storage demand shocks. On a more localized level, we find that shifts in precautionary demand account for much of the oil price variation during periods of adverse sociopolitical conditions in the Middle-East, such as the 1979 oil crisis, The Iran-Iraq War of 1980 and the Persian Gulf War of 1990. This point has been recognized for a long time (e.g. Hamilton (2003); Barsky and Kilian (2004a); Kilian (2009)), but this is the first time that the effects of such shocks has been quantified in a fully structural model that explicitly identifies precautionary demand shocks. In addition to finding an import role for precautionary demand, we also find that speculative demand was an important driver of the real price of oil collapse associated with the disbandment of OPEC in 1985. In line with existing research, however, we observe no evidence of rising speculative demand after 2003, with flow demand shocks accounting for much of the oil price dynamics during the 2003-08 oil price surge (Kilian and Murphy, 2014; Kilian and Lee, 2014), a result that is generally attributed to unexpectedly high demand from emerging Asia (Kilian and Hicks, 2013; Aastveit et al., 2015). Consistent with results in Zhou (2019), we also find that flow demand shocks were the primary driver behind the oil price collapse during the Great Recession, while both flow demand and supply shocks account for much of the oil price decline in 2014/15.

In addition to these new results, our model enables us also to examine macroeconomic effects of the previously confounded precautionary and speculative demand shocks. For instance, Kilian (2009) finds that *oil-market specific demand shocks*—a residual shock after accounting for flow demand and supply shocks—lower real GDP and raise consumer prices. Repeating this exercise with our structural model reveals that identifying the underlying precautionary and speculative motives that drive the real price of oil matters for US macroeconomic performance. In particular, we observe that speculative demand shocks have no impact on real GDP but raise the CPI price level, while precautionary demand shocks depress real GDP, and have no impact on prices. This new insight is likely to be of great importance to policy makers with an inflation targeting mandate, who can deter speculation via targeted policies. It also builds on related literature that has examined the macroeconomic effects of precautionary demand and speculative demand one at a time (Elder and Serletis, 2010; Jo, 2014; Anzuini et al., 2015), by controlling for impacts of alternative oil market shocks.

The paper is organized as follows. In Section 2 we discuss the OPU index. We present the oil market model in Section 3, discuss results for the oil market in Section 4 and the macroeconomic implications in Section 5. We conclude in Section 6.

2 Construction of the Oil Price Uncertainty Index

A key challenge in empirically examining the effects of uncertainty driven precautionary motives in the global market for crude oil is that they are not directly observable. For this reason, scholars interested in examining the effects of oil price uncertainty shocks have historically relied on model based proxies such as GARCH or SV models (Elder and Serletis, 2010; Jo, 2014). Despite the popularity of these approaches, an alternative view is that volatility based measures are not good proxies of uncertainty because they do not capture the fact that what matters for economic decision making is not whether particular economic variables have become more or less disperse, but whether the economy has become more or less predictable (Diebold and Kilian, 2001; Jurado et al., 2015). As a result, uncertainty should not be defined in terms of volatility, but instead, in terms of predictability. This is not to say that modeling volatility is irrelevant for measuring uncertainty, but rather, that it is important for the predictive model to be sufficiently informative, so that the measured forecast error is first "purged of predictive content" (Jurado et al., 2015, p.1184). Only then should a volatility model be applied to extract the underlying uncertainty component of the time series. With this idea in mind, Nguyen et al. (2019) recently proposed an oil price uncertainty (OPU) index that is defined as the one-period ahead forecast error variance of a forecasting model. More precisely, the one-period ahead uncertainty, OPU_{t+1}, of an oil price series, y_t, is defined as

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

where the expectation $E(\cdot|I_t)$ is formed with respect to information available at time t. Note that the definition implies that uncertainty about oil prices will be higher when the expectation today of the squared error in forecasting y_{t+1} rises, and vice versa.

The forecast in (1) is obtained by a time series model of the form

$$y_{t+1} = \phi\left(L\right)y_t + \psi\left(L\right)X_t + \sigma_{t+1}\epsilon_{t+1}, \tag{2}$$

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

$$\begin{bmatrix}\epsilon_{t+1}\\ \eta_{t+1}\end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}\right), \tag{4}$$

where $\phi\left(L\right)$ and $\psi\left(L\right)$ are lag polynomials and X_t is a matrix of predictors which contain information that is considered robust in forecasting oil prices. The stochastic volatility parameters α, β, ω can be estimated using Bayesian methods (Kastner, 2016). Given these values, one-period-ahead uncertainty defined in (1), given all available information at date t, is then given by

$$OPU_{t+1} = \sqrt{E[(\sigma_{t+1})^2|I_t]},$$
$$= \sqrt{\exp\left(\alpha + \beta\log(\sigma_t)^2 + \frac{\omega^2}{2}\right)}. \quad (5)$$

It should be noted that with longer-horizon forecasts, uncertainty is not equal to stochastic volatility in residual σ_{t+1}. Instead, there are additional autoregressive terms, stochastic volatility in additional predictors and covariance terms (Jurado et al., 2015).

Two decisions must be made when constructing the index. First is the choice of an appropriate oil price series, and second is to select a matrix of variables that are useful predictors of the selected oil price series.

In the first stage, we use the IRAC in place of the IMFs crude oil price index used in Nguyen et al. (2019). While the use of the IMF's series is sufficient for a wide range of applications, the IRAC is by far the most commonly used measure of the global price of crude oil in academic studies that investigate the underlying drivers of the real price of crude oil. This includes both Kilian and Murphy (2014) and Zhou (2019), whom we build on in this paper.

In the second stage, we forecast the real price of crude oil using a set of additional variables from a state of the art oil price forecasting model in Alquist et al. (2013). In contrast, Nguyen et al. (2019) use an autoregressive model with four lags. Our set of variables includes the set of fundamental oil market variables suggested by Kilian and Murphy (2014): oil production, real economic activity and above-ground oil inventories, and additional variables that have been shown to be important drivers of the price of oil: US CPI inflation and the M1 money supply, commodity currency exchange rates, and excess co-movement with other commodity prices. The number of lags for both the autoregressive and predictor polynomials is set to be 24. The choice of a long lag length is known to be essential when modeling oil prices as it allows for a richer dynamic relationship (Kilian and Lütkepohl, 2017). Finally, following Bai and Ng (2008), the predictors X_t that we ultimately use in the predictive equation (2) in each forecast is restricted to those that have significant predictive power, as defined by a $|t - stat| > 2.575$.

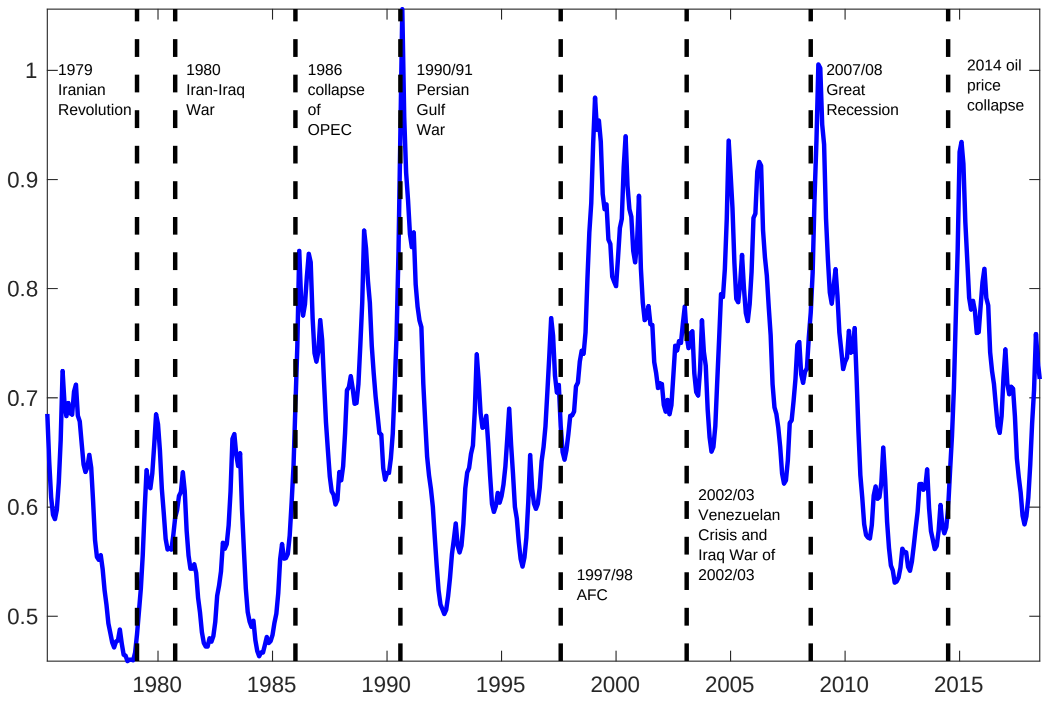

Figure 1: Oil price uncertainty (OPU) index

Notes: The figure plots the oil price uncertainty index (OPU) constructed in Section 2 from 1975:2 to 2018:6.

The resulting OPU index is plotted in Figure 1, along with major events associated with the oil market. Overall, the general trend is that the uncertainty index displays clear spikes around significant events. This includes sociopolitical events such as the Iranian revolution, the Iran-Iraq War, the disbandment of OPEC in 1986, and the Persian Gulf War. It also includes other well known episodes of significance, such as the Asian crisis of 1997/98, when the real price of oil fell to an all-time low, the large price decline during the Great Recession and the more recent 2014/15 price drop.

In the Online Appendix we examine the role of using additional predictors and compare the OPU with various other uncertainty measures. We here summarize the results. First, we show that an OPU with no predictors will overstate the degree of oil price uncertainty. The most important predictors are commodity exchange rates and excess co-movement terms. Information about above-ground oil inventories, US inflation and M1 money stock affects the OPU to a lesser extent, while we see little effect from removing the real economic activity index. Second, we show that our oil price uncertainty measure is distinct from the CBOE Oil Price Volatility Index (OVX) and three widely used sources of alternatively uncertainty measures: financial uncertainty, as measured by the CBOE (stock price) Volatility Index (VIX); the US Economic Policy Uncertainty (EPU) index proposed by Baker et al. (2016); and the US macroeconomic uncertainty (JLN) index constructed by Jurado et al. (2015). In particular, our OPU does not pick up high uncertainty about the Dotcom crisis or the European Debt Crisis that are otherwise detected by the VIX since those events are more relevant to the stock exchange. In addition, neither the VIX or JLN macro uncertainty index detects any surge in oil uncertainty during 2000/02 or 2015/16. Taken together, this suggests that the OPU index is able to pick up uncertainty events that are highly specific to the oil market.

3 Empirical Methodology

3.1 The Structural VAR Model

The structural VAR model of the global market for crude oil is given by

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{b} + \sum_{j=1}^{24} \mathbf{B}_j\mathbf{y}_{t-j} + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{I}), \tag{6}$$

where $\mathbf{y}_t = (\%\Delta prod_t, rea_t, rpo_t, \Delta inv_t, OPU_t)'$ in which: $\%\Delta prod_t$ is the percent change in global crude oil production, rea_t is a measure of global real economic activity, rpo_t is the natural logarithm of the global real price of oil, Δinv_t is the change in above-ground global crude oil inventories and OPU_t is the oil price uncertainty index discussed in Section 2. The lag order of 24 is in line with existing studies, e.g. Kilian (2009), Kilian and Murphy (2014) and Zhou (2019).

3.2 Data

The reduced form version of the above structural VAR model is estimated with a data set that contains monthly observations on the four fundamental oil market variables from 1973:1 to 2018:6, plus our oil price uncertainty index. First, *crude oil production* is taken from the U.S. Energy Information Administration (EIA) and converted to percent changes. Second, *real economic activity* is taken to be the dry cargo shipping rate business cycle index proposed in Kilian (2009) and subsequently revised in Kilian (2019). This index is stationary by construction. Third, the *real price of crude oil* is defined as the US refiners' acquisition cost for imported crude oil, as reported by the EIA, extrapolated from 1974:1 back to 1973:1 as in Barsky and Kilian (2001) and deflated by the US consumer price index (all items), which are obtained from the FRED database. Fourth, *above-ground crude oil inventories* are measured using total US crude oil inventories scaled by the ratio of OECD petroleum stocks over US petroleum stocks, all of which are obtained from the EIA. In order to facilitate proper computation of the oil demand elasticity in use, the resulting proxy for global crude oil inventories is expressed in changes. Finally, following Kilian and Murphy (2014) and Zhou (2019), we deseasonalized each of these variables before estimating the model.

3.3 Identification

To identify the global oil market shocks, we use four sets of identifying assumptions. This consists of the (1) static sign restrictions, (2) elasticity restrictions (3) dynamic sign restrictions, and (4) narrative restrictions in Zhou (2019). To identify the precautionary and speculative components underlying their speculative demand shock, we make modifications to steps (1) and (4), and direct the reader to Zhou (2019, p.132) for details of steps (2) and (3).[4]

3.3.1 Static Sign Restrictions

The first stage of identification utilizes the set of static sign restrictions in Table 1 to obtain a set of admissible models in which the variables contemporaneously respond to the four structural shocks are in line with economic theory.[5] Following Kilian and Murphy (2014), a flow supply shock (column 1), here described as a supply disruption, reduces real economic activity, while increasing the real price of oil. Such events may occur due to supply disruptions associated with exogenous political events in oil-producing countries and unexpected politically motivated supply decisions by OPEC members (Hamilton, 2003; Kilian, 2008, 2009). In contrast, a flow demand shock (column 2) increases each of oil production, real economic activity and the real price of oil. In both cases, the inventory response is unspecified, thereby allowing the data to determine the reaction. This shock has been shown to have played, and continue to play, a leading role in determining real oil price dynamics (Barsky and Kilian, 2001, 2004b; Kilian, 2009; Kilian and Murphy, 2012, 2014; Aastveit et al., 2015; Zhou, 2019).

[4]In short, (2) amounts to imposing a lower bound on the short-run demand elasticity of -0.8 and an upper bound on the short-run supply elasticity of 0.04. Also, (3) amounts to restricting the responses of oil production and global real activity to an unanticipated flow supply disruption to be negative for the first 12 months, while the real price of oil response is restricted to be positive.

[5]The sign restrictions are implemented with the algorithm in Antolín-Díaz and Rubio-Ramírez (2018) which builds on the widely used procedure in Rubio-Ramirez et al. (2010) narrative restrictions.

Table 1: Sign restrictions

	flow supply shock	flow demand shock	speculative demand shock	precautionary demand shock
Oil production	$-$	$+$	$+$	$\times$
Real Economic Activity	$-$	$+$	$-$	$-$
Real oil price	$+$	$+$	$+$	$+$
Inventories	$\times$	$\times$	$+$	$+$
Uncertainty	$\times$	$\times$	$\times$	$+$

Notes: $+$ and $-$ respectively indicate positive and negative responses, while $\times$ leaves the effect unrestricted. In the event that the signs in column four (the precautionary demand shock) are the same as columns one (flow supply shock) or three (speculative demand shock), we assume that the precautionary demand shock induces a larger response in uncertainty (i.e. element (5,4) is larger than elements (5,1) or (5,3)).

To identify their storage demand shock, Kilian and Murphy (2014) postulate that such a shock will reduce real economic activity, while increasing oil production, the real price of oil and above-ground inventories. Since storage demand is a convolution of precautionary and speculative motives, we use the same sign restrictions on each of these two shocks (columns 3 and 4), with one exception. That is, we remain agnostic about the contemporaneous response of oil production to a precautionary demand shock. This is motivated by the fact that higher uncertainty may increase the quantity of oil produced as postulated in Kilian and Murphy (2014), but it may instead elicit a *real options* effect on oil producers—i.e., they delay production as they wait and see what happens to oil prices in the future (Bernanke, 1983). This point is also in line with the general equilibrium model of Alquist and Kilian (2010) who argue that oil producers may sell oil futures to protect against endowment uncertainty, however the strength of this mechanism remains an empirical question. In light of this theoretical mechanism, we think it is prudent to not impose or prevent such an *a priori* response, and instead allow the data to inform us about the empirical validity of such behavior.[6]

Finally, it is important to note that our decision to remain agnostic does not come without costs. In particular, the precautionary demand shock may elicit the same sign pattern in

[6]Technically, real options theory does relates to long-run uncertainty, however it's common to use short-run uncertainty in empirical studies (see, e.g. Castelnuovo (2019) and references therein).

the contemporaneous responses as the flow supply or speculative demand shocks. To achieve identification, we therefore exploit the fact that precautionary motives are associated with high uncertainty to impose the additional restriction that oil price uncertainty will be relatively larger after a precautionary demand shock than a shock to flow supply or speculative demand. In other words, we assume element (4,4) of Table 1 is greater than elements (4,1) and (4,3). After identifying these four shocks, we then treat any remaining variation as an unexplained residual.

3.3.2 Narrative Sign Restrictions

We also modify the set of narrative restrictions implemented in Zhou (2019). Motivated by discussions in Kilian and Murphy (2014, p.460, 469) and Kilian and Lee (2014, p.74), Zhou (2019) postulated the following five narrative sign restrictions on the historical decomposition. First, consistent with anecdotal evidence of a dramatic surge of inventory building in the oil market during that time, storage demand shocks are assumed to (cumulatively) raise the log real price of oil by at least 0.2 (or approximately 20%) between May and December of 1979. Second, following the collapse of OPEC in December of 1985, storage demand cumulatively lowered the log real price of oil by at least 0.15 up until December 1986. Third, in line with the established belief that Iraq would invade its neighbors, storage demand shocks raised the log real price of oil by at least 0.1 cumulatively between June 1990 and October 1990. Fourth, following the invasion of Kuwait and the cessation of Iraqi and Kuwaiti oil production in early August of 1990, flow supply shocks are assumed to have raised the log real price of oil cumulatively by at least 0.1 between July and October of 1990. Fifth and final, the cumulative effect of flow demand shocks on the log real price of oil between June and October of 1990 is bounded by 0.1, given that the oil price spike of 1990 was not associated with the global business cycle.

One difficulty in directly applying these narrative restrictions in our framework is that it remains unclear which component of storage demand, i.e. speculative and precautionary motives, is associated with the first three of the above restrictions. Since imposing a restriction on the wrong component would bias our results, we instead impose the narrative restrictions on the sum of their responses. For instance, the first restriction translates to imposing that the log real price of oil increased by at least 0.2 as a result of precautionary and speculative shocks between May and December of 1979.

4 Oil Market Results

The SVAR model is estimated using Bayesian methods. In each figure, the boldface (black) line corresponds to the most likely structural model, while the thin (red) lines correspond the 68% highest posterior density joint credible set. Computational details for these sets can be found in Inoue and Kilian (2013, 2019).

4.1 Responses of Variables to Oil Market Shocks

The impulse response functions from each of the demand and supply shocks in our model are shown in Figure 2. Following convention in the literature, all shocks have been normalized such that they imply an increase in the real price of oil. In particular, the flow supply shock refers to an unanticipated flow supply disruption.

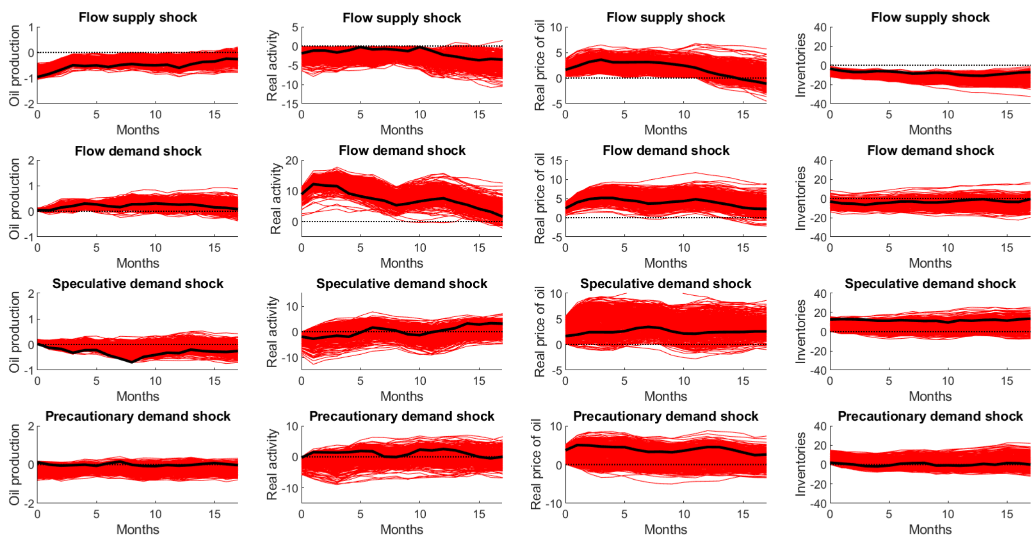

Figure 2: Structural impulse response functions

Notes: The response in boldface represents the most likely structural model are shown in boldface and the remaining responses are from the 68% joint credible set obtained from the posterior distribution of 1000 structural models. Oil production and inventories are expressed as the cumulative percent change of the respective impulse responses.

The size and qualitative patterns of the responses presented in the first two rows of Figure 2 are comparable to those in Kilian and Murphy (2014) and Zhou (2019). For instance, a negative flow supply shock is associated with a reduction in oil production, global real activity and oil inventories while increasing the real price of oil. We also observe that the price of oil rises only temporarily, peaking after about three months and declining below it's starting value after about one year, due to the drop in real activity. In contrast, a positive shock to the flow demand for crude oil, is associated with a slight increase in oil production as firms meet the persistent demand associated with the increased real activity. Such shocks also cause a persistent hump-shaped increase in the real price of oil and have a negligible effect on inventories.

Since we are the first to jointly identify the precautionary and speculative demand components underlying storage demand, the results in rows three and four are new. First, focusing on the third row, we observe that the most likely response to a positive speculative demand shock is an immediate and persistent jump in the real price of oil, which is accompanied by a large persistent increase in above-ground inventories. Such shocks also generate a gradual decline in oil production and a temporary reduction in real activity. These responses are in line with the proposed mechanism outlined in Kilian and Murphy (2014). Specifically, when speculators purchase a large quantity of inventories, they signal to oil producers that they expect higher prices in the future. This causes oil producers to withhold oil from the market in order to sell the stored oil at the higher price. Such withholding can take place by either increasing holdings of above-ground inventories or reducing the number of barrels pumped out of the ground. Our result that a speculative demand shock elicits an immediate increase in above-ground inventories and a gradual decline in oil production, suggesting that both types of behavior are at play. Taken together with the persistent increase in the real price of oil, our model thereby provides empirical support for this theoretical mechanism.

Finally, the results in row four show that an unanticipated increase in uncertainty induced precautionary demand elicits an immediate, significant, and persistent positive effect on the real price of oil that is highly statistically significant. The magnitude of the oil price response suggests that precautionary demand shocks, on average, have the largest impact on the real price of oil, illustrating the importance of disentangling such shocks from speculative demand shocks. Such shocks are also associated with a temporary increase in real economic activity, but do not decrease in global oil production or increase inventories.

While it is not directly related to our primary research questions, the result that an unexpected increase in oil price uncertainty is most likely to have a negligible effect on the production of crude oil is especially relevant to the related literature on real options theory. Real options theory posits that an increase in oil price uncertainty may impact the decision-making process of irreversible firm-level investments (Bernanke, 1983). The key mechanism is that an increase in oil price uncertainty causes firms to postpone major purchases of capital goods and wait-and-see what happens to the oil price. If such a real options channel is important in the market for crude oil, then a positive precautionary demand shock should result in a sustained increase in inventories, and associated reductions in oil production and real economic activity until the oil price situation manifests. The response path from the most likely structural model is not in line with this theoretical mechanism. Following a precautionary demand shock, our results suggest that firms do not reduce production or increase their inventories resulting in a decline of real economic activity. Instead, the response of oil production and inventories is negligible, with output being weakly positive. This is in contrast to Elder and Serletis (2010), Jo (2014) and Nguyen et al. (2019) who find evidence of a real options effect in global oil market models that abstract from speculative demand. That being said, it is important to note that the alternative response paths in our credible set suggest that such shocks may have a negative impact on oil production, while increasing inventories, as theory suggests (Alquist and Kilian, 2010). Thus, while the most likely response is not in line with real options theory, we can not conclusively dismiss such behavior.

4.2 Reassessing the Historical Narrative

Our results so far suggest that, on average, the precautionary and speculative demand components underlying conventional storage demand shocks have different effects on the real price of oil. In light of this evidence, our objective in this section is to reassess the underlying historical narrative of what caused the ups and downs in the real price of oil and changes in inventories since the late 1970s. The historical decomposition in Table 2 enables us to draw inference on the causal underlying dynamics of the real price of oil and above-ground inventories during the 1979 oil crisis, the Iran-Iraq War of 1980, the collapse of OPEC in 1986, Iraq's invasion of Kuwait in 1990, the early millennium surge in the real price of oil between 2003 and mid-2008, the price drop in the Great Recession of 2008 and the oil price collapse of 2014/15.

Three important external insights used in the narrative sign restrictions of Zhou (2019), were that shifts in storage demand played an important role during the oil price shock episodes of the twentieth century (see Section 3.3.2). By decomposing the aggregate effect of storage demand into its underlying precautionary and speculative components, our model provides new insights on what drove the dynamics during these periods.

The results in the first column reveal that the rise in the real price of oil in late 1979 associated with the Iranian Revolution was mainly driven by a sharp increase in precautionary demand associated with uncertainty around future supply shortfalls. This result supports the hypothesis in Kilian (2009) that the increased importance of his "oil market–specific demand shocks" starting in 1979 is consistent with an increase in precautionary demand. As stated in that paper, this period was plagued by various sociopolitical events, including Khomeini's arrival in Iran, the Iranian hostage crisis and the Soviet invasion of Afghanistan. All of these events were associated with persistent fears of a regional war and the destruction of oil fields in Iran and Saudi Arabia, thus spiking precautionary demand for oil. In addition to this result, we also observe that such shocks played a key role in shaping the real oil price dynamics during the two wars of 1980 and 1990, however we also find evidence that supply disruptions also had significant impacts during these periods.

While uncertainty driven precautionary motives are important for explaining the real oil price dynamics during the two wars and adverse sociopolitical events, our results reveal that oil price decline following OPEC's collapse in late 1985 was largely the result of poor global economic conditions and speculative demand.

In addition to these new insights, we also find supporting evidence that economic fundamentals on the demand side of the oil market explain most of the real price of oil dynamics since the turn of the century (Kilian, 2009). For instance, we find overwhelming support that the primary cause of the early millennium surge in the real price of oil between 2003 and mid 2008 was associated with a sustained global economic expansion, which is generally attributed to unexpectedly high growth from emerging Asia (Kilian and Hicks, 2013; Aastveit et al., 2015), and that such shocks were also the primary driver behind the price drop during the Great Recession. In line with discussions in Fattouh et al. (2013) and Kilian and Murphy (2014), we also find no evidence that speculative demand shocks were responsible for the real price of oil dynamics in this period. Finally, our analysis suggests that flow demand shocks also played an important role in determining the real price of oil during the 2014/15 price decline, with precautionary and speculative demand shocks playing a much smaller role.

Table 2: Cumulative effects on the real price of oil (percent) and oil inventories (change)

		1979 oil crisis	Iran-Iraq War	Collapse of OPEC	Persian Gulf War	2003/08 Price Surge	Great Recession	2014/15 Price Drop
		1979:1-1980:1	1980:9-1980:12	1985:12-1986:12	1990:5-1990:10	2002:7-2008:6	2008:6-2008:12	2014:6-2015:12
Real oil price	Flow Supply Shocks	-6	11	2	30	12	-1	-36
	Flow Demand Shocks	35	-2	-19	-8	113	-83	-38
	Speculative Demand Shocks	9	-6	-30	-1	-13	-15	-9
	Precautionary Demand Shocks	37	6	-7	43	18	-23	-10

Notes: Cumulative effects on the real price of oil (percent) and oil inventories (change) from the workhorse oil market model.

5 Macroeconomic Implications

A question that has received considerable interest in economics is how the structural oil market innovations affect US macroeconomic aggregates (see, e.g. Herrera et al. (2019) and references therein). We consequently investigate whether or not our newly identified precautionary and speculative shocks have similar or distinct impacts on US real GDP growth and CPI inflation. In the spirit of Kilian (2009), we address this question through the use of distributed lag models in which the macroeconomic aggregates are regressed on the structural shocks obtained from the oil market model in (6). The second-stage model in which the response of US macroeconomic aggregates to the various oil market shocks is given by

$$z_t = \alpha_j + \sum_{h=0}^{12} \phi_{jh} \hat{\zeta}_{jt-h} + u_{jt}, \quad j = 1, 2, 3, 4, \tag{7}$$

where z_t denotes the macroeconomic aggregate of interest, u_{jt} is a stochastic error term, and $\hat{\zeta}_{jt-h}$ refers to the estimated structural shock from our SVAR model. Accordingly, $\hat{\zeta}_{jt-h}, j = 1, 2, 3, 4$, respectively denote disturbances in flow supply, flow oil demand, speculative demand and precautionary demand. The parameters ϕ_{jh} therefore yield the impulse response functions at horizon h. The maximum horizon of the impulse response functions is determined by the number of lags in the regression model, which is set to 12 quarters.

Since real GDP growth data is only available at a quarterly frequency, we construct measures of quarterly shocks by averaging the monthly structural innovations for each quarter. Formally, we define the j-th quarterly structural $\hat{\zeta}_{jt}$ shock as

$$\hat{\zeta}_{jt} = \frac{1}{3} \sum_{i=1}^{3} \hat{\varepsilon}_{jti}, \quad j = 1, 2, 3, 4,$$

where $\hat{\varepsilon}_{jti}$ refers to the j-th estimated structural shock in the i-th month of the t-th quarter of the sample.

This approach works because the structural shocks are approximately mutually uncorrelated at lower than monthly frequencies and are contemporaneously predetermined to the US macroeconomic aggregates (Kilian and Vega, 2011). Since we need to evaluate the second-stage regression for each admissible posterior draw of the oil market model, estimation is done using the procedure in Herrera and Rangaraju (2019).

Responses for the level of US real GDP and the CPI to each of the four structural shocks in our model are shown in Figure 3. While the qualitative nature of the modal responses following both flow demand and supply shocks are similar to the point estimates presented in Kilian (2009), a new insight offered by our model is that we are able to isolate the underlying precautionary and speculative effects that are confounded in the oil-market specific demand shock—i.e. a residual shock after accounting for flow supply and demand shocks—used in Kilian (2009).

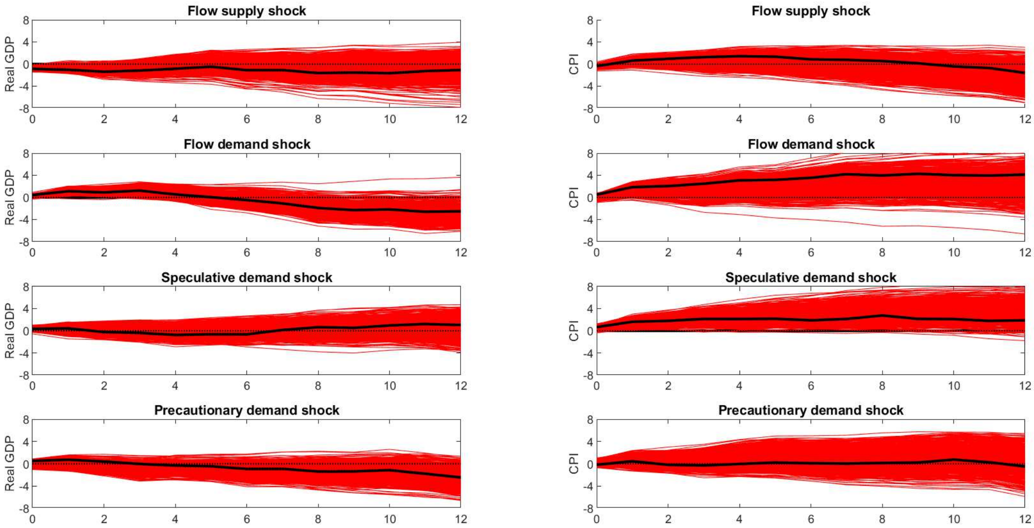

Figure 3: Responses of US real GDP and CPI level to each structural shock

Notes: The response in boldface represents the most likely structural model are shown in boldface and the remaining responses are from the 68% joint credible set obtained from the posterior distribution of 1000 structural models.

Looking first at the third row of the Figure, we observe that the modal impact of speculative demand shocks is near zero for real GDP but results in a higher CPI price level. In contrast, the precautionary demand shocks (row four) are found to depress real GDP, while having no impact on the CPI price level. An explanation for this result can be drawn from our earlier findings in Section 4.1. There we found that a precautionary demand shock elicits a short-term real options effect in which producers of oil delay their irreversible investment decisions until their uncertainty about future oil price increases diminishes. This reduction in oil production is met by a decline global output, however the most likely model exhibited no change in the real price of oil. Thus, while the decline in US output is indicative of a real options effect, there is no reason to expect that such shocks would induce an inflationary response. Moreover, the weak output and large price level responses associated with speculative demand shocks is also in line with our earlier results. This new finding on the relative effects of precautionary and speculative demand shocks also helps us to understand what is driving the responses to an oil-specific demand shock in Kilian (2009). The precautionary demand shocks underlie the observed reduction in real GDP, while the speculative demand shocks underlie the observed increase in the price level.

While this relative difference between precautionary and speculative demand shocks is new, the finding that increased uncertainty about the real price of oil (in aggregate) has tended to cause US real GDP growth to decline is in line with Jo (2014). In the broader literature on the economic effects of macroeconomic uncertainty, it is also common to observe that unexpected uncertainty increases generate recessionary conditions several months after the shock (Jurado et al., 2015). Our results therefore build on the empirical evidence provided in this general literature on the economic effects of uncertainty shocks.

6 Conclusion

The workhorse oil market model allows researchers to examine the effects of *storage demand* shocks in addition to more conventional *flow demand* and *flow supply* shocks. The key idea underlying the identification of storage demand shocks is that latent expectation shifts about future oil market conditions are reflected by observable changes in above-ground crude oil inventories. Implicit in this assumption, however, are two very different types of economic behavior. On the one hand, *speculative demand* for oil occurs because buyers are anticipating future demand or supply conditions. In contrast, *precautionary demand* for oil occurs in response to heightened uncertainty about the future price of oil. Despite this distinction, the fact that these underlying motives are latent and share similar transmission mechanisms renders the joint identification of these two distinct shocks difficult in practice.

Our contribution in this paper was to generalize the workhorse oil market model to jointly allow for precautionary and speculative demand for oil, in addition to more conventional flow demand and flow supply shocks, and assess their relative effects in the global market for crude oil and US macroeconomic aggregates. Central to our identification procedure was the refinement and application of a monthly oil price uncertainty (OPU) index. Unlike conventional volatility based proxies, the OPU index captured the fact what matters for economic decision making is not whether the real price of oil has become more or less variable, but rather whether it has become less or more predictable, i.e. uncertain. We showed that the index captures all of the major oil price shocks over the past five decades, and was distinct from other sources of uncertainty, such as financial, macroeconomic and policy uncertainty.

Our analysis provided important new insights on the relative roles of precautionary and speculative behavior in driving both the real price of crude oil. Overall, we found that uncertainty driven precautionary demand for crude oil is, on average, the primary driver underlying fluctuations in the real price of oil that have previously been associated with storage demand shocks. At a more localized level, we also provided new insights on the roles of uncertainty induced precautionary motives and pure speculation in various episodes of historical significance. For instance, we found that shifts in precautionary demand associated with adverse sociopolitical conditions in the Middle-East explained a vast majority of the oil price spikes during the 1979 oil crisis and the Wars of 1980 and 1990, while speculative demand was a more important driver during the disbandment of OPEC.

Finally, in addition to examining the relative roles of precautionary and speculative demand in the world market for crude oil, we also investigated the macroeconomic significance of these distinct shocks. This was done by investigating their impact on two key US macroeconomic aggregates: real GDP growth and CPI Inflation. Using distributed lag regressions, we found that speculative demand shocks have no statistically significant impact on real GDP, but results in a higher CPI price level. Conversely, precautionary demand shocks were found to elicit a statistically significant impact on real GDP, but no price level response. This new insight is likely to be of great importance to policy makers with an inflation targeting mandate, who can deter speculation via targeted policies.

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—ONLINE APPENDIX—

NOT FOR PUBLICATION

Oil Price Uncertainty Index

Examining the Role of Additional Predictors

To examine the role of including additional predictive information when estimating the measure of oil price uncertainty, we re-estimate the OPU index using potentially misspecified models in which we replace (2) with: (i) a constant conditional mean equation, i.e. $y_{t+1} = \mu + \hat{\sigma}_{t+1}\hat{\epsilon}_{t+1}$, and (ii) autoregressive terms only, i.e. $y_{t+1} = \phi(L)\, y_t + \hat{\sigma}_{t+1}\hat{\epsilon}_{t+1}$. A comparison of these models reveals how our measure of uncertainty are affected by the predictable variation in oil prices. The resulting indices are shown in Figure 4. In contrast to Nguyen et al. (2019), we observe that there is a substantial predictable component in the selected oil price series. In particular, our refined OPU index is significantly lower than the misspecified measures of uncertainty in every peak, suggesting that an OPU with either no predictors or AR terms only will overstate the degree of oil price uncertainty.

To further examine the role of each individual predictor in driving the refined OPU index, we now investigate how the index changes when we subsequently remove a variable in X_t.[7] The results in Figure 5 show that the most frequently selected predictors are commodity exchange rates and excess co-movement terms as removing these variables affects the OPU most. Omitted information about above-ground oil inventories, US inflation and M1 money stock affects the OPU to a lesser extent, while we see little effect from removing the real economic activity index.

[7]For example, to see the contribution of commodity exchange rates, we start from the retained list of regressors that passes the hard threshold test. We then run a regression of y_{t+1} on a constant, the AR terms and the retained regressors without commodity exchange rates. Then we compute a measure of uncertainty that does not utilize information on commodity exchange rates.

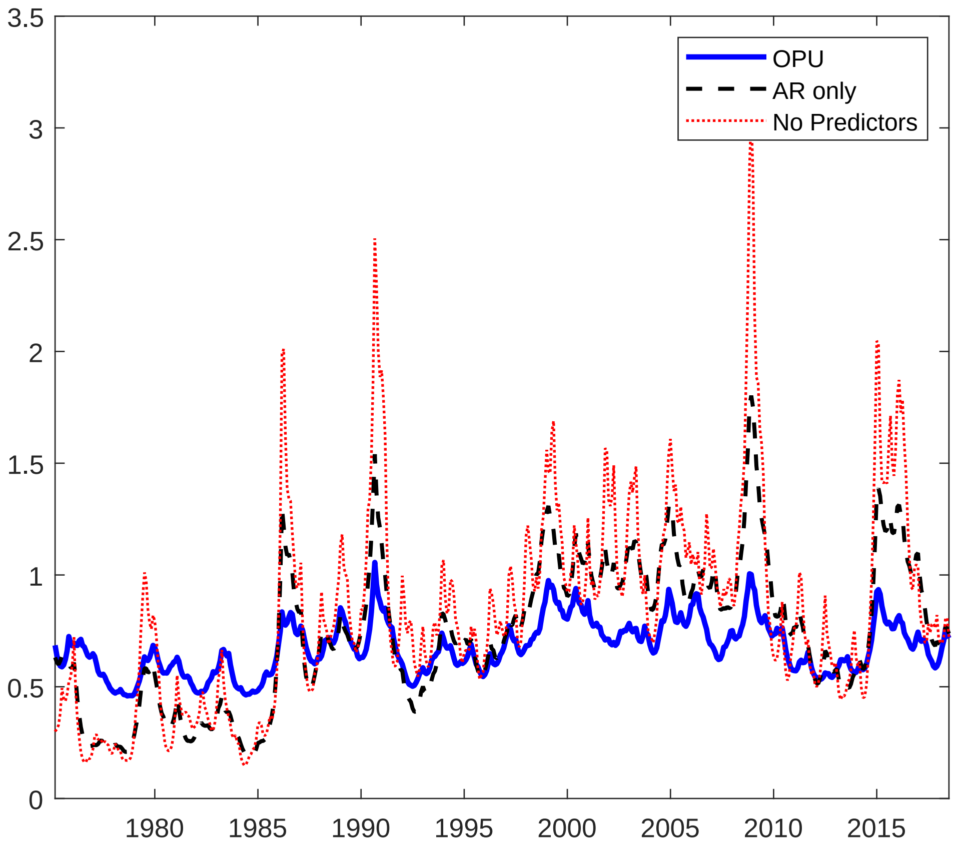

Figure 4: The role of incorporating predictive information

Notes: The figure contains (i) our oil price uncertainty index (OPU), (ii) a potentially misspecified model in which we only include an intercept (dotted line), and (iii) a model in which only autoregressive terms are included to forecast (dashed line) from 1975:2 to 2018:6.

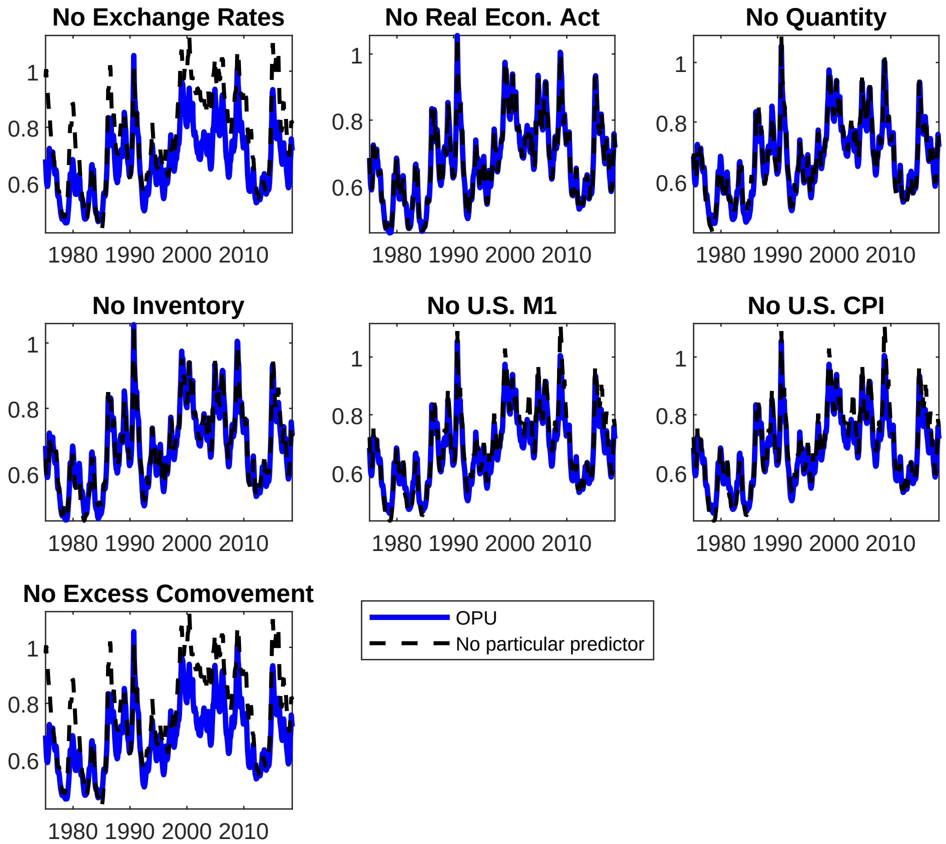

Figure 5: The role of individual predictor

Notes: The figure shows the oil price uncertainty index (OPU) (solid line) and an OPU in which only once particular predictor in X_t is removed at one time (dashed line) from 1975:2 to 2018:6.

Comparison with Other Uncertainty Measures

A natural question is whether our oil price uncertainty measure is distinct from alternative measures of uncertainty. To investigate this point, we compare our OPU measure with the CBOE Oil Price Volatility Index (OVX) and three widely used sources of alternatively uncertainty measures: financial uncertainty, as measured by the CBOE (stock price) Volatility Index (VIX); the US Economic Policy Uncertainty (EPU) index proposed by Baker et al. (2016); and the US macroeconomic uncertainty (JLN) index constructed by Jurado et al. (2015).

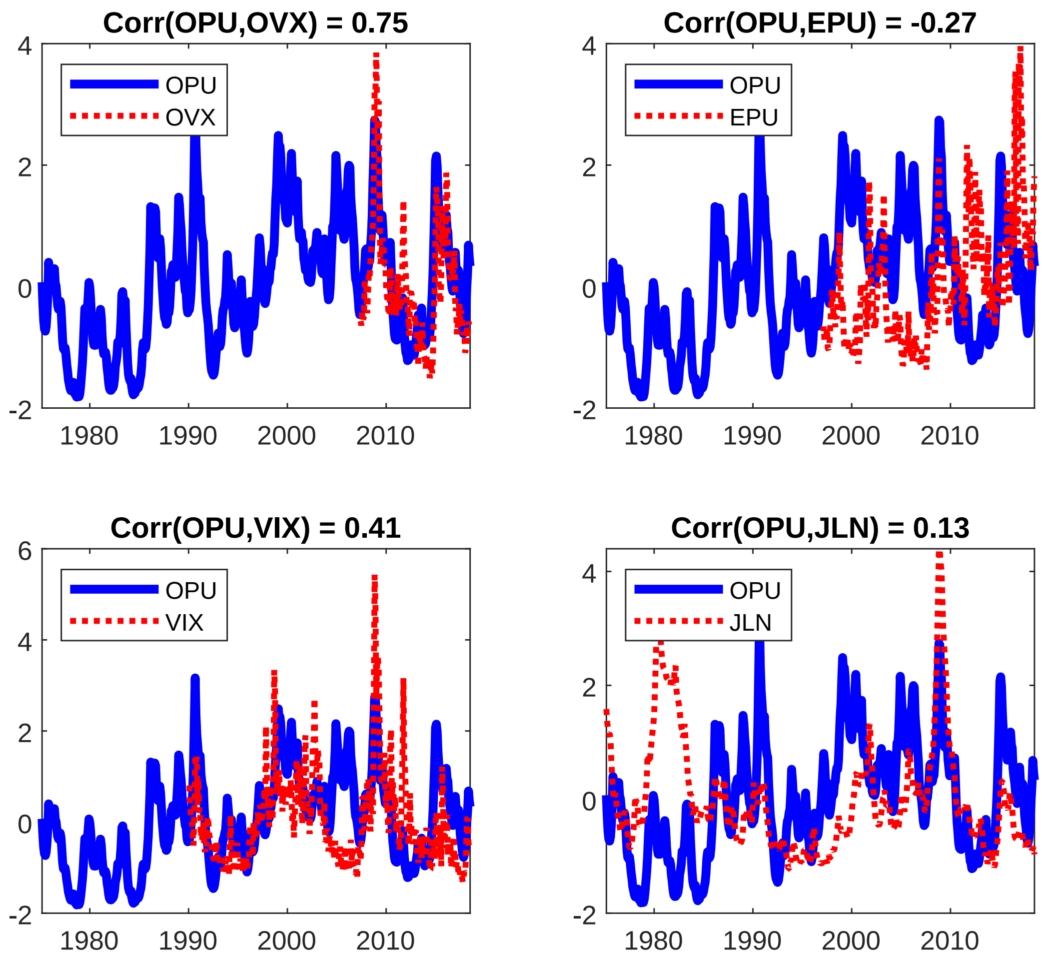

Figure 6: Oil price uncertainty (OPU) index: Comparison with other uncertainty indices

Notes: The figure compares the oil price uncertainty index (OPU) constructed in Section 2 from 1975:2 to 2018:6 to: (i) The CBOE Oil Price Volatility Index (OVX) from 2007:5 to 2017:6, (ii) The Global Economic Policy Uncertainty index (EPU) by Baker et al. (2016) from 1997:1 to 2017:6, (iii) The CBOE volatility index (VIX) from 1994:7 to 2017:6 and (iv) The uncertainty index (JLN) for the U.S by Jurado et al. (2015) from1975:2 to 2018:6. All series are normalized to have means of zero and standard deviations of one.

The comparison in Figure 6 reveals that the dynamics of OPU are most consistent with the OVX index. Since option prices are driven by both precautionary and speculative motives, the moderately high correlation between the two series is expected. The major distinction between the OPU and the OVX is that the OPU does not report any heightened uncertainty around 2011. Next, the lack of correlation with the EPU index suggests that oil price uncertainty is highly different from economic policy uncertainty. Last, although oil price uncertainty correlates moderately with both stock market (VIX) and macroeconomic uncertainty in the

US (JLN), there are still some notable differences. While the OPU detects spikes following the collapse of the OPEC in 1986 and the 1990/91 Persian Gulf War, these high-uncertainty events are not reported by the JLN index. The OPU does not pick up high uncertainty about the Dotcom crisis or the European Debt Crisis that are otherwise detected by the VIX since those events are more relevant to the stock exchange. In addition, neither the VIX nor the JLN macro uncertainty index detects any surge in oil uncertainty during 2000-2002 and during 2015-2016. Taken together, this suggests that the OPU index is able to pick up uncertainty events that are highly specific to the oil market.