Time-Varying Oil Price Volatility and Macroeconomic Aggregates

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Abstract

This paper studies how exogenous changes in oil price uncertainty affect GDP and other macroeconomic variables. To identify exogenous changes in oil price uncertainty in a VAR, we introduce an article count index related to OPEC, which rises following important OPEC meetings, political upheaval in OPEC nations, and terrorist attacks. Positive innovations in the index lead to increased oil price uncertainty and small but statistically significant declines in the growth rate of U.S. real GDP. A New Keynesian model in which oil usage is required for the utilization of both capital and durable goods also produces declines in GDP and other macroeconomic variables following an increase in real oil price uncertainty. Both the empirical and theoretical results are shown to be robust to a number of variations to the models.

Keywords: DSGE model, energy, oil price, stochastic volatility

JEL Classifications: C32, E21, E22, Q43

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1 Introduction

Oil price uncertainty often increases following wars, terrorist attacks, and political upheaval in OPEC countries. These changes stem from events exogenous to U.S. economic activity. Nevertheless, they potentially have real effects on the U.S. economy, as households and firms change their behavior in response to greater uncertainty about the future path of oil prices. This paper studies the effects that exogenous changes in oil price uncertainty have on the U.S. economy.

Using different models and measures of oil price uncertainty, various empirical works have found that increased oil price uncertainty is associated with weaker macroeconomic activity. Using a vector autoregression (VAR), this paper also finds that exogenous changes in oil price uncertainty have a negative impact on GDP. Importantly, our empirical analysis differs in that we attempt to control for the source of variations in oil price uncertainty. Specifically, we document that oil price uncertainty is affected by changes in general macroeconomic uncertainty, and attempt to control for this in our empirical model.

To help isolate the movement in oil price uncertainty due to exogenous events, we introduce an index similar in spirit to the economic policy uncertainty index of Baker, Bloom, and Davis (2013). More specifically, we construct an index based on the frequency of article counts on OPEC from several sources, hypothesizing that uncertainty related to OPEC could be an important driver of oil price uncertainty. We find that this index rises around important OPEC meetings, political upheaval in OPEC member countries, and other events, such as wars and terrorist attacks.

After controlling for the possibility that the article count index is influenced by oil supply shocks, we use the index in a VAR model that includes the VIX as a measure of general economic uncertainty, U.S. real GDP growth, and a forward-looking market-based measure of oil price uncertainty. We find that unexpected increases in the OPEC index lead to increased oil price uncertainty, as well as short-lived, but statistically significant declines in U.S. real GDP. These results are shown to be robust to several variations in the empirical model, the construction of the OPEC index, and the variable used to measure oil price uncertainty.

Given this empirical support for the negative relationship between exogenous changes in oil price uncertainty and economic activity, we then consider the theoretical interaction among output, consumption, investment, and oil price volatility in a standard New Keynesian model. In this model, oil is used for both production and utility purposes, as oil usage is required for the utilization of both capital and durable goods. The model is calibrated to match features of U.S. business cycles and data on U.S. oil consumption. To consider the effects of oil price uncertainty, we estimate a stochastic volatility process for the real price.
of oil using Bayesian methods, similar to Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011), and embed the estimated process in the model. The model is solved using perturbation methods and a third-order approximation.

Two key findings emerge from our theoretical exercises. First, an exogenous increase in real oil price volatility generates a slowdown in economic activity. GDP, non-durable and durable consumption, and investment all decline in response to the shock. This recessionary effect is due to countercyclical markups, stemming from precautionary savings motives interacting with nominal rigidities, as highlighted by Basu and Bundick (2012). Without nominal rigidities, the model predicts that increased real oil price volatility has a positive effect on real GDP, as precautionary savings motives lead hours worked and investment to increase. Second, we find that the quantitative response of GDP on impact is relatively small in size. The qualitative and quantitative results are shown to be robust to a wide range of model parameterizations. Significantly larger responses are possible, but occur only with unreasonable assumptions about oil usage in the economy. One important caveat to interpreting our quantitative results is that we abstract from irreversible investment decisions, which are likely to enhance the negative effects that occur in the theoretical model.

Our work is related to several branches of the literature. A large body of empirical work investigates how oil price uncertainty affects U.S. macroeconomic activity. Federer (1996) uses a historical volatility measure of oil product prices in a VAR and finds that increased uncertainty predicts declines in industrial production. Guo and Kliesen (2005), using OLS regressions and a measure of historical volatility, finds that increased oil price volatility predicts lower growth in the U.S. GDP. Elder and Serletis (2010) uses a GARCH-in-mean VAR and shows that increased oil price uncertainty predicts lower U.S. real GDP growth, as well as declines in other macroeconomic variables. Using similar approaches, Elder and Serletis (2009), Elder and Serletis (2011), Elder, Bredin, and Fountas (2011), and Pinno and Serletis (2013) also find a dampening of economic activity for a broader sample of countries, time frames, and model specifications. However, Kilian and Vigfusson (2011a) and Kilian and Vigfusson (2011b) raise concerns about the econometric approach of Elder and Serletis (2011) and also highlight inconsistencies between their results and economic theory. Jo (2013) uses a stochastic volatility-in-mean VAR and finds that an increase in oil price uncertainty, independent of any change to the price of oil, predicts lower world industrial production.\footnote{The possibility that oil price uncertainty could impact economic activity has also been discussed in a number of papers which were not exclusively about the topic, including Kilian and Vigfusson (2011a), Kilian and Vigfusson (2011b), and Edelstein and Kilian (2009). Kellogg (2014) also found that oil price uncertainty has an important impact on drilling in the oil industry.} Our empirical work complements this literature, yet remains distinct in that it attempts to control for the endogenous influence that economic events have on oil price.
uncertainty.

This paper also is related to the literature that considers how OPEC-related events influence oil price uncertainty. Horan, Peterson, and Mahar (2004) use an event study approach and find that implied volatility for crude oil often rises in the days before an OPEC meeting. Schmidbauer and Rosch (2012) find that the volatility of daily oil price changes, measured using GARCH models, is affected before OPEC meetings. Charles and Darne (2014) also find that OPEC-related events and meetings affect oil price uncertainty. These studies utilize daily data and focus on very short-lived effects that OPEC-related events have on oil price uncertainty. In contrast, we consider quarterly data, capturing more persistent effects and also show how these events affect variables beyond oil price uncertainty.

Finally, our work also has connections to the theoretical literature on the importance of oil price uncertainty. Theoretical studies have focused mainly on partial equilibrium analysis (e.g. Bernanke (1983) and Pindyck (1991)). Two recent papers have examined the effects of oil price volatility in general equilibrium models [Baskaya, Hulagu, and Kucuk (2013) and Castillo, Montoro, and Tuesta (2010)]. Our paper complements these works, but differs in important ways. Baskaya, Hulagu, and Kucuk (2013) abstracts from the role of durables and household energy usage and employs a small open economy model. Castillo, Montoro, and Tuesta (2010) show analytically how a change in the unconditional oil price volatility affects average inflation in a simple New Keynesian model. However, their model abstracts from investment decisions and does not consider the dynamic implications of changes in oil price volatility. Our focus is on the dynamic responses of firms and households to changes in oil price volatility, particularly on their influence on GDP.

The rest of the paper is organized as follows. Section 2 presents empirical evidence of oil price volatility and its effects on real GDP. Section 3 introduces the model and our estimation of time-varying volatility for the U.S. real oil price. Section 4 examines the dynamic effects of changes in oil price volatility, and section 5 concludes.

2 Empirical motivation

In this section, we present some evidence on the presence of time-varying oil price uncertainty, its relationship with more general macroeconomic uncertainty, and its possible impacts on U.S. economic activity. We are especially interested in documenting the effect that exogenous changes in oil price uncertainty have on U.S. real GDP.
2.1 Oil price uncertainty data

To measure oil price uncertainty, we use the implied volatility from options on the one-month ahead futures contract for the West Texas Intermediate (WTI) crude oil. This variable, hereafter IVOIL1, measures the market’s expectations of near-term volatility in the nominal price of WTI. As a proxy for general macroeconomic uncertainty, we use the Chicago Board Options Exchange (CBOE) VIX index, which measures the market’s expectation of near-term volatility in the S&P 500 index.\footnote{Others have also considered the VIX as a measure of uncertainty. See, for example, Bloom (2009), Bloom (2013) and the references there in.} Figure 1 plots the VIX index (dashed lines) and IVOIL1 (solid lines) from 1993Q3 to 2012Q4.\footnote{Daily observations of IVOIL1 are available starting in July of 1993. The OVX index, similar to the VIX index except that it measures oil price uncertainty, would have been preferred, but it is only available since 2007.} Both are quarterly averages of daily observations, and both show significant variation over time.

Guo and Kliesen (2005) suggest that variation in oil price uncertainty is often driven by events exogenous to U.S. economic activity, such as terrorist attacks and conflicts in the Middle East. This seems plausible, as IVOIL1 rose around the time of 9/11, the second Gulf War, and the events in Libya in 2011. However, figure 1 also suggests a relationship between general economic uncertainty and oil price uncertainty. For example, both VIX and IVOIL1 rose dramatically when the global economy entered the recession in late 2008, and the two have an in-sample, cross-correlation of 0.77. Given the negative relationship between the VIX and U.S. economic activity documented in Bloom (2009), this high correlation between the VIX and IVOIL1 creates some uncertainty about the source of the negative relationship between economic activity and oil price uncertainty found in previous empirical works. It could be due to exogenous events, such as political upheaval in OPEC countries. Alternatively, it could be due to responses in oil price uncertainty driven by changes in macroeconomic uncertainty, or perhaps a combination of both exogenous events and macroeconomic uncertainty.

To help isolate the movement in oil price uncertainty due to events exogenous to economic activity, we construct an index similar in spirit to the economic policy uncertainty index in Baker, Bloom, and Davis (2013). More specifically, we hypothesize that uncertainty related to OPEC could be an important source of oil price uncertainty. To measure changes in oil price uncertainty due to OPEC-related issues, we construct an index based on the frequency of article counts on OPEC from several sources. During periods of intense scrutiny about OPEC actions, more articles are written about OPEC. This scrutiny could be due to war or political upheaval in one or more OPEC member countries, uncertainty due to OPEC interaction with non-OPEC countries, or uncertainty about OPEC production levels for
various other reasons.

2.2 The newspaper index

Our baseline index is based on article counts for three major newspapers: the Wall Street Journal, the Financial Times, and the New York Times. We use the Dow Jones Factiva database and search for article counts from these three newspapers using the keyword “OPEC.” We equally weight each news source and sum across article counts to get a monthly total. We re-scale this series so that 100 equals the value in January of 1993. Since this variable is constructed from newspaper article counts, we hereafter refer to it as the newspaper index.

Figure 2 plots the newspaper index from 1993Q1 to 2012Q4. We plot the index at a quarterly frequency as it is the frequency of interest in this paper. As seen in the figure, there are a number of spikes surrounding OPEC meetings, particularly emergency meetings. Other spikes include events such as the Arab Spring, the oil strike in Venezuela, and the U.S. led invasion of Iraq. One issue with this index is that it could simply be contemporaneously responding to oil supply shocks, which affect the current level of the world oil supply and, as such, are not capturing true shocks to oil price uncertainty. We use a two step procedure to control for this potential problem.

In the first stage of estimation, we consider a structural VAR model of the world oil market similar to Kilian (2009). This model is given by

$$A_0z_t = \alpha + \sum_{i=1}^{2} A_i z_{t-i} + \epsilon_t,$$

where $\epsilon_t$ is the vector of structural innovations which are serially and mutually uncorrelated. Two lags are used, as suggested by the Schwarz criterion. The vector of variables, given by $z_t$, includes those of Kilian (2009), namely the percent change in global crude oil production, an index of real, world economic activity, and the real price of oil. In addition, we include our newspaper index as a fourth variable in the model. We follow the recursive identifying

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4See the online appendix for the original monthly index. Additional data on the index is available prior to 1993 from the authors upon request.
restrictions used in Kilian (2009), so that the reduced-form errors, given by $e_t$, are such that:

$$
e_t = \begin{pmatrix} \Delta \text{prod} \\ e_t^{\text{rea}} \\ e_t^{\text{rpo}} \\ e_t^{\text{article}} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix} \begin{pmatrix} \text{oil supply shock} \\ \epsilon_t^{\text{aggregate demand shock}} \\ \epsilon_t^{\text{oil specific-demand shock}} \\ \epsilon_t^{\text{article count shock}} \end{pmatrix}.$$

After obtaining the structural innovations, $\epsilon_t^{\text{article count shock}}$, we generate quarterly observations by averaging across the monthly values,

$$\hat{\xi}_t^{\text{article count shock}} = \frac{1}{3} \sum_{i=1}^{3} \epsilon_{t,i}^{\text{article count shock}} ,$$

where $\hat{\xi}_t^{\text{article count shock}}$ is our quarterly estimate for the structural innovation in quarter $t$.$^5$

The data for $\hat{\xi}_t^{\text{article count shock}}$ are used as an input into our quarterly VAR model. We note that the structural innovations and the raw newspaper index are highly correlated, but not perfectly. The in-sample correlation from 1993 to 2012 was found to be 0.84. Most importantly, large positive values of the the structural innovation are generally associated with clearly defined exogenous events, including the events in Libya, 9/11, Gulf War II, and the Venezuela oil strike (see the graph in the online appendix).

2.3 The baseline model

In the second stage of estimation, we estimate a VAR on quarterly data from 1993Q3 to 2012Q4. Our VAR model includes a constant, the structural innovations to the newspaper index, the VIX index, the annualized quarterly growth rate of U.S. real GDP, and IVOIL1. For the baseline case, one lag is chosen for the VAR, as suggested by the Schwarz criterion.

Shocks are identified with a recursive ordering, with the newspaper index variable ordered first, VIX second, real GDP growth third, and IVOIL1 last. The newspaper index shock is intended to identify changes in oil price uncertainty driven by OPEC-related events that could also affect macroeconomic uncertainty and economic activity in the U.S. The VIX shock is intended to capture changes in general macroeconomic uncertainty due to all factors aside from the newspaper index innovations. The structural shock to IVOIL1 is intended to be a residual, which captures all changes in near-term oil price uncertainty not driven by OPEC-related factors, changes in general macroeconomic uncertainty, or surprise changes in U.S.

$^5$We note that this exercise is similar in spirit to the exercise done in Kilian (2009), whereby the structural shocks from the oil model were averaged up to quarterly observations and then used to examine the relationship between those shocks and U.S. real GDP and inflation.
economic activity.

Figure 3 plots the responses of the variables to a positive one-standard deviation shock to the newspaper index. 95 percent confidence intervals, computed from 5000 Monte-Carlo draws assuming normal innovations, are also displayed. An increase in the article count index causes both the VIX and the IVOIL1 to increase, while leading to declines in real GDP growth. IVOIL1 increases by almost 2.5 percentage points while the VIX rises by about 2/3 of a percentage point. We find that the former response is statistically significant while the latter is not. Real GDP growth declines by an annualized 0.5 percent on impact, and is statistically significant. GDP growth remains low in the quarters following the initial shock, however the results are not significant. To put the responses of real GDP growth in perspective, the mean quarter-over-quarter growth rate in real GDP over the sample period is close to 2.5 percent, with a standard deviation of 2.6. As a result, while the negative effects from this shock are non-zero, they do not appear overly large when put into context of the typical changes in real GDP seen in the data.

A positive VIX shock (not pictured) also increases oil price uncertainty and causes a decline in real GDP.\(^6\) We view this shock as reflecting periods of time in the U.S. economy where increased uncertainty coincides with depressed economic activity (and vice-versa). The VIX shock has no statistically significant impact on the newspaper index. The other two structural shocks do not produce any statistically significant movements except in their own variables. This latter finding is not sensitive to the ordering of the last two variables.

To summarize, changes in oil price uncertainty appear to be driven by three predominant factors: OPEC-related events, general macroeconomic uncertainty, and changes in uncertainty due to oil-market factors, which appear unrelated to the previous two factors and also U.S. economic activity. Changes in oil price uncertainty caused by both OPEC-related events and the VIX shock are associated with lower real GDP growth in the U.S. However, the latter shock may not be completely exogenous with respect to the U.S. economy. Given the weaker U.S. growth generated by the VIX shock, the effect is perhaps best viewed as an endogenous response of oil price uncertainty to changes in macroeconomic conditions and/or uncertainty.

2.4 Robustness checks

We consider a battery of robustness checks in regards to the growth rate of real GDP’s response following a positive innovation to our article index. The responses for all of the alternative estimations are given in figure 4. In all cases, the impact response is similar, with

\(^6\)The impulse responses for all three of the other shocks from the VAR are given in the online appendix.
annualized real GDP growth declining between roughly 0.4 to 0.6 percent, and statistically significant at the 90 percent level, at least.

The first three variations to the model examine the importance of the variable ordering, the lag length, and the sample period. We first considered a model where VIX is ordered first in the Cholesky decomposition, and the structural innovation for the newspaper index second (dotted-dashed lines of figure 4). The response is similar to the baseline model. In the second variation, four lags are used instead of one (dotted line of figure 4). This introduces richer dynamics, but most of the responses after the impact decline are statistically insignificant. A third model ended the sample at 2007Q4, instead of 2012Q4, which removed the influence of the Great Recession, as well as the Arab Spring (solid starred lines of figure 4). The impact response is quantitatively similar to the baseline model. The dynamics after that are slightly different but those responses were not found to be significant.

Next, to determine how sensitive the results are to the measure of oil price uncertainty, we replace IVOIL1 in the VAR with the oil price uncertainty measure embedded in our DSGE model (see section 3). As explained in more detail in section 3.7, after estimating a stochastic volatility process for the real price of oil, we calculated smoothed estimates of the time-varying volatility of the real oil price. As seen from the solid, marked line of figure 4, using this measure instead of IVOIL1 produces only minor changes in the response of the growth rate of GDP. The result suggests that the data source for measuring oil price volatility makes little difference for the response of GDP.

Finally, we consider two alternative constructions of our article index. One measure, referred to as the Bloomberg index, is constructed using the News Trends Graph function on the Bloomberg terminal to count the number of articles posted that match the keyword “OPEC” in a given quarter. As with the newspaper index, we convert the raw article count to an index, embed the index into the Kilian (2009) model, and use the structural innovations to the Bloomberg index in the second stage VAR estimation. The response of GDP growth in this case is denoted by the dashed line of figure 4. As a second alternative, we skip the first stage of our estimation and simply embed the raw newspaper index into the quarterly VAR model (dashed-circled line of figure 4). We find that the qualitative implications are similar for the raw index, but that using the raw index appears to overstate the impacts the shock may have on real GDP growth.

Overall, our findings indicate that time-varying oil price uncertainty is present in the data and that a sizeable portion of this variation is attributable to uncertainty related to OPEC, as well as macroeconomic uncertainty and other oil-market specific factors. The VAR model shows that increases in oil price uncertainty driven by OPEC-related events have a

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7On the Bloomberg terminal this is the NT command with Source 1 selected as Keyword.
short-lived, negative impact on the growth rate of U.S. real GDP. In the next section, we introduce a theoretical model and examine the model’s ability to produce results consistent with our findings regarding oil price uncertainty’s impact on U.S. real GDP.

3 Theoretical Model

The model economy is a New Keynesian business cycle model in which oil usage is tied to a variable utilization rate. The economy consists of a representative household, a final goods producer, and intermediate monopolistically competitive goods producers.

3.1 Modeling Real Oil Price Uncertainty

Oil is imported from abroad at an exogenous world price. Trade is balanced each period, as oil imports are paid for with exports of domestic output.

The real world price of oil, $P_o^t$, evolves according to a stochastic volatility model given by

$$
\ln P_o^t = (1 - \rho_p) \ln \bar{P}_o + \rho_p \ln P_o^{t-1} + \exp\{\eta_p^t\} \epsilon_t, \quad (2)
$$

$$
\eta_p^t = (1 - \rho_{\eta_p}) \bar{\eta}_p + \rho_{\eta_p} \eta_p^{t-1} + \phi \zeta_t, \quad (3)
$$

where $\bar{P}_o$ is the steady state real oil price and both $\epsilon_t$ and $\zeta_t$ are normally distributed, uncorrelated shocks with mean zero and unit variance. $\epsilon_t$ shocks directly change the price level, while $\zeta_t$ shocks affect the spread of possible price changes and, therefore, uncertainty about the real oil price level.

3.2 Firms and Price Setting

The production sector consists of intermediate and final goods producing firms. A perfectly competitive final goods producer uses a continuum of intermediate goods $y_t(i)$, where $i \in [0, 1]$, to produce the final goods, $Y_t$, according to the constant-return-to-scale technology,

$$
Y_t = \left[ \int_0^1 y_t(i) d_i \right]^{\frac{\theta_p}{\theta_p - 1}}. \quad (4)
$$
where $\theta_p > 1$ is the price elasticity of demand. We denote the price of good $i$ as $p_t(i)$ and the price of final goods $Y_t$ as $P_t$.

The final goods producing firm chooses $Y_t$ and $y_t(i)$ to maximize profits subject to the technology (4). The demand for $y_t(i)$ is given by

$$y_t(i) = \left[ \frac{p_t(i)}{P_t} \right]^{-\theta_p} Y_t.$$  

Maximization implies an index for core CPI as

$$P_t = \left[ \int_0^1 p_t(i)^{1-\theta_p} di \right]^{1/1-\theta_p}.$$  

By definition, core inflation is then

$$\Pi_t = \frac{P_t}{P_{t-1}}.$$  

Intermediate goods producers are monopolistic competitors in their product market. Firm $i$ produces using the technology

$$y_t(i) = A_t L_t(i)^{\alpha} [K_{t-1}(i)u_t(i)]^{1-\alpha},$$  

where $\alpha \in [0, 1]$. Labor demand is given by $L_t(i)$, and capital services are the product of the capital stock $K_{t-1}(i)$, and the utilization rate of capital $u_t(i)$. As discussed below, oil usage affects the utilization rate of capital. $A_t$ denotes exogenous technological productivity that follows the stationary AR(1) process

$$\ln A_t = (1 - \rho_a) \ln \bar{A} + \rho_a \ln A_{t-1} + \sigma^a \epsilon^a_t, \quad \epsilon^a_t \sim N(0, 1).$$  

Each firm $i$ chooses labor, capital services, and its price so as to maximize the expected sum of discounted profits given the level of aggregate output and the aggregate price level. Price adjustments are subject to quadratic adjustment costs, measured in units of the final good, similar to Rotemberg (1982):

$$\frac{\Phi_p}{2} \left( \frac{p_t(i)}{\Pi p_{t-1}(i)} - 1 \right)^2 Y_t.$$  

where $\Phi_p > 0$ determines the magnitude of the cost and $\Pi$ denotes gross steady state inflation.
3.3 Households

A continuum of households on the unit interval, indexed by \( j \in [0, 1] \), provide differentiated labor services \( L_t(j) \), as in Erceg, Henderson, and Levin (2000). Each household \( j \) derives utility from non-durable consumption \( C_t \) and the service flow \( S_t(D, u^d) \) of a pre-determined stock of durable consumption \( D_{t-1} \) with a utilization rate of \( u^d_t \). In addition, the household receives disutility from working. Preferences are given by

\[
E_0 \sum_{t=0}^{\infty} \beta^t u_t^b \left\{ \frac{C_t(j)^{\frac{\sigma_c-1}{\sigma_c}} + \kappa_1 S_t(D(j), u^d(j))^{\frac{\sigma_c-1}{\sigma_c}}}{1 - \frac{1}{\tau}} - \kappa_2 \frac{L_t(j)^{1+\mu}}{1+\mu} \right\},
\]

where

\[
S_t(D, u^d) = D_{t-1}(j)u^d_t(j),
\]
and \( u_t^b = \sigma_b \epsilon_t^b \) and \( \epsilon_t^b \sim N(0, 1) \). The household works sufficient hours to meet the market demand for their chosen monopolistic nominal wage rate \( \tilde{W}_t(j) \) for each type of labor service \( L_t(j) \); thus, hours worked are demand-driven. The parameter \( \beta \in (0, 1) \) is the discount factor, \( \tau > 0 \) is the intertemporal elasticity of substitution, \( \mu > 0 \) the inverse Frisch elasticity of labor supply, and \( \kappa_1 \) and \( \kappa_2 \) are distribution parameters. The elasticity of substitution between non-durable consumption and the service flow is \( \sigma_c > 0 \).

The durable good and the capital stock evolve according to

\[
K_t(j) = [1 - \delta^k_t(j)] K_{t-1}(j) + I^k_t(j) - \frac{\phi^k}{2} \left( \frac{I^k_t(j)}{K_{t-1}(j)} - \bar{\delta}^k \right)^2 K_{t-1}(j),
\]

\[
D_t(j) = [1 - \delta^d_t(j)] D_{t-1}(j) + I^d_t(j) - \frac{\phi^d}{2} \left( \frac{I^d_t(j)}{D_{t-1}(j)} - \bar{\delta}^d \right)^2 D_{t-1}(j),
\]

where \( \phi^k, \phi^d > 0 \) imply convex adjustment costs to adjusting the stocks of capital and durables, as in Pindyck and Rotemberg (1983). \( \delta^d \) and \( \delta^k \) are the depreciation rates for the durable good and the capital stock and are a function of the utilization rates:

\[
\delta^k_t(j) = \frac{\omega^k_0}{\omega^k_1} u_t(j) \omega^k_t,
\]

\[
\delta^d_t(j) = \frac{\omega^d_0}{\omega^d_1} [u^d_t(j)] \omega^d_t.
\]

We assume that \( \omega^k_0, \omega^d_0 > 0, \omega^k_1, \omega^d_1 > 1 \), implying higher utilization rates depreciate the stocks more. The steady state values of the depreciation rates are given by \( \bar{\delta}^k \) and \( \bar{\delta}^d \).
In addition, the utilization rates of the capital and durable goods depend on oil usage $O_t^f(j)$ and $O_t^h(j)$. Following Finn (2000), energy is essential to the utilization of capital and durable goods, with increases in utilization requiring more energy usage:

\[
\frac{O_t^f(j)}{K_{t-1}(j)} = \frac{\nu_k^0 u_t(j)\nu_t^k}{\nu_t^k},
\]

\[
\frac{O_t^h(j)}{D_{t-1}(j)} = \frac{\nu_d^0 u_d^t(j)\nu_d^1}{\nu_d^1},
\]

where $\nu_k^0, \nu_d^0 > 0, \nu_k^1, \nu_d^1 > 1$. Thus, increasing the durable service flow or the amount of capital services provided to firms requires more energy usage. Because of this, changes to the real oil price have a direct effect on production and the durable service flow. For production, this can be seen immediately by substituting equation (15) into the production function to express production directly in terms of capital, labor, and energy usage.

The household receives wage income, capital rental income, and dividend payments ($\Gamma_t$) from firms each period. In addition, the household has access to a private nominal one-period risk-free bond that has the gross interest rate $R_t$ for bonds held from periods $t$ to $t+1$. Total household expenditures consist of non-durable and oil consumption and capital and durable investment. The agent’s real budget constraint is

\[
\tilde{W}_t(j) \frac{L_t(j)}{P_t} + R_t^k u_t(j) K_{t-1}(j) + (1 - R_{t-1}) \frac{B_{t-1}(j)}{\Pi_t} + \Gamma_t(j)
= C_t(j) + P_t^a O_t^f(j) + P_t^a O_t^h(j) + I_t^k(j) + I_t^d(j) + B_t(j) + \frac{\Phi_w}{2} \left( \frac{\tilde{W}_t(j)}{\Pi_t \tilde{W}_{t-1}(j)} - 1 \right)^2 Y_t.
\]

Individual nominal wage adjustments are subject to quadratic adjustment costs relative to the final output good.

A market competitive labor packer combines the differentiated labor services into an aggregated labor product $L_t$ supplied to firms. Maximization implies demand for individual labor services:

\[
L_t(j) = \left( \frac{\tilde{W}_t(j)}{\tilde{W}_t} \right)^{-\theta_l} L_t,
\]

where the aggregate nominal wage $\tilde{W}_t$ is equal to

\[
\tilde{W}_t = \left[ \int_0^1 \tilde{W}_t(j)^{1-\theta_l} dj \right]^{\frac{1}{1-\theta_l}}.
\]

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9Loosely speaking, one can view household oil usage as general energy usage from oil inputs, such as gasoline, diesel, and heating oil.
3.4 Monetary Policy

The monetary authority follows a Taylor-type rule, in which the nominal interest rate $R_t$ responds to its lagged value, GDP, and the current consumer inflation rate. Specifically, the interest rate is set according to

$$\frac{R_t}{\bar{R}} = \left(\frac{R_{t-1}}{\bar{R}}\right)^{\rho_y} \left(\frac{\Pi_t}{\bar{\Pi}}\right)^{(1-\rho_y)\rho_y} \left(\frac{Y^g_t}{\bar{Y}^g}\right)^{(1-\rho_y)\rho_y} \exp\sigma_r\epsilon^r_t. \tag{18}$$

where $Y^g_t$ is value-added output (GDP), $\epsilon^r_t \sim N(0, 1)$, and $\bar{R}, \bar{\Pi},$ and $\bar{Y}^g$ denote the steady state values of the nominal interest rate, gross inflation rate, and GDP.

3.5 Aggregation

We focus on a symmetric equilibrium in the goods and labor markets. After imposing equilibrium, the aggregate resource constraint for the economy is

$$Y_t = C_t + I^k_t + I^d_t + P^h_tO^h_t + P^o_tO^f_t + \Phi_p \left(\frac{\Pi_t}{\bar{\Pi}} - 1\right)^2 Y_t + \Phi_w \left(\frac{\bar{W}_t}{\Pi W_{t-1}} - 1\right)^2 Y_t. \tag{19}$$

Value-added output (GDP), denoted by $Y^g_t$, is defined as

$$Y^g_t = C_t + I^k_t + I^d_t + P^o_tO^h_t. \tag{20}$$

3.6 Calibration

Table 1 lists the calibrated values assigned to parameters. We interpret periods as quarters and calibrate the model to match economic data over the period 1986Q1 to 2012Q4, since the stochastic volatility process for the real oil price is estimated over this period. We assign values to the real oil price process parameters, some steady state variables, and structural parameters. The remaining parameters and steady state relationships are either implied by the model’s steady state equations or calculated to match business cycle statistics. A detailed description of our calibration is given in the online appendix.

The depreciation rate of capital ($\bar{\delta}_k$) is set to 0.0272, implying an annual rate of 11 percent. The depreciation rate of durables ($\bar{\delta}_d$) is set to 0.0514, implying an annual rate of 21 percent. These rates of depreciation match those of the annual Historical Cost Depreciation data from the BEA. The discount factor, $\beta$, is set to 0.99. We fix the utilization rates of steady state capital and durables to 0.7972, which is the average total industry capacity utilization rate reported by the Federal Reserve Board of Governors.
We calibrate $\tau$ so that the intertemporal elasticity of substitution is 0.5, well within the wide range of estimates in the literature (see Guvenen (2006)). We set $\mu$ so that the Frisch elasticity of labor supply is 0.5. The price elasticity of demand ($\theta_p$) is set to 6.25, which implies a steady-state product markup of 19 percent, within the range of average sectoral markups (see Martins and Scarpetta (2002) and the references therein). For symmetry, we also set $\theta_l$ to 6.25. We fix the price adjustment fixed cost parameter to be consistent with the slope of a Calvo-type Phillips curve in a log-linearized framework, when prices last on average for two quarters. This average duration is in line with micro evidence, see for example Klenow and Kryvtsov (2008). For symmetry, we fix the wage adjustment fixed cost parameter to be consistent with the slope of a Calvo-type wage equation when wages last on average two quarters.

We calibrate the Taylor rule parameters in line with estimates in the DSGE literature over similar sample periods (examples include Smets and Wouters (2007) and Del Negro, Schorfheide, Smets, and Wouters (2007)). Steady state inflation is equal to average core CPI inflation over the period 1986-2012 and implies an annualized rate of approximately 3 percent.

We calibrate $\kappa_2$ so that in the deterministic steady state households devote a third of their time to labor, $\bar{L} = 0.33$. We normalize the real oil price at steady state and GDP to one, $\bar{P}^o = \bar{Y}^g = 1$. In addition, we fix the durable investment to GDP ratio, capital investment to GDP ratio, and household and firm oil usage to GDP ratios to match the average values in the BEA’s NIPA accounts and data in table 3.6 of the Energy Information Administration’s Annual Energy Review.

The standard deviation and persistence of technology ($\sigma_A$ and $\rho_A$), standard deviations of the monetary policy and demand shocks ($\sigma_b$ and $\sigma_r$), as well as the stock adjustment costs $\phi_d$ and $\phi_k$, and the elasticity between consumption and durable services $\sigma_c$, are estimated by simulated method of moments (SMM) to match moments observed in the data. Specifically, we target the standard deviations of model-consistent GDP, capital investment, durable investment, household oil usage, inflation, and the nominal interest rate, as well as the serial correlations of model-consistent GDP, capital investment, durable investment, household oil usage, and inflation.\footnote{Household oil consumption is defined as consumption on motor vehicle fuels, lubricants, and fluids, and consumption on fuel oil and other fuels. Model consistent GDP is the sum of consumption (consisting of services and nondurables net of household oil consumption), capital and durable investment, and household oil consumption. Inflation is core CPI while the interest rate is the Fed Funds rate. All data are expressed in per capita terms, in logs, multiplied by 100, and HP-filtered (with the exceptions of inflation and the interest rate which are not HP-filtered). See the online appendix for additional details.}
3.7 Measuring Real Oil Price Volatility

We estimate the law of motion for the real price of oil assuming that the real oil price follows the stochastic volatility model given by equations (2) and (3).\textsuperscript{11}

We use U.S. quarterly data ranging from 1986Q1 to 2012Q4 and calculate the real oil price by dividing the spot price of West Texas Intermediate oil by the core CPI.\textsuperscript{12}

Given the nonlinear structure of the stochastic volatility model, we use the sequential importance resampling particle filter to evaluate the likelihood function.\textsuperscript{13} We use Bayesian methods and construct the posterior distribution of the oil process parameters using the random walk Metropolis-Hastings algorithm.\textsuperscript{14}

Given the lack of guidance for the real oil price process parameter values, we employ uniform priors that are a priori independent. The serial correlation parameters $\rho_p$ and $\rho_{\eta_p}$ are drawn from uniform priors on the unit interval. We let the average value of stochastic volatility ($\bar{\eta}_p$) vary uniformly from -20 to 20. The standard deviation of the volatility shock $\phi$ varies uniformly from 0 to 6. The upper bound implies that, on average, the standard deviation of real oil price innovations increases at most by an implausible factor of 400 following a positive stochastic volatility shock of one standard deviation.

Table 2 reports the priors along with the mean, median, and 5 and 95 credible intervals from the posterior distributions. The shocks to the level and standard deviation of the real oil price process are persistent. The median estimated value of $\bar{\eta}_p$ implies that the real oil price innovation has an average standard deviation of 10.5 percentage point. The median estimated value of $\phi$ implies that a positive stochastic volatility shock of one standard deviation increases the standard deviation of the real oil price innovation by a factor of 14.7 percentage points (or $100 \exp(\bar{\eta}_p + \phi)$).

Figure 5 plots smoothed estimates of the time-varying volatility of the real oil price ($100 \exp \eta_p$), constructed from the sequential monte carlo approximation of the forward-

\textsuperscript{11}We do not directly make use of the implied volatility measure found in section 2, IVOIL1, for several reasons. First, we have a larger sample size if we estimate a stochastic volatility model. Second, although it is possible to directly link up the daily implied volatility and oil price data, to the best of our knowledge there does not appear to be a theoretically consistent method to do so for the quarterly averages. Finally, the results in section 2 are robust to using either measure of oil price uncertainty.

\textsuperscript{12}We start the sample from 1986 as there is a well documented change in U.S. monetary policy in the 1980s compared to the 1970s. For the theoretical exercises we consider, the retail price of energy is the most relevant energy cost measure. We treat the WTI as a proxy for this variable. Kilian (2010) notes some exceptions in this approximation.

\textsuperscript{13}See Doucet, de Freitas, and Gordon (2001) and Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011) for more details on the method. We use 5,000 particles for each evaluation of the likelihood.

\textsuperscript{14}We sample 350,000 draws from the posterior distribution, discard the first 50,000 draws, thin every 5 draws, and perform diagnostic tests to ensure the convergence of the MCMC chain. See the online appendix for more details of the estimation procedure and results from alternative specifications.
backward smoothing recursion at the posterior median. For most of the sample, the quarterly volatility of the real oil price process is low. Larger increases in the volatility occurred in 1990-91 during the Gulf War, in 1999-2000 and 2001, and following the recent global financial crisis.

3.8 Model Solution and Properties

Due to our interest in the effects of stochastic volatility, we solve a third-order approximation of the model around the non-stochastic steady state. We use the posterior medians from our estimated real oil price process to calibrate the relevant parameters in equations (2) and (3). In the analysis in section 4, we examine the effects of the volatility shock when the price level is held constant. Starting with third-order approximations there are non-zero coefficients attached to the stochastic volatility term independent of other shocks and variables in the model.\footnote{For discussion of this issue, see Fernandez-Villaverde, Guerron-Quintana, and Rubio-Ramirez (2010), which provides a theorem highlighting the role of higher-order expansions for studying time-varying volatility shocks.} The third-order solution, therefore, allows us to consider how a shock to the standard deviation independently affects macro aggregates. Since this can be done independently of the shock to the price level, the volatility shock demonstrates how pure uncertainty about the future real oil price affects economic activity.

To calculate model moments and impulse responses, we prune the third order approximation as described in Andreasen, Fernandez-Villaverde, and Rubio-Ramirez (2013). We calculate the ergodic mean of model variables and obtain impulse responses by perturbing the ergodic mean by $n\%$ to shock $s$ and subtracting the ergodic mean from the implied path of variables.

Table 3 lists standard deviations, autocorrelations, and correlations with model-consistent GDP for both the data and model.\footnote{We HP filter all model and data variables except for inflation and the interest rate, using an HP parameter of $\lambda = 1600$. Data for the utilization is taken from the Board of Governors industrial production and capacity utilization series. Wage data is taken from the BLS’ nonfarm business, hourly compensation index. See footnote 10 for remaining data sources. For the model simulations, we simulate 50,500 quarters and discard the first 500 observations.} The benchmark model performs fairly well in matching the moments of most of these variables, even though our SMM procedure did not attempt to match them all. Notable exceptions are the correlations between nominal values and GDP, most likely due to the fact that supply shocks dominate in our calibration. The calibration also implies responses to a real oil price level shock, as well as monetary policy, preference, or technological productivity shocks, that are in line with standard responses from theory.\footnote{Results available in the online appendix.} The next section discusses the responses to real oil price volatility shocks.
4 Theoretical Effects of Real Oil Price Uncertainty

Our focus is on the effects of exogenous changes in real oil price uncertainty. We consider a scenario where in period \( t \) the shock to the volatility of the real oil price, \( \zeta_t \), is increased by two standard deviations. All future values of \( \zeta \) are set equal to 0, as are the contemporaneous and future values of the other shocks in the model, including the oil price level shock \( \epsilon \). A two standard deviation shock captures the large, infrequent increases in the oil price volatility documented in section 3.7 that potentially have a large impact on the economy. In addition, it is a standard experiment in the uncertainty literature (see for example Bloom (2009) and Fernandez-Villaverde, Guerron-Quintana, Kuester, and Rubio-Ramirez (2012)), facilitating comparison between oil price volatility and other forms of volatility considered in the literature. In these experiments, agents continue to pay the same amount for oil but understand that future shocks to the real oil price have a larger spread.

The solid lines of figure 6 present the results for the baseline calibration given in table 1. We find that an exogenous increase in real oil price uncertainty has a negative impact on economic activity.\(^{18}\) Following the shock, capital investment, non-durable and durable consumption, hours worked, and real GDP decline. We find that the quantitative impacts are fairly small. At their troughs, GDP and durable and capital investment contract by 0.04, 0.07, and 0.13 annualized percentage points respectively. The cumulative change in GDP is -0.15 annualized percentage points.

The qualitative features of the results are driven mainly by the interaction of nominal rigidities with the household’s precautionary savings motive.\(^{19}\) On impact, agents know that the future spread of the real oil price has increased, while the price today remains unchanged. This induces a negative wealth effect, leading households to want to increase precautionary savings. Thus, agents are willing to work more on impact to increase income, and in turn savings, to provide higher future income given the heightened future uncertainty. However, the desire to increase the labor supply decreases wages and marginal costs, and, in turn, increases firm markups, which causes labor demand to decline. In equilibrium, labor and

\(^{18}\)Our theoretical exercise differs from the empirical counterpart in that we obtain impulse responses as deviations from steady state, while the empirical analysis considers deviations from trend growth. However, on impact, GDP growth will decrease in our model, given the decline in GDP, consistent with the impact response of our empirical analysis. If we added an exogenous trend to TFP to generate exogenous growth in the model, the responses following a real oil price volatility shock would be similar to the current ones, as there would be no change in exogenous growth following the real oil price volatility shock.

\(^{19}\)Since at least Sandmo (1970), it has been known that higher uncertainty can lead agents to consume less and save more, i.e. the precautionary savings motive (see Carroll and Kimball (2008) for a survey of the literature). Precautionary savings have been discussed previously in the context of energy prices in Edelstein and Kilian (2009) and Kilian and Vigfusson (2011a).
output decrease.\footnote{See Basu and Bundick (2012) for more discussion on the comovement of hours worked and volatility shocks in dynamic, stochastic, general equilibrium models.}

As GDP/income falls, households lower expenditures. Households have access to two durable assets: the durable good \((D)\) and the capital good \((K)\). Heightened energy cost uncertainty implies that the service flow from both of these assets are potentially more expensive, leading capital and durable investment to decline for several quarters. Since adjustment costs to durables are low in the benchmark calibration, the precautionary savings motive dominates on impact, leading households to increase investment in durables for one quarter.\footnote{If adjustment costs are increased slightly, durable investment declines for all quarters. See the online appendix for a comparison of the impact responses as a function of parameters.} Finally, core inflation rises following the elevated oil price uncertainty, due partly to an “upward pricing bias channel” as defined in Fernandez-Villaverde, Guerron-Quintana, Kuester, and Rubio-Ramirez (2012). Given the demand function for a good, equation (5), firms prefer to bias their prices upward, as profit losses are largest if firm’s prices today are low relatively to the preferred price tomorrow.

The presence of nominal rigidities is key to generating these responses. In an economy without adjustment costs to wages and prices, an exogenous increase in real oil price uncertainty has positive effects on real GDP, investment, and labor (see dashed lines of figure 6). In this case, a willingness to increase labor supply translates into higher equilibrium hours worked and output. Households choose to use the increased income to increase their precautionary savings, increasing investment in physical capital and durable goods while decreasing non-durable spending. In addition, without nominal rigidities, the quantitative effects of the real oil price volatility shock are smaller. These results provide an example of the mechanism in Basu and Bundick (2012), highlighting the importance of nominal rigidities in generating negative effects from uncertainty shocks. We also note that the conclusions from the RBC model differ from Bernanke (1983), in that heightened uncertainty in our model without nominal rigidities implies an increase in real GDP when there is increased oil price uncertainty. One important caveat to that finding is that the RBC model abstracts from irreversible investment decisions, which were key to the findings of Bernanke (1983).

### 4.1 Robustness checks

The baseline model suggests that exogenous increases in oil price uncertainty have small, but negative, effects on economic activity. To examine how sensitive the results are to the baseline calibration, we compare the responses of GDP to a two standard deviation real oil price volatility shock over a range of parameter values. Figure 7, in which each panel
varies one parameter at a time, displays the results. In each panel, the solid line denotes the benchmark calibration, the dashed line reduces the parameter of interest by 75%, and the dotted-dashed line increases the parameter of interest by 75%.\textsuperscript{22}

The top panel shows that when the monetary authority responds more weakly to inflation (that is, when $\alpha_r$ is high, $\alpha_\pi$ is low, or $\alpha_y$ is high), GDP is higher in the short run, but falls more over time. In these cases, inflation rises more on impact, since firms know that the central bank is less responsive to changes in inflation. In the short run, precautionary savings motives dominate, as marginal costs and the demand for labor decline less, while households still desire to increase their labor supply. Thus, GDP rises in the short run. Over time, GDP declines and remains below the steady state longer than in the benchmark calibration, as demand contracts following the higher prices and slows down the adjustment to steady state.

The middle panel of figure 7 shows the implications of more or less rigid prices and wages, and of greater adjustment costs to durable goods. GDP initially rises in response to higher oil price volatility when prices are flexible. Very sticky prices dampen the response of GDP in the short run, as the economy adjusts to the volatility shock with more delay. Over time, firms increase their prices in response to the volatility shock, contracting demand, and causing GDP to remain below the steady state even after 10 quarters. Stickier wages make real GDP less responsive to real oil price uncertainty shocks. With higher durable or capital (not pictured) adjustment costs, investment declines more on impact, causing GDP to decrease more.

Turning to the bottom panel of figure 7, we see that larger values of the intertemporal elasticity of substitution ($\tau$) dampen GDP’s response. In this case, households are more willing to substitute consumption across time, and precautionary savings motives are lower, reducing the overall effect of the volatility shock. Demand responds less to the volatility shock when the elasticity of substitution between non-durables and services ($\sigma_c$) is lower, lowering the overall response of GDP. Finally, a lower Frisch value implies that the labor supply is less responsive, which reduces incentives to save as labor income is expected to be less volatile. In this case, capital and durable investment respond more to the negative cost effect and decrease more over time, leading to a pronounced decline in GDP.

Although the impact response of GDP varies across parameter values, for the most part the cumulative responses are of fairly similar size. To see this, figure 8 plots GDP’s cumulative deviation from the stochastic steady state following a two standard deviation real

\textsuperscript{22}There are two exceptions to this. To ensure determinacy, the low value of $\alpha_r$ is 1.01 while the high value of $\alpha_r$ is 0.97.
oil price volatility shock over a range of parameter values.\footnote{Cumulative responses are calculated over 100 periods.} In each panel, one parameter is varied on the horizontal axis, while the vertical line indicates the benchmark calibration value. For most of the parameter values, the cumulative change ranges between -0.1 and -0.2 annualized percentage points. Even for parameter values that give a positive impact response of GDP (as seen from some combinations in figure 7), the cumulative deviations from stochastic steady state are usually negative, as seen from the graph.

Figure 9 shows that the responses of GDP can be much larger if steady state household and firm oil consumption to GDP ratios are larger. In these cases, the oil price affects a larger share of household income, causing households to respond more aggressively to heightened real oil price uncertainty. This is particularly true for the amount of oil used by firms in the economy. The top panel shows that on impact, GDP can decline by -0.035 and -0.45 annualized percentage points in the benchmark model if the household and firm oil shares are increased to 25% of GDP, respectively. The bottom panel shows that the cumulative effects of the volatility shock are also more pronounced, as the cumulative decline in GDP is -0.4 and -1.6 annualized percentage points when the household and firm oil shares are increased to 25% of GDP, respectively. However, such high oil shares are inconsistent with U.S. data. Even with a liberal definition of energy consisting of oil, gas, and electricity, over our calibrated sample period, the largest shares were in 2008, when household and firm energy to model-consistent GDP ratios were 0.048 and 0.066.\footnote{The ratios are slightly lower using actual GDP, thus biasing our results in favor of larger effects.}

We next consider how the quantitative effects vary under two alternative model structures. First, we eliminate variable utilization from the model, and instead assume that energy enters production and utility directly via a nested CES function, similar to Kim and Loungani (1992). In this case, the intermediate production technology for the $i$th firm is given by

$$y_t(i) = A_i L_t(i)^\alpha \left[ K_{t-1}(i)^{\frac{1}{1-\theta}} + aO_f^i(i)^{\frac{1}{1-\theta}} \right]^\frac{\theta}{1-\theta},$$

where $\theta$ is the elasticity of substitution between capital and energy and $\alpha$ is a distribution.
parameter. Similarly, durable services in the \( j \)th household’s utility function are given by

\[
S_t(D, u^d) = \left[ D_{t-1}(j)^{\frac{\eta_d}{1-\eta_d}} + bO_t^h(i)^{\frac{\eta_d}{1-\eta_d}} \right]^{\frac{1}{\eta_d-1}},
\]

where \( \eta_d \) is the elasticity of substitution between durables and energy and \( b \) is a distribution parameter. We calibrate \( \eta = \eta_d = 0.25 \) to ensure a low price-elasticity of demand for oil products and keep the remaining parameters at the benchmark calibration.\(^{25}\) The dotted line of figure 10 displays the response of GDP to a two standard deviation oil price volatility shock in this case. For comparison, the solid line denotes the response from the benchmark model specification. In this case, oil consumption responds less to heightened uncertainty, and investment in capital and durables (not pictured) decreases more on impact, but quickly returns to steady state. As a result, while GDP declines more on impact, its cumulative change (-0.09) is much lower than the benchmark model.

The second model alteration allows for non-separable preferences similar to Greenwood, Hercowitz, and Huffmann (1988) (hereafter GHH):

\[
E^\infty_0 \sum_{t=0}^{\infty} \beta^t u^b_t \left\{ C_t^{\sigma_c-1} \left[ \frac{\kappa_1 S_t(D, u^d)}{\sigma_c} \right]^{\sigma_c-1} - \kappa_2 L_t^{1+\mu} \right\} \left( 1 - \frac{1}{\tau} \right)^{1-\frac{1}{\tau}}.
\]

The dotted-dashed line of figure 10 displays the response of GDP to a volatility shock in this case. GHH-style preferences reduce the wealth effect on labor supply.\(^{26}\) With the smaller wealth effect on the labor supply, labor responds more to the negative cost effects. In this case, equilibrium labor declines more than the benchmark model, as does capital and durable investment and GDP.

Finally, we compare how our model performs under an alternative sample period calibration. Given the large oil price changes of the 1970s, we re-calibrate our model over the period 1974Q1 to 2012Q4. To do so, we first re-estimate the stochastic volatility model using the refiner acquisition cost (RAC) for imported crude oil, calibrate steady state values to match sample averages over the periods, and conduct our SMM analysis to match sample moments over the longer period.\(^{27}\) Figure 10 compares the responses of GDP to a

\(^{25}\)See the online appendix for additional model details.

\(^{26}\)The presence of durable services in the utility function implies that the wealth effect on the labor supply is not completely eliminated, even though its effect is dampened considerably with GHH-style preferences. See the online appendix for additional details of the model set-up. Dey and Tsai (2012) also discuss GHH preferences in a model with durables.

\(^{27}\)Ramey and Vine (2010) discuss issues with alternative measures for the price of oil (including the WTI) in the 1970s. Details of the stochastic volatility estimation, SMM analysis, and calibration in this case are
two standard deviation real oil price volatility shock under the benchmark calibration (solid lines) and the alternative, longer sample calibration (dashed lines). The longer sample does increase GDP’s quantitative response, as the peak loss of GDP is -0.067, as opposed to -0.04 in the benchmark model. GDP remains below the stochastic steady state longer as well. These results are due to the fact that the alternative calibration has a higher estimate of the persistence of the real oil price volatility shock, which extends the duration of the shock’s effect. In addition, the longer sample period implies larger sample means for household and firm oil to GDP ratios, which enhances the effects.

Overall, the qualitative and quantitative results are robust to a wide range of alternative model parameterizations and specifications. An exogenous increase in real oil price volatility generates a slowdown in economic activity, and the quantitative response of GDP is relatively small in size. The largest impact responses occur by assuming GHH-style preferences, counterfactually high oil-to-GDP ratios, and/or a more persistent process to the real oil price volatility shock (as seen in the long sample). The results of the theoretical model are similar in spirit to the findings of our empirical analysis. In the latter, we found that exogenous changes in oil price uncertainty produce short-lived declines in real GDP growth. The size of these declines were relatively small in comparison to the size of the changes in GDP often seen in the data.

5 Conclusion

In this paper we present empirical and theoretical evidence that real oil price uncertainty has small, but negative impacts on economic activity. Our first contribution was to estimate a VAR model that controls for the fact that various sources, such as OPEC-related events and general economic uncertainty, influence oil price uncertainty. We use the VAR model to analyze the effect of increased oil price uncertainty driven by exogenous events and find they lead to small and short-lived, but statistically significant, declines in the growth rate of U.S. real GDP. The result is robust to the ordering of variables in the VAR, lag length, time frame, data definitions, and the measure of oil price uncertainty.

We then investigate the relationships among output, consumption, investment, and oil price volatility in a New Keynesian model that incorporates demand for oil for both production and utility purposes. We estimate a stochastic volatility process for the real U.S. price of oil using Bayesian methods and use the estimated process in the model. Following an exogenous increase in real oil price volatility in the theoretical model, GDP and other given in the online appendix. In this case, the household and firm oil consumption to GDP shares are 2.9% and 3.3% respectively.
macroaggregates decline, although the quantitative response of GDP often is relatively small in size. This recessionary effect is due to countercyclical markups, stemming from precautionary savings motives interacting with nominal rigidities, as highlighted by Basu and Bundick (2012). The result holds for a variety of model parameterizations and specifications. Significantly larger responses are possible, but occur only with unreasonable assumptions about oil usage in the economy.

As shown in Kilian (2009), the responses of macroeconomic variables to an increase in the price of oil varies depending upon what causes the oil price to increase. Our empirical findings suggest this also holds for oil price uncertainty. An important question for future research will be to integrate an explicit role for uncertainty into DSGE models with endogenous oil prices of the type recently proposed by Bodenstein, Erceg, and Guerrieri (2011), Nakov and Pescatori (2010) and Bodenstein, Guerrieri, and Kilian (2012), perhaps by incorporating the storage framework of Arseneau and Leduc (2013).
References


Figure 1: Uncertainty measures. Dashed line: VIX; solid line: implied volatility from the one-month ahead futures contract for the West Texas Intermediate crude oil (IVOIL1 in the text).

Figure 2: Quarterly newspaper index.
Figure 3: Impulse responses following a one standard deviation innovation to the newspaper index in the baseline VAR. Dashed lines denote 95 percent bands.
Figure 4: VAR estimation of the impact of an oil price uncertainty shock on the growth rate of GDP.

Figure 5: Smoothed estimates of the time-varying volatility of the real oil price \(100 \exp \eta^p_t\), constructed from the posterior median. Solid line: at mean estimate of \(\bar{\eta}^p\).
Figure 6: Impulse responses to a two standard deviation increase in the real oil price volatility. Solid lines: benchmark, New Keynesian model. Dashed lines: model without nominal rigidities. Responses plot deviations from the stochastic steady state.
Figure 7: Parameter sensitivity analysis. GDP responses expressed in annualized percentage points following a two standard deviation increase in the real oil price volatility. In each panel, all parameters except the one indicated are held at the benchmark calibration values. Black solid lines: benchmark model; Blue dashed lines: lower parameter value; Red dotted dashed lines: higher parameter value. Responses plot deviations from the stochastic steady state.
Figure 8: Parameter sensitivity analysis. Cumulative deviation from stochastic steady state of GDP responses expressed in annualized percentage points following a two standard deviation increase in the real oil price volatility. In each panel, all parameters except the one indicated are held at the benchmark calibration values. Solid vertical lines indicate benchmark values.
Figure 9: Parameter sensitivity analysis. Top row: Impact GDP response, expressed as deviations from stochastic steady state in annualized percentage points, following a two standard deviation increase in the real oil price volatility. Bottom row: Cumulative deviation from stochastic steady state of GDP responses expressed in annualized percentage points following a two standard deviation increase in the real oil price volatility. In each panel, all parameters except the one indicated are held at the benchmark calibration values. Solid vertical lines indicate benchmark values.
Figure 10: GDP impulse responses to a two standard deviation increase in real oil price volatility. Solid lines: benchmark model, calibrated over 1986-2012; Dashed lines: calibration over 1974-2012; Dotted-dashed lines: GHH preferences; Dotted lines: No utilization channel for energy. Responses plot deviations from the stochastic steady state.
Table 1: Benchmark Parameters.

<table>
<thead>
<tr>
<th>Calibrated</th>
<th>Estimated with SMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intertemporal Elasticity of Substitution $\tau = 0.5$</td>
<td>Elasticity of Substitution between $C$ and $S$ $\sigma_c = 0.91$</td>
</tr>
<tr>
<td>Discount Factor $\beta = 0.99$</td>
<td>Durable adjustment cost $\omega_d = 2.13$</td>
</tr>
<tr>
<td>Inverse Frisch Elasticity of Labor Supply $\mu = 2$</td>
<td>Standard deviation of technology $\sigma_A = 0.0087$</td>
</tr>
<tr>
<td>Steady state Labor $\bar{L} = 0.33$</td>
<td>Capital adjustment cost $\omega_k = 3.57$</td>
</tr>
<tr>
<td>Steady state capital utilization $\bar{\bar{u}} = 0.7972$</td>
<td>Standard deviation of monetary policy $\sigma_r = 3.8 \times 10^{-4}$</td>
</tr>
<tr>
<td>Steady state durable utilization $\bar{\bar{u}}^d = 0.7972$</td>
<td>Technology AR(1) $\rho_A = 0.89$</td>
</tr>
<tr>
<td>Depreciation of durables $\bar{\delta}_d = 0.0514$</td>
<td>Standard deviation of pref. shock $\sigma_b = 2.5 \times 10^{-6}$</td>
</tr>
<tr>
<td>Price elasticity of demand $\theta_p = 6.25$</td>
<td>RESPONSE TO INFLATION $\rho_r = 0.8$</td>
</tr>
<tr>
<td>Wage elasticity of demand $\theta_w = 6.25$</td>
<td>Response to output growth $\rho_y = 0.1$</td>
</tr>
<tr>
<td>Household Oil Consumption to GDP ratio $\frac{P^o \bar{O}_h}{\bar{Y}} = 0.025$</td>
<td>Labor share* $\alpha = 0.72$</td>
</tr>
<tr>
<td>Firm Oil Consumption to GDP ratio $\frac{P^o \bar{O}_f}{\bar{Y}} = 0.026$</td>
<td>Wage adjustment cost* $\Phi_w = 84.3$</td>
</tr>
<tr>
<td>Steady State Oil Price $\bar{P}^o = 1$</td>
<td>Price adjustment cost* $\Phi_p = 10.4$</td>
</tr>
<tr>
<td>Steady State Inflation $\bar{\Pi} = 1.0069$</td>
<td>Steady state GDP $\bar{\bar{Y}} = 1$</td>
</tr>
<tr>
<td>Lagged interest rate response $\rho_r = 0.8$</td>
<td>Steady State Inflation $\bar{\Pi} = 1.0069$</td>
</tr>
<tr>
<td>Response to output growth $\rho_y = 0.1$</td>
<td>Lagged interest rate response $\rho_r = 0.8$</td>
</tr>
<tr>
<td>Wage adjustment cost* $\Phi_w = 84.3$</td>
<td>Response to output growth $\rho_y = 0.1$</td>
</tr>
<tr>
<td>Price adjustment cost* $\Phi_p = 10.4$</td>
<td>Wage adjustment cost* $\Phi_w = 84.3$</td>
</tr>
</tbody>
</table>

Note. Parameters with * indicate those implied by the calibration.
Table 2: Prior and Posterior for Stochastic Volatility Model Parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Prior</th>
<th>Mean</th>
<th>Median</th>
<th>90% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{\eta}$</td>
<td>Uniform(0,1)</td>
<td>0.63</td>
<td>0.65</td>
<td>(0.30, 0.87)</td>
</tr>
<tr>
<td>$\rho_p$</td>
<td>Uniform(0,1)</td>
<td>0.68</td>
<td>0.68</td>
<td>(0.55, 0.80)</td>
</tr>
<tr>
<td>$\bar{\eta}$</td>
<td>Uniform(-20,20)</td>
<td>-2.25</td>
<td>-2.25</td>
<td>(-2.48, -2.04)</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Uniform(0,6)</td>
<td>0.34</td>
<td>0.33</td>
<td>(0.19, 0.44)</td>
</tr>
</tbody>
</table>

Table 3: Second Moments for the Benchmark Economy.

<table>
<thead>
<tr>
<th>Variable</th>
<th>$100\sigma_X$</th>
<th>$\text{Corr}(X_t, X_{t-1})$</th>
<th>$\text{Corr}(X_t, Y^*_t)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y^g$</td>
<td>1.76</td>
<td>0.93</td>
<td>1</td>
</tr>
<tr>
<td>$P^oO^h$</td>
<td>9.34</td>
<td>0.69</td>
<td>0.67</td>
</tr>
<tr>
<td>$I^d$</td>
<td>3.62</td>
<td>0.78</td>
<td>0.76</td>
</tr>
<tr>
<td>$I^k$</td>
<td>5.01</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td>$\Pi$</td>
<td>0.27</td>
<td>0.83</td>
<td>0.35</td>
</tr>
<tr>
<td>$R$</td>
<td>0.65</td>
<td>0.98</td>
<td>0.46</td>
</tr>
<tr>
<td>$C$</td>
<td>0.86</td>
<td>0.90</td>
<td>0.95</td>
</tr>
<tr>
<td>$u$</td>
<td>2.79</td>
<td>0.91</td>
<td>0.83</td>
</tr>
<tr>
<td>$W$</td>
<td>1.04</td>
<td>0.70</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Note. The data are for 1986Q1 to 2012Q4. See section 3.8 for detailed data definitions.