# Oil Price Uncertainty and Real Economic Activities: Importance of Disentangling the Diffusive and Jump Components*

Sang Baum Kang†, Xuhui Pan‡, and Jialin Zhao§

November 18, 2016

**Abstract**

Most of the econometric works to date rely on realized volatility or option-implied volatility to study how oil price uncertainty adversely affects the macroeconomy. In this paper, we argue that the continuous diffusive oil price volatility predicts real economic activities better than other common oil volatility measures. We quantify the continuous and jump components of oil price volatility based on bipower variation. The estimated diffusive volatility has significant adverse impacts on future economic growth, consumption, and real investment. We further reveal important differences in diffusive volatility and jumps. The continuous diffusive volatility is strongly associated with the economy-wide uncertainty both in-sample and out-of-sample; while jumps are mainly driven by growth in oil market-specific supply and demand.

JEL Classification: G12, G13

Keywords: Crude oil; uncertainty; real economic activity; jump-diffusion process; high-frequency.

*We would like to thank Lutz Kilian, Michel Robe, Jing (Cynthia) Wu, and seminar participants at Illinois Institute of Technology for their comments. We especially thank Christiane Baumeister for providing the global oil production data in Baumeister and Hamilton (2015). We also thank Kasper Vinther Olesen for the early development of research ideas in the paper.

†Stuart School of Business, Illinois Institute of Technology. E-mail: skang21@stuart.iit.edu.

‡Freeman School of Business, Tulane University. Email: xpan@tulane.edu.

§Stuart School of Business, Illinois Institute of Technology. E-mail: jialin.zhao11@gmail.com.

# 1 Introduction

Oil price uncertainty may adversely affect aggregate investment, output, and consumption in the U.S. (e.g., Pindyck, 1991; Ferderer, 1996). Recent work demonstrates that oil price uncertainty also plays a role in determining foreign exchange rates and influencing import and export strategies of oil-heavy countries (Canuto, Crain, and Davig, 2016). To examine the role of oil price uncertainty on the macroeconomy, most of the econometric works to date rely on historical volatility estimated from daily prices, parametric characterization of conditional variance such as a GARCH process, or option-implied volatility (see, e.g., Guo and Kliesen, 2005; Elder and Serletis, 2010; Gao et al., 2016). However, when we use these measures, the significance of the relationship between oil price uncertainty and the real economy is sensitive to the control variables and time periods of the regression model. The empirical evidence is often mixed and inconclusive.

In this paper, we measure oil price uncertainty as realized variance using high-frequency oil prices from the liquid WTI oil futures market (as opposed to daily spot prices) to study the causes and consequences of oil price uncertainty. Recent literature suggests that the realized variance measured from high frequency data provides an accurate estimate of the true variance of asset prices (e.g., Andersen et al., 2003). Building on the fundamental notion in finance that the price dynamics of financial assets have both a continuous path and jumps (Merton, 1976) and the theoretical work of bipower variation in variance estimation by Barndorff-Nielsen and Shephard (2004, 2006), we quantify the continuous and the jump components of oil price volatility. The variance decomposition in this paper is in line with Andersen, Bollerslev, and Diebold's (2007) who claim that conditional variance can be best described by a smooth sample process and less persistent jumps. Our decomposition of oil price uncertainty is also motivated by the puzzling fact that impacts of oil price uncertainty on real economic activities are inconclusive, although the theoretical literature (such as Bernanke, 1983; Bloom, 2009) highlighted the importance of the macro uncertainty on the aggregate economy, and oil price is clearly an important macro state variable. When separating the continuous diffusive path and jump from the oil price uncertainty, we find that only the continuous part has predictive power of various real economic activities. More interestingly, the forecasting power of the continuous part is more robust and stronger than the oil price uncertainty measured by total variance.

Our second objective is to explore the economic drivers of oil price uncertainty and its components. Some papers have related stock market volatility to economic variables and have included macroeconomic fundamental variables in volatility forecast models (e.g., Schwert, 1989; Paye, 2012; Engle, Ghysels, and Sohn, 2013). Kilian (2014) argued that fluctuations in oil prices are endogenously determined by economic fundamentals including global demand and supply growth, rather than exogenous geopolitical events. To further Kilian's work, we attempt to address the question of whether oil price uncertainty is driven by fundamental economic forces. To this end, we examine a large cross section of economic variables and identify those that can significantly forecast oil price uncertainty. We identify three major predictors that include growth in global oil supply, oil demand, and macroeconomic uncertainty. We also find that the estimated continuous part is strongly associated with economy-wide aggregate uncertainty, while the jump component is mainly determined by oil-market specific information such as growth in oil supply and demand. Our decomposition of oil price uncertainty not only results in significant gains in predicting real economic activities relative to other measures, but also provides new and novel insights on the different roles of oil price uncertainty attributable to continuous price changes and that attributable to unexpected price jumps.

We measure oil price uncertainty as realized variance using high-frequency data from the liquid WTI oil futures market spanning from 1987 to 2014. Our nonparametric estimation of realized variance follows the sampling approach of Andersen, Bollerslev, and Meddahi (2011) which has been shown to be robust to the impact of microstructure noises. We further decompose realized oil variance into the continuous and jump parts based on the theory of bipower variation (Barndorff-Nielsen and Shephard, 2004, 2006). Andersen, Bollerslev, and Diebold (2007) and Tauchen and Zhou (2011) have extended this method to detect jumps in the equity and bond markets. This procedure enables us to understand how oil price uncertainty responds to economic factors reflecting investors' expectation in continuous oil price changes or large and sudden price shocks.

We present three main findings about oil price uncertainty. First, we find that while oil price uncertainty in general dampens real economic activity,[1] the uncertainty due to the continuous price movements and jumps has distinct impacts. For example, a standard deviation increase in oil price uncertainty, measured by oil price variance, lowers the real GDP and GNP growth in the next quarter by 17.1% and 20.5% in the next quarter in the univariate regression. A standard deviation increase of the uncertainty due to the continuous price movements decreases the real GDP and GNP growth in the next quarter by 21.8% and 26.1%. Jump volatility does not have significant impacts. Other measures of real economic activity, such as industrial production growth, real personal consumption, and real investment, react to oil price uncertainty and its components in a similar way.

[1]Plante and Traum (2012) illustrate the theoretical relation between oil price uncertainty and economic activity in a real business cycle model. Jo (2014) documents the negative effects of oil price uncertainty on world industrial production.

Second, we show that the expected continuous volatility has more robust forecasting power of real economic activities than the total realized variance and option-implied volatility. When we include other macro variables such as default spread or term spread, the impact of realized oil variance on macroeconomic activities largely diminishes. But the continuous component of oil price uncertainty robustly forecasts real economic activities after controlling for these macro variables. The impact of continuous oil price uncertainty on real personal consumption of durable goods, and on real investment is particularly strong. This strong effect is consistent with theoretical works of, e.g., Bernanke (1983), Majd and Pindyck (1987), Hamilton (1988), and Pindyck (1991).

Third, growth in global oil production, commodity demand, and the uncertainty about the economy significantly predict oil price uncertainty both in-sample and out-of-sample. We also reveal the different dynamics between the continuous and jump components of realized variance by exploring a large cross-section of potential economic determinants. The continuous variance is strongly associated with the aggregate macroeconomic uncertainty index, proposed by Jurado, Ludvigson, and Ng (2015); while the jump variance is mostly determined by oil and commodity market-specific information such as global oil supply and demand. To further reinforce our findings based on OLS regressions, we adapt the dimension reduction technique of the three-pass regression filter (henceforth, 3PRF) proposed by Kelly and Pruitt (2015). Since we explore the economic drivers of oil price uncertainty from a large number of predictors, it is important to effectively extract the information from the dataset and eliminate potential econometric problems in multivariate OLS regressions. The 3PRF is superior to the traditional principal component analysis, because an econometrician can choose important variables based on direct statistical evidence. Using the 3PRF approach, we confirm the results from our OLS analysis. It also helps us understand the reason why the continuous oil volatility can predict real economic activities so well.

This paper is related to and contribute to two distinct strands of literature. First, our paper belongs to the fast-growing literature that concerns the economic fundamentals of the financial market volatility. Among a large body of literature of studying stock market volatility, Schwert (1989) relates U.S. stock market volatility to macroeconomic variables; Paye (2012) asserts limited benefit of macroeconomic information when forecasting stock market volatility. Engle and Rangel (2008) characterize the low-frequency component of stock market volatility and show that macroeconomic fundamentals drive this long-term volatility. Great improvements have also been made in understanding the causes of oil and commodity market volatility, including Prokopczuk and Symeonids (2015), and Robe and Wallen (2016). Using high-frequency price data and a large cross section of economic variables, this paper contributes to this strand of literature by identifying predictors of oil price uncertainty.

Second, our paper enriches the literature of the interactions between crude oil and the macroeconomy, where many papers have focused on oil price shocks (e.g., Hamilton, 1996, 2003; Loungani, 1986; Lee and Ni, 2002; Elder and Serletis, 2010; Kilian and Vigfusson, 2011; Jo, 2014). By decomposing oil price uncertainty into the parts attributable to expected continuous price movements and unexpected jumps, we distinguish the different roles they play on how oil price uncertainty affects economic activity. The continuous component of oil price uncertainty robustly predicts real economic activities even after controlling for oil return; whereas the jump component does not. Our results suggest that the impact of the continuous part of oil price uncertainty on real economy dominates the impact from oil price returns. Furthermore, we document that economy-wide macro uncertainty (e.g., Ludvigson's index) predicts the continuous diffusive part but does not predict the jump component of oil price realized variance, which explains why the continuous part of oil price return variance predicts various real macroeconomic indicators. However, the continuous component's predictability of real economic activities is not subsumed by Ludvigson's index. Hence, the diffusive variance of oil price returns contains unique information on predicting macroeconomic aggregates.

The rest of the paper proceeds as follows. We present the estimation of oil price uncertainty in Section 2. Section 3 investigates how oil price uncertainty, and its continuous and jump components affect real economic activities. In Section 4 we explore the economic forces of the components of oil price uncertainty. Section 5 concludes.

# 2 Oil Price Uncertainty Measured from High-Frequency Crude Oil Futures Prices

We use high-frequency intraday WTI crude oil futures prices traded in CME to estimate oil price uncertainty.[2] We use realized variance as the proxy of oil price uncertainty. Comparing to implied volatility inferred from option prices to quantify oil price uncertainty, realized variance has a longer time series and does not contain the variance risk premia. High-frequency price data offer evident advantages over daily prices to estimate variance. First, realized variance (RV, hereafter) calculated from high frequency data provides more accurate measurement of variance than that calculated from low frequency daily data. Second, high-frequency data allow an econometrician to decompose the variance to the continuous

[2] Many other papers estimate oil price uncertainty from daily oil prices (e.g., Jo, 2014; Elder and Serletis, 2010; Guo and Kliesen, 2005; Hamilton, 2003).

price movement part and the price jump part, which could be driven by difference economic forces. By decomposing oil price uncertainty into the parts attributable to continuous price movements and jumps, we distinguish the different roles they played on how oil price uncertainty affects economic activity. In this section, we discuss the econometric framework of computing realized variance from high-frequency intraday crude oil futures prices; and how we decompose realized variance into the continuous and the jump components.

## 2.1 Econometric Methodology

### 2.1.1 Oil Price Realized Variance

We follow the notion that the price dynamics of financial assets have both a continuous path and jumps (Merton, 1976) and conditional variance can be best described by a smooth sample process and less persistent jumps (Andersen, Bollerslev, and Diebold, 2007). We consider that logged oil futures price $p_T$ evolves as jump-diffusion process in continuous time:

$$p_T = \int_0^T \mu_s ds + \int_0^T \sigma_s dW_s + J_T,$$

where the drift $\mu_s$ is predictable (i.e., constant for an infinitesimally small time interval) and locally bounded; the continuous part of volatility $\sigma_s$ is cádlág (i.e., right-continuous with a well-defined left-limit); $W_s$ is a standard Brownian motion, and $J_T$ is a pure jump process where the sign of jump is either positive or negative. The quadratic variation of this process from time 0 to $T$ is

$$[p, p] = \int_0^T (\sigma_s)^2 ds + \sum_{0<s\leqslant T} (\triangle p_s)^2 , \tag{1}$$

which has both the continuous part as the first term of the right hand side and the jump part as the second term, where $\triangle p_s$ is the amount of jump at time $s$ if there is any. We define RV as:

$$RV \equiv \sum_{i=1}^{n} (r_i)^2 ,$$

where the logged return $r_i \equiv p_i - p_{i-1}$; $p_i$ is a logged price at time $\tau_i$; $\tau_0 = 0 < \tau_1 < \tau_2 < ... < \tau_n = T$; and the subintervals are equally spaced. This measure of RV converges in probability to the quadratic variation (1). Empirical finance literature has demonstrated that RV calculated from intraday high-frequency price returns is a more accurate estimator of the quadratic variation (1) than that from interday low-frequency returns. See Patton and Sheppard (2015) and Andersen and Bollerslev (1998) for a similar discussion.

In the absence of microstructure noise, RV calculated from futures returns sampled at a higher frequency is more accurate than that at a lower frequency. However, there is a downside of using higher-frequency price returns $-$ the estimation of RV may be biased because of microstructure noises. Therefore, we follow Andersen, Bollerslev, and Meddahi's (2011) approach which has been shown to be robust to the impact of microstructure noises. In a preprocessing step, we calculate RV with a fixed sampling frequency for a trading date $t$ as

$$RV_t^{sparse}(h,j) \equiv \sum_{i=1}^{N_j} (r_{j+ih}^{(t,h)})^2, \tag{2}$$

where $h$ is the width of sample interval, e.g., 5 minutes; $j = 0, ..., (h-1)$ is the offset (initiator) to start the RV calculation; $N_j$ is the number of sample intervals of a trading date $t$ with the total trading minutes $D_t$; $N_j \equiv D_t/h$ if $j = 0$ and $N_j \equiv (D_t/h - 1)$ if $j = 1, ..., (h-1)$; $r_s^{(t,h)} \equiv \log(F_{t,T}(s)/F_{t,T}(s-h))$ is the log return of the futures contract with delivery time $T$ at the trading minute $s$ on day $t$. Within this setting, Andersen, Bollerslev, and Meddahi (2011) propose the "average" $RV_t^{sparse}(h,j)$ over $j = 0, ..., (h-1)$, namely,

$$RV_t^{average}(h) \equiv \frac{1}{h} \sum_{j=0}^{h-1} RV_t^{sparse}(h,j) \tag{3}$$

to minimize microstructure noise in the high-frequency data. To calculate RV on a trading date $t$, we set $h = 5$ minutes and add over-night returns squared to $RV_t^{average}(h)$.

For each trading day in our sample period of 1987 to 2014, we compute such daily RV from intraday crude oil futures prices, and then aggregate them into a monthly or quarterly time series.

#### 2.1.2 Decomposition into the Continuous and Jump Components

Building on the theoretical work of bipower variation in variance estimation by Barndorff-Nielsen and Shephard (2004, 2006), we next decompose of RV into the continuous and jump components. The bipower variation (BV, hereafter) converges in probability to the continuous part of the quadratic variation (1). In other words,

$$BV \equiv \frac{\pi}{2} \sum_{i=2}^{n} |r_i| \, |r_{i-1}|$$

converges in probability to $\int_0^T (\sigma_s)^2 \, ds$, whereas $RV$ converges to $\int_0^T (\sigma_s)^2 \, ds + \sum_{0<s\leqslant T} (\triangle p_s)^2$. Observe that $RV$ includes both the continuous part and the jump part of the quadratic variation, whereas $BV$ singles out only the continuous part.

On a trading day $t$ in the absence of price jumps, $RV$ and $BV$ should be very close to each other. However, on a trading day $t$ with the presence of price jumps, $RV$ will be greater than $BV$. Following Busch, Christensen, and Nielsen (2011), we formally construct a test statistics $Z_t$ for the null hypothesis that no price jump occurs on each trading day $t$:

$$Z_t = \sqrt{N_0} \frac{\left(RV_t - BV_t\right)/RV_t}{\sqrt{\left(\frac{\pi^2}{4} + \pi - 5\right) \max\left(1, \frac{TQ_t}{(BV_t)^2}\right)}} \xrightarrow{d} N(0,1),$$

where $N_0$ is the number of high-frequency returns; $RV_t$, $BV_t$, and $TQ_t$ is RV, BV, and tripower quarticity, respectively. Under the null hypothesis of no jump, $Z_t$ asymptotically converges in probability to the standard normal distribution.

To detect a price jump on a trading day $t$, we perform a one-side test using $Z_t$. If a price jump is statistically significantly identified on the trading day $t$, the jump component of RV, $J_t$, is defined as $(RV_t - BV_t)$, and otherwise, the jump component is zero. In other words,

$$J_t = I_{\{Z_t > \phi_{1-\alpha}\}} \left(RV_t - BV_t\right)$$

where $\phi_{1-\alpha}$ is the $(1-\alpha)$ percentile of standard normal distribution. In this paper, we mainly use $\alpha = 0.05$. It follows that the continuous part of RV, $C_t$. is

$$C_t = RV_t - J_t.$$

## 2.2 Characteristics of Crude Oil Price Uncertainty

We use high-frequency intra-day WTI crude oil futures prices from Tick Data from 1987 to 2014, when the oil futures market is liquid. Our data period covers three U.S. recessions and several consequential geopolitical events such as gulf wars and recent financial recession and recovery, and therefore offers rich information context for us to investigate the interaction between oil market and the real economy. Since the first month futures contract is far more liquid than other contracts, our calculation of oil price uncertainty mainly focuses on price changes of this contract.

Figure 1 plots the time variation of monthly crude oil price uncertainty, as measured by crude oil price variance. We multiply all calculation results by 10000. Oil price uncertainty usually spikes during the recessions, and gradually declines to a low level as the economy recovers. Although geopolitical events are important to the crude oil market and affect oil price variance in the short horizon, we do not see clear association of high oil price uncertainty with these events, at least at the monthly frequency. The mid and low panels of Figure 1 plots the uncertainty attributable to the continuous price movement and unexpected price jump. The continuous part contributes to the total variance about 80.8% and the jump part contributes about 19.2% in our time period. The jump contribution is slightly higher than the one in the equity market and treasury bond market (Andersen, Bollerslev, and Diebold, 2007). Meanwhile, the continuous and the jump parts display very different dynamics. For example, there is a large spike in jump in 1998 when the level and the continuous part of oil price variance are at a moderate level. We also observe that oil price uncertainty is high during recession due to a high level of both the continuous part and the jump part.

We report descriptive statistics of oil price variance and its decompositions in Table 1. Oil price variance is positively skewed and has a high level of kurtosis, so do its decompositions. Variance and its continuous part are also persistent with the AR(1) coefficient equal to 0.7 and 0.8. Partial autocorrelation functions of oil price variance suggest that the autocorrelation coefficients beyond two lags are typically insignificant. Based on this observation, we use the AR(2) model as a benchmark when we gauge whether economic variables predict oil variance in the time series regression. Realized variance and its components all pass the unit-root test based on the ADF statistics.

# 3 Crude Oil Price Uncertainty and Real Economic Activity

To investigate how oil price uncertainty affects future real economic activity, we consider various macroeconomic indicators in the U.S. spanning production, consumption and investment. They include the growth rate in real GDP and GNP, real personal consumption expenditures durable goods (RPC_Durable), real personal consumption expenditures services (RPC_Service), investment in the private sectors (Real Inv), and government investment (Real GPDInv). Many papers have argued that oil price uncertainty may affect firm's investment decision as well as real consumption of households (e.g., Bernanke, 1983; Edelstein and Kilian, 2007; Kellogg, 2014).

We obtain the macroeconomic data from Federal Reserve Bank of St. Louis. First we direct check whether oil price uncertainty and its decompositions predict measures of economic activity. To gauge the marginal effect of oil price uncertainty on real economic activity, we further control for default spread, term spread, S&P 500 index return, and crude oil price return. This choice of control variables is motivated by two reasons. Firstly, Guo and Kliesen (2005) use the similar set of variables to study the effect of oil price variance on the U.S. macroeconomic activity. However, they measure oil price variance as squared daily price changes and we use high-frequency data. Secondly, default spread and term spread are highly correlated with other macroeconomic indicators. For example the correlation between default spread and the ADS index (Ludvigson's uncertainty) is -68.1% (79.9%). Term spread is also highly correlated with Bloom's uncertainty index with 43.1%. We also include oil price return as a forecasting variable of real economic activities, given the fact that most of U.S. recessions were preceded by spikes in oil prices (e.g., Hamilton, 1996).

Since our measure of oil price uncertainty is monthly while real economic activity variables are quarterly, we use the following method to aggregate monthly oil price uncertainty into quarterly. For any quarter $q$,

$$RV_q = \frac{1}{6}(RV_{q,(1)} + 2RV_{q,(2)} + 3RV_{q,(3)}),$$

where $RV_{q,(1)}$, $RV_{q,(2)}$, and $RV_{q,(3)}$ denote monthly realized variance in the first, second, and third month within the quarter $q$. This aggregation approach essentially shares the spirit of mixed data sampling (MIDAS) in Ghysels, Santa-Clara, and Valkanov (2006), but we assign higher weight to the later informational content of RV.

## 3.1 Oil Realized Variance and Real Economic Activity

We first report the fact the total realized variance employed by the literature (e.g., Guo and Kliesen, 2005) can be inconclusive. Panel A of Table 2 shows how realized variance affects real economic activities in the univariate regression. In this setting, oil realized variance negatively predicts all macroeconomic indicators including GDP and GNP growth, real consumption, and investment. A standard deviation increase in realized variance decrease the real GDP growth in the next quarter by 17.1% and real investment in the next quarter by 17.9%. However, this predictability is largely subsumed by other macro variables such as default spread and term spread. As shown in Table 3, realized variance loses forecasting power of most macroeconomic indicators after we include default spread or term spread in regressions. In appendix Table A1, we show that the forecasting power becomes even weaker when we include the determinants of oil price uncertainty we identify in Section (4). We also present, in appendix Table A2, the evidence the option-implied oil volatility does not predict real economic activities in our sample, although it is a forward-looking measure and captures the ex-ante uncertainty.

These inconclusive findings are puzzling because the theoretical literature (such as Bernanke, 1983; Bloom, 2009) highlights the importance of the macro uncertainty on the aggregate economy, and oil price is clearly an important macro variable. We next investigate whether the continuous and jump components of oil price uncertainty can predict these major economic indicators.

## 3.2 The Continuous Variance and Real Economic Activity

We do find that the continuous volatility can robustly predict real economic activities, but the jump volatility has no forecasting power. Since total realized variance is the combination of the continuous and jump components, its forecasting power is naturally dampened. From the Panel B of Table 2, we see the continuous volatility has stronger predicting power of all real economic activities than realized variance in both the magnitude and the significance level, but the jump volatility shows no significance. Macroeconomic aggregates mainly respond to the continuous part of oil price uncertainty.

Table 4 reports the results when we control for other variables. We observe that the forecasting power of the continuous volatility on real economic activities largely remains robust comparing to Table 2. For example, one standard deviation increase in the continuous volatility dampens the GNP growth in the next quarter by 18.8% to 29.9% (vs. 26.1% in Table 2) depending on the control variable we use; one standard deviation increase in the continuous volatility dampens the real investment in the next quarter by 23.0% to 31.6% (vs. 27.9% in Table 2). The impact of continuous oil price uncertainty on real personal consumption of durable goods, and on real investment is particularly strong. This strong effect is consistent with theoretical works of, e.g., Bernanke (1983), Majd and Pindyck (1987), Hamilton (1988), Pindyck (1991).

It is another interesting finding that the impact of oil price uncertainty on real economic activities dominates the one of oil price returns. When we control oil price returns in our all analyses (column 4 in Tables 3 and 4), oil price uncertainty (both RV and the continuous volatility) negatively predicts real economic activities. The coefficients of oil price returns are negative, but they are not significant at the presence crude oil price uncertainty.[3] The results indicate that oil price increases are associated with the slowdown of the U.S. economy in the following quarter. But the impact of oil price on real economy is subsumed by oil price uncertainty. An increase in the continuous oil volatility lowers the growth rate of GDP and GNP by a much larger magnitude than oil price return. Oil price uncertainty seems to have more important impact on real economic activity than oil price returns.

Overall, we argue that the continuous component of oil realized variance has stronger forecasting power of real economic activities, supporting the theoretical literature of the macro uncertainty and the real economy. The jump volatility does not predict real eco-

[3] We do not report the coefficients of control variables to manage the size of the tables.

nomic activities (at least at the quarterly frequency). We next investigate the differences of dynamics of the continuous and jump components and offer the explanation of the above findings.

# 4 Economic Determinants of Crude Oil Price Uncertainty

In this section, we explore the economic drivers of crude oil price uncertainty and its components. We start by introducing the set of economic variables in our analysis. Then we report the in-sample and out-of-sample forecast results using OLS regressions. Lastly we present the 3PRF results that we can achieve better oil price uncertainty forecasts both in-sample and out-of-sample by including certain economic variables.

## 4.1 Overview of Economic Predictors

We include a number of variables in our analysis that are potentially relevant for the oil market that can capture the impact of macroeconomic uncertainty, general economic condition, oil supply-demand and geopolitical events.

Predictors related to the macroeconomic uncertainty are as follows:

**Ludvigson's macro uncertainty index.** This index, developed by Jurado, Ludvigson, and Ng (2015), is to quantify macroeconomic uncertainty from a large number of macroeconomic and firm specific time series. Ludvigson's index is not dependent on a specific macroeconomic theory, and is designed as the summary of unpredictable parts in many economic indicators. We take the first difference of this variable in regressions.

**Bloom's economic policy uncertainty index.** To quantify economic policy uncertainty, Baker, Bloom, and Davis (2015) propose a measure calculated from the frequency that policy uncertainty is mentioned in media, the number of taxation policy changes, and the heterogeneity in professional forecasts of inflation and government spending. We gather this time series from Nicholas Bloom's website, and we take the first difference of this variable in regressions.

**CBOE's volatility index.** VIX is often called the "fear gauge index". Because VIX, which is calculated from the cross-section of options including both at-the-money and out-of-the-money strikes, is only available from 1990, we use the "old VIX" (VXO), calculated from at-the-money option prices, for 1987 to 1989 in order to complete a time series from 1987 to 2014.

**Volatility of industrial production**. We follow Paye (2012) and calculate this variable as the conditional volatility of growth in U.S. industrial production.

**Volatility of inflation growth.** It is the conditional volatility for inflation growth based on the Producer's Price Index (PPI), following Paye (2012).

Predictors related to U.S. and global economic activities, which also capture aggregate demand for oil, are as follows:

**Aruoba-Diebold-Scotti (ADS) Business Condition Index.** ADS index is to quantify a real business condition at a high frequency from raw data including weekly initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real GDP. Many policy makers including Philadelphia Fed and academics use the ADS index.

**Baltic Dry Index (BDI).** BDI index, calculated by Baltic Exchange, quantifies the price of moving the materials by the sea. In the literature and practice, BDI index is used as a proxy for global real economic activities (see, e.g., Bakshi, Panayotov, and Skoulakis, 2013). We detrend Baltic index using the AR(1) model.

**Kilian's Real Index.** This index, also calculated from cargo ship freight rates, is regarded as a proxy for global economic activities related to commodities (Kilian, 2009). Global real activity as a proxy of demand for all commodities including crude oil. Fluctuations in demand can cause fluctuations in oil price.

**Industrial production.** Following Baumeister and Hamilton (2015), we aggregate the global industrial production of OECD and 6 regions (Brazil, Russia, India, China, Indonesia, and South Africa), and we take the first difference of this variable.

Next, we include the following predictors specific to oil markets:

**Global oil production.** Following Kilian and Park (2009) and many others, we calculate the monthly percentage change in global oil production. We use this variable as the main proxy for oil supply. Global oil production data is from Baumeister and Hamilton (2015).

**U.S. oil production.** This time series gathered from U.S. Energy Information Administration (hereafter, EIA) is to quantify domestic oil production. We calculate the monthly percentage growth.

**U.S. inventory.** We gather U.S. inventory from EIA and calculate the monthly percentage growth..

**Oil price returns.** We use crude oil futures prices to get returns, because our oil volatilities are measured from oil futures market. This is to investigate whether oil price returns and oil price uncertainty have distinct effects on the macroeconomy.

**Geopolitical events.** Our definition of consequential geopolitical events affecting the oil market follows the U.S. EIA report.[4] Hamilton (2011) argues that the effect of an oil supply disruption on oil prices tends to be small, short-lived, and insignificant. What drives the oil price is economic forces rather than geopolitical events. Geopolitical events matter for oil supply, but not as comparable as their impact on expectations of potential oil production disruptions, or demand shocks.

Moreover, we also include the additional predictors that Paye (2012) identifies as a predictor of the stock market volatility. They are commercial paper-to-treasury spread, expected equity return, default return, term spread, and net payout yield. We take first difference of default spread, term spread and net payout yield in our following regression analysis.

Table 5 reports descriptive statistics of economic predictors. To ensure the stationarity in our time series regression analysis, we transform the economic predictors as the growth rate or first difference. Although we do not report, correlations among all transformed variables are in general very low. These low correlations indicate that each variable contains very different informational contents. The only exceptions are VIX is highly correlated with expected stock market returns (-0.65); growth of the global industrial production is correlated with ADS index (0.36).

## 4.2 Predictive Regression

We next conduct univariate, multivariate, and 3PRF regression analysis and investigate the economic drivers of oil price uncertainty. For each approach, we start from in-sample predictive regression results. We then use out-of-sample forecast to demonstrate the predictability of oil price uncertainty using economic predictors.

### 4.2.1 Univariate Regression

We first conduct the in-sample univariate forecast exercise, i.e., at every month $t$, we run the following univariate regression

$$RV_t = \alpha + \beta^i X_{t-1}^i + \rho_1 RV_{t-1} + \rho_2 RV_{t-2} + \varepsilon_t, \tag{4}$$

where $X_{t-1}^i$ denotes the economic predictor $i$ at month $t-1$. As motivated by the significance of autocorrelation coefficients, we include the AR(2) in all model specifications. Meanwhile, we also use the AR(2) process as the benchmark model to compare the relative forecast

[4] The report is available at: http://www.eia.gov/pressroom/presentations/sieminski_09172012.pdf

improvement,

$$RV_t = \alpha + \rho_1 RV_{t-1} + \rho_2 RV_{t-2} + \varepsilon_t. \tag{5}$$

The first two columns in Table 6 report the estimated coefficient of our interest $\beta^i$ and the incremental adjusted $R^2$ comparing the model (4) and the benchmark model (5). A higher level of uncertainty about the general economy, as summarized by the Ludvigson's uncertainty index, significantly forecasts oil price uncertainty. A standard deviation increase in the Ludvigson's index increases oil price variance by 17.9%. Indicators of deteriorating economic condition such as higher default spread and higher VIX predict higher oil price uncertainty in the next month. There is also evidence that oil demand and oil supply have different impacts on oil price uncertainty. It appears that aggregate demand, measured by the Baltic index and Kilian's index, decrease the oil price uncertainty level; global oil supply, on the other hand, increases the oil price uncertainty. Among all significant predictors, the Ludvigson's uncertainty index has the strongest forecasting power since it raises adjusted $R^2$ by 2.9% comparing to the benchmark model. This parallels the previous literature that uncertainty about future macroeconomic condition has direct impacts on stock return volatility (Schwert, 1989).

If we look at the decompositions of oil price uncertainty, different economic forces drive the continuous part and the jump part. Both default spread and Ludvigson's uncertainty index increase the continuous part of oil price uncertainty. Global oil production and VIX increase the uncertainty due to oil price jump, while aggregate demand, measured by the Baltic index and the Kilian's real index, decreases oil price uncertainty due to oil price jump. All these predictors increase adjusted $R^2$ comparing to the benchmark model.

We next investigate the out-of-sample forecast performance of economic variable. In this analysis, we use a rolling window exercise by fitting oil price variance in a fixed month window and we predict oil price uncertainty of the next month. We first use the period of January 1987 to December 2004 to fit the model using each predictor, and we predict oil price variance for January 2005; then we move our in-sample window and out-of-sample window forward by one month. Given the high level of oil volatility after 2005, this choice of the out-of-sample of course makes our forecasts very challenging.

Panel A of Table 9 reports the relative RMSE and adjusted $\mathrm{R}^2$ comparing to the benchmark AR(2) model out-of-sample. We find that forecasting oil price uncertainty with Ludvigson's uncertainty index, VIX, ADS index, and growth in industry production can achieve lower RMSE and higher adjusted $\mathrm{R}^2$. In particular, Ludvigson's uncertainty index strongly predicts the continuous volatility. Jumps are more difficult to predict out-of-sample. Only VIX and ADS index can marginally forecast the jump part better than the benchmark AR(2) model.

### 4.2.2 Multivariate Regression

The univariate analysis identifies several important predictors of oil price uncertainty and its components. It is also interesting to gauge the relative importance and contribution of each economic predictor. Multivariate model is a natural choice to address this question. At every month $t$, we run the following multivariate regression

$$RV_t = \alpha + \Sigma_i \beta^i X^i_{t-1} + \rho_1 RV_{t-1} + \rho_2 RV_{t-2} + \varepsilon_t, \tag{6}$$

where $X^i_{t-1}$ denotes the economic predictor $i$ at month $t-1$. We again compare the model performance with the benchmark model (5).

Table 7 reports the multivariate forecasting results. The important predictors of the oil price uncertainty are the Ludvigson's uncertainty index, global oil production, the Baltic index and VIX. The Ludvigson's uncertainty index strongly predicts the uncertainty due to continuous change of oil prices, but not unexpected jump. Oil supply positively forecast oil price uncertainty and especially the part due to oil price jumps. Oil demand, as measured by the global and U.S. aggregate economic condition such as the Kilian index and the Baltic index, lowers oil price uncertainty. VIX, Kilian's index and growth in global oil supply can predict the jump part of oil variance. Overall, the in-sample multivariate forecast results are consistent with the univariate results.

Panel B of Table 9 shows that the out-of-sample gain of predicting oil price uncertainty using the full economic predictors is marginal. We may get smaller RMSE; but adjust $\mathrm{R}^2$ mostly decreases, which is not surprising.

### 4.2.3 Three Pass Regression Filter Analysis

Although multivariate prediction helps us identify important predictors, it may suffer from the curse of dimensionality including the multi-collinearity problems. We next adapt the 3PRF method to reduce the dimension of economic variables. Kelly and Pruitt (2015) have demonstrated the superior forecasting performance of 3PRF comparing to traditional approaches to condense the number of predictors such as principal component analysis. To reduce the dimension of predictors, the 3PRF calculates the time-series sensitivities of all predictors to important predictors, and makes a forecast using the mapping of all cross-sectional predictors onto such time-series sensitivities (see Appendix A for further details). The 3PRF is better than other methodology such as the principal component regression, because an econometrician can choose important variables based on statistical evidence. This procedure essentially cleanses the noise of important variables using the space of all available predictors.

Based on univariate and multivariate predictive regression results, we are able to identify three important variables: macroeconomic uncertainty, proxy for oil demand, and global oil production. The choice of these three variables is motivated by the fact they yield most consistent predictions in the univariate and multivariate models, and therefore are good information variables for dimension reduction.

Table 8 presents the 3PRF regression results for oil price uncertainty and its decompositions. The 3PRF results are largely consistent with our univariate and multivariate results in Tables 6 and 7. Ludvigson's uncertainty index strongly predicts oil price uncertainty, especially the part attributable to the continuous price movement. The jump component of oil price uncertainty is mainly associated with global oil supply and Baltic index (a proxy for oil and other commodities demand). Including the three important economic variables, we can get better forecast for realized variance and its two components than the benchmark model as suggested by lower RMSE and higher adjusted $R^2$.

Panel C of Table 9 reports the out-of-sample forecast results. We obtain significant out-of-sample predictability of oil price uncertainty using these three economic predictors. For example, adjusted $R^2$ of realized variance and its jump part increase for 11.1% and 17.1%. If we use these three variables to forecast the continuous part of oil price uncertainty, root mean squared errors decrease by 8.9% out-of-sample. In summary, oil price uncertainty is driven by several economic variables including the uncertainty about future macroeconomic condition, and the fundamental condition of the oil market such as global oil supply and demand.

The continuous oil variance is strongly associated with the general economic uncertainty, while the jumps are largely associated oil market-specific demand and supply. It at least partially explains our findings that the continuous component negatively predicts real economic activities even better than the realized variance itself.

## 4.3 Robustness Tests

If oil price uncertainty is predicted by economy-wide uncertainty and oil market-specific demand and supply, it is natural to ask whether the predictive regression of real economic activities (Table 4) are subsumed by these three variables. To answer this question, we further control for macroeconomic uncertainty, proxy for oil demand, and global oil production and report the quantitative results in Table 10. Observe that jumps do not significantly predict any measure of real economic activities. In contrast, the continuous diffusive variance often exhibits statistically significant predictability. The quantitative results are particularly strong for real GNP, real personal consumption on durable goods, and real investment. For example, observe from column (3) that one standard deviation increase in the continuous variance decreases real GNP, real personal consumption on durable goods, and real investment by 20.8%, 19.3%, and 21.1% after those three variables and S&P 500 returns are controlled for. For these three macro indicators, the coefficient of continuous diffusive variance is always statistically significant throughout columns (1) to (4). These results imply that the continuous oil variance contains unique information content for real economic activities.

This subsection presents two more robustness checks for our main empirical results. First, we repeat the univariate, 3PRF, and out-of-sample results using two alternative measures of oil price uncertainty from high-frequency data: $\sqrt{RV}$. Overall the quantitative results are in line with our main results. We report the results in Tables A3 and A4 in appendix.

Second, we present structural model estimation results, because oil price and price volatility may be endogenously determined in the economy (Kilian, 2014) and regressions including 3PRF may be susceptible to the endogeneity issue. More specifically, we estimate a structural vector autoregressive model (hereafter, SVAR) of a 4 variable system consisting of macro uncertainty, commodity demand, oil supply, and oil price uncertainty, where oil price uncertainty is realized oil variance.[5] Appendix B has the details and Figure A1 reports the results. Overall the findings are consistent with our 3PRF results.

# 5 Conclusion

This paper empirically investigates the causes and consequences of oil price uncertainty. We measure oil price uncertainty as realize variance estimated from high-frequency intraday oil futures data and we decompose oil price uncertainty into the parts attributable to continuous price movements and jumps. We argue that it is important to distinguish the different roles they play on how oil price uncertainty affects real economic activities.

This paper presents the novel finding that only the continuous diffusive variance robustly predicts real economic activities and its forecasting power is stronger than other measures used by the literature, such as the total realized variance and option-implied volatility. We further reveal that the continuous variance is strongly associated with the aggregate macroeconomic uncertainty, and the jump variance is mostly determined by oil market-specific

[5] Another alternative is to use a dynamic stochastic general equilibrium model. For related discussion, see Kilian (2014).

information such as global oil supply and demand. This distinction explains why the continuous component of oil price return variance predicts various real macroeconomic aggregates well. Hence, we advocate the continuous part of oil price realized variance when examining the interactions between oil and the macroeconomy.

While our analyses focus on the macro-level indicators of the U.S. economy, micro-level responses of individual firm investment and individual consumption to oil price uncertainty deserve further scrutiny. In particular, it is interesting to examine how investment decision of individual firms or household consumption reacts to oil price uncertainty, especially the continuous diffusive variance.

# Appendix A: The three-pass regression filter

Because we consider a large sample of predictors of oil price uncertainty, potential deficiencies of multivariate regression, e.g., multicollinearity problems, call for an advanced econometric technique to reduce a dimension. The three-pass regression filter (3PRF), recently proposed by Kelly and Pruitt (2015), provides a way to consistently predict a univariate time series with a reduced dimension but without excluding any of the predictor variables available to an econometrician.

The 3PRF methodology posits that there exist several factors which predict the time series of interest; predictor variables have their loadings to those factors; and proxy variables measure such factors with measurement error. As the name of 3PRF suggests, it consists of three steps of OLS: In the first-pass, it runs a series of time series regressions of predictor variables on proxy variables; in the second-pass, it fits a series of cross sectional regressions of predictor variables on the time series sensitivities; in the third-pass, it performs a predictive regression of the variable of interest on the mapping of time series sensitivities on the cross section of all predictors.

Let $X$ be a $N$-by-$T$ matrix containing predictors where $N$ is the number of predictors and $T$ is the number of periods. Let $Z$ be a $p$-by-$T$ matrix containing proxies where $p$ is the number of proxies. Finally, let $y_t$ be the time-$t$ value of the variable to be predicted. The 3PRF forecasts $\widehat{y}_{t+1}$ as follows.

1. Run time series regressions of $x_{i,\cdot}$ on the $p$ proxies in $Z$ for $i = 1, ..., N$. That is, for each predictor $i$, fit a time series OLS $x_{i,t} = \phi_{i,0} + (Z_{\cdot,t})' \times \phi_i + \epsilon_{i,t}$ to calculate the sensitivities of each predictor $i$ to the proxies in $Z$. Retain these sensitivities $\widehat{\phi}_i$s, which are a $p$-by-1 column vector.

2. Run cross sectional regressions of $x_{\cdot t}$ on $\widehat{\phi}_i$ for $t = 1, ..., T$. That is, for each time $t$, fit a cross sectional OLS $x_{i,t} = \phi_{0,t} + \left(\widehat{\phi}_i\right)' \times F_t + \varepsilon_{i,t}$. Retain $\widehat{F}_t$, which quantifies how sensitivities $\widehat{\phi}_i$ are mapped to the cross section of *all* predictors $x_{\cdot t}$. The predictive factors $\widehat{F}_t$ is a $p$-by-1 column vector.

3. Run a predictive regression of $y_{t+1}$ on predictive factors $\widehat{F}_t$ using OLS. That is, $y_{t+1} = \beta_0 + \left(\widehat{F}_t\right)' \times \beta + \eta_{t+1}$ delivers a forecast $\widehat{y}_{t+1}$.

Kelly and Pruitt (2015) proposed a couple of ways to calculate or choose the proxy variables for the 3PRF: First, an empiricist can use an automatic proxies algorithm: The first automatic proxy is $y_t$ itself, the second proxy is the residuals of the third-pass regression using the first proxy, the third proxy is the residuals of the third-pass regression using the first and second proxies, etc. A 3PRF method with such proxy variables are called the target-proxy 3PRF. Unfortunately the target proxy 3PRF may not always allow logical interpretation of each proxy. Second, an econometrician can also choose proxy variables motivated by economic theory or statistical arguments. A 3PRF method using such proxies are called the theory-proxy 3PRF. To understand the determinants of oil RV, we use the theory-proxy 3PRF where we choose a proxy for oil production shock, a proxy for oil demand shock, and another proxy for economic uncertainty, as motivated by our regression results.

# Appendix B: Structural Vector Autoregressive Analysis

Consider a vector

$$X_t = \begin{bmatrix} \text{Macro Uncertainty} \\ \text{Commodity Demand} \\ \text{Oil Supply} \\ \text{Oil Price Uncertainty} \end{bmatrix}$$

where the variables in $X_t$ are normalized for ease of interpretation. Guided by our 3PRF results, we use the Ludvigson's index and the detrended Baltic Dry Index as our proxies for macro uncertainty and global commodity demand. Following Kilian and Park (2009) and many others, we use the monthly percentage growth of global oil supply as our empirical proxy for oil supply. Consider a reduced form vector auto-regressive model:

$$X_t = a + \sum_{i=1}^{L} A_i \times X_{t-i} + \begin{bmatrix} e_t^{\text{Macro Uncertainty}} \\ e_t^{\text{Commodity Demand}} \\ e_t^{\text{Oil Supply}} \\ e_t^{\text{Oil Price Uncertainty}} \end{bmatrix}$$

where $a$ is the intercept; $L$ is the number of auto-regressive lags; $A_i$ is the auto-regressive coefficient of lag $i$; $e_t$ is a vector containing the non-orthogonal shocks. To be consistent with our predictive regression and 3PRF results, we mainly use $L = 1$. However, we also analyze $L = 24$ because many papers including Hamilton (2003) use historical 2 years of data.

We further impose exclusion restrictions to estimate a structural model using orthogonal shocks $\varepsilon_t$ :

$$\begin{bmatrix} e_t^{\text{Macro Uncertainty}} \\ e_t^{\text{Commodity Demand}} \\ e_t^{\text{Oil Supply}} \\ e_t^{\text{Oil Price Uncertainty}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ b_{2,1} & 1 & 0 & 0 \\ b_{2,2} & b_{2,3} & 1 & 0 \\ b_{4,1} & b_{4,2} & b_{4,3} & 1 \end{bmatrix} \times \begin{bmatrix} \varepsilon_t^{\text{Macro Uncertainty Shock}} \\ \varepsilon_t^{\text{Commodity Demand Shock}} \\ \varepsilon_t^{\text{Oil Supply Shock}} \\ \varepsilon_t^{\text{Oil Price Uncertainty Shock}} \end{bmatrix}. \tag{7}$$

The exclusion restriction (7) allows us to convert the reduced-form model to a structural model where error terms are orthogonal to each other:

$$X_t = a^* + \sum_{i=1}^{L} A_i^* \times X_{t-i} + \begin{bmatrix} \varepsilon_t^{\text{Macro Uncertainty Shock}} \\ \varepsilon_t^{\text{Commodity Demand Shock}} \\ \varepsilon_t^{\text{Oil Supply Shock}} \\ \varepsilon_t^{\text{Oil Price Uncertainty Shock}} \end{bmatrix}$$

where $a^*$ and $A_i^*$ are determined by a constrained maximization of the concentrated log-likelihood function.

The order of shocks can be justified as follows:

- Macro uncertainty shock may decrease commodity demand shock;
- Commodity demand shock may increase oil supply shock;
- As our 3PRF results suggest, macro uncertainty shock, commodity demand shock, and oil supply shock may predict oil price uncertainty.

Estimating this SVAR model, we calculate impulse response functions and their bootstrapped confidence intervals to understand the structural relationship between economic variables and oil price uncertainty. Figure A1 depicts the results:

- Observe from the first column and the second row that the macro uncertainty shock decreases the commodity demand shock;
- Observe from the first column and the fourth row that the macro uncertainty shock increases the oil price uncertainty shock, consistently with our regression and 3PRF results;
- Observe from the second column and the third row that the commodity demand shock increases the oil supply shock;
- Observe from the second column and the fourth row that the commodity demand shock increases the oil price uncertainty, consistently with our regression and 3PRF results;
- Observe from the third column and the fourth row that the oil supply shock increases the oil price uncertainty, consistently with our regression and 3PRF results.

All in all, the SVAR results provide additional confidence on our major findings from OLS and 3PRF analyses.[6]

[6] As an additional robustness check we also estimate an SVAR model with an alternative order of

# References

[1] Andersen, Torben G., Bollerslev, Tim, Diebold, Francis X., "Roughing it up: including jump components in the measurement, Modeling and forecasting of return volatility." *The Review of Economics and Statistics*, 89 (2007), 701–720.

[2] Andersen, Torben G., Bollerslev, Tim, Diebold, Francis X., Labys, Paul. "Modeling and forecasting realized volatility." *Econometrica*, 71 (2003), 579–625.

[3] Andersen, Torben G., Tim Bollerslev, and Nour Meddahi. "Realized volatility forecasting and market microstructure noise." *Journal of Econometrics,* 160 (2011), 220-234.

[4] Andersen, Torben G., and Tim Bollerslev. "Deutsche mark–dollar volatility: intraday activity patterns, macroeconomic announcements, and longer run dependencies." *Journal of Finance* 53 (1998), 219-265.

[5] Baker, Scott R., Nicholas Bloom, and Steven J. Davis. "Measuring economic policy uncertainty", NBER Working paper (2015), Stanford University.

[6] Bakshi, Gurdip., George Panayotov, and Georgios Skoulakis. "In search of explanation for the predictive ability of the Baltic Dry Index for global stock returns, commodity returns, and global economic activity." Working paper. University of Maryland. 2013.

[7] Barndorff-Nielsen, Ole, Shephard, Neil. "Power and bipower variation with stochastic volatility and jumps." *Journal of Financial Econometrics* 2 (2004), 1–48.

[8] Barndorff-Nielsen, Ole, Shephard, Neil. "Econometrics of testing for jumps in financial economics using bipower variation." *Journal of Financial Econometrics* 4 (2006), 1–30.

[9] Baumeister, Christiane, and James D. Hamilton. "Structural interpretation of vector autoregressions with incomplete identification: revisiting the role of oil supply and demand shocks." Working paper, 2015.

[10] Bernanke, Ben S. "Irreversibility, uncertainty, and cyclical Investment." *Quarterly Journal of Economics*, 98 (1983), 85-106.

[11] Bloom, Nicholas. "The impact of uncertainty shocks." *Econometrica*, 77 (2009), 623-685.

$\varepsilon_t^{\text{Oil Supply Shock}}$, $\varepsilon_t^{\text{Macro Uncertainty Shock}}$, $\varepsilon_t^{\text{Commodity Demand Shock}}$, and $\varepsilon_t^{\text{Oil Price Uncertainty Shock}}$ because many papers including Kilian and Park (2009) put the oil supply shock in the first place. In addition, we estimated a model with L=24. Overall the results, which can be provided upon request, do not change qualitatively.

[12] Busch, Thomas, Bent Jesper Christensen, and Morten Ørregaard Nielsen. "The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets." *Journal of Econometrics* 160, no. 1 (2011): 48-57.

[13] Canuto, Otaviano, James Crain, and Troy Davig. "The impact of oil price volatility on the economy." Panel discussion, 2016 Allied Social Sciences Association Annual Meeting, January 4, 2016.

[14] Elder, John, and Apostolos Serletis. "Oil price uncertainty." *Journal of Money, Credit, and Banking,* 42 (2010), 1137-1159.

[15] Edelstein, Paul, and Lutz Kilian. "How sensitive are consumer expenditures to retail energy prices?" *Journal of Monetary Economics*, 56 (2009), 766-779.

[16] Engle, Robert F., and Jose Gonzalo Rangel. "The spline-GARCH model for low-frequency volatility and its global macroeconomic causes." *Review of Financial Studies,* 21 (2008), 1187-1222.

[17] Engle, Robert F., Eric Ghysels, and Bumjean Sohn. "Stock market volatility and macroeconomic fundamentals". *The Review of Economics and Statistics*, 95 (2013), 776–797.

[18] Ferderer, J. Peter. "Oil price volatility and the macroeconomy." *Journal of Macroeconomics*, 18 (1996), 1–26.

[19] Gao, Lin., Steffen Hitzemann, Ivan Shaliastovich, and Lai Xu. "Oil volatility risk." Working paper, 2016.

[20] Ghysels, Eric., Pedro Santa-Clara, and Rossen Valkanov, "Predicting volatility: Getting the most out of return data sampled at different frequencies." *Journal of Econometrics,* 131 (2006), 59–95.

[21] Giglio, Stefano, Bryan Kelly, Seth Pruitt, S., Systemic risk and the macroeconomy: an empirical evaluation. *Journal of Financial Economics* (2015)*,* forthcoming.

[22] Guo, Hui, and Kevin L. Kliesen. "Oil price volatility and U.S. macroeconomic activity," *Federal Reserve Bank of St. Louis Review*, 87 (2005), 669–683.

[23] Hamilton, James D. "A neoclassical model of unemployment and the business cycle." *Journal of Political Economy* (1988), 593-617.

[24] Hamilton, James D. "This is what happened to the oil price macroeconomy relationship." *Journal of Monetary Economics* 38 (1996), 215– 220.

[25] Hamilton, James D. "What is an oil Shock?" *Journal of Econometrics*, 113 (2003).363-398.

[26] Hamilton, James D. "Historical Oil Shocks." NBER Working paper (2011).

[27] Jo, Soojin. "The effects of oil price uncertainty on global real economic activity." *Journal of Money, Credit and Banking,* 46 (2014), 1113-1135.

[28] Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng. "Measuring uncertainty." *American Economic Review*, 105 (2015), 1177-1216.

[29] Kellog, Ryan. "The effect of uncertainty on investment: evidence from Texas oil drilling." *American Economic Review* 104, (2014), 1698–1734.

[30] Kelly, Bryan and Seth Pruitt. "The three-pass regression filter: A new approach to forecasting using many predictors." *Journal of Econometrics*, 186 (2015), 294-316

[31] Kilian, Lutz. "Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market." *American Economic Review*, 99 (2009), 1053-1069.

[32] Kilian, Lutz. "Oil price shocks causes and consequences." *Annual Review of Resource Economics* 6 (2014), 133-154.

[33] Kilian, Lutz, and Cheolbeom Park. "The impact of oil price shocks on the us stock market." *International Economic Review,* 50 (2009), 1267-1287.

[34] Kilian, Lutz, and Robert J. Vigfusson. "Are the responses of the US economy asymmetric in energy price increases and decreases?" *Quantitative Economics* 2, no. 3 (2011): 419-453.

[35] Lee, Kiseok and Shawn Ni. "On the dynamic effects of oil price shocks: a study using industry level data." *Journal of Monetary Economics*, 49 (2002), 823-852.

[36] Loungani, Prakash. "Oil price shocks and the dispersion hypothesis." *Review of Economics and Statistics* (1986): 536-539.

[37] Majd, Saman and Robert S. Pindyck "Time to Build, Option Value, and Investment Decisions." *Journal of Financial Economics* 18 (1987), 7-27.

[38] Merton, Robert C., "Option pricing when underlying stock returns are discontinuous." *Journal of Financial Economics,* 3 (1976), 125–144.

[39] Patton, Andrew J., and Kevin Sheppard. "Good volatility, bad volatility: Signed jumps and the persistence of volatility." *Review of Economics and Statistics,* 97 (2015): 683-697.

[40] Pindyck, Robert H. "Irreversibility, Uncertainty, and Investment." *Journal of Economic Literature*, 29 (1991), 110–148.

[41] Paye, Bradley S. "'Deja vol': predictive regressions for aggregate stock market volatility using macroeconomic variables." *Journal of Financial Economics,* 106 (2012), 527-546.

[42] Plante, Michael, and Nora Traum. "Time-varying oil price volatility and macroeconomic aggregates." Center for Applied Economics and Policy Research Working paper 2012-002 (2012).

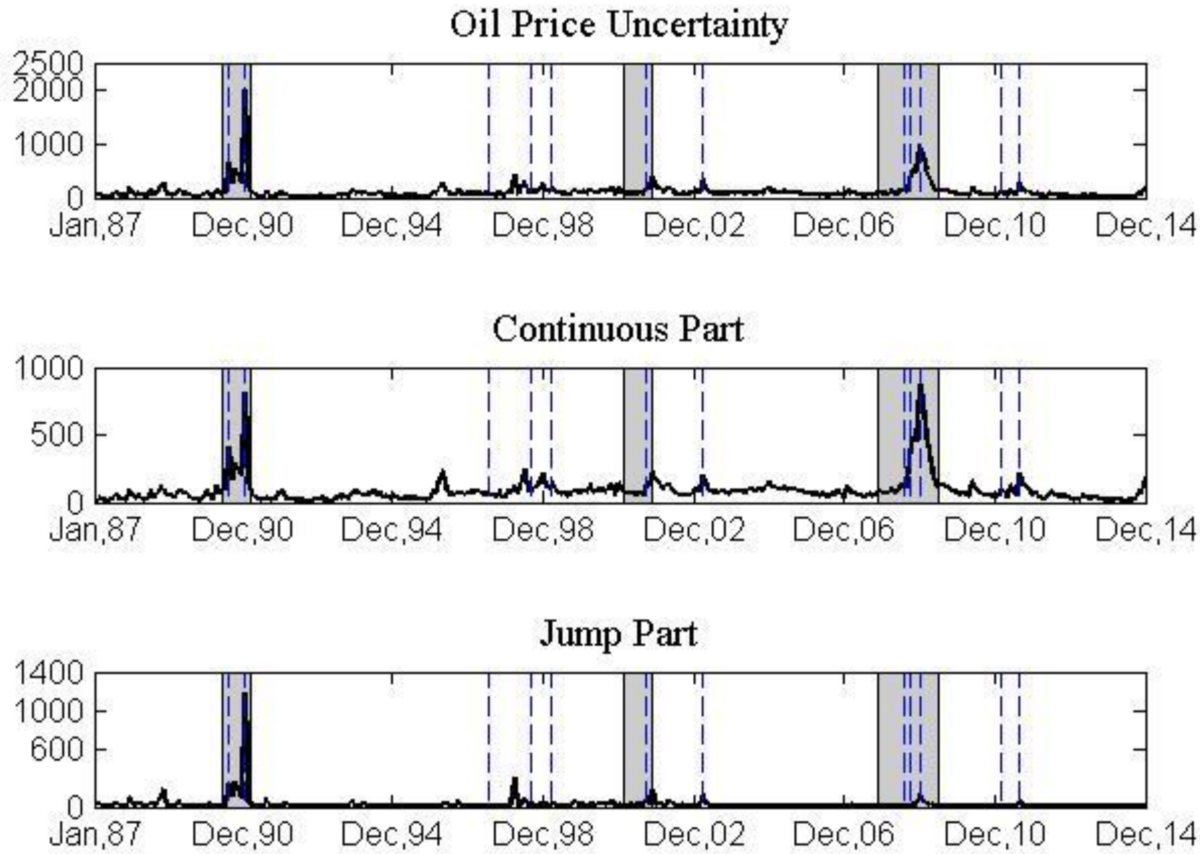
[43] Prokopczuk, Marcel, and Lazaros Symeonidis. "On the economic sources of commodity market volatility." Working paper. 2015.

[44] Robe, Michel A., and Jonathan Wallen. "Fundamentals, Derivatives Market Information and Oil Price Volatility." *Journal of Futures Markets,* 36 (2016): 317-344.

[45] Schwert, G. William. "Why does stock market volatility change over time?" *Journal of Finance,* 44 (1989), 1115-1153.

[46] Tauchen, George., and Hao Zhou, "Realized jumps on financial markets and predicting credit spreads." *Journal of Econometrics*, 160 (2011), 102-118.

**Figure 1: Oil Price Uncertainty and the Decompositions**




**Notes:** This figure plots the time series of monthly oil price uncertainty estimated from high-frequency oil futures price data in the top panel. The mid and bottom panels are the decompositions of oil price uncertainty, i.e., the uncertainty due to continuous price movements and the uncertainty due to price jumps. Shaded areas represent NBER recession periods. Dotted lines represent consequential geopolitical events following the EIA report including Iraq wars, Asian financial crisis and 9-11 attacks etc. Our data period is from January 1987 to December 2014.

**Table 1: Descriptive Statistics of Crude Oil Realized Variance, the Continuous, and the Jump Components**

| Variable | Mean | Std. Dev | Skewness | Kurtosis | ADF Test (p-value) | AR(1) | AR(2) |
|---|---|---|---|---|---|---|---|
| RV | 101.9 | 107.1 | 4.2 | 27.2 | 0.001 | 0.7 | 0.6 |
| C | 82.3 | 87.4 | 5.0 | 36.8 | 0.001 | 0.8 | 0.7 |
| J | 19.6 | 33.9 | 4.9 | 32.0 | 0.001 | 0.4 | 0.4 |

**Notes:** The table presents descriptive statistics of crude oil realized variance (RV) and the corresponding decompositions of the continuous (C) and jump (J) parts. Statistics are calculated at the monthly frequency over the period 1987-2014.

**Table 2: Oil Price Uncertainty and Real Economic Activity (Univariate Analysis)**

| | Real GDP | Real GNP | IP Growth | Real PC_Durable | Real PC_Service | Real Inv | Real GPDInv |
|---|---|---|---|---|---|---|---|
| **Panel A** | | | | | | | |
| RV | -0.171* | -0.205** | -0.205** | -0.171* | -0.194** | -0.179** | -0.335*** |
| | (-1.823) | (-2.328) | (-2.328) | (-1.981) | (-2.004) | (-2.064) | (-3.225) |
| Adj. $R^2$ | 0.163 | 0.134 | 0.134 | 0.012 | 0.372 | 0.277 | |
| **Panel B** | | | | | | | |
| C | -0.218** | -0.261*** | -0.251** | -0.259*** | -0.198** | -0.279*** | -0.299** |
| | (-2.520) | (-2.698) | (-2.472) | (-3.014) | (-2.258) | (-3.834) | (-2.436) |
| J | 0.062 | 0.056 | 0.023 | 0.085 | 0.144 | 0.117 | -0.056 |
| | (0.671) | (0.625) | (0.253) | (0.443) | (0.877) | (1.180) | (-0.663) |
| Adj. $R^2$ | 0.181 | 0.144 | 0.545 | 0.019 | 0.091 | 0.385 | 0.179 |

**Notes:** We report the regression results of using crude oil realized variance (RV) to predict real economic activities in the next quarter in Panel A; we report the predicting results of the continuous and jump components (C and J) in Panel B. Real GDP is the growth rate in real GDP; Real GNP is the growth rate in real GNP; IP growth is the growth rate of industrial production; Real PC_Durable is the real personal consumption expenditures durable goods; Real PC_Service is the real personal consumption expenditures services; Real Inv is the real investment of the private sectors; Real GDP Inv is the real investment of the government. All variables are standardized prior to regressions and thus we do not report the intercept. ***, **, and * designate statistical significance at the level of 1%, 5%, and 10%, respectively, Newey-West statistics are reported in parenthesis. Data period covers 1987-2014.

**Table 3: Oil Price Uncertainty and Real Economic Activity**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Real GDP** | | | | |
| RV | -0.077 | -0.158* | -0.140* | -0.211** |
| | (-0.861) | (-1.678) | (-1.766) | (-2.236) |
| Adj. $R^2$ | 0.184 | 0.165 | 0.189 | 0.166 |
| **Real GNP** | | | | |
| RV | -0.117 | -0.192** | -0.189** | -0.223** |
| | (-1.426) | (-2.145) | (-2.354) | (-2.519) |
| Adj. $R^2$ | 0.154 | 0.134 | 0.143 | 0.128 |
| **IP Growth** | | | | |
| RV | -0.063 | -0.206* | -0.140* | -0.226** |
| | (-0.612) | (-1.923) | (-1.835) | (-2.674) |
| Adj. $R^2$ | 0.600 | 0.538 | 0.595 | 0.538 |
| **Real PC_Durable** | | | | |
| RV | -0.149 | -0.152* | -0.163* | -0.221** |
| | (-1.465) | (-1.721) | (-1.777) | (-2.350) |
| Adj. $R^2$ | 0.004 | 0.015 | 0.020 | 0.015 |
| **Real PC_Service** | | | | |
| RV | -0.021 | -0.114 | -0.022 | -0.168 |
| | (-0.169) | (-1.100) | (-0.220) | (-1.361) |
| Adj. $R^2$ | 0.369 | 0.370 | 0.454 | 0.372 |
| **Real Inv** | | | | |
| RV | -0.124 | -0.171* | -0.146* | -0.218*** |
| | (-1.155) | (-1.953) | (-1.899) | (-2.665) |
| Adj. $R^2$ | 0.282 | 0.283 | 0.325 | 0.278 |
| **Real GPDInv** | | | | |
| RV | -0.190** | -0.327*** | -0.260*** | -0.371*** |
| | (-2.044) | (-3.158) | (-3.340) | (-3.633) |
| Adj. $R^2$ | 0.201 | 0.145 | 0.167 | 0.150 |

**Notes:** We report the regression results when we use crude oil realized variance (RV) to predict real economic activities while controlling for default spread (1), term spread (2), S&P 500 return (3), and oil price return (4). Real economic activity indicators are defined in Table 2. All variables are standardized prior to regressions and thus we do not report the intercept. ***, **, and * designate statistical significance at the level of 1%, 5%, and 10%, respectively, Newey-West statistics are reported in parenthesis. Data period covers 1987-2014.

**Table 4: The Decompositions of Oil Price Uncertainty and Real Economic Activity**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Real GDP** | | | | |
| C | -0.144* | -0.236** | -0.196** | -0.281*** |
| | (-1.840) | (-2.658) | (-2.506) | (-2.707) |
| J | 0.057 | 0.078 | 0.048 | 0.058 |
| | (0.667) | (0.907) | (0.547) | (0.732) |
| Adj. $R^2$ | 0.184 | 0.173 | 0.183 | 0.173 |
| **Real GNP** | | | | |
| C | -0.188** | -0.275*** | -0.257*** | -0.299*** |
| | (-2.153) | (-2.770) | (-2.813) | (-2.795) |
| J | 0.056 | 0.076 | 0.055 | 0.062 |
| | (0.632) | (0.878) | (0.613) | (0.722) |
| Adj. $R^2$ | 0.156 | 0.144 | 0.141 | 0.136 |
| **IP Growth** | | | | |
| C | -0.064 | -0.234** | -0.134* | -0.258** |
| | (-0.803) | (-2.428) | (-1.948) | (-2.490) |
| J | -0.008 | 0.006 | -0.025 | 0.005 |
| | (-0.113) | (0.063) | (-0.369) | (0.062) |
| Adj. $R^2$ | 0.596 | 0.538 | 0.608 | 0.540 |
| **Real PC__Durable** | | | | |
| C | -0.210*** | -0.210*** | -0.219** | -0.271*** |
| | (-2.993) | (-3.291) | (-2.472) | (-3.064) |
| J | 0.058 | 0.071 | 0.059 | 0.050 |
| | (0.338) | (0.421) | (0.336) | (0.306) |
| Adj. $R^2$ | 0.005 | 0.018 | 0.005 | 0.019 |
| **Real PC_Service** | | | | |
| C | -0.105 | -0.191** | -0.080 | -0.244* |
| | (-1.059) | (-2.267) | (-0.810) | (-1.806) |
| J | 0.098 | 0.101 | 0.072 | 0.091 |
| | (0.645) | (0.644) | (0.497) | (0.625) |
| Adj. $R^2$ | 0.129 | 0.116 | 0.174 | 0.133 |
| **Real Inv** | | | | |
| C | -0.230*** | -0.275*** | -0.228*** | -0.316*** |
| | (-3.032) | (-4.550) | (-3.640) | (-4.290) |
| J | 0.097 | 0.113 | 0.081 | 0.093 |
| | (1.000) | (1.179) | (0.822) | (1.036) |
| Adj. $R^2$ | 0.293 | 0.302 | 0.309 | 0.296 |
| **Real GPDInv** | | | | |
| C | -0.141 | -0.308** | -0.203* | -0.346** |
| | (-1.093) | (-2.483) | (-1.916) | (-2.560) |
| J | -0.075 | -0.052 | -0.092 | -0.065 |
| | (-0.938) | (-0.614) | (-1.243) | (-0.804) |
| Adj. $R^2$ | 0.194 | 0.139 | 0.202 | 0.143 |

**Notes:** We report the regression results when we use the continuous and jump variance to predict real economic activities while controlling for default spread (1), term spread (2), S&P 500 return (3), and oil price return (4). Real economic activity indicators are defined in Table 2.

**Table 5: Descriptive Statistics of Economic Predictors**

| Variables | Mean | Std. Dev. | Skewness | Kurtosis | AR(1) | AR(2) |
|---|---|---|---|---|---|---|
| Ludvigson's uncertainty index | 0.000 | 0.014 | 0.908 | 9.403 | 0.717 | 0.444 |
| Bloom's uncertainty index | -0.073 | 18.448 | 0.805 | 8.533 | -0.121 | -0.192 |
| VIX | 20.564 | 8.059 | 1.970 | 8.913 | 0.868 | 0.721 |
| Volatility of industrial production | 0.004 | 0.003 | 2.286 | 11.716 | 0.468 | 0.326 |
| Volatility of inflation growth | 0.006 | 0.006 | 2.744 | 14.036 | 0.280 | 0.345 |
| ADS index | 0.000 | 0.320 | -0.107 | 5.024 | 0.077 | -0.138 |
| Baltic index | -2.828 | 465.915 | -0.350 | 17.359 | 0.399 | 0.092 |
| Kilian’s real index | -0.604 | 23.442 | 0.613 | 2.930 | 0.950 | 0.879 |
| Global industrial production | 0.203 | 0.565 | -1.760 | 13.608 | 0.322 | 0.441 |
| Growth in global oil supply | 0.001 | 0.010 | -0.467 | 9.536 | -0.091 | -0.041 |
| Growth in U.S. oil supply | 0.001 | 0.055 | -0.373 | 5.423 | -0.570 | 0.173 |
| Growth in U.S. oil inventory | 0.000 | 0.019 | -0.600 | 4.220 | 0.196 | 0.188 |
| Oil price return | 0.003 | 0.081 | -0.259 | 5.409 | 0.314 | 0.095 |
| Geopolitical dummy | 0.034 | 0.181 | 5.164 | 27.671 | -0.035 | 0.059 |
| Growth in cp-to-treasury spread | 0.390 | 0.329 | 1.360 | 4.926 | 0.880 | 0.773 |
| Expected return | -0.009 | 0.136 | -1.554 | 7.382 | 0.738 | 0.709 |
| Default return | 0.000 | 0.016 | -0.435 | 11.718 | 0.024 | -0.038 |
| Default spread | 0.000 | 0.001 | 1.580 | 26.554 | 0.441 | 0.092 |
| Term spread | 0.000 | 0.003 | 0.456 | 3.886 | 0.164 | -0.027 |
| Net payout yield | 0.000 | 0.043 | 0.306 | 10.318 | -0.098 | 0.186 |

**Notes:** The table presents descriptive statistics of the economic predictors. Ludvigson’s uncertainty index provides estimates of time-varying macroeconomic uncertainty (Jurado, et al. 2015). Bloom’s uncertainty index measures economic policy uncertainty. VIX is the combination of CBOE’s VXO (1987-1989) and VIX (1990-2014). Volatility of growth in industrial production is a proxy for the conditional volatility of growth in industrial production. Volatility of inflation growth is a proxy for the conditional volatility for inflation growth based on the Producer’s Price Index (Paye, 2012). ADS index (i.e., Aruoba-Diebold-Scotti Business Conditions Index) tracks real business conditions. Baltic index (i.e., Baltic Dry Index) tracks the price of moving the major raw materials by sea. Killian’s real index measures global real economic activity in industrial commodity markets (Kilian, 2009). Global industrial production measures output of the OECD and six large developing countries. Growth in global oil production is growth rate in global oil supply. U.S. oil inventory is the U.S. crude oil inventory level. U.S. oil production is the U.S. crude oil supply. Oil price returns is based on one-mon crude oil futures. Growth in cp-to-treasury spread is the change in difference between the three-mon commercial paper rate and three-mon Treasury bills. Expected return is a regression-based estimate of the expected excess return of the S&P 500 Index (Paye, 2012). Default return is the difference between long-term corporate bond and long-term government bond returns. Default spread is the difference between the yield on BAA-rated corporate bonds and the yield on AAA-rated corporate bonds. Term spread is the difference between the long term yield on government bonds and the T-bill rate. Net payout yield is constructed using aggregated market capitalization, dividends, and net equity issuance (Paye, 2012). Statistics are calculated at a monthly frequency over the period 1987-2014.

**Table 6: In-Sample Univariate Forecast of Oil Price Uncertainty and Its Components**

| Variable | RV | | C | | J | |
|---|---|---|---|---|---|---|
| | $\hat{\beta}$ | $\Delta$adj. $R^2$ | $\hat{\beta}$ | $\Delta$adj. $R^2$ | $\hat{\beta}$ | $\Delta$adj. $R^2$ |
| Ludvigson's uncertainty index | 0.179*** | 0.029 | 0.185*** | 0.029 | 0.047 | 0.000 |
| | (3.604) | | (3.591) | | (1.475) | |
| Bloom's uncertainty index | -0.010 | -0.001 | -0.013 | -0.001 | -0.011 | -0.002 |
| | (-0.211) | | (-0.304) | | (-0.343) | |
| VIX | 0.160* | 0.016 | 0.116 | 0.008 | 0.136*** | 0.014 |
| | (1.765) | | (1.450) | | (2.723) | |
| Volatility of industrial production | 0.110 | 0.008 | 0.108 | 0.008 | 0.019 | -0.002 |
| | (1.155) | | (1.283) | | (0.296) | |
| Volatility of inflation growth | 0.085 | 0.005 | 0.084 | 0.005 | 0.015 | -0.002 |
| | (1.276) | | (1.364) | | (0.314) | |
| ADS index | -0.094 | 0.007 | -0.077 | 0.005 | -0.061 | 0.001 |
| | (-1.617) | | (-1.342) | | (-1.557) | |
| Baltic index | -0.124* | 0.014 | -0.111 | 0.011 | -0.065** | 0.002 |
| | (-1.667) | | (-1.551) | | (-2.397) | |
| Kilian’s real index | -0.023 | -0.001 | 0.001 | -0.001 | -0.112** | 0.009 |
| | (-0.629) | | (0.031) | | (-2.433) | |
| Global industrial production | -0.153 | 0.018 | -0.139 | 0.014 | -0.054 | 0.000 |
| | (-1.596) | | (-1.593) | | (-1.082) | |
| Growth in global oil supply | 0.081** | 0.005 | 0.064 | 0.003 | 0.122** | 0.012 |
| | (2.050) | | (1.574) | | (2.253) | |
| Growth in U.S. oil supply | -0.054 | 0.001 | -0.056 | 0.002 | -0.041 | -0.001 |
| | (-1.197) | | (-1.419) | | (-0.602) | |
| Growth in U.S. oil inventory | -0.011 | -0.001 | -0.002 | -0.001 | -0.020 | -0.002 |
| | (-0.254) | | (-0.056) | | (-0.464) | |
| Oil price returns | -0.080 | 0.005 | -0.093 | 0.007 | 0.043 | -0.001 |
| | (-0.885) | | (-1.215) | | (0.442) | |
| Geopolitical dummy | 0.102 | -0.001 | -0.017 | -0.001 | -0.022 | -0.003 |
| | (0.511) | | (-0.095) | | (-0.173) | |
| Growth in cp-to-treasury spread | 0.085 | 0.006 | 0.072 | 0.004 | 0.090* | 0.005 |
| | (1.354) | | (1.225) | | (1.959) | |
| Expected return | -0.086 | 0.004 | -0.074 | 0.003 | -0.018 | -0.002 |
| | (-1.108) | | (-1.293) | | (-0.282) | |
| Default return | -0.082 | 0.005 | -0.084 | 0.006 | -0.023 | -0.002 |
| | (-1.292) | | (-1.250) | | (-0.840) | |
| Default spread | 0.146* | 0.019 | 0.149* | 0.019 | 0.028 | -0.002 |
| | (1.706) | | (1.874) | | (0.484) | |
| Term spread | -0.009 | -0.001 | -0.008 | -0.001 | 0.009 | -0.002 |
| | (-0.295) | | (-0.280) | | (0.196) | |
| Net payout yield | -0.023 | -0.001 | -0.037 | 0.000 | 0.014 | -0.002 |
| | (-0.743) | | (-1.353) | | (0.359) | |

**Notes:** The table presents in-sample predictive regression of crude oil realized variance and its components. We report regression results from

$$RV_t = \alpha + \rho_1 RV_{t-1} + \rho_2 RV_{t-2} + \beta X_{t-1} + \varepsilon_t.$$

$$C_t = \alpha + \rho_1 C_{t-1} + \rho_2 C_{t-2} + \beta X_{t-1} + \varepsilon_t.$$

$$J_t = \alpha + \rho_1 J_{t-1} + \rho_2 J_{t-2} + \beta X_{t-1} + \varepsilon_t.$$

where $RV_t$, $C_t$, and $J_t$ are realized variance, the continuous part, and the jump part, respectively. $X_{t-1}$ is the economic predictor. For each predictive variable, the table presents the estimated coefficient $\hat{\beta}$ and the incremental adjusted $R^2$ compared to the benchmark AR(2) model. All variables are standardized prior to regressions and thus we do not report the intercept. ***, **, and * designate statistical significance at the level of 1%, 5%, and 10%, respectively, Newey-West statistics are reported in parenthesis. Data period covers 1987-2014.

**Table 7: In-Sample Multivariate Forecast of Oil Price Uncertainty**

| Variable | RV | C | J |
|---|---|---|---|
| Ludvigson's uncertainty index | 0.127** | 0.125** | 0.074 |
| | (2.152) | (2.393) | (1.264) |
| Bloom's uncertainty index | -0.046 | -0.044 | -0.034 |
| | (-1.110) | (-1.114) | (-0.867) |
| VIX | 0.159** | 0.113* | 0.219** |
| | (2.216) | (1.874) | (2.403) |
| Volatility of industrial production | 0.072 | 0.069 | 0.011 |
| | (1.250) | (1.285) | (0.230) |
| Volatility of inflation growth | 0.022 | 0.010 | 0.046 |
| | (0.596) | (0.293) | (1.261) |
| ADS index | -0.037 | -0.027 | -0.052 |
| | (-0.852) | (-0.648) | (-1.114) |
| Baltic index | -0.054** | -0.045* | -0.035 |
| | (-1.991) | (-1.748) | (-1.229) |
| Kilian’s real index | -0.011 | 0.020 | -0.134** |
| | (-0.328) | (0.806) | (-2.322) |
| Global industrial production | -0.073 | -0.071* | 0.000 |
| | (-1.455) | (-1.663) | (0.001) |
| Growth in global oil supply | 0.083** | 0.056 | 0.140** |
| | (2.094) | (1.643) | (2.335) |
| Growth in U.S. oil supply | -0.048 | -0.044 | -0.047 |
| | (-1.140) | (-1.398) | (-0.648) |
| Growth in U.S. oil inventory | 0.009 | 0.012 | 0.011 |
| | (0.243) | (0.335) | (0.260) |
| Oil price returns | 0.015 | -0.015 | 0.108 |
| | (0.280) | (-0.365) | (1.186) |
| Geopolitical dummy | -0.125 | -0.142 | -0.155 |
| | (-0.678) | (-0.862) | (-0.882) |
| Growth in cp-to-treasury spread | -0.017 | -0.020 | 0.017 |
| | (-0.435) | (-0.642) | (0.276) |
| Expected return | 0.024 | 0.003 | 0.122 |
| | (0.345) | (0.069) | (1.199) |
| Default return | -0.007 | -0.017 | 0.028 |
| | (-0.131) | (-0.338) | (0.588) |
| Default spread | 0.052 | 0.063 | -0.010 |
| | (0.841) | (1.078) | (-0.123) |
| Term spread | -0.038 | -0.029 | -0.031 |
| | (-1.235) | (-1.066) | (-0.795) |
| Net payout yield | -0.042 | -0.056* | 0.015 |
| | (-1.263) | (-1.793) | (0.368) |
| Adj. $R^2$ | 0.588 | 0.712 | 0.212 |
| $\Delta$Adj. $R^2$ | 0.054 | 0.051 | 0.024 |

**Notes:** The table presents in-sample multivariate regression of crude oil realized variance, the continuous part and the jump part. We consider a full set of forecasting variables and report results from regression

$$RV_t = \alpha + \rho_1 RV_{t-1} + \rho_2 RV_{t-2} + \sum_i \beta^i X_{t-1}^i + \varepsilon_t.$$

$$C_t = \alpha + \rho_1 C_{t-1} + \rho_2 C_{t-2} + \sum_i \beta^i X_{t-1}^i + \varepsilon_t.$$

$$J_t = \alpha + \rho_1 J_{t-1} + \rho_2 J_{t-2} + \sum_i \beta^i X_{t-1}^i + \varepsilon_t.$$

where $RV_t$, $C_t$, and $J_t$ are crude oil realized variance, the continuous part, and the jump part, respectively. $X_{t-1}^i$ includes the full set of forecasting variables. We report estimated $\hat{\beta}^i$ for each forecasting variable, adjusted $R^2$, and the incremental adjusted $R^2$ compared to the benchmark AR(2) model. ***, **, and * designate statistical significance at the level of 1%, 5%, and 10%, respectively. Newey-West statistics are reported in parenthesis. Data period covers 1987-2014.

**Table 8: In-Sample Three Passing Regression Filter (3PRF) Forecast of Oil Price Uncertainty and Its Components**

| | RV | C | J |
|---|---|---|---|
| Ludvigson's uncertainty index | 0.204*** | 0.247*** | 0.019 |
| | (3.614) | (3.330) | (0.744) |
| Baltic index | -0.166* | -0.161 | -0.087** |
| | (-1.774) | (-1.628) | (-2.586) |
| Global oil production | 0.117* | 0.118 | 0.113** |
| | (1.958) | (1.487) | (2.025) |
| Adj. $R^2$ | 0.571 | 0.676 | 0.207 |
| RMSE | 0.653 | 0.568 | 0.890 |
| $\Delta$Adj. $R^2$ | 0.037 | 0.015 | 0.018 |
| $\Delta$RMSE | -0.030 | -0.015 | -0.013 |

**Notes:** The table presents regression results of crude oil realized variance and the continuous and jump parts using the 3PRF approach (Kelly and Pruitt, 2015). We report estimated coefficient for each factor, along with adjusted $R^2$ , root-mean-square error (RMSE), incremental adjusted $R^2$ and RMSE compared to the benchmark univariate AR(2). ***, **, and * designate statistical significance at the level of 1%, 5%, and 10%, respectively. Newey-West statistics are reported in parenthesis. Sampling period covers 1987-2014.

**Table 9: Out-of-Sample Forecast of Oil Price Uncertainty and its Components**

| Variable | RV | | C | | J | |
|---|---|---|---|---|---|---|
| | ΔRMSE | Δadj. $R^2$ | ΔRMSE | Δadj. $R^2$ | ΔRMSE | Δadj. $R^2$ |
| **Panel A:** Univariate Regression | | | | | | |
| Ludvigson's uncertainty index | -0.050 | 0.009 | -0.053 | 0.006 | 0.000 | 0.001 |
| Bloom's uncertainty index | 0.017 | -0.017 | 0.017 | -0.012 | 0.010 | -0.005 |
| VIX | -0.036 | 0.026 | -0.035 | 0.007 | -0.009 | 0.310 |
| Volatility of industrial production | 0.001 | 0.015 | -0.008 | 0.005 | 0.021 | 0.107 |
| Volatility of inflation growth | -0.015 | -0.010 | -0.015 | -0.004 | 0.000 | -0.005 |
| ADS index | -0.008 | 0.004 | -0.002 | -0.001 | -0.001 | 0.042 |
| Baltic index | -0.022 | -0.002 | -0.022 | -0.002 | 0.010 | 0.087 |
| Kilian’s real index | 0.007 | -0.006 | 0.004 | -0.004 | 0.041 | 0.168 |
| Global industrial production | -0.010 | 0.019 | -0.015 | 0.011 | 0.025 | 0.085 |
| Growth in global oil supply | 0.005 | -0.006 | 0.004 | -0.003 | 0.004 | -0.020 |
| Growth in U.S. oil supply | 0.001 | -0.002 | 0.002 | -0.003 | 0.004 | 0.019 |
| Growth in U.S. oil inventory | 0.005 | -0.007 | 0.003 | -0.004 | 0.005 | -0.015 |
| Oil price returns | 0.005 | -0.020 | -0.010 | -0.003 | 0.057 | -0.008 |
| Geopolitical dummy | 0.006 | -0.007 | 0.006 | -0.006 | 0.002 | -0.012 |
| Growth in cp-to-treasury spread | -0.022 | 0.009 | -0.023 | 0.007 | -0.015 | 0.017 |
| Expected return | -0.012 | 0.012 | -0.016 | 0.003 | 0.023 | 0.129 |
| Default return | 0.008 | -0.013 | -0.007 | -0.006 | 0.004 | -0.014 |
| Default spread | -0.038 | -0.013 | -0.048 | 0.001 | 0.007 | 0.010 |
| Term spread | 0.000 | -0.004 | 0.001 | -0.001 | 0.001 | -0.013 |
| Net payout yield | -0.002 | -0.002 | -0.002 | -0.001 | 0.001 | -0.010 |
| **Panel B:** Multivariate regression | | | | | | |
| All predictors | -0.003 | -0.102 | -0.041 | -0.060 | 0.117 | 0.123 |
| **Panel C:** 3PRF | | | | | | |
| Ludvigson’s index, Baltic Index, Global oil production | -0.114 | 0.111 | -0.089 | 0.073 | -0.001 | 0.171 |

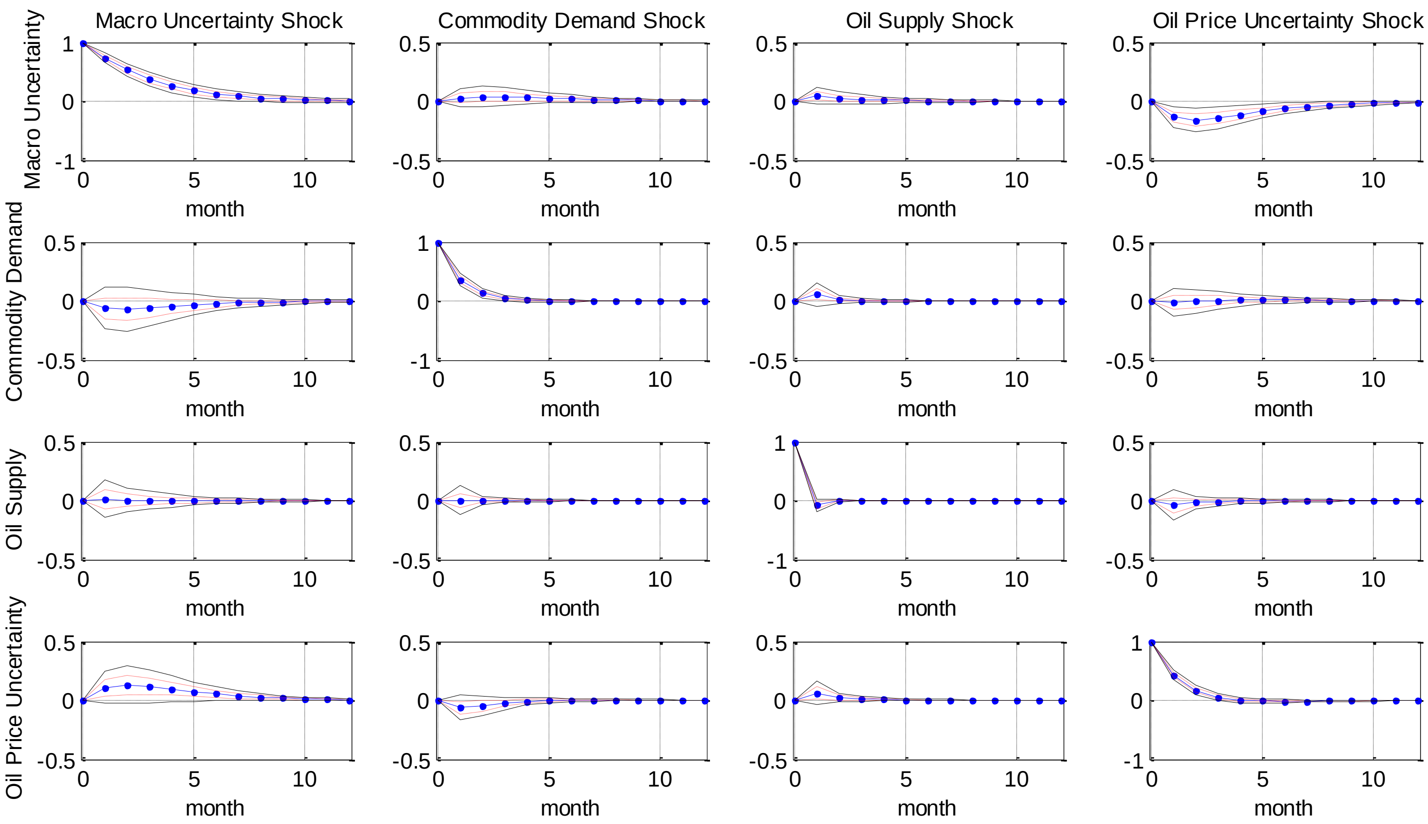
**Notes:** The table presents results of rolling window out-of-sample predictive regression of crude oil realized variance and the corresponding decompositions. Our out-of-sample covers 2005-2014. For each predictive variable $X$ in the univariate regression, Panel A reports the univariate regression results. Panel B reports the multivariate results using the full combination of predictive variables. Panel C reports out-of-sample results from the 3PRF approach.

**Table 10: The Decompositions of Oil Price Uncertainty and Real Economic Activity**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Real GDP** | | | | |
| C | -0.113 | -0.181*** | -0.167*** | -0.205*** |
| | (-1.453) | (-2.929) | (-2.712) | (-3.101) |
| J | 0.053 | 0.068 | 0.051 | 0.053 |
| | (0.795) | (0.997) | (0.742) | (0.876) |
| Adj. $R^2$ | 0.213 | 0.199 | 0.201 | 0.201 |
| **Real GNP** | | | | |
| C | -0.161* | -0.208*** | -0.208*** | -0.223*** |
| | (-1.932) | (-3.042) | (-3.145) | (-3.205) |
| J | 0.053 | 0.066 | 0.057 | 0.054 |
| | (0.715) | (0.915) | (0.782) | (0.788) |
| Adj. $R^2$ | 0.170 | 0.164 | 0.160 | 0.162 |
| **IP Growth** | | | | |
| C | -0.072 | -0.131** | -0.081 | -0.165** |
| | (-0.931) | (-2.019) | (-1.507) | (-2.271) |
| J | -0.007 | -0.006 | -0.024 | -0.011 |
| | (-0.106) | (-0.091) | (-0.416) | (-0.199) |
| Adj. $R^2$ | 0.614 | 0.604 | 0.639 | 0.613 |
| **Real PC__Durable** | | | | |
| C | -0.205*** | -0.174** | -0.193** | -0.223** |
| | (-2.992) | (-2.575) | (-2.282) | (-3.152) |
| J | 0.059 | 0.065 | 0.060 | 0.040 |
| | (0.348) | (0.390) | (0.355) | (0.242) |
| Adj. $R^2$ | 0.010 | 0.018 | 0.008 | 0.025 |
| **Real PC_Service** | | | | |
| C | -0.074 | -0.113 | -0.048 | -0.154 |
| | (-0.899) | (-1.295) | (-0.487) | (-1.530) |
| J | 0.094 | 0.085 | 0.073 | 0.076 |
| | (0.622) | (0.571) | (0.514) | (0.570) |
| Adj. $R^2$ | 0.150 | 0.159 | 0.180 | 0.171 |
| **Real Inv** | | | | |
| C | -0.236*** | -0.237*** | -0.211*** | -0.265*** |
| | (-2.903) | (-3.072) | (-2.656) | (-3.552) |
| J | 0.098 | 0.110 | 0.083 | 0.086 |
| | (1.052) | (1.179) | (0.874) | (1.001) |
| Adj. $R^2$ | 0.301 | 0.316 | 0.313 | 0.314 |
| **Real GPDInv** | | | | |
| C | -0.128 | -0.232** | -0.177* | -0.255** |
| | (-0.949) | (-2.155) | (-1.752) | (-2.153) |
| J | -0.078 | -0.065 | -0.089 | -0.075 |
| | (-1.025) | (-0.887) | (-1.296) | (-1.066) |
| Adj. $R^2$ | 0.236 | 0.201 | 0.233 | 0.207 |

**Notes:** We report the regression results when we use the continuous and jump variance to predict real economic activities while controlling for default spread (1), term spread (2), S&P 500 return (3), and oil price return (4). We include the three major economic determinants, i.e. Ludvigson's index, Baltic Index, the growth rate of global oil production in all regressions.

**Figure A1: Structural Vector Autoregressive Model Results**




**Notes:** This figure plots the impulse response functions of the SVAR system. Each column is for each orthogonal shock and each row is for each variable. All variables are normalized for ease of interpretation. The dotted lines (the solid lines) are the one standard deviation (two standard deviation) boot-strapped confidence intervals calculated from 2,000 iterations.

**Table A1: Oil Price Uncertainty and Real Economic Activity (after including oil volatility determinants)**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Real GDP** | | | | |
| RV | -0.052 | -0.109 | -0.107 | -0.142** |
| | (-0.702) | (-1.507) | (-1.574) | (-2.137) |
| Adj. $R^2$ | 0.192 | 0.196 | 0.205 | 0.211 |
| **Real GNP** | | | | |
| RV | -0.096 | -0.134* | -0.139* | -0.156** |
| | (-1.287) | (-1.859) | (-1.965) | (-2.247) |
| Adj. $R^2$ | 0.199 | 0.203 | 0.202 | 0.211 |
| **IP Growth** | | | | |
| RV | -0.068 | -0.121 | -0.092 | -0.156** |
| | (-0.765) | (-1.571) | (-1.376) | (-2.369) |
| Adj. $R^2$ | 0.636 | 0.626 | 0.650 | 0.638 |
| **Real PC__Durable** | | | | |
| RV | -0.143 | -0.115 | -0.134 | -0.180* |
| | (-1.420) | (-1.167) | (-1.343) | (-1.885) |
| Adj. $R^2$ | 0.023 | 0.034 | 0.024 | 0.044 |
| **Real PC_Service** | | | | |
| RV | 0.005 | -0.044 | 0.011 | -0.088 |
| | (0.044) | (-0.393) | (0.101) | (-0.831) |
| Adj. $R^2$ | 0.137 | 0.141 | 0.224 | 0.161 |
| **Real Inv** | | | | |
| RV | -0.126 | -0.126 | -0.122 | -0.170** |
| | (-1.219) | (-1.394) | (-1.418) | (-2.037) |
| Adj. $R^2$ | 0.301 | 0.317 | 0.332 | 0.316 |
| **Real GPDInv** | | | | |
| RV | -0.182** | -0.264*** | -0.234*** | -0.293*** |
| | (-2.137) | (-3.308) | (-3.290) | (-3.475) |
| Adj. $R^2$ | 0.216 | 0.202 | 0.208 | 0.212 |

**Notes:** This table reports the coefficient of crude oil realized variance when using it to predict real economic activities. We control for default spread (1), term spread (2), S&P 500 return (3), and oil price return (4). We include the three major economic determinants, i.e., Ludvigson's index, Baltic Index, the growth rate of global oil production in all regressions.

**Table A2: Oil Implied volatility and Real Economic Activity**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Real GDP** | | | | |
| Imp. Vol. | -0.108 | -0.167 | -0.147 | -0.179* |
| | (-1.157) | (-1.523) | (-1.486) | (-1.667) |
| Adj. $R^2$ | 0.202 | 0.169 | 0.189 | 0.168 |
| **Real GNP** | | | | |
| Imp. Vol. | -0.166* | -0.219* | -0.212* | -0.226** |
| | (-1.663) | (-1.888) | (-1.943) | (-1.989) |
| Adj. $R^2$ | 0.168 | 0.133 | 0.138 | 0.129 |
| **IP Growth** | | | | |
| Imp. Vol. | -0.075 | -0.168 | -0.111 | -0.171* |
| | (-0.721) | (-1.643) | (-1.266) | (-1.675) |
| Adj. $R^2$ | 0.608 | 0.525 | 0.612 | 0.524 |
| **Real PC__Durable** | | | | |
| Imp. Vol. | -0.130 | -0.131 | -0.120 | -0.166 |
| | (-1.235) | (-1.284) | (-1.086) | (-1.499) |
| Adj. $R^2$ | 0.001 | 0.003 | 0.002 | 0.001 |
| **Real PC_Service** | | | | |
| Imp. Vol. | -0.057 | -0.125 | -0.009 | -0.152 |
| | (-0.568) | (-1.236) | (-0.098) | (-1.239) |
| Adj. $R^2$ | 0.117 | 0.085 | 0.204 | 0.095 |
| **Real Inv** | | | | |
| Imp. Vol. | -0.122 | -0.164* | -0.111 | -0.172* |
| | (-1.134) | (-1.705) | (-1.053) | (-1.739) |
| Adj. $R^2$ | 0.347 | 0.342 | 0.378 | 0.332 |
| **Real GPDInv** | | | | |
| Imp. Vol. | -0.124 | -0.255* | -0.191 | -0.258* |
| | (-1.180) | (-1.755) | (-1.483) | (-1.908) |
| Adj. $R^2$ | 0.235 | 0.133 | 0.191 | 0.132 |

**Notes:** We report the regression coefficients when we use the oil option-implied volatility to predict real economic activities while controlling for default spread (1), term spread (2), S&P 500 return (3), and oil price return (4). Oil option-implied volatility is non-parametrically estimated from the cross-section of out-of-money crude oil futures option. The period is from 1990 to 2014 due to the availability of quality option data.

**Table A3: In-Sample Three-Pass Regression Filter (3PRF) Forecast (Using Square Root of Realized Variance)**

| | Sqrt RV | Sqrt C | Sqrt J |
|---|---|---|---|
| Ludvigson's uncertainty index | 0.233*** | 0.273*** | 0.054* |
| | (5.579) | (5.472) | (1.758) |
| Baltic Dry Index | -0.036 | -0.029 | -0.071** |
| | (-0.954) | (-0.679) | (-2.313) |
| Global oil production | 0.154*** | 0.155*** | 0.097* |
| | (3.509) | (3.212) | (1.706) |
| Adj. $R^2$ | 0.253 | 0.194 | 0.240 |
| RMSE | 0.864 | 0.897 | 0.871 |
| $\Delta$ Adj. $R^2$ | 0.077 | 0.108 | 0.015 |
| $\Delta$RMSE | -0.046 | -0.061 | -0.012 |

**Notes:** The table presents regression results of forecasting square root of RV and the corresponding decompositions (squared root of the continuous and jump parts from realized variance) using the 3PRF approach. The table reports estimated coefficient for each factor, along with adjusted $R^2$, in-sample incremental adjusted $R^2$ and root-mean-square error (RMSE) compared to the benchmark univariate AR(2). ***, **, and * designate statistical significance at the level of 1%, 5%, and 10%, respectively. Newey-West statistics are reported in parenthesis. Data period covers 1987-2014.

**Table A4: Out-of-Sample Forecast of Oil Price Uncertainty (Using Square Root of Realized Variance)**

| Variable | Sqrt RV | | Sqrt C | | Sqrt J | |
|---|---|---|---|---|---|---|
| | ΔRMSE | Δadj. $R^2$ | ΔRMSE | Δadj. $R^2$ | ΔRMSE | Δadj. $R^2$ |
| **Panel A:** Univariate Regression | | | | | | |
| Ludvigson's uncertainty index | -0.107 | 0.114 | -0.131 | 0.114 | -0.003 | 0.006 |
| Bloom's uncertainty index | 0.010 | -0.003 | 0.012 | -0.004 | 0.005 | -0.011 |
| VIX | 0.011 | -0.011 | 0.014 | -0.008 | 0.003 | 0.240 |
| Volatility of industrial production | 0.039 | -0.004 | 0.038 | -0.003 | 0.031 | -0.006 |
| Volatility of inflation growth | -0.006 | -0.002 | 0.001 | -0.001 | 0.018 | 0.022 |
| ADS index | -0.003 | -0.004 | 0.001 | -0.004 | 0.000 | 0.007 |
| Baltic index | -0.005 | -0.007 | -0.003 | -0.008 | 0.001 | 0.011 |
| Kilian's real index | 0.004 | -0.008 | 0.004 | -0.008 | 0.017 | 0.036 |
| Global industrial production | 0.001 | -0.021 | 0.004 | -0.004 | 0.000 | 0.098 |
| Growth in global oil supply | 0.009 | 0.003 | 0.010 | -0.002 | 0.002 | -0.021 |
| Growth in U.S. oil supply | -0.003 | 0.012 | -0.005 | 0.009 | 0.001 | 0.001 |
| Growth in U.S. oil inventory | 0.009 | 0.002 | 0.008 | 0.000 | 0.005 | -0.022 |
| Oil price returns | 0.004 | -0.003 | -0.004 | -0.007 | 0.013 | -0.025 |
| Geopolitical dummy | 0.028 | 0.028 | 0.024 | 0.016 | 0.007 | -0.021 |
| Growth in cp-to-treasury spread | -0.017 | -0.013 | -0.014 | -0.010 | -0.017 | 0.077 |
| Expected return | 0.015 | -0.011 | 0.012 | -0.008 | 0.027 | 0.110 |
| Default return | 0.001 | 0.038 | -0.001 | 0.041 | 0.000 | -0.009 |
| Default spread | -0.031 | -0.006 | -0.025 | 0.004 | -0.009 | 0.031 |
| Term spread | 0.002 | -0.006 | 0.003 | -0.006 | 0.002 | -0.014 |
| Net payout yield | 0.000 | -0.008 | 0.000 | -0.009 | 0.000 | -0.009 |
| **Panel B:** Multivariate Regression | | | | | | |
| All variables | 0.034 | -0.003 | 0.009 | -0.028 | 0.110 | -0.031 |
| **Panel C:** 3PRF | | | | | | |
| Ludvigson's index, Baltic index, Global oil production | -0.103 | 0.048 | -0.110 | 0.030 | -0.005 | 0.100 |

**Notes:** The table presents results of rolling window out-of-sample predictive regression of the squared root of crude oil realized variance and it decompositions. We report the incremental adjusted $R^2$ and RMSE compared to the benchmark univariate AR(2) using the univariate regression (Panel A), multivariate regression (Panel B), and 3PRF (Panel C). The out-of-sample period covers the last ten years (2005-2014).