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Oil Price Uncertainty and the Macroeconomy

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Abstract

This paper examines the impact of oil price uncertainty shocks on economic activity. To do so, we define the uncertainty shock as the unanticipated component of oil price fluctuations. We find that this unanticipated component has a significantly negative and long-lasting impact on economic activity, with its cumulative effect on the US macroeconomy being much larger compared to that of popular uncertainty proxies such as stock market volatility and Economic Policy Uncertainty. Unlike our preferred measure of oil price uncertainty, volatility and the price spikes in oil futures prices present only a small and transitory effect on the real economy. Overall, our findings show that the US economy is significantly impaired when the degree of oil price unpredictability rises, while it is relatively immune to predictable fluctuations in the oil market.

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1. Introduction

The macroeconomic consequences of oil price fluctuations have been extensively examined since the early 1970s. The empirical findings in the extant literature show that the oil-macroeconomy relation is both time-varying and asymmetric; specifically, on this latter point, the recessionary effect of oil price increases are typically larger in magnitude and persistence compared to the expansionary effect of oil price decreases (Hamilton, 1983, 1996, 2003; Hamilton and Herrera, 2004; Kilian, 2009; Kilian and Vigfusson, 2011, 2013, 2017; Rotemberg and Woodford, 1996).[1] Amongst other things, the rationale for this asymmetry has proved controversial. For example, the VAR models of Bernanke, Gertler and Watson (1997, 2004) which control for endogenous monetary policy reactions to oil price shocks show that a large amount, if not all of the reduction in US GDP following the extreme shocks of 1973, 1979 and 1990, could be mitigated by the monetary authority "shutting off" movement in the federal funds rate. On the other hand, Hamilton and Herrera (2004) critique both the idea that the Federal Reserve has such capability and the choice of VAR lag length underpinning the Bernanke *et al*. results.

Another strand of the literature relates the recessionary impact of oil price fluctuations to theories of real options and investment under uncertainty (Aguerrevere, 2009; Bernanke, 1983; Brennan and Schwartz, 1985; Henry, 1974; Pindyck 1991, 1993; Triantis and Hodder, 1990). This theory predicts that higher price uncertainty will lead to the simultaneous decision of firms to postpone irreversible investment (in

[1] In terms of a time-varying relation, Hooker (1996) shows that post-1973 oil prices no longer Granger cause the US macroeconomic indicators. Likewise, Hamilton (2003) shows that the effect of several oil price measures is insignificant in the post-1980 period. Finally, Blanchard and Gali (2007) conclude that the impact of the crude oil shocks was much smaller in magnitude after the 1980s when compared with the respective impact of such shocks in early 1970s.

other words, exercise their option to wait) till price uncertainty is reduced to the level that future cash flows, and hence the expected return of investment, can be estimated with a greater level of confidence. For example, such uncertainty may lead to delays in research and development projects in various industries which are directly impacted by the price of oil such as automobile, natural gas and biofuel industries. At the macroeconomic level, the synchronous postponement of firm investment ultimately leads to a diminution in economic activity[2].

Amongst other work, the empirical findings of Elder and Serletis (2010), Jo (2014), Ferderer (1996) and Guo and Kliesen (2005) verify the significant recessionary impact of simple proxies of oil price uncertainty on economic activity. Elder and Serletis (2010) and Jo (2014) show that rising oil price uncertainty (approximated by volatility modeled either via a GARCH-type model, or as stochastic volatility model) has a significantly negative effect on various US economic indicators. Moreover, Ferderer (1996) and Guo and Kliesen (2005) show that oil price volatility helps in forecasting output growth when used as an additional (to oil prices) variable in macroeconomic forecasting models. In addition, according to Ferderer (1996) and Guo and Kliesen (2005), a large part of the asymmetric effect of oil price increases on output can be explained by the macroeconomic response to oil price volatility shocks. Overall, the relevant literature has shown that both the asymmetric (oil price) and symmetric (oil volatility) effects are of macroeconomic significance, with the exact oil-specific recessionary effect being hard to estimate, since part of it may be attributed to changes in monetary policy anticipating oil inflationary pressures.

[2] The recent findings in the literature provide support to the claim that uncertainty shocks have a negative effect on the macroeconomy (Baker *et al*., 2016; Bachmann *et al*., 2013; Bloom, 2009; Caggiano *et al*., 2014; Jurado *et al*., 2015; Ferrara and Guerin, 2018; among others).

In this paper, we contribute to the existing literature by firstly constructing a more refined measure of oil price uncertainty. Specifically, we redefine an oil price uncertainty shock as the purely unanticipated component of oil price fluctuations. Motivated by the approach of Elder and Serletis (2010) and Baumeister and Kilian (2016), and extending the work of Jurado *et al*. (2015) to an oil context, we estimate oil price uncertainty as the squared forecast error of a predictive regression on oil prices using a variety of oil-specific and macroeconomic factors related to the oil market.[3] In other words, we empirically estimate the oil price uncertainty shock as the conditional volatility of the component of the oil price change which is purely unforecastable by economic agents.[4]

Our next contribution is an empirical examination of the role of unanticipated oil price shocks on economic activity. Strikingly, our results reveal that such shocks provide a far greater dampening and long-lasting impact on US economic activity than predictable analogues. Specifically, we find that the dampening effect of our oil price uncertainty factor is larger in magnitude and persistence when compared with the asymmetric (rising oil prices) and the symmetric (rising oil price volatility) macroeconomic effects of oil price fluctuations. The estimated impulse response functions (IRFs) of our multivariate VAR model, in which we include oil prices and volatility as endogenous variables, show that the macroeconomic impact of our oil

[3] Baumeister and Kilian (2016) define the oil shock as the "gap between the price of oil that was expected and its eventual outcome."

[4] Hence, we remove the largest possible amount of oil price fluctuations which are not related to uncertainty. Jurado *et al*. (2015) promulgate this view by arguing that some popular and widely accepted uncertainty proxies like the stock market volatility (Bloom, 2009) may fluctuate for several other reasons which are not at all related to uncertainty. According to Jurado *et al*. (2015), "stock market volatility can change over time even if there is no change in uncertainty about economic fundamentals, if leverage changes, or if movements in risk aversion or sentiment are important drivers of asset market fluctuations. Cross-sectional dispersion in individual stock returns can fluctuate without any change in uncertainty if there is heterogeneity in the loadings on common risk factors. Similarly, cross-sectional dispersion in firm-level profits, sales, and productivity can fluctuate over the business cycle merely because there is heterogeneity in the cyclicality of firms' business activity."

price uncertainty measure is *three to five times larger* when compared to the impact of observable oil price and volatility shocks.

The VAR analysis also shows that our measure of oil price uncertainty has a more significant and long-lasting negative impact on the macroeconomy compared to the impact of popular proxies of economic uncertainty such as stock-market volatility (Bloom, 2009), Economic Policy Uncertainty (Baker *et al.*, 2016) and geopolitical uncertainty (Alesina *et al*., 1996; Julio and Yook, 2012), verifying that the uncertainty shock with the most significant dampening effect on US macroeconomy is the oil uncertainty shock. We also find that a positive shock to oil price uncertainty results in a significant and long-lasting reduction in US imports and exports; thus, having a negative impact on international trade as well. Interestingly, it appears that rising oil price uncertainty has a larger dampening effect on the US economy in the post-2004 period (i.e., perhaps characterized as a period of relatively more uncertain aggregate demand driven oil shocks) as compared with the pre-2004 period (i.e., a period with relatively more anticipated oil supply shocks). These findings provide further support to earlier literature which identifies a stronger recessionary effect of aggregate demand-driven oil shocks compared to oil price changes driven by supply shocks (Baumeister and Peersman, 2013; Jiang, *et al.,* 2018; Kilian, 2008, 2009; Hamilton, 2009).

Finally, least squares predictive regression models show that our oil price uncertainty factor is a significant predictor of future US economic activity and its components and its predictive power remains robust to the inclusion of oil prices and volatility (Elder and Serletis, 2010; Kilian, 2009) and other popular predictors of economic activity including the slope of the term structure of interest rates (Estrella and Hardouvelis, 1991), stock-market volatility (Bloom, 2009) and Economic Policy Uncertainty (Baker *et al.*, 2016). Overall, our results suggest that it is the time-varying uncertainty regarding the future state of oil prices and not the observable oil price fluctuations that matters the most for investment decisions. When oil prices fluctuate in a predictable manner, even if they become extremely volatile, they have a smaller and transitory impact on economic activity and its forecastability.

The rest of the paper is structured as follows: Section 2 discusses the data and methodology. Turning to the empirical evidence, Section 3 provides both descriptive statistics and regression-based analyses, whilst Section 4 outlines a number of robustness checks. Finally, Section 5 provides conclusions.

2. Data and Methodology

2.1 Oil-specific and stock market variables

We obtain high-frequency (5-minute) prices for the S&P 500 index and crude oil futures prices[5]. The 5-minute frequency was chosen to avoid potential microstructure effects. We estimate realized variance (RV) by summing squared intraday logarithmic returns (filtered through an MA(1) process) as in Andersen *et al.* (2001):

$$RV_t = \sum_{i=1}^{n} r_i^2 \qquad (1)$$

where $r_i = \log(p_i - p_{i-1})$, with p denoting the filtered price series and i the number of intraday observations in each period. To decompose RV into its continuous and

[5] The high frequency data for the S&P index are obtained from Pi Trading, whereas for crude oil futures they are from Tick Data.

jump components, we estimate bipower variation (BV)[6], which captures the continuous component of RV, following Barndorff-Nielsen and Shephard (2006):

$$BV_t = \mu_1^{-2} \sum_{i=2}^{n} |r_i||r_{i-1}| \tag{2}$$

where $\mu_1 = \sqrt{2/\pi}$ and p, i are defined as previously. The difference between these two estimators provides an estimate of the variation due to jumps according to Equation (3) below:

$$JUMPOIL_t = RV_t - BV_t \tag{3}$$

To examine any potential asymmetric effects of oil price volatility jumps, we use positive and negative semivariance (i.e., the part of variance due to positive and negative price moves) to obtain signed jump variation following Barndorff-Nielsen *et al*. (2010) and Patton and Shephard (2015):

$$\Delta J^2 = RS^+ - RS^- \tag{4}$$

with

$$RS^+ = \sum_{i=1}^{n} r_i^2 \, I\{r_i > 0\} \tag{5}$$

$$RS^- = \sum_{i=1}^{n} r_i^2 \, I\{r_i < 0\} \tag{6}$$

denoting positive and negative semivariance, respectively. *I* denotes the indicator function whereas *r* and *i* are defined as previously. We label OILRV the quarterly realized variance of crude oil compiled using high-frequency returns under equation (1), OILPOSVAR and OILNEGVAR are the quarterly variables which measure the

[6] Following the suggestion by Patton and Shephard (2015), we calculate bipower variation as the average of skip-0 through skip-4 bipower variation to obtain a more robust estimator.

realized variance of positive and negative high frequency oil returns under equations (5) and (6), OILTOTJUMP is the variable which measures the oil price fluctuations which are attributed to oil price jumps under Equation (3), and OILSIGNJUMP is the quarterly variable which measures the difference between positive and negative jumps in the oil market in each quarterly period, which is given in (4)[7]. We additionally estimate the same set of realized variance and jump tail risk for the stock-market using the same methodology for the 5-minute S&P500 stock-market index. The respective stock-market volatility and tail risk variables are the SP500RV (S&P500 realized variance), the SP500TOTJUMP (the jump component of SP500RV), the SP500POSVAR and SP500NEGVAR (the positive and negative semivariance for the S&P500 index) and the SP500SIGNJUMP (the difference between the positive and negative price jumps in the S&P500 index in each quarterly period).

The quarterly time series for global US crude oil inventories and production are contained in the Monthly Energy Review of Energy Information Administration (EIA) (for more details see Kilian and Murphy (2014)). The oil futures basis data (defined as the ratio of 3-month crude oil futures to nearest to maturity futures) are downloaded from DataStream. The volume of 3-month maturity oil futures, the data for the Working T Index and the market-share of non-commercial traders in the oil market (this is a proxy for speculation in the oil market - see Buyuksahin and Robe (2014)) are downloaded from the Commodity Futures Trading Commission (CFTC).

2.2 Macroeconomic data

[7] We choose to estimate the quarterly realized variance in the oil market, since the macroeconomic indicators of economic activity (US GDP growth and US Investment growth) which we use in our predictive models can only be found in quarterly frequency. In our online Appendix, we provide results for our monthly estimates of oil price volatility as well.

We obtain quarterly series for the unemployment rate, 3-month Treasury Bill rates, 10-year constant maturity Treasury yields, WTI crude oil prices, Fed fund rate and US effective exchange rate. We additionally obtain quarterly time series for real US GDP, domestic investment, and US imports and US exports. The data for quarterly macroeconomic series are downloaded from the FRED database. The term spread (TERM), defined as the slope of the US-Treasury yield curve, is estimated as the difference between the 10-year US-Treasury yield and the 3-month US-Treasury bill rate. The global real economic activity index (*GACT*) is based on the work of Kilian (2009) and Kilian and Murphy (2014). This index is closely related to international trade since it measures shifts in the global use of industrial commodities.[8] The geopolitical risk index (*GEOP*) is based on the empirical approach of Caldara and Iacoviello (2018) and measures the uncertainty related to geopolitical tensions as reflected in leading international newspapers.[9] Overall, the time series covers the period from January 1987 till December 2017[10].

2.3 Measuring uncertainty in the crude oil market

Instead of measuring the uncertainty shock in the oil market as the conditional variance of the monthly returns of crude oil prices (estimated by a GARCH model[11]), or the realized volatility of crude oil returns, we follow the theoretical approach of Jurado *et al*. (2015) for the measurement of uncertainty shocks. According to Jurado

[8] The global real economic activity index is downloaded from http://www-personal.umich.edu/~lkilian.
[9] The geopolitical risk index is downloaded from https://www2.bc.edu/matteo-iacoviello/gpr.htm.
[10] In our online Appendix, we additionally use the respective monthly time series dataset in which we additionally include the Industrial Production Index in our analysis. The monthly time series data cover the same period and they are also downloaded from the same databases.
[11] Alsaman (2016), Bredin et al (2011), Chang and Serletis (2016), Elder and Serletis (2010), Rahman and Serletis (2011) and Diaz *et al*. (2016) measure oil price uncertainty as the conditional volatility of daily returns of crude oil prices by using a GARCH-in-mean model and Jo (2014) uses a stochastic volatility to model oil price uncertainty. Jo (2014), Elder (2017), Elder and Serletis (2010), Kang *et al*. (2016), Ferderer (1996), Rahman and Serletis (2011) and Guo and Kliesen (2005) show that oil price uncertainty shocks (modeled by a GARCH or stochastic volatility model) have a negative effect on aggregate investment, consumption and output.

et al. (2015), uncertainty cannot be proxied by realized volatility or the degree of predictable variations, but by the unpredictable component of these variations. Thus, our measure of uncertainty in the crude oil market is the squared error of a forecasting regression model in which we include all the well-known determinants of crude oil returns on the right-hand side of our regression model:

$$\varepsilon_{t+k}^2 = E[(OILRET_{t+\kappa} - E(OILRET_{t+\kappa}/I_t)^2/I_t] \qquad (7)$$

where ε_{t+k} represents the *k*-period ahead error term in our forecasting regression on quarterly crude oil price returns (*OILRET*).[12] In Equation (7), if the squared forecast error (conditional on all the available information today) rises, the uncertainty regarding future oil prices also rises. The OILRET variable is the log difference of the quarterly West Texas Intermediate (WTI) crude oil price.[13] Our baseline regression model for forecasting oil prices is given in Equation (8) below:

$$OILRET_{t+k} = a + b_1 OILRET_t + b_2 INVENT_t + b_3 BASIS_t + b_4 OILPROD_t + b_5 SPECUL_t + b_6 WORKT_t + b_7 VOLUME_t + b_8 GEOP_t + b_9 USTBILL3_t + b_{10} IPI_t + b_{11} SP500RV_t + b_{12} OILRV_t + b_{13} EXCH_t + b_{14} GACT_t + b_{15} INFL_t + \varepsilon_{t+\kappa} \qquad (8)$$

[12] Although it is common in the relevant literature (e.g. Elder and Serletis, 2010) to use the log-levels of oil prices, one might express concerns with respect to the non-stationarity of the series. To address such concerns, we estimate oil *return* uncertainty (OILR) by regressing the log-differences of monthly (or quarterly) oil prices instead of the log-levels. In order for our oil uncertainty measure to be comparable and in-line with the relevant literature, we additionally perform the same analysis for estimating oil price uncertainty using the log-levels (instead of the log-differences) in the left-hand side of our predictive regression equation which is given in Equation (8). Using these, instead of the OILR variables in our analysis, leaves our results unchanged. These results can be found in our on-line Appendix.

[13] Since we focus on the recessionary impact of oil prices on the US macroeconomy, we choose WTI crude oil prices for our empirical analysis. Several other studies on the oil macroeconomics literature (for example Kilian, 2009; Kilian and Vigfusson, 2013; among others) use the composite refiners acquisition cost as their measure of global oil price, but as Elder and Serletis (2010) point out, the WTI and the RAC crude oil price time series are highly positively correlated. For robustness purposes, we measure the oil price uncertainty using the RAC measure for monthly oil prices and our main findings remain unaltered. These additional results can be provided upon request.

In Equation (8) INVENT is the quarterly growth rate (log-difference) of the global crude oil inventory level, BASIS is the 3-month basis of crude oil futures, OILPROD is the quarterly growth rate of the global level of crude oil production, SPECUL is the quarterly growth rate of the speculation index in the crude oil market (we estimate the speculation in the oil market as the market share of non-commercial traders in the crude oil futures market), WORKT is the quarterly growth in the Working-T-index, VOLUME is the quarterly growth rate of the aggregate trading volume of 3-month maturity crude oil futures contracts, GEOP is the logarithm of the Geopolitical Uncertainty index of Caldara and Iacoviello (2018), USTBILL3 is the US-Treasury Bill rate with 3-month maturity, IPI is the quarterly growth rate of the US Industrial Production Index, SP500RV is the quarterly realized variance of the intra-day (5-minute) returns of the S&P 500 stock-market index, OILRV is the quarterly realized variance of the intra-day (5-minute) returns of the nearby crude oil futures prices, EXCH is the quarterly growth rate of the US Effective Exchange rate, GACT is the global real economic activity index of Kilian and Murphy (2014) and INFL is the quarterly US inflation rate (the quarterly growth of US Consumer Price Index).

The squared forecast errors (residuals) of our OLS regression model presented in Equation (8) are the oil return uncertainty (OILR) shocks. Hence, by OILR1, OILR2, OILR3 and OILR4 we denote the estimated squared forecast errors (based on Equation (7)) of the forecasting regression model given in Equation (8) for $k = 1, 2, 3$ and 4 quarters forecasting horizon respectively[14].

[14] For the estimation of the monthly oil return uncertainty, we use our monthly time series dataset and estimate the OILR1 (1-month ahead), OILR3 (3-month ahead) and OILR6 (6-month ahead) oil return uncertainty using the regression Equation (8) on monthly time series dataset. The time series and the

2.3 OLS regression models

We follow the empirical methodology of Estrella and Hardouvelis (1991) and estimate univariate regressions of oil price uncertainty (k-quarters ahead) on the GDP growth having k-quarters forecasting horizon. In this regard, we empirically examine whether the uncertainty about the future path of oil prices explains the time variation in economic activity. The univariate explanatory regression model is given in Equation (9) below:

$$\ln(GDP_t/GDP_{t-1}) = b_0 + b_1 OILR(K)_{t-k} + \varepsilon_t \tag{9}$$

In the regression model given in Equation (9) we use the k-quarter ahead oil price uncertainty (OILR(K)) to explain the time variation in US GDP growth k-quarters ahead. We additionally run the same set of explanatory regressions on Investment, Import and Export growth. Moreover, in order to empirically examine the predictive information content of oil price uncertainty, we run, instead of explanatory, predictive regressions of oil price uncertainty on US economic activity and its components by increasing the lag order of the oil uncertainty factor in the regression by one. Hence, in this type of regression, the information about oil price uncertainty used in each quarterly period is indeed available to the forecaster at the same period. Our univariate predictive regression model is given in Equation (10) below:

$$\ln(GDP_t/GDP_{t-1}) = b_0 + b_1 OILR(K)_{t-k-1} + \varepsilon_t \tag{10}$$

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respective econometric results when using our monthly oil price uncertainty measures can be found in our on-line Appendix.

Moreover, in order to examine whether the explanatory power of oil price uncertainty remains robust to the inclusion of oil-related variables like oil prices and oil and stock-market volatility which have already been identified as significant predictors of economic activity in the oil-macroeconomics literature (Hamilton, 2003; Kilian and Vigfusson, 2017; Elder and Serletis, 2010; Elder, 2018; among others), we run multivariate regression models on US GDP growth using oil price uncertainty and controlling for oil prices and volatility. To control for the asymmetric effects of oil price shocks (Hamilton, 1983; Hamilton, 1996; Rahman and Serletis, 2011), we additionally include variables which measure the separate impact of positive and negative oil price jumps. More specifically, we use positive semivariance (OIL POS VAR), negative semivariance (OIL NEG VAR), variation due to jumps (OIL TOT JUMP), as well as signed jump variation (OIL SIGN JUMP). To control for the volatility and jumps in the stock-market, we include the same Realized Variance (SP500RV) and its respective jump tail risk components. We additionally control for some fundamental macro-variables which are associated with changes in economic activity like lagged inflation (INFL), lagged GDP growth (GDP) and lagged Fed fund rate (FFR). The multivariate regression models are given in Equations (11) to (16) below:

$$\ln(GDP_t/GDP_{t-1}) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln(GDP_{t-1}/GDP_{t-2}) + e_t \quad (11)$$

$$\ln(GDP_t/GDP_{t-1}) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln(GDP_{t-1}/GDP_{t-2}) + b_4 OILPOSVAR_{t-1} + b_5 OILNEGVAR_{t-1} + b_6 SP500POSVAR_{t-1} + b_7 SP500NEGVAR_{t-1} + e_t \quad (12)$$

$$\ln(GDP_t/GDP_{t-1}) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln(GDP_{t-1}/GDP_{t-2}) + b_4 OILTOTJUMP_{t-1} + b_5 SP500TOTJUMP_{t-1} + e_t \quad (13)$$

$$\ln(GDP_t/GDP_{t-1}) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln(GDP_{t-1}/GDP_{t-2}) + b_4 OILSIGNJUMP_{t-1} + b_5 SP500SIGNJUMP_{t-1} + e_t \quad (14)$$

$$\ln(GDP_t/GDP_{t-1}) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln(GDP_{t-1}/GDP_{t-2}) + b_4 OILRV_{t-1} + b_5 SP500RV_{t-1} + e_t \quad (15)$$

$$\ln(GDP_t/GDP_{t-1}) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln(GDP_{t-1}/GDP_{t-2}) + b_4 OILRV_{t-1} + b_5 SP500RV_{t-1} + b_5 OILR1_{t-1} + e_t \quad (16)$$

The regression models given in Equations (11) to (16) capture the explanatory power of the different oil-related and macroeconomic factors which are empirically verified as significant predictors of economic activity. Moreover, the regression model of Equation (16) is designed to demonstrate the incremental explanatory power of our oil uncertainty factor when compared to oil volatility, stock-market volatility and macroeconomic fundamentals. We also run a multivariate regression model on US GDP growth with forecasting horizon ranging from 1 up to 4 quarters ahead. In this multivariate regression setting, we additionally control for some major indicators of US economic activity, like the quarterly returns of WTI oil prices (OILRET) (Hamilton, 1983; Kilian, 2009; Kilian and Vigfusson, 2017), the logarithm Economic Policy Uncertainty (EPU) (Baker *et al.*, 2016), the logarithm of Geopolitical Uncertainty (GEOP), the level of US unemployment rate (UNEMP), the growth rate of US effective exchange rate (EXCH) and the slope of term structure of the US-

Treasury Yields (TERM) (Estrella and Hardouvelis, 1991)[15]. The multivariate regression model is given in Equation (17) below:

$$\ln(GDP_t/GDP_{t-1}) = a + b_1\ln(GDP_{t-k}/GDP_{t-k-1}) + b_2INFL_{t-k} + b_3FFR_{t-k} + b_4UNEMP_{t-k} + b_5OILRV_{t-k} + b_6SP500RV_{t-k} + b_7OILR(K)_{t-k} + b_8OILRET_{t-k} + b_9TERM_{t-k} + b_{10}EXCH_{t-k} + b_{11}EPU_{t-k} + b_{12}GEOP_{t-k} + e_t \quad (17)$$

Similarly to the univariate predictive model given in Equation (10) we estimate the model given in Equation (17) with the lag-order of the oil uncertainty factor increased by one. Hence, this model is our baseline multivariate forecasting regression model on US economic activity. The multivariate forecasting regression model is given in Equation (18) below:

$$\ln(GDP_t/GDP_{t-1}) = a + b_1\ln(GDP_{t-k}/GDP_{t-k-1}) + b_2INFL_{t-k} + b_3FFR_{t-k} + b_4UNEMP_{t-k} + b_5OILRV_{t-k} + b_6SP500RV_{t-k} + b_7OILR(K)_{t-k-1} + b_8OILRET_{t-k} + b_9TERM_{t-k} + b_{10}EXCH_{t-k} + b_{11}EPU_{t-k} + b_{12}GEOP_{t-k} + e_t \quad (18)$$

We run identical multivariate explanatory and predictive regression models on US investment growth (INVEST), on US import growth (IMP) and on US export growth (EXP)[16].

2.4 Baseline VAR model

[15] Following Baker et al (2016), we use the logarithm of the EPU index in the right-hand side of our regression models on US economic activity. Similarly, we also use the logarithm of the geopolitical risk index (GEOP) as additional explanatory variable.

[16] For robustness purposes, we additionally estimate identical regression models on alternative measures of economic activity, like US unemployment rate, US Industrial Production Index growth and on global real economic activity. These regression results can be found in our on-line Appendix.

We estimate the macroeconomic impact of these uncertainty shocks based on VAR analysis and we compare our estimated responses of oil uncertainty shocks with findings provided in the literature (Elder and Serletis, 2010; Elder, 2018; among others). We estimate a 6-factor reduced-form VAR model with 4 lags. Although the Akaike and Schwarz information criteria give an optimal lag-length of 3 lags, we follow the standard practice in the literature and use 4 lags to allow for more dynamics in the system (Elder and Serletis, 2010; Hamilton, 1996; Hamilton and Herrera, 2004; Jo, 2014)[17]. The choice of 4 lags is based on the approach of Hamilton (1996) and Hamilton and Herrera (2004) according to which the effect of oil shocks on economic activity occurs at or before one year after the initial oil shock so the inclusion of one year of lags is necessary. The reduced form VAR model is given in Equation (19):

$$Y_t = A_0 + A_1 Y_{t-1} + \ldots + A_k Y_{t-k} + \varepsilon_t \tag{19}$$

Where A_0 is a vector of constant terms, A_1 to A_k are coefficient vectors and ε_t is the vector of independent and identically distributed disturbances with zero mean and a variance-covariance matrix $E(\varepsilon_t, \varepsilon_t') = \sigma_\varepsilon^2 I$. Y_t is the vector of endogenous variables. Following Bekaert *et al.* (2013), we order macroeconomic variables like GDP growth, first, while the SP500RV, the OILRV and the OILR(K) are placed last in the VAR ordering[18]. This captures the fact that oil-specific and stock-market variables respond instantly to economic shocks, while the macroeconomic variables have more sluggish

[17] Our VAR results remain unaltered when using 3 lags as suggested by the Akaike and the Swartz information criteria. These additional findings can be provided upon request.

[18] We must state at this point that our estimated Orthogonalized Impulse Response Functions (OIRFs) remain robust when using alternative VAR orderings. These additional VAR results can be provided upon request.

responses. Hence, the ordering of the endogenous variables of our 6-factor VAR model is given in Equation (20):

$$Y_t = [GDP_t \; GEOP_t \; INFL_t \; SP500RV_t \; OILRV_t \; OILR(k)_t] \tag{20}$$

Moreover, we estimate an otherwise identical reduced-form VAR model using some alternative proxies for economic activity (and some components of GDP as well) as the first variable in our VAR ordering. These alternative estimations allow us to investigate which components of economic activity are more severely affected by rising uncertainty in the oil market. More specifically, we estimate a VAR model in which instead of GDP growth, we use the quarterly US investment growth, with the ordering of endogenous variables given in Equation (21):

$$Y_t = [INVEST_t \; GEOP_t \; INFL_t \; SP500RV_t \; OILRV_t \; OILR(k)_t] \tag{21}$$

Similarly, we estimate VAR models on US exports growth and US imports growth as the first variable in our VAR ordering, given in Equations (22) and (23):

$$Y_t = [EXP_t \; GEOP_t \; INFL_t \; SP500RV_t \; OILRV_t \; OILR(k)_t] \tag{22}$$

$$Y_t = [IMP_t \; GEOP_t \; INFL_t \; SP500RV_t \; OILRV_t \; OILR(k)_t] \tag{23}$$

We additionally use the monthly growth rates of US Industrial Production, US unemployment rate (UNEMP) and on the monthly measure of global real activity (GACT) of Kilian (2009) and Kilian and Murphy (2014)[19].

3. Empirical analysis

3.1 Descriptive statistics

In this section we present the descriptive statistics for our quarterly time series sample covering the full (Q1 1987- Q4 2017) period[20]. **Table 1** below presents the descriptive statistics for our oil-related variables and **Table 2** presents the correlation matrix for our explanatory variables used in the analysis.

[Insert Table 1 Here]

[Insert Table 2 Here]

Tables 1 and **2** show that our oil price uncertainty factors are weakly positively correlated with the other popular uncertainty proxies like oil volatility (OILRV), stock-market volatility (SP500RV) and Economic Policy Uncertainty (EPU). In addition, we reject the hypothesis of unit root for all our explanatory variables (except the Fed fund rate and the unemployment rate)[21]. **Figure 1** shows the time series

[19] For the monthly VAR model on Industrial Production growth and global real activity, we use our monthly time series dataset. These additional VAR results can be found in our on-line Appendix.
[20] The descriptive statistics of our monthly time series dataset can be found in our on-line Appendix.
[21] We reject the hypothesis of a unit root using the ADF unit root test at the 5% significance level. The results of our unit root tests can be found in our on-line Appendix. Although the Fed fund rate is a close to unit root process, it has been extensively used as explanatory variable proxying for the monetary policy stance (see Bekaert *et al*. (2013)). The same is true for the US unemployment rate which is used in predictive regressions on inflation (Stock and Watson, 1999). Our findings remain robust when using the first differences for these variables (which are stationary series). These additional regression results can be provided upon request.

variation of oil price uncertainty and the respective time series of US real GDP growth.

[Insert Figure 1 Here]

Figure 1 shows that our oil price uncertainty is associated with subsequent drops in US economic activity. More specifically, the oil price uncertainty spike in 2008 coincides with the 2008 recession.

3.2 Forecasting US real output using oil uncertainty

In this section we present the results of our OLS forecasting regression models on economic activity using oil price uncertainty as predictor. Following the empirical approach of Bakshi *et al*. (2011) and Estrella and Hardouvelis (1991), we run univariate explanatory and predictive OLS regressions on quarterly US real GDP growth using oil price uncertainty in the right-hand side of the regression equations[22] as shown in Equations (9) and (10) in Subsection 2.3. **Tables 3** and **4** below present the regression results of our explanatory and predictive univariate regressions on US real GDP growth, on Investment growth, Import growth and Export growth respectively.

[Insert Table 3 Here]

[Insert Table 4 Here]

[22] We use the term explanatory to emphasize the fact that our variable is forward-looking since it is estimated using the squared forecast error 1 up to 4 quarters ahead. For this reason, we state that the regression models of **Table 3** are explanatory since we regress the oil price uncertainty for the k-quarters ahead with the GDP growth k-quarters ahead. On the other hand, the regressions presented in **Table 4** are predictive regressions since we regress the oil price uncertainty k-1 quarters ahead with the GDP growth k quarters ahead.

The regression results of **Table 3** show that oil price uncertainty explains a large part of time variation in US GDP growth and its components. More specifically, the rising oil price uncertainty for 1, 2, 3 and 4 quarters ahead is associated with drop in US economic activity and in US trade flows in the respective quarters. The explanatory power is significant in both short and long horizons, but it is larger for long (3 and 4 quarter horizons). For example, the R^2 value in the univariate regression on GDP growth rises from 12.2% to 24.2% when moving from one quarter horizon to four quarter horizon. The monotonic increase in the explanatory power as the horizon increases is also the case when regressing oil price uncertainty on Investment, Exports and Import growth rate. These results show that the oil price uncertainty for the next 3 and 4 quarters has a more dampening effect on US economic activity and trade flows when compared with the respective impact of OILR1 and OILR2 respectively. These results reveal that uncertainty about the future path of oil prices has a more significant impact on investment decisions and economic activity during the next 6-12 months, with the recessionary effect of rising oil price uncertainty for shorter-term horizons remaining much smaller in magnitude. Interestingly, our analysis shows that the rising oil price uncertainty explains approximately 30% of the fluctuation in US imports and exports growth (for 3 and 4 quarters forecasting horizon).

Moreover, the results of our predictive regressions presented in **Table 4** show that our proxies for oil price uncertainty are statistically significant predictors of GDP growth and its components for forecasting horizons ranging from 1 up to 4 quarters. In **Table 4**, we add one more lag in the oil uncertainty factor, hence this regression indicates the predictive power of the oil uncertainty, since the information about oil uncertainty in each period is available to the predictive modeler the time the forecast is being made. According to the results of **Table 4**, the rising oil price uncertainty predicts a fall in GDP growth, falling aggregate investment and a significant drop in US exports and imports. More specifically, we report negative and statistically significant coefficients for OILR1, OILR2, OILR3 and OILR4 variables which correspond to the oil return uncertainty for 1, 2, 3 and 4 quarters ahead respectively. The predictive power on GDP growth and investment growth is higher for 2, 3 and 4 quarters ahead oil return uncertainty (OILR2, OILR3 and OILR4) when compared to the OILR1 uncertainty series. These findings show that the rising uncertainty about oil prices in the distant future (three and four quarters ahead) has a more recessionary impact when compared to the rising oil uncertainty over short-term horizon (OILR1). In conclusion, our regression models show that the rising uncertainty in the oil market is a significant determinant and early warning signal of economic recessions and drops in US trade flows.

In **Table 5** we present the results of our multivariate regression models (given in Equations (11) to (16)) in which we control for observable symmetric (oil volatility) and asymmetric (positive and negative oil price jumps) effects of oil price fluctuations.

[Insert Table 5 Here]

The results of **Table 5** indicate that the rising oil price volatility has a dampening effect on GDP growth since the estimated coefficients of oil price volatility (OILRV) are negative and statistically significant. These results are line with the findings of

Ferderer (1996) and Elder and Serletis (2010) according to which the rising oil price volatility has a dampening effect on US real GDP growth. On the other hand, when examining the asymmetric effect of oil price shocks, we report insignificant coefficients for the monthly positive and negative semivariance as predictors of US GDP growth. The same is true for the signed jumps in oil prices (OILSIGNJUMP), which are also insignificant predictors of US GDP growth. These results lead us to the conclusion that only the symmetric (oil price volatility) shocks have a significant recessionary impact, while the asymmetric shocks (oil price increases) are insignificant indicators of falling economic activity. Our findings contrast with the findings of Hamilton (1983) who reports a strong asymmetric (non-linear) relationship between oil prices and US GDP growth by finding that the recessionary impact of oil price increases is bigger in magnitude and persistence when compared with the respective expansionary macroeconomic effect of oil price drops. Our findings lead us to the opposite conclusion since we show that the relationship between asymmetric oil price shocks and subsequent economic activity is insignificant. Our findings are broadly in line with the theory of 'Investment under Uncertainty' (Bernanke, 1983; Bloom, 2009; Pindyck, 1991) according to which rising uncertainty leads to a fall in investment and economic activity. In addition, our empirical findings are broadly in line with the oil macroeconomics literature, according to which the rising oil price volatility has a negative impact on US economic activity and its components (Elder, 2018; Elder and Serletis, 2010; Ferderer, 1996; Jo, 2014). Moreover, our multivariate forecasting regression models on GDP growth show that our oil price uncertainty factor contains all the oil-related predictive information regarding future economic activity. The predictive power of our oil price uncertainty factor remains robust to the inclusion of oil price volatility

(OILRV), stock-market volatility (SP500RV) and to macroeconomic fundamentals like inflation and Fed fund rate. More specifically, the inclusion of oil price uncertainty (OILR1) significantly improves the forecasting performance of the OLS forecasting regression model, with the adjusted R^2 increasing from 22.1% to 26.0% when including the oil price uncertainty (OILR1) into the information variable set[23]. In conclusion, the oil price uncertainty adds significant macroeconomic forecasting power when added to the information variable set which includes all the observable measures of oil price fluctuations.

Furthermore, we estimate an alternative multivariate regression model which is described in Equations (17) and (18) of Subsection 2.3. **Tables 6 and 7** present the regression results of our multivariate explanatory regression model (Equation 17) and our multivariate forecasting regression model (Equation 18) respectively.

[Insert Tables 6 and 7 Here]

The regression results of **Tables 6** and **7** show that the explanatory power of our oil price uncertainty factor remains robust to the inclusion of EPU, OILRET and the TERM into the information variable set. On the other hand, the predictive power of oil price uncertainty on GDP growth statistically significant and robust to the inclusion of these additional macro-factors for 2 and 3 and 4 quarter forecasting horizons. More specifically, our analysis shows that the rising OILR(K) factor (the uncertainty regarding future oil returns k quarters ahead) is associated with

[23] We choose to include the OILR1 uncertainty series since time series corresponds to the time forecasting horizon. Our findings remain robust irrespectively of whether we choose OILR2 or OILR3 for this forecasting regression model. These additional results can be provided upon request.

subsequent drops in economic activity k quarters ahead. Overall, our multivariate regression analysis is the first to show that the oil price uncertainty factor absorbs the predictive information content of oil prices, oil price volatility, inflation, the term spread and EPU when forecasting US Real GDP growth having 2 up to 4 quarters forecasting horizon. Our findings are in line with those of Ferderer (1996) who shows that a large part of the asymmetric relationship between oil prices and economic activity can be explained by oil price volatility. We provide robustness to Ferderer's (1996) findings by showing that all the predictive information embedded in oil prices is absorbed by oil price uncertainty instead. The real options approach on the theory of investment under uncertainty is empirically verified in our analysis, since we show that unlike rising oil prices, the rising oil price uncertainty has the most significant dampening effect on US GDP growth.

In order to further examine the empirical validity of the theory of investment under uncertainty (Bernanke, 1983; Pindyck, 1991, 1993) for the case of the oil market, we additionally investigate the predictive power of oil price uncertainty on the quarterly growth of US Domestic Investment. We run the same set of multivariate OLS forecasting regression models on US Investment growth. **Tables 8, 9** and **10** show the respective regression results of our multivariate regression models on US Investment growth.

[Insert Tables 8, 9 and 10 Here]

The regression results of **Tables 8, 9** and **10** show that the oil price uncertainty has a negative and statistically significant coefficient when forecasting aggregate investment under all the alternative multivariate regression specifications. The predictive power of the oil return uncertainty remains robust to the inclusion of oil-specific and macroeconomic factors for both short and long-term forecasting horizons and absorbs the predictive power of already empirically verified predictors of real output and aggregate investment like EPU (Baker *et al.*, 2016) and the Term Spread (Estrella and Hardouvelis, 1991). In addition, our empirical findings indicate that the rising oil prices and oil price volatility (OILRV) are not statistically significant predictors of aggregate investment in this multivariate regression setting. These results are the first to show that the uncertainty shock which better predicts a drop in aggregate investment is the latent oil uncertainty shock and not the observable increases in oil prices and volatility. Our empirical analysis provides further insights on the theory of Investment under Uncertainty (Bernanke, 1983; Pindyck, 1991), since we find that oil return uncertainty (in the form of rising degree of unanticipated oil return changes) is the most significant early warning signal of postponement of US investment. Overall our analysis identifies the stock-market volatility and the oil return uncertainty as the two most significant predictors of US investment. Our results are broadly in line with the recent empirical findings of Elder and Serletis (2010) who use the forecast error of a GARCH-in-mean process for oil prices as their proxy for oil price uncertainty and find that the rising oil price uncertainty is associated with subsequent drops in US domestic investment. We lastly run the same multivariate regression setting on the quarterly US import and export growth. **Tables 11** to **14** below report the regression results of our explanatory and predictive regressions on US imports and exports respectively.

[Insert Tables 11 to 14 Here]

Interestingly, our predictive regressions show that our oil return uncertainty factor has statistically significant predictive power over the growth of US imports and exports for horizons ranging from 1 up to 4 quarters. Our analysis is the first to show that our oil return uncertainty factor has extra predictive power on US trade flows when compared with the predictive power of US effective exchange rate, inflation and lagged imports and exports. On the other hand, we find that the oil prices and oil price volatility have predictive power on US trade flows only for short-term (1-quarter) forecasting horizon.

3.4 Dynamic responses of real output to oil return uncertainty

3.4.1 Real GDP growth responses

In this section we provide the results of our baseline 6-factor VAR model described in Equation (19) and (20). The advantage of our multivariate VAR model is that we control for the dynamic interactions between real output, inflation, oil price volatility, oil uncertainty and stock-market volatility. By including inflation as an endogenous variable, we can examine the separate inflationary and real macroeconomic impact of rising oil return uncertainty shocks. The recent relevant empirical studies (Elder and Serletis, 2010; Jo, 2014; Ferderer, 1996) do not include inflation as an endogenous variable into their VAR model, thus, they cannot discriminate which part of their output responses to oil shocks is inflationary (nominal) and which is recessionary (real). Our analysis is the first to shed light on this separate empirical investigation of the inflationary and the real impact of oil return uncertainty shocks. Furthermore, the inclusion of stock-market volatility controls for possible volatility spillovers and interactions between the oil and stock-markets (Arouri *et al.,* 2011). We firstly conduct a Granger causality analysis between the endogenous variables of our baseline reduced-form VAR model given in Equations (19) and (20). The results of our Granger causality tests are shown in **Table 15** below.

[Insert Table 15 Here]

The Granger causality tests show a unidirectional causal relationship from oil return uncertainty to US GDP growth. On the other hand, the observable oil realized variance (OILRV) and the stock-market realized variance do not Granger cause GDP growth. Moreover, the Granger causality test on our VAR model on Investment growth, shows that the oil return uncertainty Granger causes US investment, while oil price volatility does not cause a change in US investment. We continue our analysis by presenting the estimated Orthogonalized Impulse Response Functions (OIRFs) of the baseline VAR model given in Equation 3. **Figure 2** below shows the estimated OIRFs of GDP growth on a positive shock on oil return uncertainty, oil volatility and stock-market volatility.

[Insert Figure 2 Here]

The estimated OIRFs of GDP growth show that a one standard deviation positive shock in the oil return uncertainty results to a persistent fall in GDP growth for about 6 quarters after the initial uncertainty shock. More specifically, a positive shock in the OILR3 results to a fall in US GDP growth of about 0.2% (20 basis points) 3 quarters after the initial oil uncertainty shock, with the effect remaining negative and statistically significant for 5 quarters after the initial shock. In order to compare the dynamic effect of oil return uncertainty with the observable oil price and stock-market volatility, we estimate the OIRFs of GDP growth to a positive OILRV and SP500RV shock. The estimated GDP growth response to observable oil price volatility shock is negative but quite smaller in magnitude and persistence compared to the respective response to oil return uncertainty shocks. More specifically, a positive one standard deviation shock in OILRV decreases real GDP growth about 0.06% (6 basis points) points after 3 quarters, with the effect being statistically insignificant. Hence, the estimated impact of oil return uncertainty on GDP growth (20 basis points) is more than 3 times larger when compared with the respective impact of observable oil price volatility (OILRV). On the other hand, the response of GDP growth to stock-market volatility is negative for the first two quarters after the stock-market shock and turns to positive after the third quarter with the estimated responses being insignificant. The shape of the estimated OIRFs of GDP to stock-market volatility is in line with the findings and the respective VAR analysis of Bloom (2009).

3.4.2 US investment responses

In this section we provide the results of our 6-factor VAR model with US domestic investment as the first endogenous variable described in Equation (21). Hence, we estimate the dynamic responses in the form of OIRFs of US investment growth to oil return uncertainty shocks. **Figure 3** depicts the estimated OIRFs of quarterly US investment growth to oil price uncertainty, oil volatility and stock-market volatility shocks.

[Insert Figure 3 Here]

The estimated OIRFs given in **Figure 3** show that the responses of US investment to oil return uncertainty shocks are persistently negative and statistically significant. More specifically, the estimated response to either an OILR1, OILR2 or OILR3 shock remains negative and statistically significant for 5 quarters after the initial shock. Interestingly, according to our VAR analysis, a positive shock in OILR3 reduces US investment growth by almost 1.4% four quarters after the initial shock. The estimated responses of US investment to OILRV are much smaller (about 0.3-0.35% which is one fifth of the estimated OIRF to oil return uncertainty) when compared to the estimated responses of the oil return uncertainty shocks. In addition, the responses to OILRV shock are not statistically significant. The respective responses to stock-market volatility (SP500RV) are negative for the first two quarters and then turn to positive three quarters after the initial stock-market volatility shock. The estimated response of US investment to our oil return uncertainty measure is much larger when compared to the respective estimated response of US investment to the oil uncertainty shock as defined in Guo and Kliesen (2005) and Ferderer (1996). Hence, our empirical analysis shows that the impact of oil uncertainty shocks to US investment is more significant when defined as the unpredictable component of oil price fluctuations and less significant when modeled as the realized volatility of oil prices. On the other hand, our findings are broadly in line with the findings of Elder and Serletis (2010) and Jo (2014) who find that the oil price uncertainty shock (measured as the forecast error of GARCH-in-mean process for oil prices has a negative impact on economic activity. Our findings also provide further robustness to theory of investment under uncertainty (Bernanke, 1983; Pindyck, 1991, 1993; Triantis and Hodder, 1990), according to which the rising uncertainty leads to postponement of investment (firms exercise their option to wait to invest when faced with uncertainty about future costs and revenues-oil price uncertainty affects the revenue and the cost side of many oil-related industries).

3.4.3 The impact of oil return uncertainty on US Trade flows

In this section we present the dynamic responses of the trade flows (US export growth and US import growth) to oil shocks, as estimated by the VAR models given in Equations (22) and (23)**. Figure 4** depicts the respective OIRFs of the quarterly US export growth.

[Insert Figure 4 Here]

The estimated OIRFs show an instantaneous response of US exports to oil return uncertainty shocks. For example, the estimated responses of US export growth to OILR3 shock are negative and statistically significant from the first till the firth quarter after the oil shock and they reach a maximum of 1.2% three quarters after the initial shock. The response of 1.2% of US exports shows the tremendous impact of oil return uncertainty on US trade, which is many times larger than the respective impact of exchange rates and monetary policy as shown in previous studies (Batten and Belongia, 1986; Kim, 2001)[24]. Unlike the oil return uncertainty shocks, the rise in oil price volatility (OILRV) and stock-market volatility has a much smaller and insignificant impact on US export growth. For example, while a shock in OILR3 reduces US export growth by 1.2%, the respective OILRV shock reduces exports by 0.2%, with the effect being statistically insignificant.

[24] We additionally estimate an 8-factor VAR model in which we control for US effective exchange rate and monetary policy (Fed fund rate), and we find that the estimated negative responses of US exports and US imports are more than 3 times larger (in absolute value) to exchange rates depreciation and to expansionary monetary policy shocks. These additional results can be provided upon request.

Figure 5 presents the estimated OIRFs of US imports to oil return uncertainty (OILR1, OILR2, OILR3), oil volatility (OILRV) and stock-market volatility (SP500RV) respectively.

[Insert Figure 5 Here]

The estimated OIRFs shown in **Figure 5** indicate that US imports fall rapidly when oil return uncertainty rises. The estimated responses of US imports to oil return uncertainty are negative and statistically significant for five quarters after the uncertainty shock. The rising oil return uncertainty is associated with a drop in both US exports and imports subsequently observed. According to our VAR estimates and just like US exports, the US import growth reduces by more than 1.5% three quarters after the oil return uncertainty shock. Hence, our VAR analysis clearly identifies the negative impact of oil return uncertainty to US international trade. On the contrary, the OILRV and the SP500RV have a much smaller and insignificant impact on US imports. Our findings are line and provide further empirical insights to the findings of Bodenstein *et al*. (2011) and Kilian *et al*. (2009) who find that oil price shocks have a significant dampening effect on trade balances and with the findings of Backus and Krucini (2000) who find that oil shocks affect significantly the terms of trade of the G7 economies. We contribute to this literature by finding that uncertainty about oil prices has a negative impact on both US export and import growth, with the effect on imports being larger (more negative) and more persistent compared with the response of exports.

4. Robustness

In our on-line Appendix we provide various robustness checks for our OLS and VAR models presented in the paper. More specifically, we perform the same VAR analysis using alternative proxies for economic activity like US unemployment rate and Industrial Production and show that our main findings remain unaltered. In order to examine the impact of oil return uncertainty on global economic activity, we perform the same econometric analysis on the global real activity measure of Kilian and Kilian and Murphy (2014). Our analysis shows that the rising oil price activity significantly dampens global real activity as well. Moreover, motivated by the empirical approach of relevant studies (Elder and Serletis, 2010; Jo, 2014) we additionally perform the same VAR analysis using OILP1, OILP2, OILP3 and OILP4 as our proxies for oil uncertainty (These proxies are estimated as the squared forecast errors of the regressions on the log-oil price levels instead) and we show that our main findings remain unaltered. The VAR estimations are robust to alternative VAR orderings and to the inclusion of different macroeconomic variables as proxies for economic activity.

We additionally run some probit forecasting regression models on NBER recessions and find that our main conclusions remain unaltered since rising oil uncertainty positively affects the probability of an economic recession. In order to examine the role of oil return uncertainty on the production side of the US macroeconomy, we run the same set of multivariate forecasting regression models on the monthly growth of US Industrial Production Index. Our results are broadly in line with the findings of Rahman and Serletis (2011), Elder (2018) and Bredin *et al.* (2011) who find that the observable oil price volatility has a significant negative effect on US and of G7 countries Industrial Production. We also estimate an 8-factor VAR model in which we control for monetary policy, and we show that our oil return uncertainty factor has a significant recessionary impact even when controlling for monetary policy shocks, while the respective recessionary impact of oil price shocks is much less under this VAR indentation scheme. Moreover, our 8-factor VAR analysis shows that while rising oil prices are inflationary, the rising oil return uncertainty is deflationary. Lastly, when performing a subsample analysis (for the pre and the post 2004 period), we find that the recessionary impact of oil return uncertainty is significantly reduced in the pre-2004 period (where the more predictable aggregate supply driven oil price shocks are more frequent) while it is significantly increased in the post-2004 period (where the less predictable oil demand shocks are more frequent). These findings are in line with the findings of Jiang *et al*. (2018) and Leduc and Liu (2016) according to which the uncertainty shocks are essentially demand-driven shocks. These findings strengthen our main conclusion according to which the rising uncertainty in the oil market is the most significant driver and indicator of macroeconomic downturns.

5. Conclusions

In this paper we empirically examine the macroeconomic impact of oil price uncertainty by initially redefining the uncertainty shock as the *purely* unanticipated oil price change. *Ex-ante*, we posit that observable (and potentially anticipated) changes in oil prices do not significantly affect real output, whilst the unanticipated counterparts are still of macroeconomic significance. Employing a battery of empirical tests and robustness checks, our analysis is the first to show that the unobservable oil uncertainty shocks are the most significant oil-related determinants of real output and its components.

There are a number of interesting and related findings within the paper. For example, our analysis shows that oil return uncertainty shocks result in a reduction in both US imports and exports. Additionally, our oil uncertainty factor produces improved forecasts regarding real output drops and US recessions when compared with the respective predictive power of popular uncertainty proxies in the extant literature such as stock-market volatility and Economic Policy Uncertainty (EPU). Finally note that the recessionary impact of oil return uncertainty has increased substantially in the recent post-2004 period when the oil prices (and oil price shocks) are driven primarily by the less predictable aggregate demand (for) oil shocks.

Why is uncertainty so important? At least in part, unforecastable variations in prices generate additional uncertainty regarding the future path of prices and volatility in the crude oil market, and as a corollary, make the real option to postpone production and investment in oil-related projects more expensive for economic agents. One could argue that, since our measure of oil return uncertainty is not observable and cannot be estimated *ex-ante* (i.e., prior the forecast being made), then, while it can act as a non-standard indicator of economic downturns, it cannot be used for policy making since it is a difficult target to track. Whilst this might be true, we posit that what matters most for economic agents is their degree of anticipation of oil price fluctuations, and not the oil price fluctuations *per se*. The hidden policy implication behind our findings is that policymakers should turn their attention to reducing uncertainty in the oil market, and not just aim to maintain oil prices and volatility at relatively low levels.

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Table 1: Descriptive statistics for the quarterly time series dataset

Panel A: Oil related variables

	OILR1	OILR2	OILR3	OILR4	OILRV	OILRET	OILTOTJUMP	OILSIGNJUMP	OILPOSVAR	OILNEGVAR
Mean	0.003	0.004	0.004	0.004	0.009	0.004	0.001	0.000	0.004	0.004
Median	0.001	0.001	0.001	0.001	0.003	0.011	0.000	0.000	0.001	0.001
Maximum	0.048	0.061	0.077	0.084	0.093	0.172	0.010	0.003	0.046	0.047
Minimum	0.000	0.000	0.000	0.000	0.000	-0.306	0.000	-0.003	0.000	0.000
Std. Dev.	0.006	0.007	0.009	0.009	0.014	0.065	0.002	0.001	0.007	0.007
Skewness	4.232	5.323	5.650	5.855	3.132	-1.041	2.893	-0.009	3.121	3.176
Kurtosis	26.105	38.752	43.372	57.129	16.010	6.887	13.241	15.060	15.765	16.348

Panel B: Macroeconomic and stock-market variables

	INFL	EXCH	GEOP	EPU	UNEMP	TERM	SP500RV	FFR	GDP	INVEST
Mean	0.003	0.006	4.245	4.634	0.060	0.018	0.006	0.035	0.006	0.011
Median	0.003	0.007	4.129	4.607	0.056	0.019	0.003	0.035	0.007	0.011
Maximum	0.007	0.102	6.140	5.375	0.101	0.036	0.086	0.097	0.018	0.082
Minimum	-0.010	-0.038	3.361	4.145	0.039	-0.006	0.001	0.001	-0.022	-0.136
Std. Dev.	0.002	0.024	0.501	0.262	0.015	0.011	0.009	0.028	0.006	0.031
Skewness	-1.830	0.507	0.832	0.368	1.027	-0.234	6.779	0.232	-1.159	-1.129
Kurtosis	12.386	3.798	3.835	2.581	3.325	1.995	60.196	1.910	6.666	7.069

Note: In this table we report the descriptive statistics of our explanatory variables. The US unemployment rate (UNEMP) and the Fed fund rate (FFR) are expressed in levels. The Economic Policy Uncertainty (EPU) and the Geopolitical Uncertainty (GEOP) index are used in logarithms. The TERM variable is the difference between 10-year and 3-month US Treasury yields. All the other macroeconomic variables are expressed in log-differences (quarterly growth rates). The descriptive statistics of the factors which we use as predictors of the oil price for the estimation of oil price uncertainty (as shown in Equations (7) and (8)), can be found in our on-line Appendix.

Table 2. Correlation matrix

	OILR1	OILR2	OILR3	OILR4	OILRV	OILRET	INFL	EXCH	GEOP	EPU	UNEMP	TERM	SP500RV	FFR	GDP	INVEST
OILR1	1.00															
OILR2	0.09	1.00														
OILR3	0.24	0.25	1.00													
OILR4	0.02	0.36	0.18	1.00												
OILRV	0.25	0.07	0.01	0.06	1.00											
OILRET	-0.21	0.12	0.02	0.10	-0.33	1.00										
INFL	-0.01	0.18	0.15	0.12	-0.42	0.66	1.00									
EXCH	0.12	0.00	-0.08	-0.11	0.18	-0.55	-0.36	1.00								
GEOP	0.21	0.05	0.01	0.05	0.24	-0.01	-0.09	-0.24	1.00							
EPU	0.11	-0.09	0.04	0.00	0.39	-0.17	-0.15	-0.05	0.20	1.00						
UNEMP	-0.07	-0.12	-0.13	-0.08	0.19	-0.03	-0.15	-0.10	-0.04	0.71	1.00					
TERM	-0.03	-0.08	-0.09	-0.08	0.13	-0.05	-0.19	-0.08	0.21	0.48	0.67	1.00				
SP500RV	0.17	-0.02	0.07	0.02	0.38	-0.42	-0.54	0.28	0.05	0.34	0.09	0.10	1.00			
FFR	-0.05	0.02	0.04	-0.01	-0.51	0.09	0.46	0.12	-0.36	-0.45	-0.54	-0.60	-0.18	1.00		
GDP	-0.30	0.01	-0.17	-0.08	-0.41	0.26	0.21	-0.13	-0.23	-0.43	-0.18	-0.04	-0.52	0.19	1.00	
INVESTMENT	-0.25	-0.06	-0.12	-0.19	-0.29	0.20	0.16	0.01	-0.16	-0.21	0.04	0.10	-0.40	-0.02	0.75	1.00

Table 3: Bivariate explanatory OLS regression models on US real GDP and its components using oil return uncertainty (OILR)

Panel A

$$\ln(GDP_t / GDP_{t-1}) = b_0 + b_1 OILR(K)_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% Adj.* R^2
1q	0.007***	12.208	-0.341**	-2.534	12.2
2q	0.007***	11.793	-0.322***	-3.148	14.2
3q	0.007***	12.717	-0.328***	-4.985	22.5
4q	0.007***	12.329	-0.329***	-7.108	24.2

Panel B

$$\ln(INVEST_t / INVEST_{t-1}) = b_0 + b_1 OILR(K)_{t-k} + \varepsilon_t$$

k	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% Adj.* R^2
1	0.015***	5.492	-1.316**	-2.516	6.4
2	0.016***	5.294	-1.294***	-4.529	8.2
3	0.017***	6.050	-1.561***	-5.021	18.8
4	0.016***	5.108	-1.352***	-5.270	15.2

Panel C

$$\ln(IMP_t / IMP_{t-1}) = b_0 + b_1 OILR(K)_{t-k} + \varepsilon_t$$

k	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% Adj.* R^2
1	0.023***	7.212	-2.338***	-3.698	19.4
2	0.022***	7.175	-2.152***	-3.259	20.6
3	0.023***	7.905	-2.291***	-4.860	35.8
4	0.022***	7.351	-2.037***	-8.533	29.4

Panel D

$$\ln(EXP_t / EXP_{t-1}) = b_0 + b_1 OILR(K)_{t-k} + \varepsilon_t$$

k	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% Adj.* R^2
1	0.022***	6.863	-1.911***	-4.119	17.3
2	0.022***	6.825	-1.728***	-3.304	18.6
3	0.022***	7.222	-1.744***	-4.870	29.1
4	0.021***	6.894	-1.607***	-9.259	26.0

The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. OILR(K) corresponds to the squared oil return uncertainty residual having k-month forecasting horizon. Panels A, B, C and D correspond to the explanatory regressions on GDP growth, Investment growth, Import growth and Export growth respectively. For explaining the time variation of our US macroeconomic variables k-months ahead, we use the k-month ahead oil uncertainty factor respectively.

Table 4. Forecasting OLS regression models on US real GDP and its components using oil return uncertainty (OILR)

Panel A

$$\ln(GDP_t / GDP_{t-1}) = b_0 + b_1 OILR(K)_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% Adj.* R^2
1q	0.007***	11.131	-0.227**	-2.414	5.0
2q	0.007***	11.268	-0.258***	-4.404	8.8
3q	0.007***	10.574	-0.215***	-4.966	9.5
4q	0.007***	9.899	-0.195***	-5.189	8.0

Panel B

$$\ln(INVEST_t / INVEST_{t-1}) = b_0 + b_1 OILR(K)_{t-k-1} + \varepsilon_t$$

k	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% Adj.* R^2
1	0.018***	5.948	-2.035***	-3.435	16.4
2	0.018***	6.383	-2.087***	-5.868	22.6
3	0.017***	5.763	-1.780***	-5.996	25.7
4	0.017***	5.635	-1.528***	-5.252	20.1

Panel C

$$\ln(IMP_t / IMP_{t-1}) = b_0 + b_1 OILR(K)_{t-k-1} + \varepsilon_t$$

k	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% Adj.* R^2
1	0.021***	6.018	-2.089**	-2.210	14.9
2	0.022***	5.962	-2.178**	-2.362	21.2
3	0.021***	6.501	-1.828***	-3.131	22.5
4	0.021***	6.563	-1.775***	-3.781	22.1

Panel B

$$\ln(EXP_t / EXP_{t-1}) = b_0 + b_1 OILR(K)_{t-k-1} + \varepsilon_t$$

k	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% Adj.* R^2
1	0.020***	5.572	-1.363**	-2.046	8.5
2	0.021***	5.984	-1.453**	-2.405	13.0
3	0.019***	5.874	-1.137***	-2.673	12.0
4	0.019***	5.851	-1.084***	-2.986	11.7

The t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. OILR(K) corresponds to the squared oil return uncertainty residual having k-month forecasting horizon. Panels A, B, C and D correspond to the explanatory regressions on GDP growth, Investment growth, Import growth and Export growth respectively. For the forecasting of the US macroeconomic variables k-months ahead, we use the k-1 month ahead oil uncertainty factor respectively.

Table 5. Explanatory regressions on US real GDP growth (GDP) when controlling for oil and stock-market volatility and jumps.

The general form of the models is the following (eq. 11-16):

$$\ln(GDP_t/GDP_{t-1}) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln(GDP_{t-1}/GDP_{t-2}) + \sum_{i=4}^{n} b_i FACTOR_{i,t-1} + e_t$$

$$FACTOR \in \{OILPOSVAR, OILNEGVAR, SP500POSVAR, SP500NEGVAR, OILTOTJUMP, SP500TOTJUMP, OILSIGNJUMP, SP500SIGNJUMP, OILRV, SP500RV, OILR1\}$$

		(1)	(2)	(3)	(4)	(5)	(6)
Const	Coef.	0.004***	0.009***	0.006***	0.005***	0.009***	0.009***
	t-stat	(3.174)	(5.544)	(5.041)	(5.997)	(5.459)	(5.804)
INFL	Coef.	-0.327	-0.871*	-0.397	-0.420	-0.915**	-0.827**
	t-stat	(-1.072)	(-1.901)	(-1.328)	(-1.222)	(-1.926)	(-2.353)
FFR	Coef.	0.021	0.015	0.009	0.020	0.017	0.020
	t-stat	(1.246)	(0.660)	(0.566)	(1.099)	(0.775)	(0.963)
GDP	Coef.	0.381**	0.183**	0.309**	0.321***	0.168**	0.121
	t-stat	(2.555)	(2.317)	(2.347)	(3.090)	(2.144)	(1.550)
OILRV	Coef.					-0.088**	-0.065*
	t-stat					(-2.040)	(-1.705)
SP500RV	Coef.					-0.238***	-0.229***
	t-stat					(-2.834)	(-2.996)
OILPOSVAR	Coef.		0.743				
	t-stat		(1.160)				
SP500POSVAR	Coef.		-1.512				
	t-stat		(-1.180)				
OILNEGVAR	Coef.		-0.930				
	t-stat		(-1.364)				
SP500NEGVAR	Coef.		1.048				
	t-stat		(0.830)				
OILTOTJUMP	Coef.			-0.647*			
	t-stat			(-1.752)			
SP500TOTJUMP	Coef.			-0.874			
	t-stat			(-0.968)			
OILSIGNJUMP	Coef.				1.474		
	t-stat				(1.516)		
SP500SIGNJUMP	Coef.				0.888		
	t-stat				(0.517)		
OILR1	Coef.						**-0.212** **
	t-stat						**(-2.317)**
% adj. R^2		13.4	21.8	15.2	14.9	22.1	26.0

The t-statistics reported in the relevant columns are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. The OILR1 variable corresponds to the squared oil return uncertainty residual having 1-quarter forecasting horizon.

Table 6. Explanatory OLS regression models on GDP growth (GDP) when controlling for additional macroeconomic determinants of US economic activity.

$$\ln(GDP_t/GDP_{t-1}) = a + b_1\ln(GDP_{t-k}/GDP_{t-k-1}) + b_2INFL_{t-k} + b_3FFR_{t-k} + b_4UNEMP_{t-k} + b_5OILRV_{t-k} + b_6SP500RV_{t-k} + b_7OILR(K)_{t-k} + b_8OILRET_{t-k} + +b_9TERM_{t-k} + b_{10}EXCH_{t-k} + b_{11}EPU_{t-k} + b_{12}GEOP_{t-k} + e_t$$

Horizon (k)		k=1	k=2	k=3	k=4
Const	Coef.	0.026*	0.011	0.015	0.017
	t-stat	(1.976)	(0.842)	(1.141)	(1.330)
GDP	Coef.	0.087	0.270***	-0.038	0.083
	t-stat	(0.912)	(2.821)	(-0.307)	(0.664)
INFL	Coef.	-0.401	-0.637	-0.440	-0.238
	t-stat	(-0.826)	(-1.365)	(-0.836)	(-0.780)
FFR	Coef.	0.019	0.042	0.010	0.013
	t-stat	(0.494)	(1.436)	(0.415)	(0.546)
UNEMP	Coef.	0.023	0.050	-0.038	-0.027
	t-stat	(0.425)	(1.047)	(-0.638)	(-0.431)
OILRV	Coef.	-0.048	-0.030	-0.096**	-0.052
	t-stat	(-1.144)	(-0.961)	(-2.161)	(-1.530)
SP500RV	Coef.	-0.202**	-0.051	-0.087	0.069
	t-stat	(-2.171)	(-0.989)	(-1.080)	(0.923)
OILR(K)	Coef.	-0.250***	-0.299***	-0.298***	-0.304***
	t-stat	(-2.711)	(-3.610)	(-4.982)	(-7.050)
OILRET	Coef.	-0.013	0.009	-0.007	-0.005
	t-stat	(-0.996)	(0.747)	(-0.518)	(-0.548)
TERM	Coef.	0.071	0.057	0.114	0.147**
	t-stat	(1.191)	(0.987)	(1.438)	(2.341)
EXCH	Coef.	0.006	0.015	0.004	-0.016
	t-stat	(0.322)	(0.716)	(0.190)	(-0.639)
EPU	Coef.	-0.005	-0.003	-0.001	-0.002
	t-stat	(-1.645)	(-1.580)	(-0.333)	(-0.733)
GEOP	Coef.	0.001	0.002	0.000	-0.000
	t-stat	(0.453)	(1.275)	(0.088)	(-0.364)
% adj. R^2		25.6	24.6	25.0	26.4

The reported t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. OILR(K) corresponds to the squared oil return uncertainty residual having k-month forecasting horizon. For explaining the time variation of US GDP growth k-months ahead, we use the k-month ahead oil uncertainty factor (OILRK) respectively.

Table 7. Forecasting OLS regression models on US real GDP growth (GDP) while controlling for macroeconomic fundamentals.

$$\ln(GDP_t/GDP_{t-1}) = a + b_1\ln(GDP_{t-k}/GDP_{t-k-1}) + b_2INFL_{t-k} + b_3FFR_{t-k} + b_4UNEMP_{t-k} + b_5OILRV_{t-k} + b_6SP500RV_{t-k} + b_7OILR(K)_{t-k-1} + b_8OILRET_{t-k} + +b_9TERM_{t-k} + b_{10}EXCH_{t-k} + b_{11}EPU_{t-k} + b_{12}GEOP_{t-k} + e_t$$

Horizon (k)		k=1	k=2	k=3	k=4
Const.	Coef.	0.024*	0.008	0.016	0.018
	t-stat	(1.729)	(0.502)	(1.173)	(1.438)
GDP	Coef.	0.131	0.231**	0.049	0.032
	t-stat	(1.274)	(2.212)	(0.438)	(0.287)
INFL	Coef.	-0.815	-0.709	-0.541	-0.291
	t-stat	(-1.044)	(-1.364)	(-1.188)	(-0.852)
FFR	Coef.	0.035	0.048	0.026	0.012
	t-stat	(0.795)	(1.499)	(0.758)	(0.513)
UNEMP	Coef.	0.032	0.052	0.025	-0.037
	t-stat	(0.613)	(0.852)	(0.384)	(-0.606)
OILRV	Coef.	-0.051	-0.036	-0.067	-0.069*
	t-stat	(-1.174)	(-0.845)	(-1.276)	(-1.701)
SP500RV	Coef.	-0.206*	-0.061	-0.052	0.064
	t-stat	(-1.972)	(-1.034)	(-0.583)	(0.722)
OILR(K)	Coef.	-0.077	-0.165**	-0.180***	-0.183***
	t-stat	(-0.855)	(-2.338)	(-2.904)	(-4.796)
OILRET	Coef.	-0.003	0.003	-0.000	-0.007
	t-stat	(-0.186)	(0.252)	(-0.013)	(-0.707)
TERM	Coef.	0.077	0.064	0.114	0.177**
	t-stat	(1.328)	(1.047)	(1.591)	(2.521)
EXCH	Coef.	0.007	0.011	0.024	-0.012
	t-stat	(0.338)	(0.514)	(0.876)	(-0.393)
EPU	Coef.	-0.004	-0.003	-0.004	-0.002
	t-stat	(-1.488)	(-1.286)	(-1.071)	(-0.696)
GEOP	Coef.	0.000	0.002	0.001	-0.001
	t-stat	(0.346)	(1.038)	(0.886)	(-0.644)
% adj. R^2		19.9	15.1	13.2	11.5

The reported t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. The OILR(K) corresponds to the squared oil return uncertainty residual having k-month forecasting horizon.

Table 8. Explanatory regressions on US Investment growth (INVEST) when controlling for oil and stock-market volatility and jumps.

The general form of the models is the following (similar to eq. 11-16):

$$\ln(INVEST_t/INVEST_{t-1}) = a + b_1 INFL_{t-1} + b_2 FFR_{t-1} + b_3 \ln(INVEST_{t-1}/INVEST_{t-2}) + \sum_{i=4}^{n} b_i FACTOR_{i,t-1} + e_t$$

$$FACTOR \in \{OILPOSVAR, OILNEGVAR, SP500POSVAR, SP500NEGVAR, OILTOTJUMP, SP500TOTJUMP, OILSIGNJUMP, SP500SIGNJUMP, OILRV, SP500RV, OILR1\}$$

		(1)	(2)	(3)	(4)	(5)	(6)
Const	Coef.	0.005	0.034***	0.019**	0.010***	0.034**	0.034***
	t-stat	(0.822)	(4.962)	(3.048)	(2.623)	(4.932)	(5.399)
INFL	Coef.	3.222	-0.722	2.815	2.300	-0.654	-0.288
	t-stat	(1.591)	(-0.388)	(1.500)	(1.356)	(-0.355)	(-0.190)
FFR	Coef.	-0.205**	-0.261***	-0.306***	-0.231***	-0.267***	-0.265***
	t-stat	(-2.277)	(-2.840)	(-3.432)	(-2.774)	(-2.855)	(-3.094)
INVEST	Coef.	0.293**	0.089	0.216*	0.224**	0.090	0.067
	t-stat	(1.991)	(1.018)	(1.678)	(2.011)	(1.066)	(0.828)
OILRV	Coef.					-0.453**	-0.371**
	t-stat					(-2.377)	(-2.023)
SP500RV	Coef.					-1.659***	-1.602***
	t-stat					(-4.447)	(-4.842)
OILPOSVAR	Coef.		-2.605				
	t-stat		(-0.934)				
SP500POSVAR	Coef.		-3.404				
	t-stat		(-0.343)				
OILNEGVAR	Coef.		1.672				
	t-stat		(0.587)				
SP500NEGVAR	Coef.		-0.126				
	t-stat		(-0.013)				
OILTOTJUMP	Coef.			-4.182**			
	t-stat			(-1.994)			
SP500TOTJUMP	Coef.			-5.066			
	t-stat			(-0.663)			
OILSIGNJUMP	Coef.				3.737		
	t-stat				(0.725)		
SP500SIGNJUMP	Coef.				15.669		
	t-stat				(1.279)		
OILR1	Coef.						**-0.715***
	t-stat						**(-1.723)**
% adj. R^2		13.6	29.9	17.1	16.1	30.9	32.3

The t-statistics reported in the relevant columns are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. The OILR1 corresponds to the squared oil return uncertainty residual having 1 quarter forecasting horizon.

Table 9. Explanatory OLS regression models on US Investment growth (INVEST) when controlling for macroeconomic fundamentals.

$$\ln(INVEST_t/INVEST_{t-1}) = a + b_1\ln(INVEST_{t-k}/INVEST_{t-k-1}) + b_2INFL_{t-k} + b_3FFR_{t-k} \\ +b_4UNEMP_{t-k} + b_5OILRV_{t-k} + b_6SP500RV_{t-k} + b_7OILR(K)_{t-k} + b_8OILRET_{t-k} + +b_9TERM_{t-k} \\ + b_{10}EXCH_{t-k} + b_{11}EPU_{t-k} + b_{12}GEOP_{t-k} + e_t$$

Horizon (k)		k=1	k=2	k=3	k=4
Const	Coef.	0.152***	0.012	-0.029	0.044
	t-stat	(2.712)	(0.216)	(-0.435)	(0.875)
INVEST	Coef.	0.016	0.069	-0.048	-0.085
	t-stat	(0.183)	(0.809)	(-0.551)	(-0.978)
INFL	Coef.	2.808	-5.579	-4.167	-2.905
	t-stat	(1.492)	(-1.446)	(-1.250)	(-1.175)
FFR	Coef.	-0.336**	0.146	0.075	0.079
	t-stat	(-2.321)	(0.767)	(0.437)	(0.422)
UNEMP	Coef.	0.420	0.421	0.255	0.519
	t-stat	(1.537)	(1.577)	(0.937)	(1.159)
OILRV	Coef.	-0.294	-0.178	-0.227	-0.167
	t-stat	(-1.466)	(-1.020)	(-1.035)	(-0.750)
SP500RV	Coef.	-1.461***	-1.358***	-0.820*	0.290
	t-stat	(-3.688)	(-3.235)	(-1.975)	(0.999)
OILR(K)	Coef.	-0.848*	-0.962***	-1.264***	-1.242***
	t-stat	(-1.693)	(-3.185)	(-5.050)	(-5.652)
OILRET	Coef.	-0.091*	0.086	0.014	0.038
	t-stat	(-1.802)	(1.063)	(0.299)	(0.630)
TERM	Coef.	0.187	0.312	0.375	0.505*
	t-stat	(0.727)	(1.126)	(1.237)	(1.685)
EXCH	Coef.	0.078	-0.147	-0.036	-0.019
	t-stat	(0.748)	(-1.242)	(-0.319)	(-0.142)
EPU	Coef.	-0.031*	-0.002	0.007	-0.014
	t-stat	(-1.969)	(-0.194)	(0.513)	(-0.951)
GEOP	Coef.	-0.003	0.000	0.002	0.000
	t-stat	(-0.415)	(0.100)	(0.281)	(0.064)
% adj. R^2		35.2	27.2	23.2	23.8

The reported t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. OILR(K) corresponds to the squared oil return uncertainty residual having k-month forecasting horizon. For explaining the time variation of US Investment growth k-months ahead, we use the k-month ahead oil uncertainty factor (OILRK) respectively.

Table 10. Forecasting OLS regression models on US Investment growth (INVEST) while controlling for macroeconomic fundamentals.

$$\ln(INVEST_t/INVEST_{t-1}) = a + b_1\ln(INVEST_{t-k}/INVEST_{t-k-1}) + b_2INFL_{t-k} + b_3FFR_{t-k}$$
$$+b_4UNEMP_{t-k} + b_5OILRV_{t-k} + b_6SP500RV_{t-k} + b_7OILR(K)_{t-k-1} + b_8OILRET_{t-k} + +b_9TERM_{t-k}$$
$$+ b_{10}EXCH_{t-k} + b_{11}EPU_{t-k} + b_{12}GEOP_{t-k} + e_t$$

Horizon (k)		k=1	k=2	k=3	k=4
Const	Coef.	0.142**	0.009	0.011	0.047
	t-stat	(2.586)	(0.148)	(0.204)	(0.875)
INVEST	Coef.	0.046	0.082	-0.043	-0.082
	t-stat	(0.457)	(0.971)	(-0.503)	(-1.090)
INFL	Coef.	1.011	-3.677	-3.270	-1.574
	t-stat	(0.381)	(-1.494)	(-1.136)	(-0.860)
FFR	Coef.	-0.238	0.127	0.098	-0.016
	t-stat	(-1.562)	(0.886)	(0.564)	(-0.123)
UNEMP	Coef.	0.456*	0.458	0.469	0.366
	t-stat	(1.769)	(1.622)	(1.655)	(1.084)
OILRV	Coef.	-0.243	-0.065	-0.065	-0.239
	t-stat	(-1.110)	(-0.304)	(-0.351)	(-1.021)
SP500RV	Coef.	-1.411***	-1.109***	-0.489	0.579**
	t-stat	(-2.857)	(-4.046)	(-1.443)	(2.121)
OILR(K)	Coef.	-0.546	-1.494***	-1.580***	-1.557***
	t-stat	(-1.133)	(-5.452)	(-6.131)	(-7.574)
OILRET	Coef.	-0.050	0.025	0.039	0.008
	t-stat	(-0.904)	(0.411)	(0.730)	(0.138)
TERM	Coef.	0.228	0.269	0.445	0.593**
	t-stat	(0.939)	(0.952)	(1.525)	(2.035)
EXCH	Coef.	0.085	-0.130	0.066	-0.031
	t-stat	(0.784)	(-1.126)	(0.521)	(-0.221)
EPU	Coef.	-0.029*	-0.005	-0.010	-0.011
	t-stat	(-1.937)	(-0.391)	(-0.957)	(-0.798)
GEOP	Coef.	-0.002	0.002	0.006	-0.002
	t-stat	(-0.417)	(0.452)	(0.988)	(-0.312)
% adj. R^2		33.2	32.4	30.2	30.7

The reported t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. OILR(K) corresponds to the squared oil return uncertainty residual having k-month forecasting horizon.

Table 11. Explanatory OLS regressions on US Import growth (IMP) while controlling for macroeconomic fundamentals.

$$\ln(IMP_t/IMP_{t-1}) = a + b_1\ln(IMP_{t-k}/IMP_{t-k-1}) + b_2INFL_{t-k} + b_3FFR_{t-k} + b_4UNEMP_{t-k} + b_5OILRV_{t-k} + b_6SP500RV_{t-k} + b_7OILR(K)_{t-k} + b_8OILRET_{t-k} + +b_9TERM_{t-k} + b_{10}EXCH_{t-k} + b_{11}EPU_{t-k} + b_{12}GEOP_{t-k} + e_t$$

Horizon (k)		k=1	k=2	k=3	k=4
Const	Coef.	0.042	0.116*	0.055	0.089
	t-stat	(0.824)	(1.818)	(0.891)	(1.250)
IMP	Coef.	0.257	0.001	-0.085	-0.303**
	t-stat	(1.382)	(0.007)	(-0.844)	(-2.051)
INFL	Coef.	-5.941***	-7.170	-3.285	-1.442
	t-stat	(-3.036)	(-1.419)	(-1.628)	(-0.444)
FFR	Coef.	0.273*	0.406	0.245	0.143
	t-stat	(1.916)	(1.505)	(1.560)	(0.920)
UNEMP	Coef.	0.196	0.638*	0.545	0.454
	t-stat	(0.696)	(1.801)	(1.367)	(0.935)
OIL RV	Coef.	0.049	-0.001	-0.237	-0.152
	t-stat	(0.237)	(-0.004)	(-1.123)	(-0.837)
SP500 RV	Coef.	-1.617***	-0.775	0.419	0.227
	t-stat	(-2.995)	(-1.243)	(1.409)	(0.603)
OILR(K)	Coef.	-1.191**	-1.813***	-2.054***	-2.008***
	t-stat	(-2.518)	(-2.957)	(-4.786)	(-9.923)
OILRET	Coef.	0.141**	0.064	0.020	0.064
	t-stat	(2.228)	(0.596)	(0.414)	(1.282)
TERM	Coef.	0.385	0.350	0.159	0.384
	t-stat	(1.640)	(1.139)	(0.405)	(1.329)
EXCH	Coef.	-0.184	-0.255*	-0.090	-0.043
	t-stat	(-1.246)	(-1.720)	(-0.743)	(-0.303)
EPU	Coef.	-0.006	-0.033**	-0.026	-0.030
	t-stat	(-0.470)	(-2.002)	(-1.528)	(-1.165)
GEOP	Coef.	0.000	0.006	0.013*	0.010
	t-stat	(0.035)	(0.967)	(1.684)	(1.323)
% adj. R^2		55.0	32.3	39.6	34.2

The reported t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. OILR(K) corresponds to the squared oil return uncertainty residual having k-month forecasting horizon. For explaining the time variation of US Imports growth k-months ahead, we use the k-month ahead oil uncertainty factor (OILRK) respectively.

Table 12. Forecasting OLS regression models on US Imports growth (IMP) while controlling for macroeconomic fundamentals.

$$\ln(IMP_t/IMP_{t-1}) = a + b_1\ln(IMP_{t-k}/IMP_{t-k-1}) + b_2INFL_{t-k} + b_3FFR_{t-k} + b_4UNEMP_{t-k} + b_5OILRV_{t-k} + b_6SP500RV_{t-k} + b_7OILR(K)_{t-k-1} + b_8OILRET_{t-k} + +b_9TERM_{t-k} + b_{10}EXCH_{t-k} + b_{11}EPU_{t-k} + b_{12}GEOP_{t-k} + e_t$$

Horizon (k)		k=1	k=2	k=3	k=4
Const	Coef.	0.035	0.094	0.122**	0.066
	t-stat	(0.619)	(1.284)	(2.224)	(1.062)
IMP	Coef.	0.283*	0.024	-0.181	-0.187
	t-stat	(1.802)	(0.143)	(-1.289)	(-1.485)
INFL	Coef.	-8.017**	-6.123*	-2.597	-1.437
	t-stat	(-2.222)	(-1.808)	(-1.237)	(-0.372)
FFR	Coef.	0.335	0.417*	0.305**	0.101
	t-stat	(1.609)	(1.802)	(2.006)	(0.512)
UNEMP	Coef.	0.202	0.681*	0.926*	0.313
	t-stat	(0.746)	(1.725)	(1.936)	(0.803)
OILRV	Coef.	-0.011	0.066	-0.051	-0.232
	t-stat	(-0.047)	(0.239)	(-0.305)	(-1.110)
SP500RV	Coef.	-1.739***	-0.585	0.636	0.520
	t-stat	(-2.894)	(-1.324)	(1.623)	(1.158)
OILR(K)	Coef.	-0.162	-1.691**	-1.840***	-1.729***
	t-stat	(-0.410)	(-2.305)	(-3.571)	(-4.008)
OILRET	Coef.	0.185**	-0.004	0.074	0.028
	t-stat	(2.153)	(-0.062)	(1.622)	(0.401)
TERM	Coef.	0.427*	0.315	0.304	0.477
	t-stat	(1.848)	(0.938)	(0.925)	(1.603)
EXCH	Coef.	-0.191	-0.246**	0.038	-0.014
	t-stat	(-1.300)	(-2.227)	(0.257)	(-0.085)
EPU	Coef.	-0.003	-0.032*	-0.053**	-0.022
	t-stat	(-0.222)	(-1.884)	(-2.451)	(-1.101)
GEOP	Coef.	-0.002	0.008	0.019**	0.008
	t-stat	(-0.349)	(0.963)	(2.474)	(1.269)
% adj. R^2		50.6	28.4	33.7	25.6

The reported t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. OILR(K) corresponds to the squared oil return uncertainty residual having k-month forecasting horizon.

Table 13. Explanatory OLS regression models on US Export growth while controlling for macroeconomic fundamentals.

$$\ln(EXP_t/EXP_{t-1}) = a + b_1 \ln(EXP_{t-k}/EXP_{t-k-1}) + b_2 INFL_{t-k} + b_3 FFR_{t-k} + b_4 UNEMP_{t-k} + b_5 OILRV_{t-k} + b_6 SP500RV_{t-k} + b_7 OILR(K)_{t-k} + b_8 OILRET_{t-k} + +b_9 TERM_{t-k} + b_{10} EXCH_{t-k} + b_{11} EPU_{t-k} + b_{12} GEOP_{t-k} + e_t$$

Horizon (k)		k=1	k=2	k=3	k=4
Const	Coef.	-0.017	0.032	-0.016	0.077
	t-stat	(-0.405)	(0.557)	(-0.253)	(1.095)
EXP	Coef.	0.257	0.090	-0.017	-0.114
	t-stat	(1.325)	(0.595)	(-0.117)	(-0.849)
INFL	Coef.	-3.447*	-4.916	-1.084	1.417
	t-stat	(-1.858)	(-1.322)	(-0.746)	(0.825)
FFR	Coef.	0.506***	0.620***	0.402**	0.241
	t-stat	(3.501)	(2.643)	(2.428)	(1.473)
UNEMP	Coef.	0.518**	0.920***	0.856**	0.816*
	t-stat	(2.055)	(2.808)	(2.079)	(1.809)
OILRV	Coef.	0.349**	0.300**	-0.055	0.144
	t-stat	(2.527)	(2.059)	(-0.331)	(1.099)
SP500RV	Coef.	-0.966**	-0.287	0.376	0.705**
	t-stat	(-2.608)	(-0.792)	(1.429)	(2.099)
OILR(K)	Coef.	-1.220***	-1.546***	-1.562***	-1.567***
	t-stat	(-3.263)	(-3.589)	(-4.888)	(-8.414)
OILRET	Coef.	0.063	0.063	-0.008	0.006
	t-stat	(1.243)	(0.875)	(-0.199)	(0.137)
TERM	Coef.	0.257	0.186	-0.016	0.132
	t-stat	(1.052)	(0.618)	(-0.044)	(0.387)
EXCH	Coef.	-0.252*	-0.199	-0.054	-0.070
	t-stat	(-1.765)	(-1.488)	(-0.553)	(-0.652)
EPU	Coef.	-0.009	-0.030*	-0.024	-0.037
	t-stat	(-0.768)	(-1.793)	(-1.248)	(-1.657)
GEOP	Coef.	0.008	0.014**	0.020***	0.011
	t-stat	(1.635)	(2.301)	(2.813)	(1.544)
% adj. R^2		50.1	34.0	36.6	28.8

The reported t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. OILR(K) corresponds to the squared oil return uncertainty residual having k-month forecasting horizon. For explaining the time variation of US Exports growth k-months ahead, we use the k-month ahead oil uncertainty factor (OILRK) respectively.

Table 14. Forecasting OLS regression models on US Exports growth while controlling for macroeconomic fundamentals.

$$\ln(EXP_t/EXP_{t-1}) = a + b_1\ln(EXP_{t-k}/EXP_{t-k-1}) + b_2INFL_{t-k} + b_3FFR_{t-k} + b_4UNEMP_{t-k} + b_5OILRV_{t-k} + b_6SP500RV_{t-k} + b_7OILR(K)_{t-k-1} + b_8OILRET_{t-k} + +b_9TERM_{t-k} + b_{10}EXCH_{t-k} + b_{11}EPU_{t-k} + b_{12}GEOP_{t-k} + e_t$$

Horizon (k)		k=1	k=2	k=3	k=4
Const	Coef.	-0.030	0.021	0.023	0.072
	t-stat	(-0.582)	(0.343)	(0.340)	(1.032)
EXP	Coef.	0.321*	0.044	-0.064	-0.107
	t-stat	(1.961)	(0.279)	(-0.425)	(-0.776)
INFL	Coef.	-5.787*	-4.218	-1.356	1.532
	t-stat	(-1.680)	(-1.504)	(-0.812)	(0.713)
FFR	Coef.	0.566***	0.643***	0.488***	0.218
	t-stat	(2.752)	(3.021)	(2.634)	(1.257)
UNEMP	Coef.	0.499**	0.979**	1.171**	0.758*
	t-stat	(2.052)	(2.525)	(2.516)	(1.782)
OILRV	Coef.	0.296*	0.325*	0.084	0.067
	t-stat	(1.900)	(1.842)	(0.548)	(0.458)
SP500RV	Coef.	-1.043**	-0.222	0.454	0.811**
	t-stat	(-2.494)	(-0.683)	(1.324)	(2.051)
OILR(K)	Coef.	-0.261	-1.195**	-1.118***	-1.088***
	t-stat	(-0.668)	(-2.479)	(-3.817)	(-3.205)
OILRET	Coef.	0.112*	0.017	0.030	-0.009
	t-stat	(1.677)	(0.297)	(0.692)	(-0.180)
TERM	Coef.	0.294	0.190	0.074	0.243
	t-stat	(1.190)	(0.589)	(0.208)	(0.677)
EXCH	Coef.	-0.235*	-0.218*	0.029	-0.051
	t-stat	(-1.758)	(-1.848)	(0.269)	(-0.407)
EPU	Coef.	-0.005	-0.030*	-0.042*	-0.035
	t-stat	(-0.330)	(-1.680)	(-1.872)	(-1.626)
GEOP	Coef.	0.007	0.015**	0.024***	0.010
	t-stat	(1.387)	(2.008)	(3.375)	(1.415)
% adj. R^2		43.8	26.4	25.2	14.0

The reported t-statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. *, ** and *** denotes statistical significance at the 10%, 5% and 1% level respectively. OILR(K) corresponds to the squared oil return uncertainty residual having k-month forecasting horizon.

Table 15. Granger causality tests for the baseline 6-factor VAR model on GDP growth

Panel A: Granger causality tests for US GDP growth

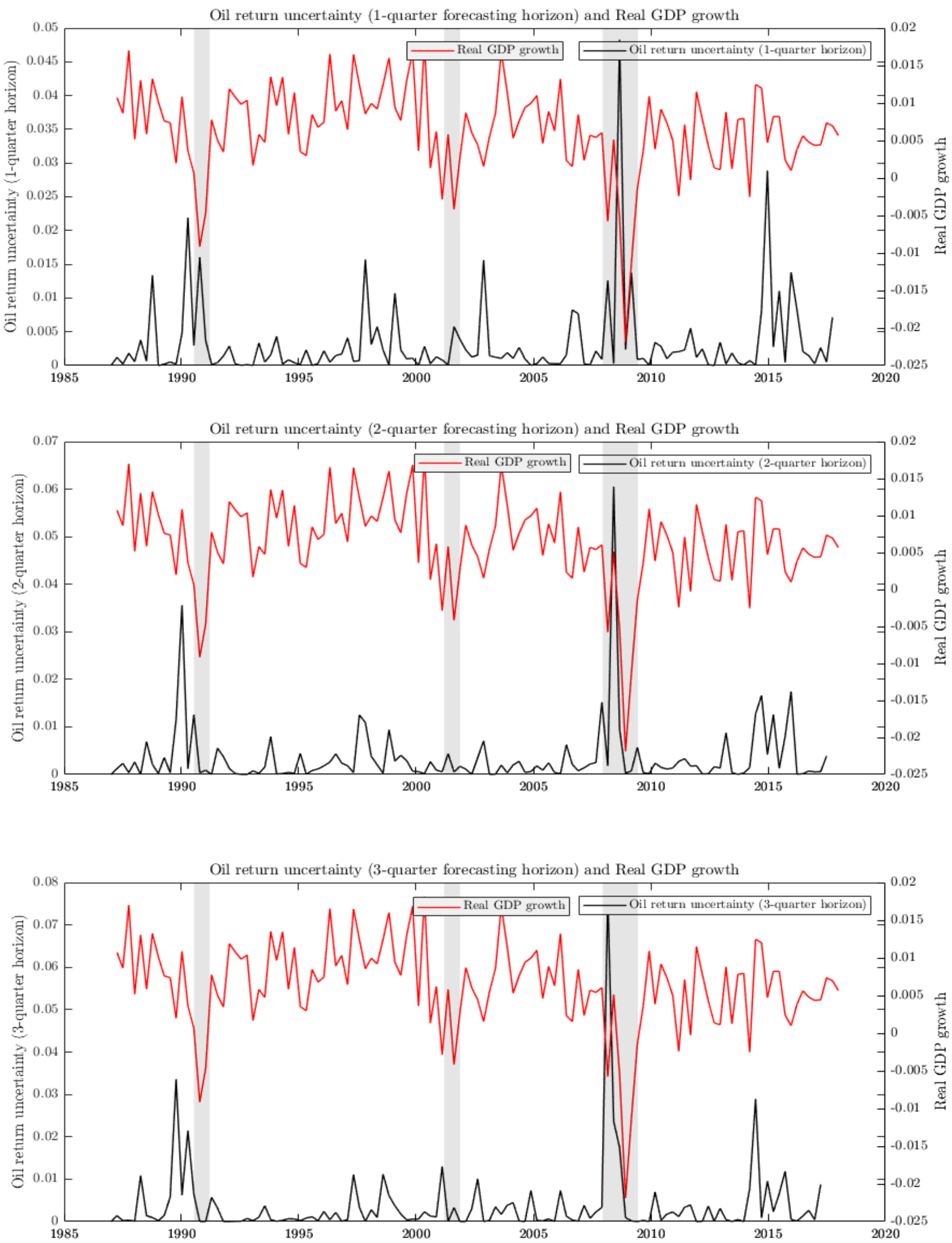
Dependent variable	Independent variable	Chi-square	p-value
GDP	GEOP	0.565	0.967
GDP	INFL	5.055	0.282
GDP	SP500RV	6.553	0.161
GDP	OILRV	3.867	0.424
GDP	OILR2	17.707***	0.001

Panel B: Granger causality tests for US Investment growth

Dependent variable	Independent variable	Chi-square	p-value
INVEST	GEOP	5.247	0.263
INVEST	INFL	2.345	0.672
INVEST	SP500RV	12.868**	0.012
INVEST	OILRV	2.868	0.580
INVEST	OILR2	18.812***	0.000

This table shows the results of the Granger causality tests between the six endogenous variables of our baseline VAR model (with 4 lags) on GDP growth given in Equation (20) using the OILR2 return uncertainty-the results of the Granger causality tests do not differentiate if we use OILR1, OILR3 or OILR4 as our measure of oil uncertainty. The null hypothesis is that the Independent variable does not Granger cause the Dependent variable. With * , ** and *** we reject the null hypothesis of no causality at the 10%, 5% and 1% confidence level respectively. Panel A shows the results of the Granger causality tests for the VAR model for GDP growth and Panel B shows the results of the Granger causality tests for the VAR model for Investment growth.

Figure 1. Oil return uncertainty and Real GDP growth



Note: The shaded areas represent US (NBER) economic recessions.

Figure 2. Orthogonalized Impulse Response Functions of quarterly US Real GDP growth (GDP) to oil return uncertainty and volatility shocks.

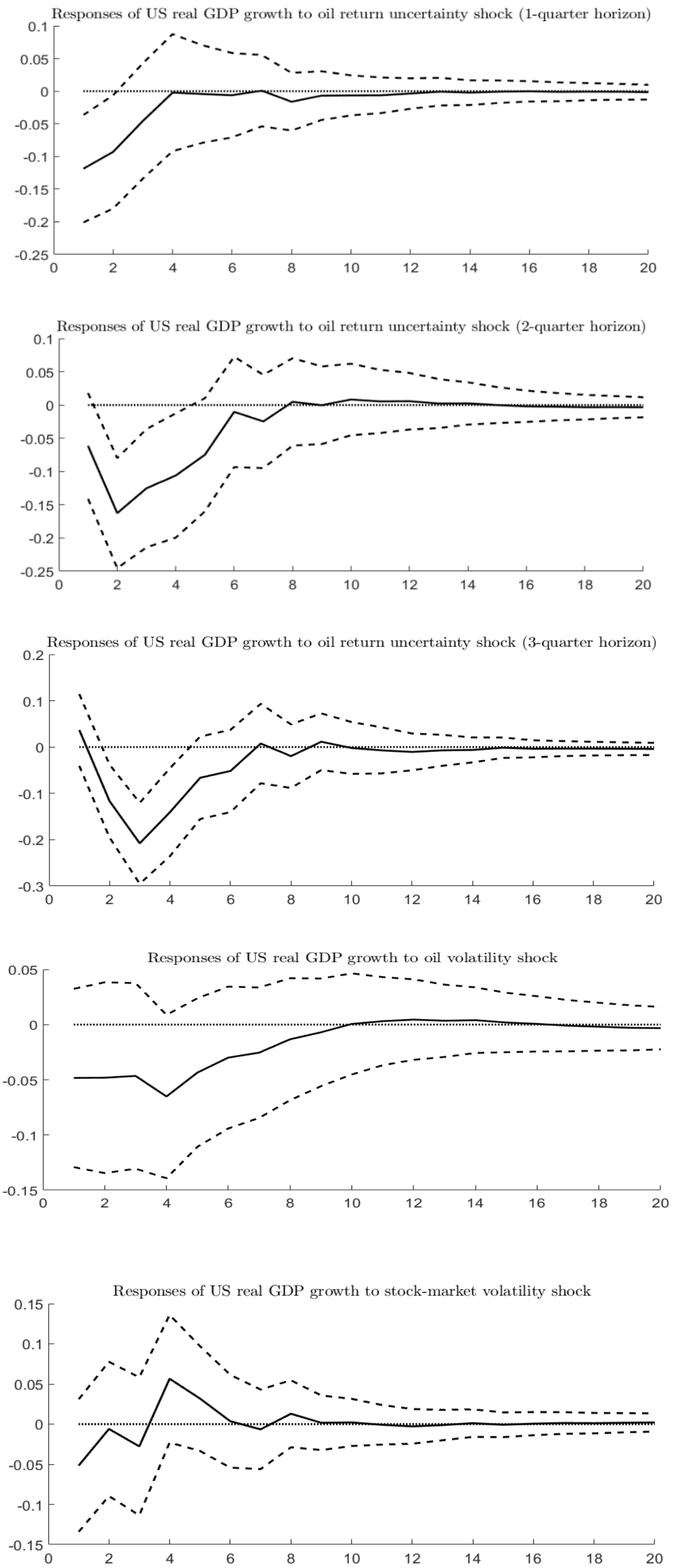


Figure 3. Orthogonalized Impulse Response Functions of quarterly US Investment growth to oil return uncertainty and volatility shocks.

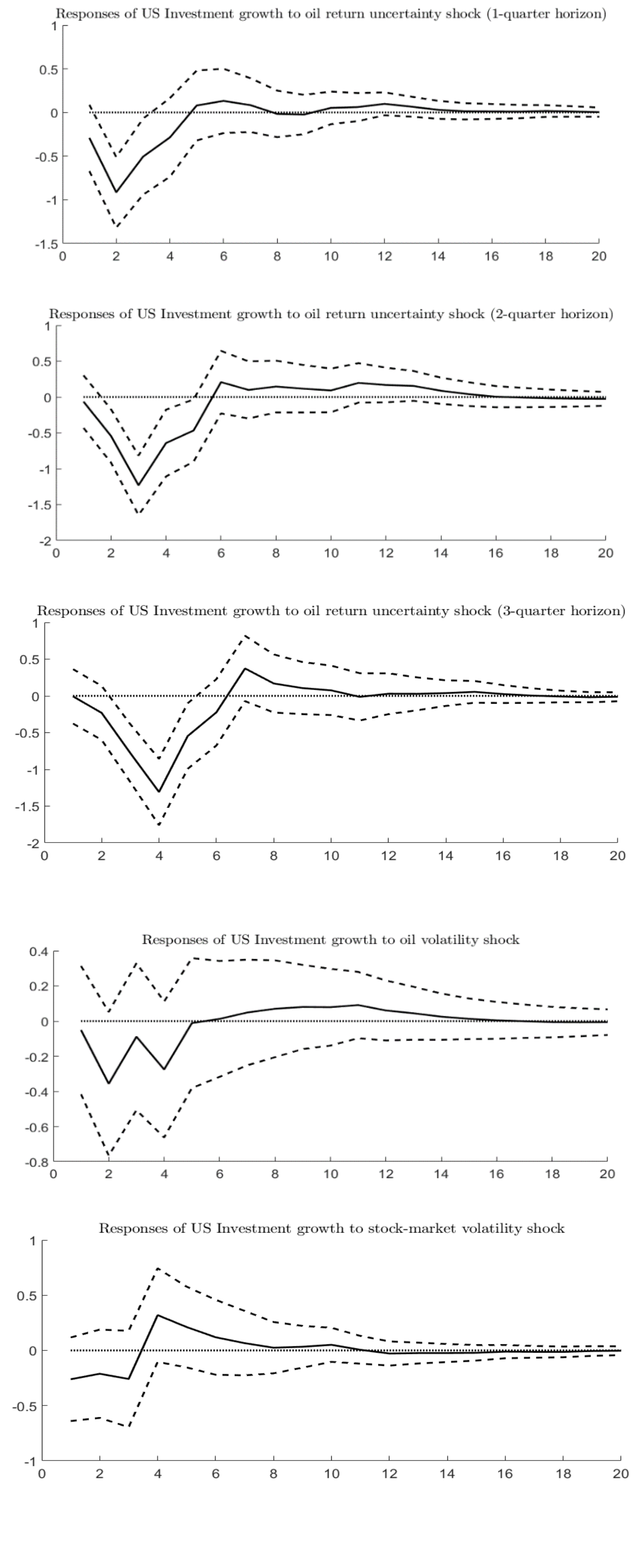


Figure 4. Response of quarterly US Exports growth (EXP) to oil return uncertainty and volatility shocks.

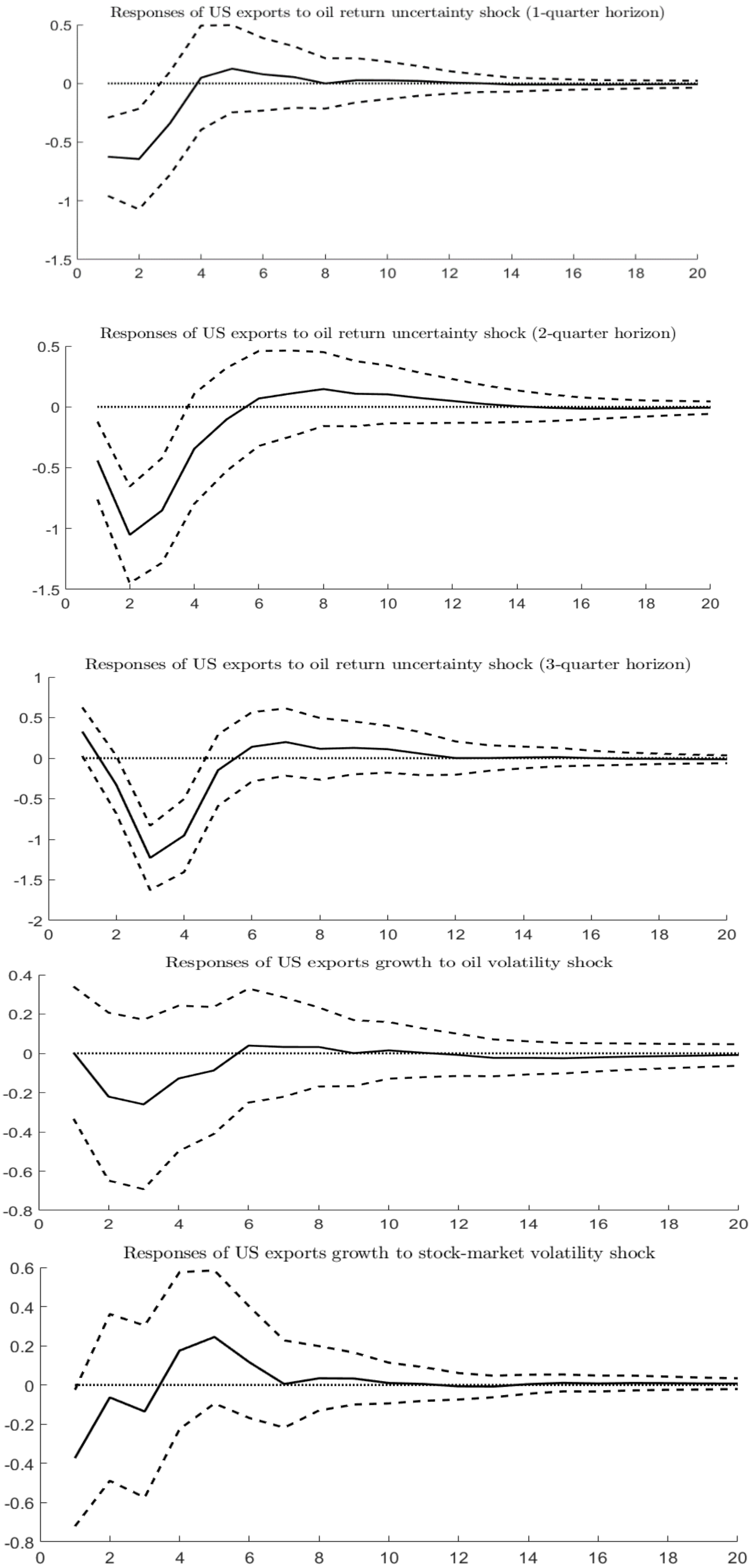


Figure 5. Response of quarterly US Imports growth (IMP) to oil return uncertainty and volatility shocks.