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Oil price uncertainty as a predictor of stock market volatility

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Abstract

In this paper we empirically examine the impact of oil price uncertainty shocks on US stock market volatility. We define the oil price uncertainty shock as the unanticipated component of oil price fluctuations. We find that our oil price uncertainty factor is the most significant predictor of stock market volatility when compared with various observable oil price and volatility measures commonly used in the literature. Moreover, we find that oil price uncertainty is a common volatility forecasting factor of S&P500 constituents, and it outperforms lagged stock market volatility and the VIX when forecasting volatility for medium and long-term forecasting horizons. Interestingly, when forecasting the volatility of S&P500 constituents, we find that the highest predictive power of oil price uncertainty is for the stocks which belong to the financial sector. Overall, our findings show that financial stability is significantly damaged when the degree of oil price unpredictability rises, while it is relatively immune to observable fluctuations in the oil market.

JEL Classification:

Keywords: Stock market, Oil, Uncertainty, Realized Variance, Volatility

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1. Introduction

Sudden changes in the oil market significantly affect the economy and the stock market. The consensus in the relevant literature is that positive oil price and volatility shocks have a negative impact on economic activity and the equity market (Basher and Sadorsky, 2006; Elder and Serletis, 2010; Feng *et al.*, 2017; Hamilton, 1983, 2003; Jo, 2014; Kilian, 2009; Kilian and Park, 2009; Sadorsky, 1999; Park and Ratti, 2008, amongst others). A large corpus of research has shown that oil price fluctuations are amongst the most significant determinants of the time varying volatility of stock market returns. For example, Arouri *et al.* (2011,2012) and Khalfaoui (2015) find significant volatility spillover effects from oil to European and US equity markets, whilst Maghyereh *et al*. (2016), when using equity implied volatility indices, identify significant volatility spillovers from oil to eleven major equity markets around the globe. In this vein, Du and He (2015) identify the existence of extreme risk (tail risk) spillovers between oil and stock markets whilst Feng *et al.* (2017) show that oil price volatility has significant predictive power for stock market volatility of the G7 economies, with the predictive power of oil price volatility remaining robust to the inclusion of macroeconomic factors. Moreover, Christoffersen and Pan (2018) show that after the 'financialization of commodities' which began perhaps in the early years of the first decade of the 21st Century, oil price volatility has become a significant predictor of stock market returns and volatility.

Other recent research such as Wang *et al.* (2018) find that oil market volatility is a robust predictor of stock return volatility for short-term forecasting horizons and helps to predict future volatility for stocks of many different sectors. Similarly, Aromi and Clements (2019) suggest that information flow about crude oil influences oil and stock market volatility and more specifically, the spillovers from oil to equity markets increase when oil information flow rises. When it comes to decomposing oil price shocks, Degiannakis *et al.* (2014) argue that oil price changes attributed to aggregate demand shocks reduce stock market volatility in European economies, whilst the supply shocks and the oil-specific demand shocks have a smaller and transitory effect. Analogously, Bastianin and Manera (2018) show that stock market volatility reacts strongly to oil price shocks which are demand driven (hence, more uncertain), whilst exhibiting a smaller and more sluggish reaction to the relatively more predictable aggregate supply driven changes. Finally, Clements *et al.* (2019) demonstrate that aggregate demand driven oil price shocks have a more significant impact on stock market returns compared to the oil shocks driven by aggregate supply – especially in the post-2007 Global Financial Crisis era.

In this paper, motivated by the findings of the relevant literature which indicate the existence of volatility spillovers from oil to the stock market, as well as the significant impact of the relatively more uncertain demand driven oil shocks, we empirically examine the impact and predictive power of oil price uncertainty on stock market volatility. However, in contrast to the majority of the extant literature, we focus on oil price uncertainty instead of observable oil price and volatility shocks. Such an approach can be justified by appealing to the seminal work of Schwert (1989), according to which uncertainty about future macroeconomic conditions is the primary source of time-variation in stock market volatility. Schwert (1989) employs a discounted cash flow model, which views the stock price as the sum of the discounted expected cash flows of the stock to its stockholders:

$$P_t = E_t \sum_{i=1}^{\infty} \frac{CF_{t+i}}{(1+r_{t+i})^i} \tag{1}$$

In equation (1) above, the CF_{t+i} is the expected cash flow of the stock (i.e., the expected dividends plus the capital gains) and r_{t+i} is the future expected discount rate at period $t+i$ based on information at time t. From Equation (1), the volatility of the stock price P_t, $Var\ (P_t)$, depends on the volatility (or dispersion) of expectations about future cash flows and discount rates. Hence, if the dispersion of expectations about discount rates and expected cash flows is constant over time, then, according to Equation (1), stock price volatility will also be constant through time. Time variation in stock market volatility, is therefore linked to the time varying degree of uncertainty regarding future discount factors and expected cash flows. Since both interest rates and expected cash flows depend on the state (health) of the economy, then, according to Schwert (1989), "it is plausible that a change in the level of uncertainty about future macroeconomic conditions would cause a proportional change in stock return volatility." According to this approach, if some macroeconomic series could provide information regarding the dispersion of expectations (or uncertainty) about future cash flows or discount rates, then these series could be determinants of the time variation in stock market volatility.

The main hypothesis tested in this paper is that rising oil price uncertainty results in growing uncertainty about discount factors (through increasing uncertainty about real interest rates and expected inflation[1]) and future cash flows,[2] and consequently, predicts rising volatility in the stock market. In order to measure oil price uncertainty, we follow the approach of Jurado *et al*. (2015) according to which market uncertainty differs from volatility, specifically capturing the time varying degree of unpredictable variations in the oil market. Hence, we measure oil price uncertainty as the component that represents unpredictable (by economic agents) oil price fluctuations. In particular, we define oil price uncertainty as the squared forecast error of a multivariate forecasting regression model (using the maximum available oil-related information on the right-hand side of the regression) for oil price returns.

In order to examine the impact of oil price uncertainty shocks to the stock market while controlling for other significant oil shocks (see Kilian and Park, 2009), we estimate a structural VAR (SVAR) model in which we decompose oil shocks into supply shocks, aggregate demand shocks, oil-specific demand, oil price volatility and oil price uncertainty shocks. We then estimate the dynamic response of stock market volatility to each of these structural oil shocks and find that the oil price uncertainty shock has the highest and most significant impact on stock market volatility, whilst the observable oil price (oil demand) and oil price volatility shocks have a transitory and statistically insignificant impact on stock market volatility. Our SVAR analysis shows that a one standard deviation structural shock on the uncertainty about oil prices for the next k monthly periods has a positive impact on stock market volatility with the effect reaching its maximum (i.e., a nearly 10 basis points increase) exactly k months after the initial oil price uncertainty shock. These results show that when there is high uncertainty regarding the future path of oil prices in the next k months, this results in rising stock-return volatility k months after

[1] Fisher (1930), Fama (1975) and Mohandy and Nandha (2011) amongst others show that discount rates are (at least partially) composed of expected inflation and real interest rates. Since oil prices are positively correlated with inflation expectations (Gordon and Rowenhorst, 2006, amongst others) and they impact the term structure of interest rates (Ioannidis and Ka, 2018) and since the monetary authority includes oil prices in its policy rule when setting the short-term interest rate (Kara, 2017), then rising oil price uncertainty results in increasing uncertainty in future discount rates which are composed of inflation expectations and real interest rates.

[2] Oil price changes affect the future cash flows of firms either positively or negatively, depending on whether the firm is an oil-consumer or oil-producer. For example, for an oil-consuming firm, rising oil prices result in rising production costs, thus, to lower profits and decreasing future cash flows (Bohi, 1981; Mork *et al*., 1984; Filis *et al.*, 2011, amongst others). Consequently, the rising uncertainty about the future path of oil prices will result in growing uncertainty about future cash flows at the firm level.

the initial oil uncertainty shock. In other words, when oil price uncertainty over the short, medium or long-term horizon rises, this foreshadows an increase in future stock-return volatility in the short, medium or long-term respectively. Notably, the dynamic impact of oil price uncertainty on stock market volatility is higher for medium and long-term forecasting horizons compared to short-term (1-month) forecasting horizon.

In addition, we perform a forecasting exercise using our oil price uncertainty factor to forecast stock market volatility. More specifically, we empirically examine whether our oil price uncertainty factor has extra predictive power when compared to traditional oil-related, macroeconomic and equity-specific predictors of time-varying volatility in the stock market, such as oil price volatility, lagged stock market volatility, the VIX index and Economic Policy Uncertainty. We find that our oil price uncertainty measure is a robust predictor of stock market volatility for forecasting horizons ranging from 3 up to 12 months. Moreover, our multivariate forecasting regression models indicate that the inclusion of oil price uncertainty significantly improves the forecasting performance of models and contains significant predictive information which is not included in lagged stock market volatility or the VIX index, especially for medium and long-term forecasting horizons. Strikingly, when forecasting the volatility of S&P500 index returns, we find that our oil price uncertainty factor outperforms the VIX and lagged realized SP500 volatility for forecasting horizons ranging between 6 and 12 months. Such results are broadly in line with Engle *et al*. (2013) who suggest that the inclusion of macroeconomic fundamentals significantly increases the predictability of stock market volatility for long-term forecasting horizons. We also find that the predictive power of our oil uncertainty factor has significantly increased in the post-financialization (post-2004) era. Our results extend the findings of Christoffersen and Pan (2018) who show that the predictive power of oil price volatility on stock market returns and volatility has increased significantly in the post-financialization period.

Finally, we examine the forecasting power of our oil price uncertainty factor on the volatility of the returns of S&P500 constituents. Forecasting regression models show that oil price uncertainty is a common volatility forecasting factor for S&P500 constituents. Interestingly, oil price uncertainty has the highest predictive power when forecasting the volatility of the returns of stocks which belong to the financial sector, consumer services and consumer goods sector, whilst it performs less well when forecasting the volatility of stocks which belong to the oil and gas sector. These results imply that rising oil price uncertainty has a higher impact on firms that are oil-consumers relative to those that are oil-producers. Moreover, even at the industry level, our forecasting regression models show that our oil price uncertainty factor outperforms the VIX when forecasting the volatility of the S&P500 constituents for medium and long-term forecasting horizons (ranging between 6 to 12 months). The increased predictability of oil price uncertainty on the stock return volatility of the firms which belong to the financial and banking sector may stem from the notion that the oil market has become more of a financial market (i.e., via financialization) so the rising uncertainty about oil prices is an extra uncertainty factor for financial firms which treat oil and commodity futures as a separate asset class in their trading books.

2. Data

2.1 Oil data

We obtain WTI crude oil spot price data and oil futures basis data (calculated as the ratio of the 3-month crude oil future price to the price of the nearest to maturity oil futures contract) from Datastream. Monthly data for US crude oil inventories and global oil production is provided by the Monthly Energy Review of the Energy Information Administration (EIA) (Kilian and Murphy (2014) provide a more detailed description). We additionally obtain other relevant oil-related variables, which include open interest (the number of all open outstanding oil futures contracts), the volume of 3-month oil futures, the Working T Index, the speculation proxy of Buyuksahin and Robe (2014) (which captures the market share of non-commercial traders in the oil market) and the total number of short and long hedge positions in the oil futures market, from the Commodity Futures Trading Commission (CFTC).

2.2 Macroeconomic time series data

Our dataset spans the period from January 1987 till December 2017. Monthly time series for the US Consumer Price Index (CPI), US effective exchange rate, Industrial Production Index (IPI), 3-month maturity US-Treasury Bill rate (USTBIL) are downloaded from the FRED database.

We use the monthly growth rate of the US CPI index as the rate of US inflation (INFL). We also employ the global real economic activity index (*GACT*) which captures changes in the global use of industrial commodities[3] (see Kilian, 2009; Kilian and Murphy, 2014). In the analysis we control for the geopolitical risk index (*GEOP*) which measures the uncertainty related to geopolitical tensions (as reflected in leading international newspapers), suggested by Caldara and Iacoviello (2018).[4]

3. Methodology

3.1 Measuring uncertainty in the crude oil market

We use a measure of oil price uncertainty that does not rely on simple estimates of oil price volatility (using either some model[5] or a model-free approach), originally suggested in Triantafyllou *et al.* (2019). This measure is based on the approach of Jurado *et al*. (2015) and extracts the unanticipated component of oil price fluctuations as the squared error of a forecasting regression model which includes all the well-known determinants of crude oil returns on the right-hand side:

$$\varepsilon_{t+k}^{2} = E[(OILRET_{t+\kappa} - E(OILRET_{t+\kappa}/I_t)^2/I_t] \tag{1}$$

where ε_{t+k} represents the *k*-period ahead error term in the forecasting regression on monthly crude oil price returns (*OILRET*). The OILRET variable is the log difference of the monthly West Texas Intermediate (WTI) crude oil price. The baseline regression model for forecasting oil prices is given in Equation (2) below:

$$\begin{aligned} OILRET_{t+k} = {} & a + b_1 OILRET_t + b_2 INVENT_t + b_3 BASIS_t + b_4 OILPROD_t + b_5 SPECUL_t + b_6 WORKT_t \\ & + b_7 VOLUME_t + b_8 GEOP_t + b_9 USTBIL_t + b_{10} IPI_t + b_{11} SP500RV_t + b_{12} OILRV_t + b_{13} EXCH_t \\ & + b_{14} GACT_t + b_{15} INFL_t + \varepsilon_{t+\kappa} \end{aligned} \tag{2}$$

[3] The global real economic activity index is available at http://www-personal.umich.edu/~lkilian.
[4] The geopolitical risk index can be found at https://www2.bc.edu/matteo-iacoviello/gpr.htm.
[5] Chang and Serletis (2016), Elder and Serletis (2010) and Rahman and Serletis (2011) measure oil price uncertainty as the conditional volatility of daily returns of crude oil prices by using a GARCH-in-mean model, whereas Jo (2014) uses a stochastic volatility model.

In Equation (2) INVENT is the monthly growth rate of the global crude oil inventory level, BASIS is the 3-month basis of crude oil futures, OILPROD is the growth rate of the global level of crude oil production, SPECUL is the 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 growth in the Working-T-index, VOLUME is the growth rate of the trading volume of 3-month maturity crude oil futures, GEOP is the logarithm of the Geopolitical Uncertainty index of Caldara and Iacoviello (2018), USTBIL is the US-Treasury Bill rate with 3-month maturity, IPI is the growth rate of the US Industrial Production Index, SP500RV is the monthly realized variance of the intra-day (5-minute) returns of the S&P 500 stock market index, OILRV is the monthly realized variance of the intra-day (5-minute) returns of the nearby crude oil futures prices, EXCH is the monthly 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 US inflation rate (the monthly growth rate of US Consumer Price Index).

We name the estimated squared forecast errors (based on Equation (1)) of the forecasting regression model given in Equation (2) for k=1, 3, 6- and 12-months forecasting horizon, OILR1, OILR3, OILR6 and OILR12, respectively. Hence the OILR1, OILR3, OILR6 and OILR12 series contain the 1, 3, 6 and 12-month ahead oil price uncertainty.

3.2 Realized variance in oil and stock market

We estimate the realized volatility of oil prices using 5-minute prices for crude oil futures[6]. The 5-minute frequency provides the best compromise between the accuracy of our estimator and the introduction of noise due to microstructure effects, both of which increase as the frequency increases. We follow Andersen *et al.* (2001) and sum squared intraday logarithmic returns (filtered through an MA(1) process) to compute monthly crude oil realized variance (OILRV):

$$OILRV_t = \sum_{i=1}^{n} oilr_i^2 \tag{3}$$

[6] The high frequency data for crude oil futures were obtained from Tick Data. The high frequency data for the S&P index and its constituents were obtained from Pi Trading.

where $oilr_i = \log(oilp_i - oilp_{i-1})$, with $oilp$ denoting the filtered oil futures price series and i the number of intraday observations in each period. Similarly, we estimate the monthly realized variance of the S&P 500 index (SP500RV) as the sum of 5-minute S&P 500 squared returns.

3.3 The structural VAR model

Following the approach of Kilian (2009), Kilian and Park (2009) and Chen *et al*. (2016), we estimate an SVAR model in which we decompose oil shocks to aggregate demand shocks, oil-specific demand shocks (oil price shocks), oil supply shocks, oil price volatility shocks and oil price uncertainty shocks. In particular, we estimate an SVAR model with the following VAR ordering:

$$Z_t = [SP500RV_t \;\; INVENT_t \;\; GACT_t \;\; OILPRICE_t \;\; OILRV_t \;\; OILR(K)_t] \qquad (4)$$

The SVAR model representation is given in Equation (5) below:

$$A_0 Z_t = b + \sum_{i=1}^{h} A_i Z_{t-i} + \varepsilon_t \qquad (5)$$

In Equation (5) h is the lag-length of the SVAR model and it is chosen according to the Akaike optimal lag-length information criterion[7]. ε_t is the vector of orthogonal structural innovations. The matrix A_0 has a recursive structure for the reduced-form innovations e_t to be decomposed as $e_t = A_0^{-1}\, \varepsilon_t$ as shown below:

$$e_t = \begin{bmatrix} e_t^{SP500RV} \\ e_t^{INVENT} \\ e_t^{GACT} \\ e_t^{OILPRICE} \\ e_t^{OILRV} \\ e_t^{OILRET3} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{SP500\ volatility\ shock} \\ \varepsilon_t^{Oil\ Supply\ shock} \\ \varepsilon_t^{Aggr\ Demand\ shock} \\ \varepsilon_t^{Oil\ demand\ shock} \\ \varepsilon_t^{Oil\ volatility\ shock} \\ \varepsilon_t^{Oil\ uncertainty\ shock} \end{bmatrix} \qquad (6)$$

[7] In particular, the Akaike information criterion gives a VAR with 7, 9, 8, 15 and 5 lags when using OILRET1, OILRET3, OILRET6, OILRET9 and OILRET12 as the endogenous oil uncertainty variable respectively. Our SVAR results remain unaltered when using the Frechet or the Schwartz information criteria for choosing the optimal lag-length of our SVAR models.

We base our SVAR analysis on the dynamic responses (Structural-form Impulse Response Functions (SIRFs)) to the structural oil supply, demand, volatility and uncertainty shocks as shown in the underlying SVAR restrictions in (6). The underlying restrictions between these types of structural shocks are analytically described in Kilian and Park (2009), Kilian and Lee (2014) and Chen *et al*. (2016)[8].

3.4 Forecasting regression models

We estimate a univariate forecasting regression model on the monthly realized variance of S&P500 returns (SP500RV) using oil price uncertainty as the predictor of stock market variance as show in Equation (7) below:

$$SP500RV_t = a + b_2 OILRET(K)_{t-(k+1)} + \varepsilon_t \tag{7}$$

SP500RV is the monthly realized variance of 5-minute S&P500 equity index returns and OILRET(K) is the oil price uncertainty over the next *k*-monthly periods (OILRET1, OILRET3, OILRET6, OILRET9 and OILRET12 respectively). We use the OILRET(K) factor (the uncertainty over the next *k*-monthly periods) to forecast the volatility using *k*-month ahead forecasting horizon. In order to avoid look-ahead bias issues in our forecasting regression model (since the *k*-month ahead oil-price uncertainty refers to the uncertainty for the *k*-month ahead oil price series), we use *k*+1 lags in our forecasting regression model (shown in (7)) in order for the oil price uncertainty variable to be available to the predictive modeler at time *t* when the forecast about future stock-return variance is being made. In order to examine the extra-predictive power of oil price uncertainty on stock market volatility (when compared to well-known determinants of equity volatility), we estimate a multivariate OLS forecasting regression model in which we include the already empirically verified and well-known in the relevant literature determinants of stock market volatility like the lagged stock market volatility and the VIX index (Corsi, 2009; Christensen and Prabhala, 1998; Bekaert and Hoerova, 2014; among others), macroeconomic factors like industrial production and inflation (Engle *et al*., 2013; Hamilton and Lin, 1996;

[8] The main difference of our model with the Chen *et al.* (2016) SVAR model is that, we include, instead of political risk, the oil price uncertainty as endogenous variable in our SVAR model.

Schwert, 1989; Paye, 2012), Economic Policy Uncertainty (Liu and Zhang, 2015), corporate bond credit spreads (Cremers *et al*., 2008; Hibbert *et al*., 2011), oil prices and oil price volatility (Degiannakis *et al.,* 2014; Khalfaoui *et al.,* 2015; Wang *et al.,* 2018, amongst others). Our baseline forecasting regression model is given in Equation (8) below:

$$SP500RV_t = \\ a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + b_3 OILRV_{t-k} + b_4 OILRET(K)_{t-(k+1)} + b_5 OILRETURN_{t-k} + \\ b_6 EPU_{t-k} + b_7 BAA_{t-k} + b_8 IPI_{t-k} + +b_9 INFL_{t-k} + b_{10} TERM_{t-k} + \varepsilon_t \tag{8}$$

where $SP500RV_t$ is the monthly realized variance of S&P500 index returns, VIX is the monthly level of the VIX index, OILRV is the realized variance of nearby oil futures prices, OILRET(K) is our oil uncertainty factor, OILRETURN is the monthly growth rate of WTI crude oil spot prices, EPU is the logarithm of the Baker *et al.* (2016) US Economic Policy Uncertainty index, BAA is the Moody's Baa corporate bond spread, IPI is the monthly growth rate of US Industrial Production Index, INFL is the monthly US inflation rate (namely the percentage change of US Consumer Price Index (all items)) and TERM is the spread between the 10-year US government bond yield and the 3-month US Treasury Bill rate.

4. Empirical analysis

4.1 Descriptive statistics

We present some descriptive statistics of our time series sample. **Table 1** shows descriptive statistics of our time series sample.

[Insert Table 1 Here]

From **Table 1** we see that the oil price uncertainty series have nearly the same mean and volatility irrespectively of the uncertainty horizon. For example, OILRET1, OILRET3, OILRET6, OILRET9 and OILRET12 have nearly the same mean value (around 0.007). Moreover, we reject the hypothesis of a unit root (at 5% confidence level) for all our time series used in our information variable set[9]. **Figure 1** below shows the contemporaneous time series of

[9] The results of the ADF unit root tests can be available upon request.

SP500RV and oil price uncertainty for our period under investigation (January 1987 till December 2017).

[Insert Figure 1 Here]

Figure 1 shows that increases in oil price uncertainty are being followed by subsequent spikes in time varying stock market volatility (SP500RV). For example, our OILRET3 and OILRET6 oil uncertainty factor spikes at the start of 2008 (3 to 6 months before the 2008 US crisis and the subsequent stock market volatility episode). On the other hand, the OILRET1 seems not to be followed by increases in stock market volatility. Overall, this is some preliminary evidence showing that uncertainty about the medium and long-term path of oil prices is significant and is followed by increasing stock market volatility.

4.2 Responses of stock market volatility to structural oil shocks

In this section we present the econometric results of our SVAR model which is described in Equations (5) and (6). Firstly, we conduct a Granger causality test between the endogenous variables of the baseline SVAR model presented in Equations (4) to (6). **Table 2** below presents the results of our Granger causality test.

[Insert Table 2 Here]

The Granger causality test shows that, for our SVAR model, the only oil-related variable which causes stock market volatility (SP500RV) is the oil price uncertainty in the way we define it in this paper. On the other hand, the other oil-related variables included in the SVAR model like the oil price volatility and the oil demand and supply shocks do not (Granger) cause stock market volatility (we fail to reject the hypothesis of no causality for these variables). This is a first empirical evidence showing the absence of volatility spillovers from oil to equity markets. Hence, our results contrast those of Aromi and Clements (2019) and Wang *et al*. (2018) who find positive volatility spillovers from oil to equity markets. What we show instead, is that, what causes stock market volatility, is not the observable oil price volatility shock, but the latent oil price uncertainty shock which in a sense captures the unpredictability of oil price fluctuations. When examining the reverse channel of causality, according to the results shown in **Table 2**, the stock market volatility causes oil price volatility, oil prices (oil demand) and oil price uncertainty.

We additionally estimate the Structural-form Impulse Response Functions (SIRFs) of our SVAR model described in Equations (4) to (6). **Figure 2** below presents the estimated SIRFs of stock market volatility (SP500RV) to oil price uncertainty shocks.

[Insert Figure 2 Here]

The estimated SIRFs of Figure 2 show that a positive oil price uncertainty shock significantly increases stock market volatility. In particular, while the positive shock in OILRET1 has a rather transitory effect in stock market volatility, the OILRET3, OILRET6, OILRET9 and OILRET12 shocks have a statistically significant and long-lasting effect on stock market volatility. For example, a one-standard deviation structural OILRET3 shock increases stock market volatility (SP500RV) by almost 10 basis points 3 months after the initial shock, with the effect remaining positive and statistically significant for 4 months after the initial oil price uncertainty shock. Interestingly, when estimating the SVAR model using OILRET6, OILRET9 and OILRET12 as our proxy for oil price uncertainty, we find that the response of stock market volatility to OILRET6, OILRET9 and OILRET12 is again positive and significant and reaches its maximum impact k-months after the respective oil uncertainty shock over the next k-month ahead period. More specifically, an OILRET6 structural shock increases stock market volatility by almost 10 basis points 6 months after the OIRET6 shock, an OILRET9 structural shock increases stock market volatility by almost 10 basis points 9 months after the OIRET6 shock and OILRET12 structural shock increases stock market volatility by almost 10 basis points 12 months after the OIRET6 shock. Our findings, which show that the rising oil price uncertainty over the k-month period has the maximum effect on stock market volatility exactly k-months after the initial uncertainty shock, reveal for the first time the tremendous effect of oil price uncertainty shocks on the US stock market. The economic interpretation of our findings is that when oil price uncertainty rises over the next k-monthly period, this results to rising uncertainty about future economic activity and firm cash flows during the same period, and ultimately, to rising stock market volatility over the next k-months. For example, a positive shock in OILRET6 (which means rising uncertainty about oil prices on the next 6-month period), results to an almost 0.1% rise in stock market volatility 6-months after the oil uncertainty shock. On the other hand, our SVAR analysis shows that stock market volatility is not significantly affected by the other oil-related shocks extensively investigated in the literature. **Figure 3** below presents the SIRFs of SP500RV to aggregate demand (global economic activity), oil-specific demand (WTI crude oil price returns), oil supply (global oil inventories) and oil price volatility (OILRV) shocks.

[Insert Figure 3 Here]

The estimated SIRFs shown in **Figure 3** show the less significant (in terms of magnitude and persistence) response of stock market volatility to oil supply, demand and volatility shocks. For example, a one standard deviation structural shock in OILRV and oil-specific demand (oil price returns) increases SP500RV by nearly 2 basis points seven months after the oil price or volatility shock respectively, with the estimated responses being statistically insignificant. In conclusion, the estimated response of stock market volatility to oil price uncertainty shocks is more than five times larger in magnitude (10 basis points increase compared to 2 basis points increase) when compared to the estimated response of SP500RV to observable oil price and volatility shocks. What we show in our analysis, is not that oil price and volatility shocks (as the relevant literature suggests – see Clements *et al.*, 2019; Christoffersen and Pan, 2018; Degiannakis *et al.,* 2014; Du and He, 2015, among others) have become insignificant determinants of stock market volatility, but, we show instead that, when controlling for latent oil uncertainty shocks in our multivariate SVAR model, then the shock with the highest impact on stock market volatility is our latent oil price uncertainty shock. In simpler words, what we show is that the oil-related impact on the US stock market does not come from observable (and anticipated) oil price fluctuations, but from the rising uncertainty about oil prices instead.

4.3 Forecasting stock market volatility using oil price uncertainty

In this section we present the findings of our OLS forecasting regression models on US stock market volatility (SP500RV). First, we estimate bivariate regression models using the oil return uncertainty factor (OILRET(K)) as predictor of stock market volatility. **Table 3** below shows the regression results of our bivariate regression models when using only oil price uncertainty (OILRET1, OILRET3, OILRET6, OILRET9 or OILRET12), lagged realized variance (SP500RV) or the VIX index (VIX) as predictors of stock market volatility. The baseline univariate regression models are shown in Subsection 3.5 (Equation (7)).

[Insert Table 3 Here]

The results of **Table 3** provide further robustness to our SVAR results since we find that our oil price uncertainty factor provides significant forecasts for medium and long-term forecasting horizons. While all the estimated regression coefficients are positive, they are not all statistically significant. For example, the OILRET1 and OILRET3 factors which are used to forecast the one-month and three-month ahead stock market volatility are not significant predictors of SP500RV. On the other hand, the OILRET9 and OILRET12 (which are used for forecasting stock market volatility having 9-month and 12-month predictive horizon respectively), are statistically significant predictors of stock market volatility. Hence, according to our OLS forecasting regression model, the rising oil price uncertainty over the next 9 and 12-month period, predicts a respective increase in stock market volatility during the same period in the future. Our results are broadly in line with the findings of Engle *et al*. (2013), according to which the inclusion of macroeconomic fundamentals (like oil uncertainty in this paper) significantly improves the forecasts when predicting stock market volatility for long-term (more than 1 quarter) forecasting horizon. Interestingly, the regression results of **Table 3** show that, while the VIX and the lagged realized variance (lagged SP500RV) outperform our oil forecasting factor for short-term forecasting horizon, our oil price uncertainty factor outperforms the VIX and the lagged SP500RV when forecasting stock market volatility having 9- and 12-months forecasting horizon. More specifically, the adjusted R^2 value when forecasting 12-month ahead SP500RV using OILRET12 is 6.5% as opposed to 0.8% and 3.0% when using the lagged SP500RV or the VIX for the same long-term (12-month ahead) volatility predictions. Moreover, in order to examine the extra predictive power of oil uncertainty factor, we estimate a set of multivariate regressions in which we use jointly the VIX, the lagged SP500RV, the OILRV and our OILRET(K) factor in the right-hand side of the regression equation. These regression results are shown in **Table 4** below.

[Insert Table 4 Here]

The regression results of **Table 4** show that our oil price uncertainty factor contains additional information for forecasting stock market volatility, which is not subsumed by other forecasting variables, such as the VIX index and lagged SP500RV, especially for long-term forecasting horizons. For example, when forecasting SP500RV using the VIX and the lagged SP500RV as predictors and using 9 and 12 months forecasting horizon, we get adjusted R^2s of 5.1% and 3.7% respectively while when we include the oil price uncertainty (OILRET) factor in the right-hand side of the regression equation the R^2 value increases to 11.9% and to 9.6% when forecasting volatility over an 9-month and 12-month horizon respectively. Unlike the long-term forecasting power, the inclusion of the oil price uncertainty does not add significant predictive power when forecasting volatility for 1 up to 6 month forecasting horizon. On the other hand, the inclusion of oil price realized volatility (OILRV) as additional predictor in this multivariate regression setting does not improve the forecasting performance of the model which has the VIX and lagged SP500RV as predictors. Interestingly, we report positive coefficients for OILRV for short-term forecasting horizons and negative coefficients for medium and long-term forecasting horizon. This finding shows that there is not a clear positive (or negative) volatility spillover from oil to equity market as found in Maghyereh *et al*. (2016) and Wang *et al*. (2018). On the other hand, according to our findings, there is a clear positive impact of oil price uncertainty on stock market volatility.

We continue the regression analysis by including in the regression some other well identified (by the relevant literature) macroeconomic determinants of stock market volatility like Economic Policy Uncertainty (EPU) (Liu and Zhang, 2015; Tsai, 2017; among others), Baa corporate default spread, US inflation (INFL), Industrial Production Index growth (IPI) and the slope of the term structure of interest rates (TERM) (Beltratti and Morana 2006; Engle *et al*., 2013; Errunza and Hogan, 1998; Schwert, 1989; Paye, 2012; among others). The multivariate forecasting regression model is analytically described in Equation (8). The respective regression results of our multivariate OLS regression model are given in **Table 5** below.

[Insert Table 5 Here]

The results presented in **Table 5** show that the predictive power of oil price uncertainty remains robust to the inclusion of well-established macroeconomic factors in the information variable set. Interestingly, when forecasting volatility for long-term forecasting horizon, we find that, apart from the VIX index, the macroeconomic factors that provide significant predictive power is oil price uncertainty, industrial production and the term spread. Our findings are broadly in line with the findings of Engle *et al.* (2013), according to which macroeconomic factors are significant determinants of 'long-term' horizon equity return volatility.

4.4 Volatility forecasting before and after the financialization era

In order to examine whether 'financialization of commodity markets', which is described as the large inflow of funds and institutional investors on commodity markets and took place around 2004 (Basak and Pavlova, 2016; Tang and Xiong, 2012; among others), has affected the relationship between oil price uncertainty and stock market volatility, we perform a subsample analysis by splitting the sample into the pre-2004 (pre-financialization period) and post-2004 (post-financialization period). **Tables 6** to **8** below report the forecasting regression results of our baseline bivariate and multivariate models presented in Subsection 4.3 for the pre-financialization period covering January 1987 till December 2003.

[Insert Tables 6 to 8 Here]

From **Tables 6** to **8** we can easily observe that the predictive power of oil price uncertainty (OILRET(K)) on stock market volatility is much less in the pre-2004 period. Moreover, the oil price uncertainty does not enter significantly into our multivariate OLS regression settings, which means that it does not add significant predictive power when compared to the already empirically verified predictors of US stock market volatility. On the contrary, the predictive power of our oil uncertainty factor is significantly higher during the post-financialization era. **Tables 9 to 11** report the relevant results for the post-financialization (post-2004) period.

[Insert Tables 9 to 11 Here]

The regression results of the **Tables 9** to **11** show that the predictive power of oil price uncertainty is tremendously higher when performing the analysis for the post-2004 period. In particular, the OILRET(K) factor provides statistically significant forecasts and predicts a rise in stock market volatility for both short-term and long-term forecasting horizons. While oil price uncertainty does not outperform the VIX for short-term forecasting horizon, it outperforms the VIX and lagged SP500RV for 6, 9- and 12-month forecasting horizon. Overall, our results are the first to show the tighter linkages between oil price uncertainty and stock market volatility after the financialization era. Our results are broadly in line with the recent empirical findings of Christoffersen and Pan (2018) who show that the financialization of commodities has created tighter interconnections between oil price volatility and stock market volatility. Although we do not find some significant relationship between oil price volatility (OILRV) and stock market volatility, we indeed empirically verify that oil price uncertainty shocks have a larger impact on stock market volatility on the recent (post-financialization era).

4.5 Volatility forecasting of S&P500 constituents

In order to examine which sectors of the stock market are mostly affected by oil price uncertainty shocks, we perform the same regression analysis on the Realized Variance (RV) of each of the 500 constituents of the S&P500 equity index[10]. We then group the S&P500 constituents with respect to the sector to which they belong (according to ICB industry classification, which defines 10 categories: Utilities, Telecommunications, Technology, Oil and Gas, Industrials, Health Care, Financials, Consumer Services, Consumer Goods and Basic Materials[11].), and we report the average R^2 values of the bivariate regressions of oil price uncertainty on RV for each stock market sector. **Figure 4** below shows the average R^2 values of the univariate regressions on each stock market sector.

[Insert Figure 4 Here]

[10] We estimate the Realized Variance of S&P500 constituents in the same way we have estimated the SP500RV, as the sum of intra-day (5-minute) returns of individual stock-market prices, as shown in Subsection 3.2 of the paper.

[11] Data for ICB industry classification are obtained from Datastream

Interestingly, from **Figure 4** we observe that the oil price uncertainty factor has highest predictive power on the volatility of stocks which belong to the financial sector. This result is somewhat unexpected, but it is the first result that reveals a positive relationship between oil price uncertainty and the stock market volatility for financial firms. Hence, according to our analysis, it seems that the financial sector is the key driver of the positive and statistically significant relationship between oil price uncertainty and US stock market volatility. In a more detailed classification (see **Panel B** of **Figure 4**), we find that the firms which belong to the banking and to the real estate investment trust sector are more heavily affected by rising oil price uncertainty. These results are also the first to identify a positive relationship and a significant predictive power of oil price uncertainty on bank market risk. These results provide further empirical insights to the recent findings of Agarwal *et al*. (2019) according to which there is a significant relationship between commodity prices and bank lending. Moreover, Figures 5 and 6 show the respective results of the bivariate regressions on S&P500 constituents when using VIX and SP500RV as predictors of the RV of S&P500 constituents. These results provide robustness to our basic conclusion according to which the oil price uncertainty outperforms the VIX and lagged SP500RV for long-term forecasting horizons, since this is also true when forecasting the RV of each of the 500 S&P constituents.

5. Conclusions

In this paper we find that oil price uncertainty, defined as the unpredictable component of oil price fluctuations, has a positive impact on US stock market volatility. When performing a multivariate SVAR analysis in which we include all types of oil shocks (i.e., supply, demand and oil price volatility and uncertainty shocks), we find that the oil shock which has the largest and most long-lasting impact on US stock market volatility is the oil uncertainty shock. Moreover, our forecasting regression models show that, unlike oil prices and oil price volatility, our oil price uncertainty factor has robust predictive power for stock market volatility, especially for medium and long-term forecasting horizons. In particular, our forecasting regression models show that the oil price uncertainty factor outperforms the VIX and lagged stock market realized volatility when forecasting volatility for long term (more than 6-month) forecasting horizons. The forecasting power of oil price uncertainty remains robust to the inclusion of well-known and already empirically verified determinants of stock market volatility into the information variable set. When controlling for financialization in commodity markets, we find that the predictive power of the oil price uncertainty factor on stock market volatility has dramatically increased over the post-financialization (post-2004) era. Lastly, when performing a sectoral analysis on volatility forecasting of S&P500 constituents, we find that the oil price uncertainty factor has the highest predictive power for the market volatility of firms which belong to the financial and banking sector.

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Figure 1. Oil return uncertainty and stock market volatility

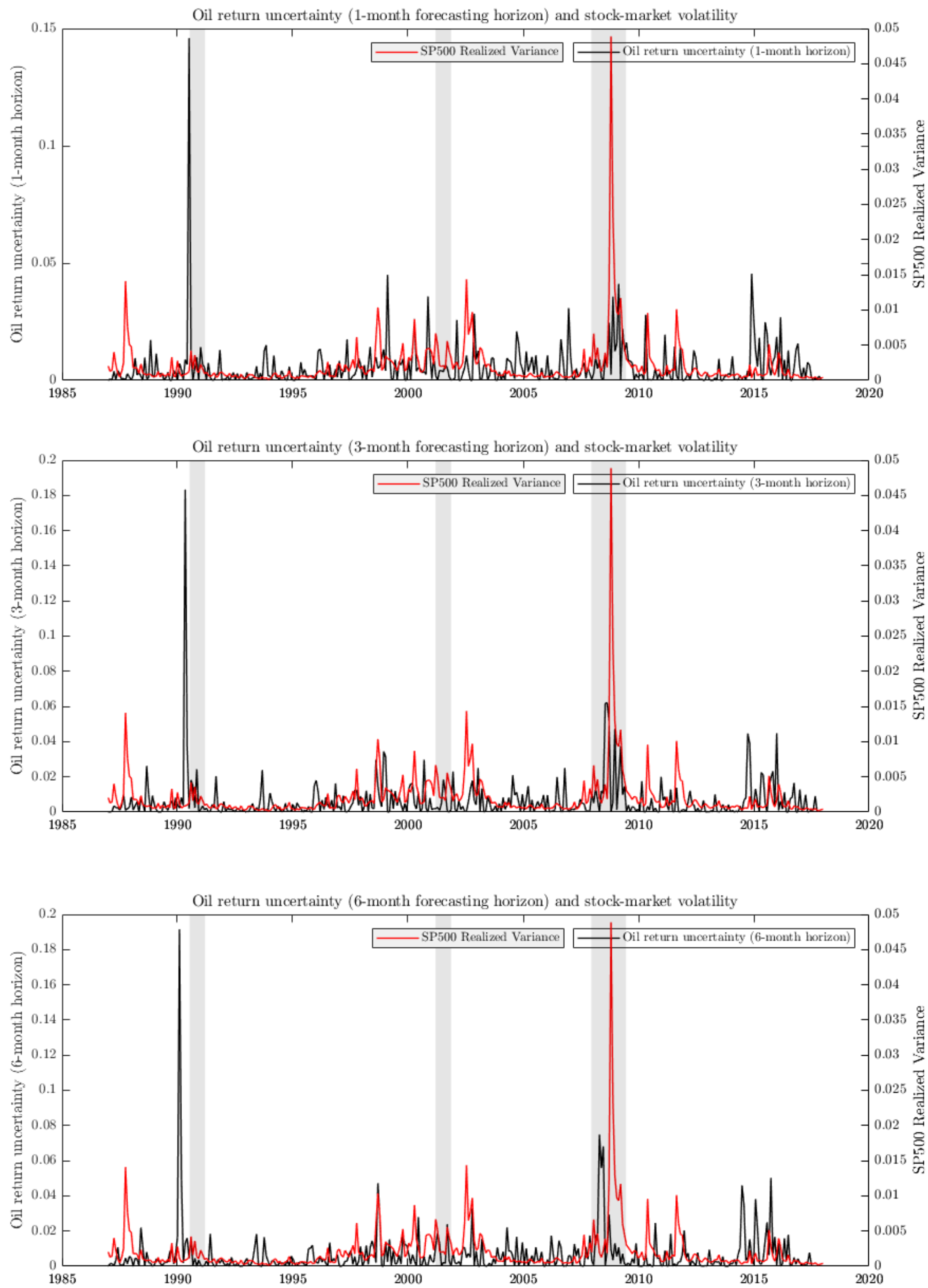


Figure 2. Structural form Impulse Response Functions of SP500 Realized Variance (SP500RV) to oil price uncertainty shocks.

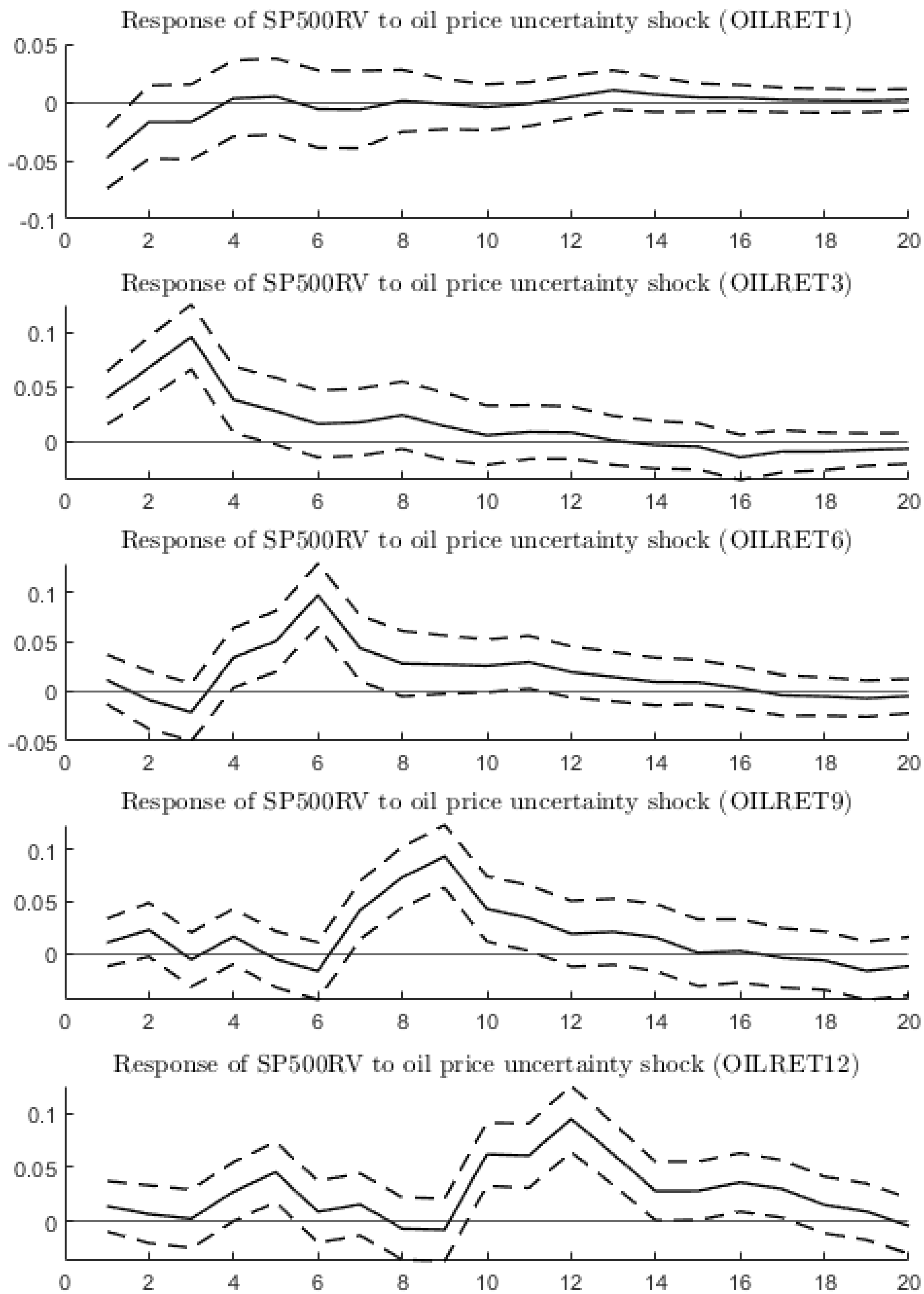


Figure 3. Structural form Impulse Response Functions of SP500 Realized Variance (SP500RV) to oil supply, aggregate demand, oil-specific demand and oil price volatility shocks.

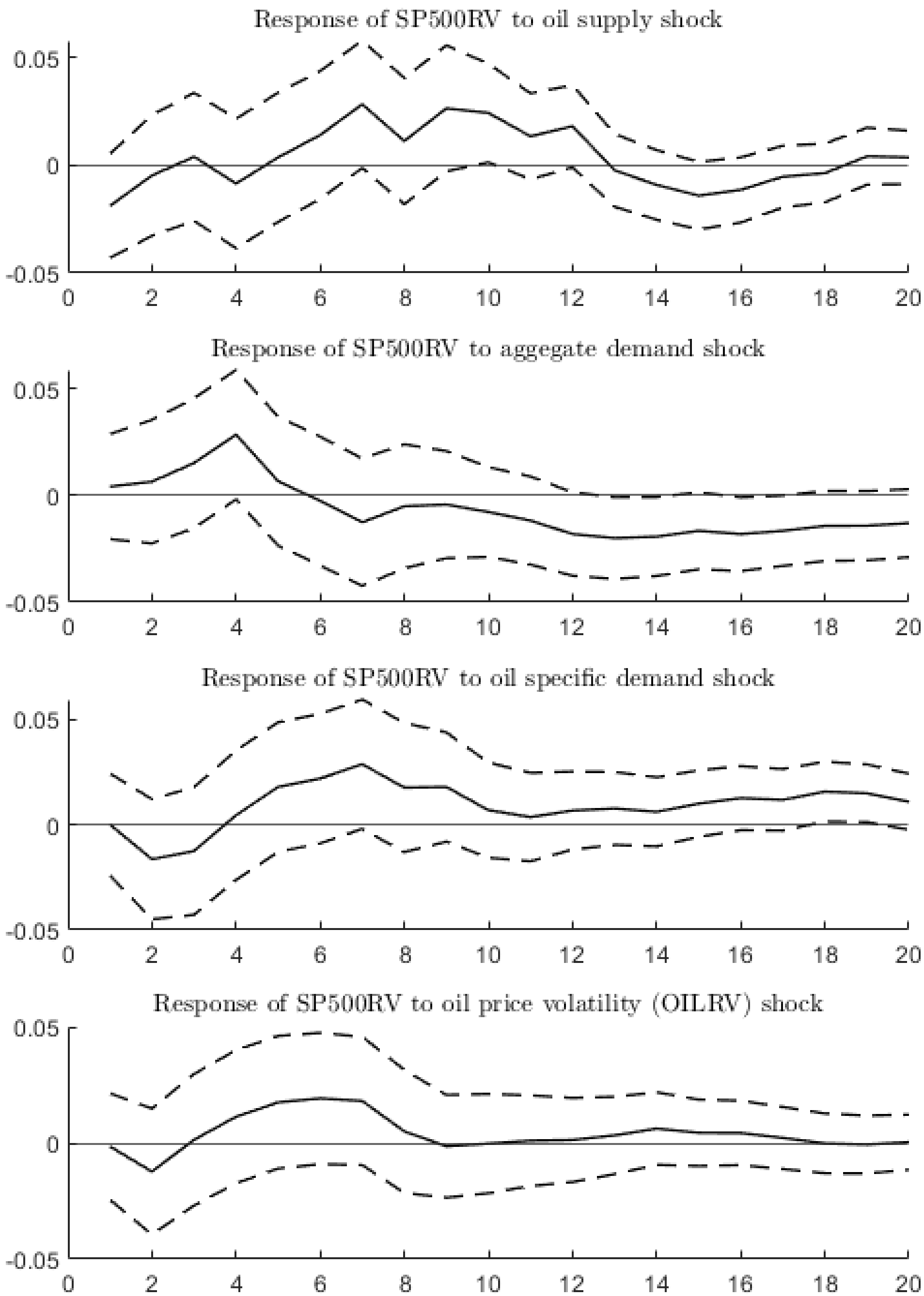
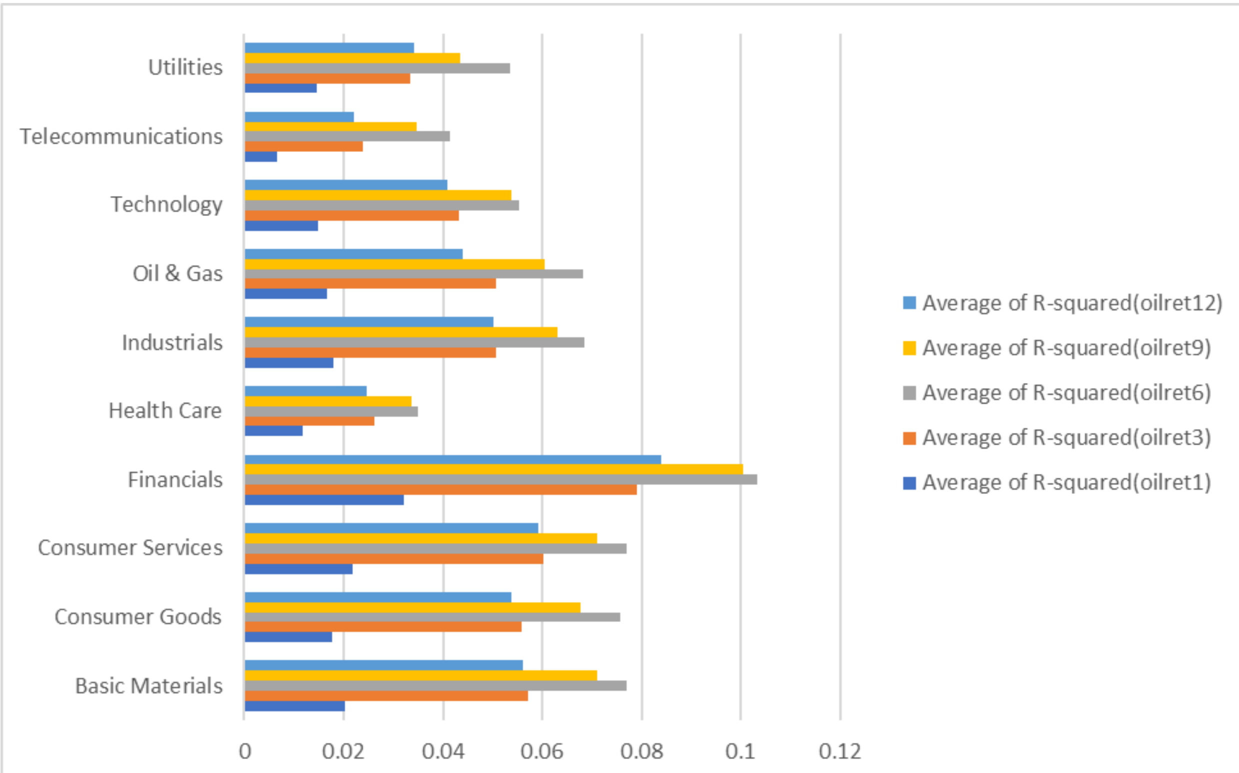


Figure 4. Sectoral regression analysis-Forecasting the volatility of S&P500 constituents using oil price uncertainty as predictor.

Panel A: Industry average R^2



Panel B: More detailed industry average R^2

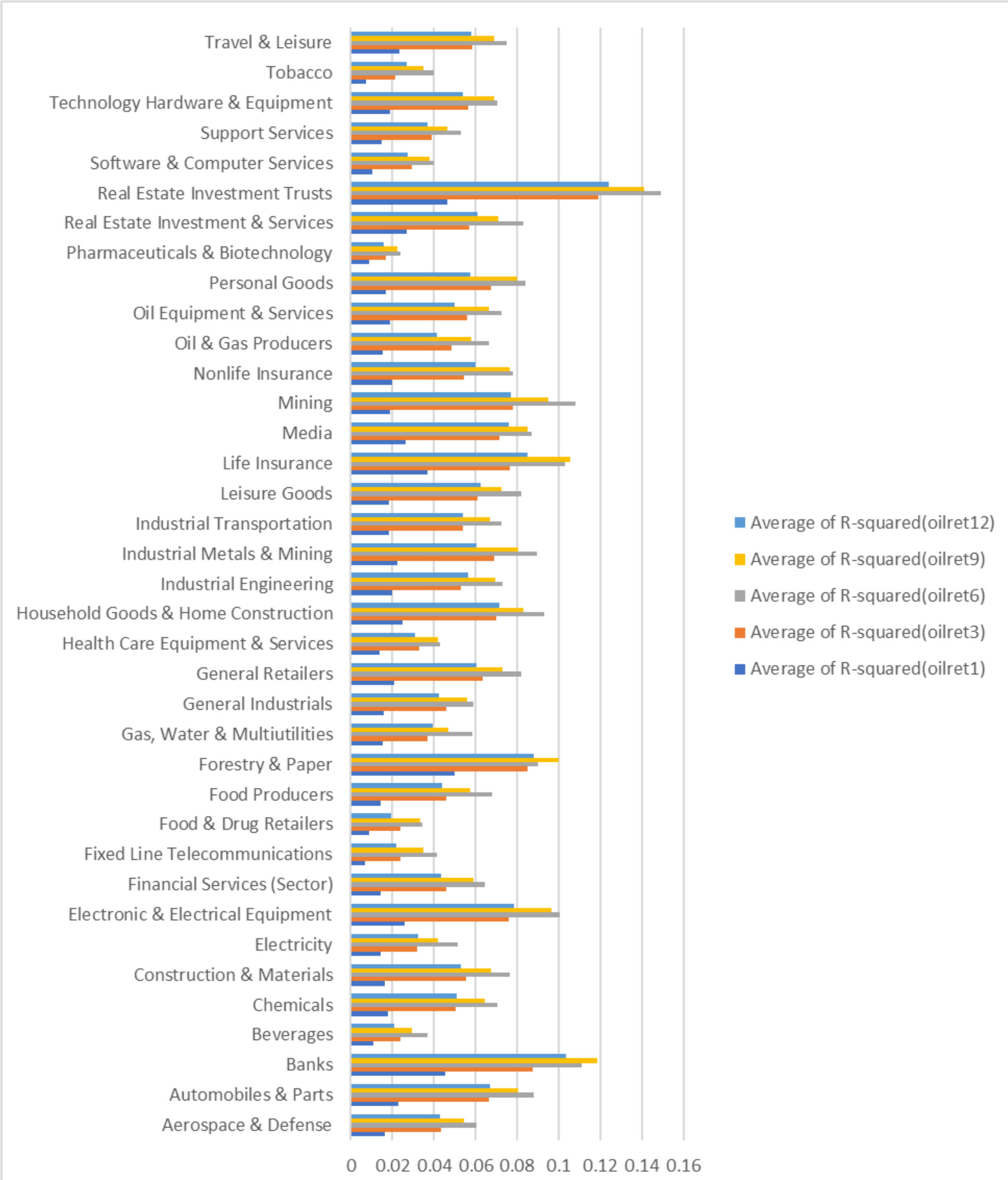
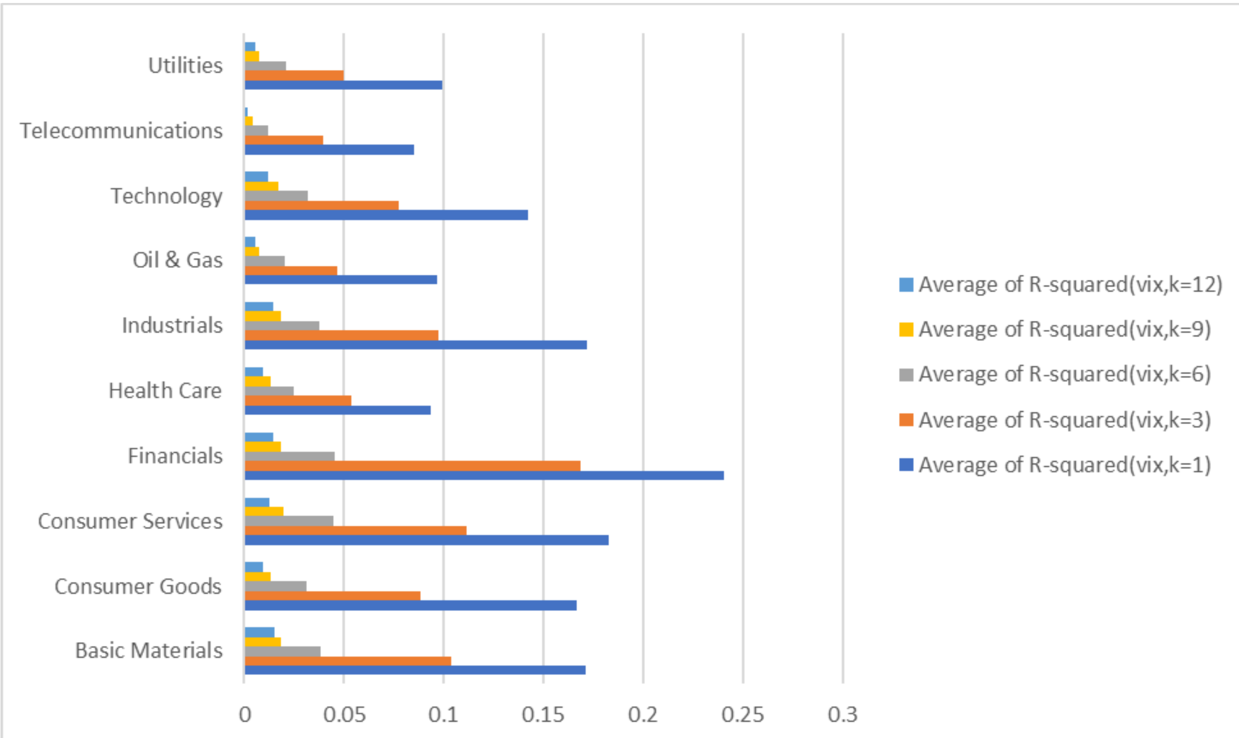


Figure 5. Sectoral regression analysis-Forecasting the volatility of S&P500 constituents using VIX as predictor

Panel A: Industry average R^2



Panel B: More detailed industry average R^2

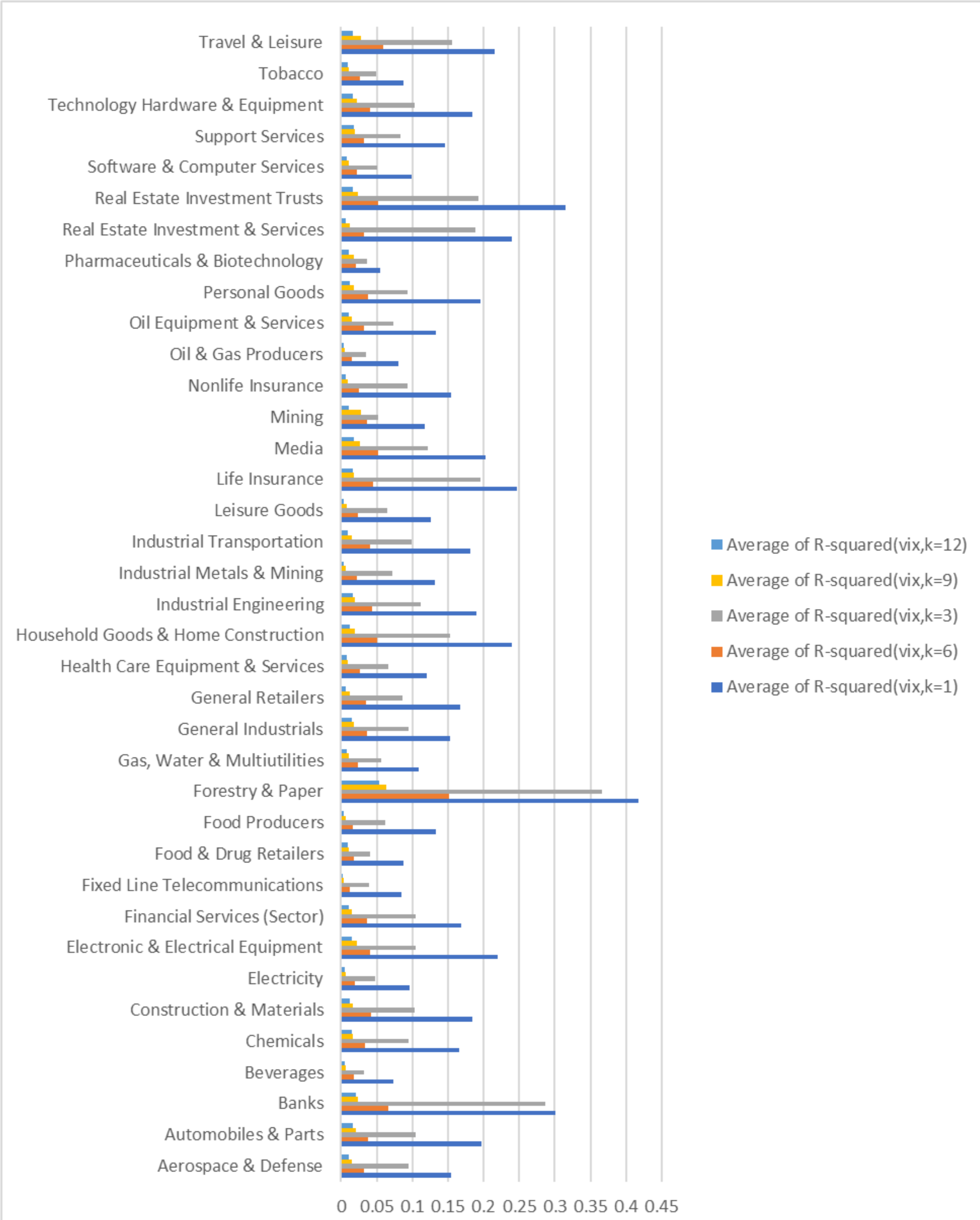
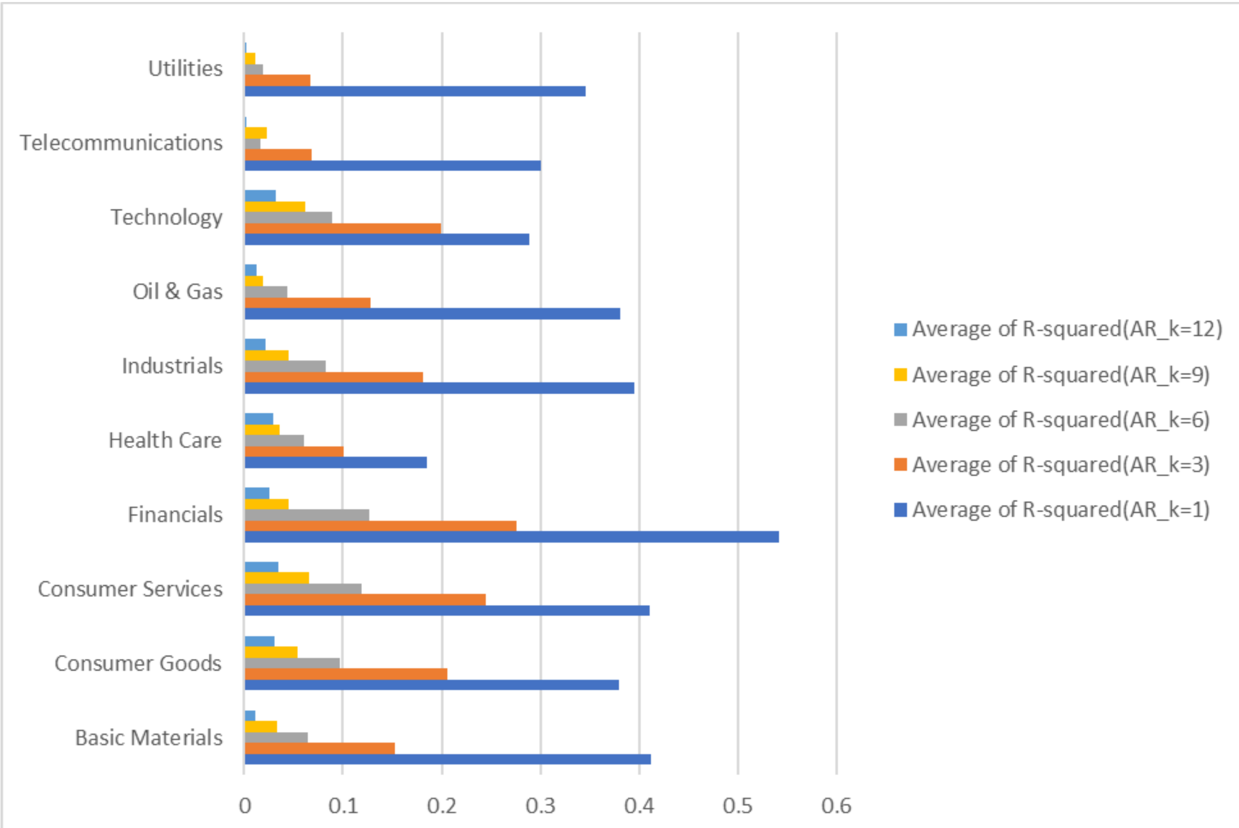


Figure 6. Sectoral regression analysis-Forecasting the volatility of S&P500 constituents using lagged RV as predictor

Panel A: Industry average R^2



Panel B: More detailed industry average R^2

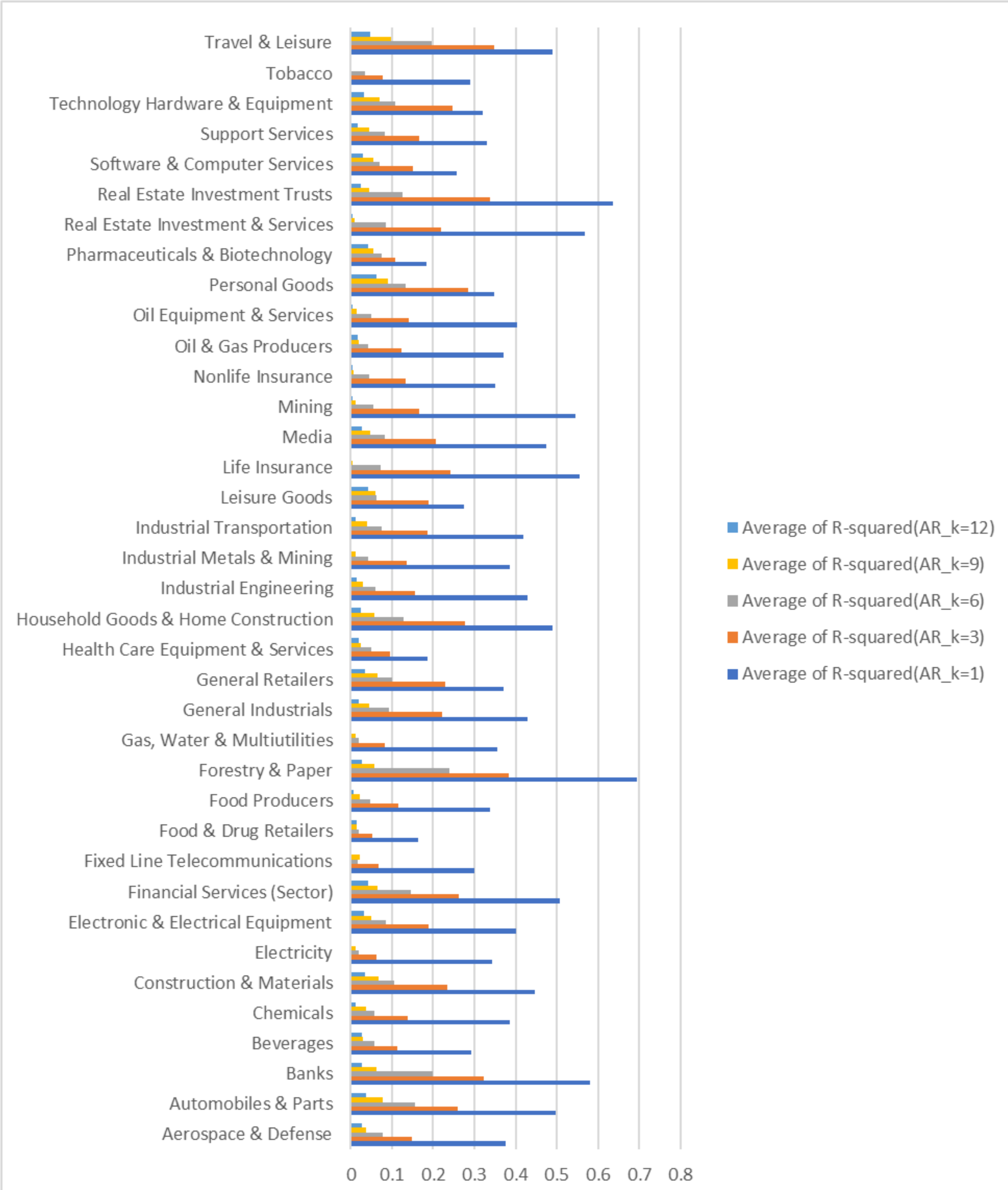
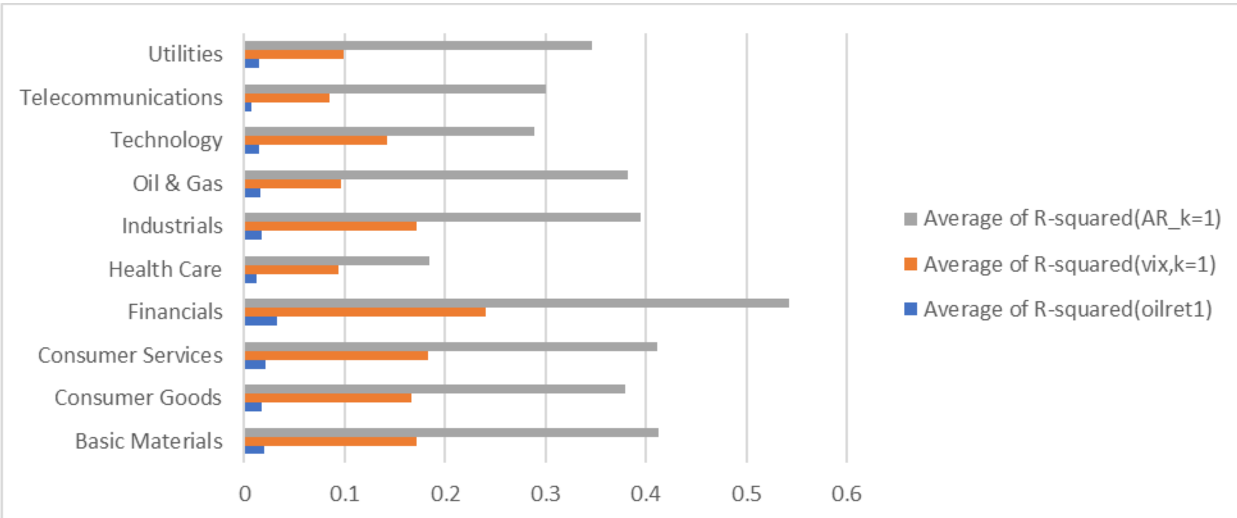
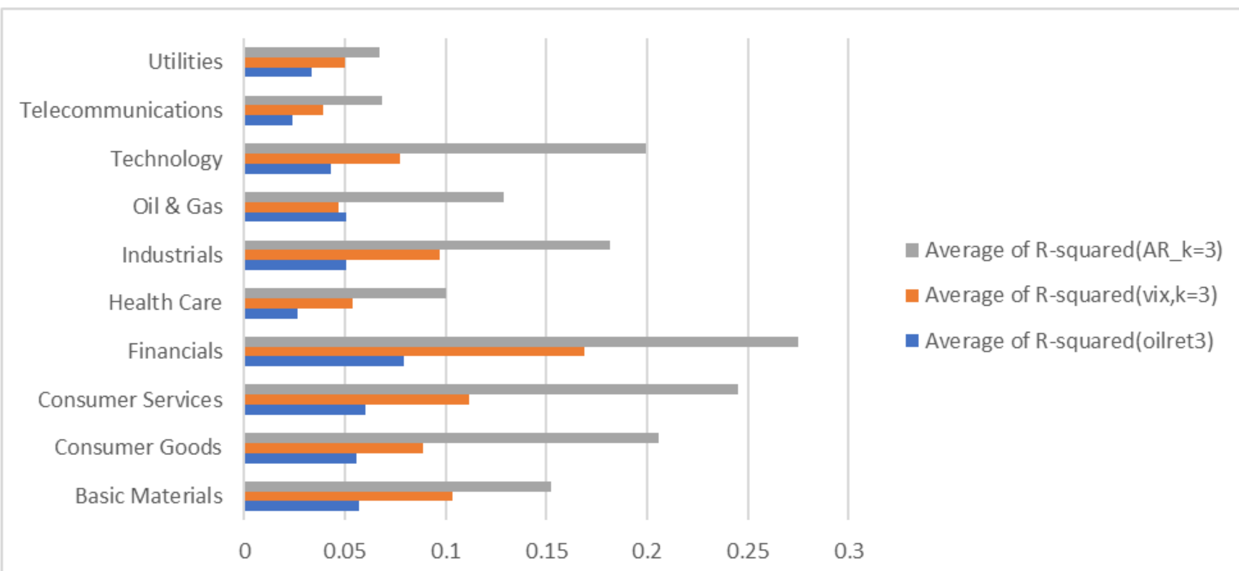
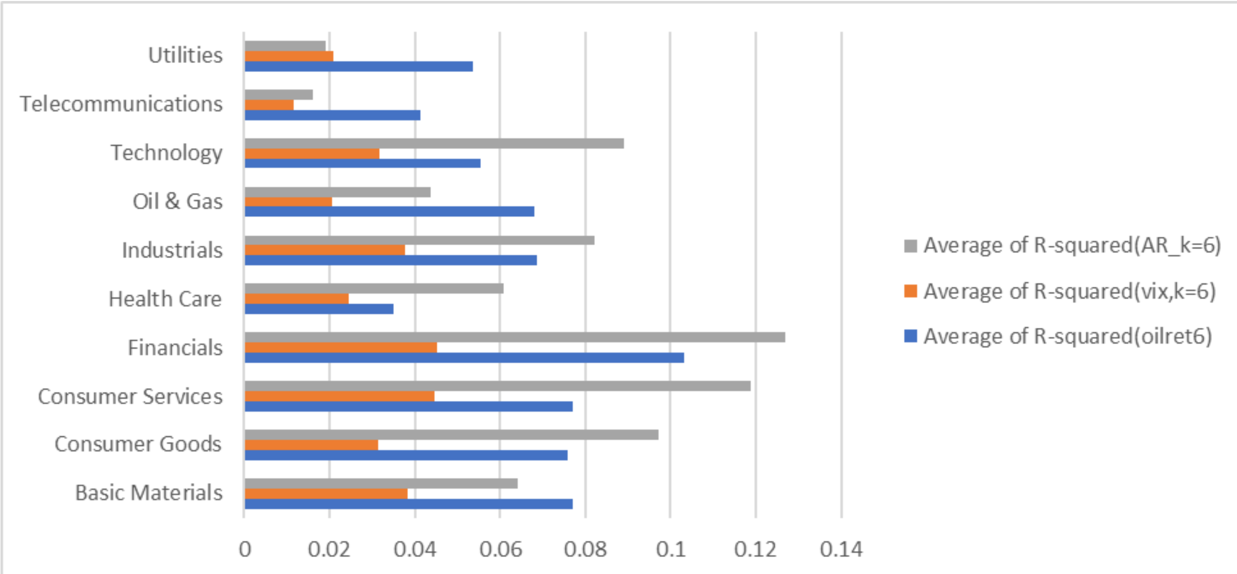


Figure 7. Sectoral regression analysis-Comparing OILR, VIX and RV

Panel A: Average R^2, k=1 to 12



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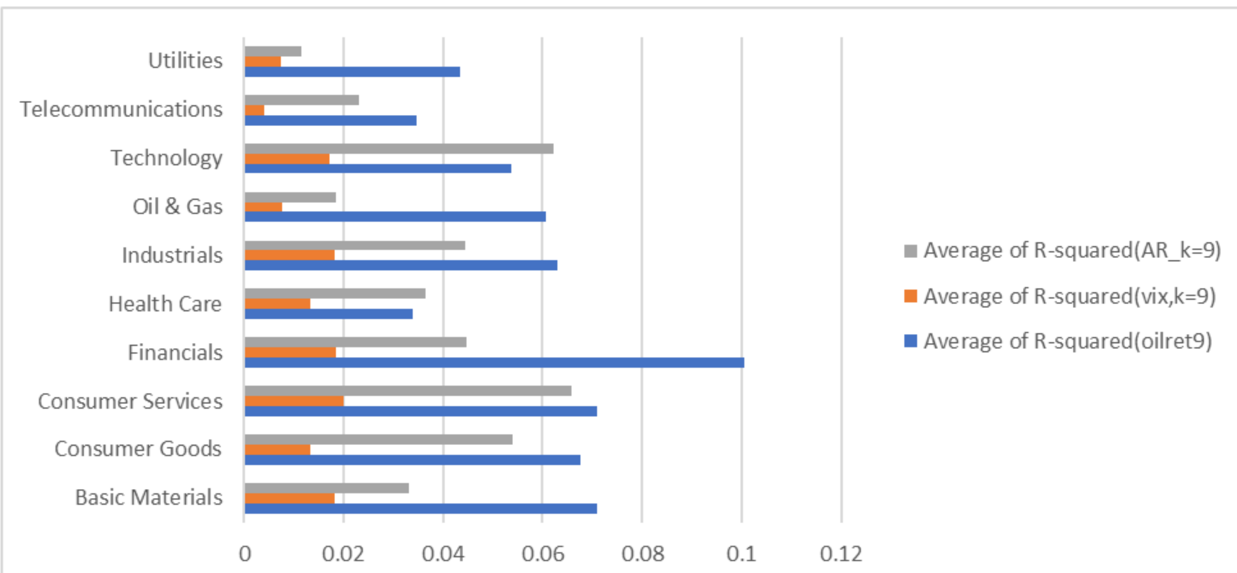
Average of R-squared(AR_k=6)
Average of R-squared(vix,k=6)
Average of R-squared(oilret6)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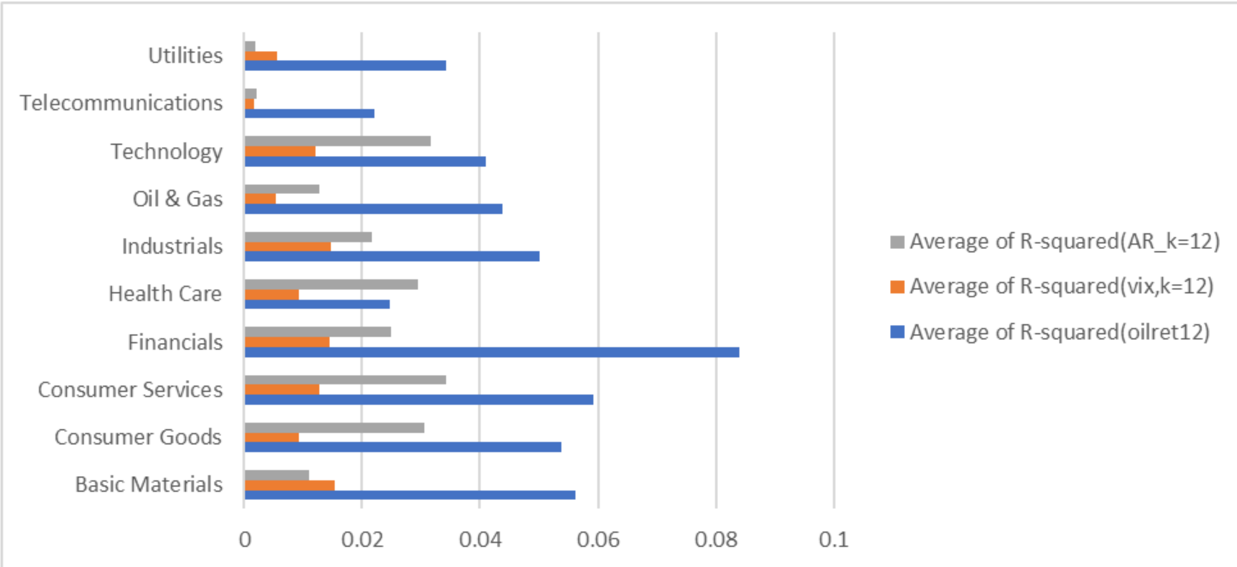
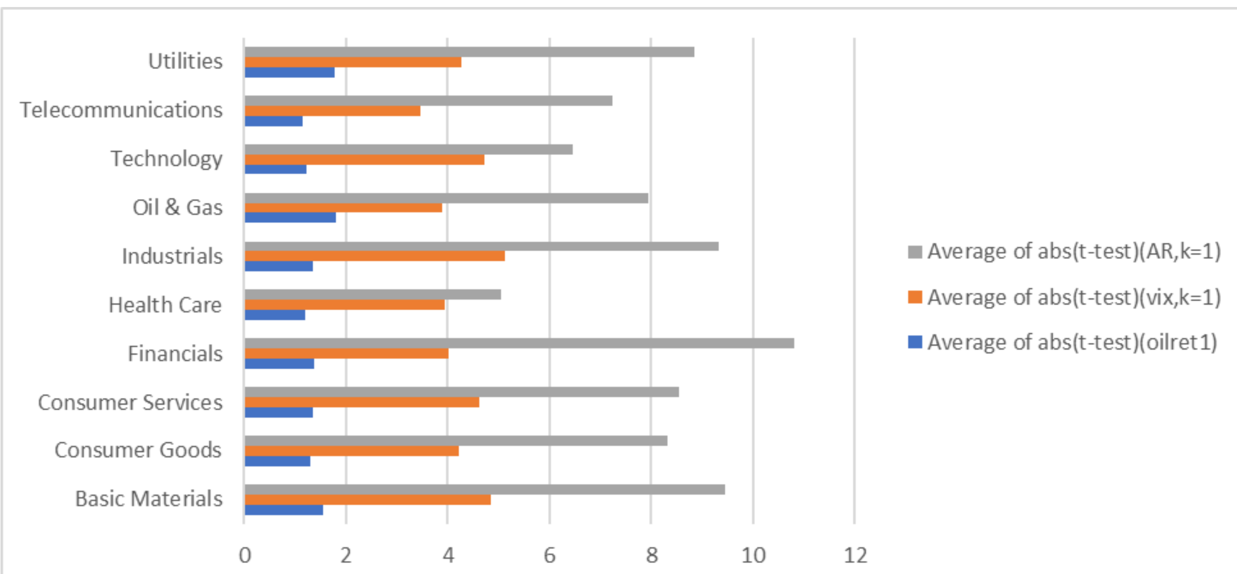
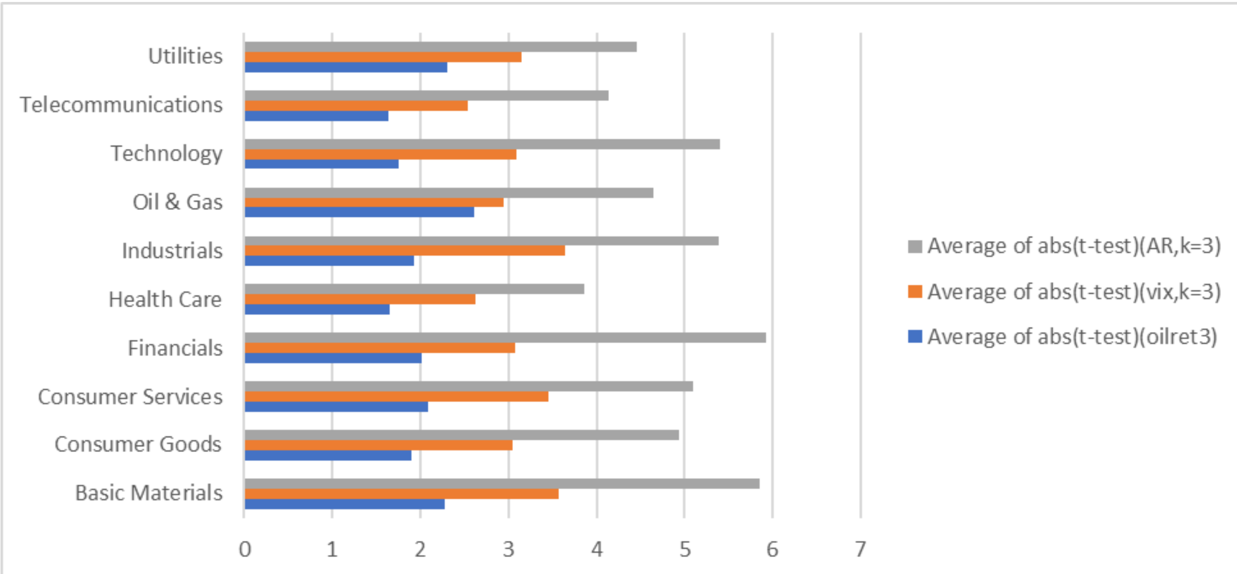
Average of R-squared(AR_k=9)
Average of R-squared(vix,k=9)
Average of R-squared(oilret9)



Panel B: Average absolute t-statistic, k=1 to 12

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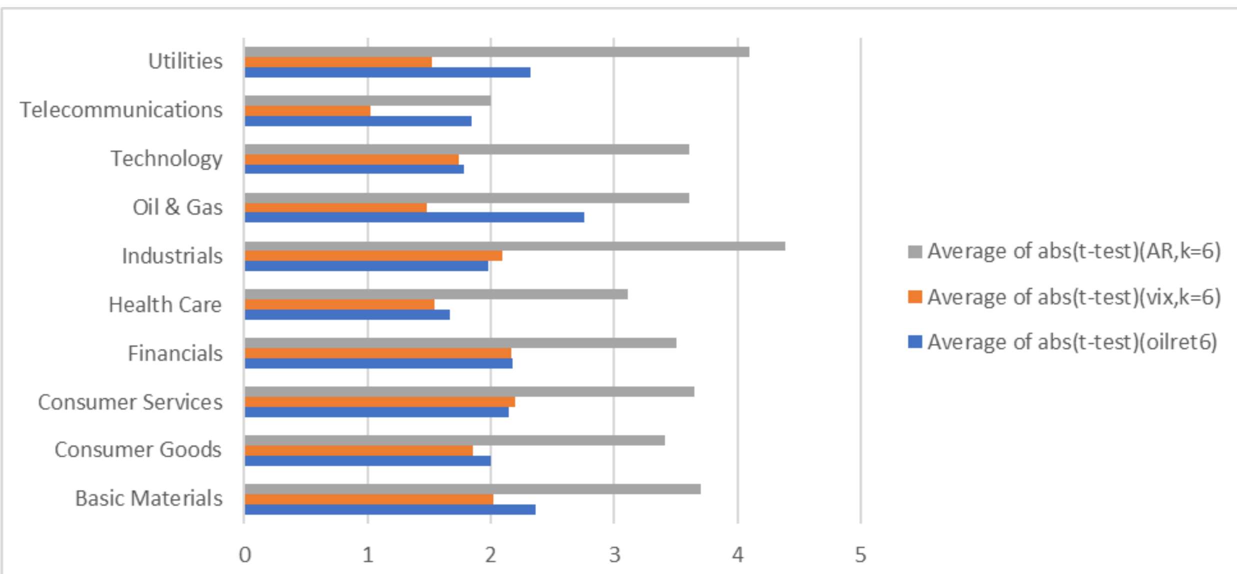
Average of abs(t-test)(AR,k=3)
Average of abs(t-test)(vix,k=3)
Average of abs(t-test)(oilret3)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Financials
Consumer Services
Consumer Goods
Basic Materials
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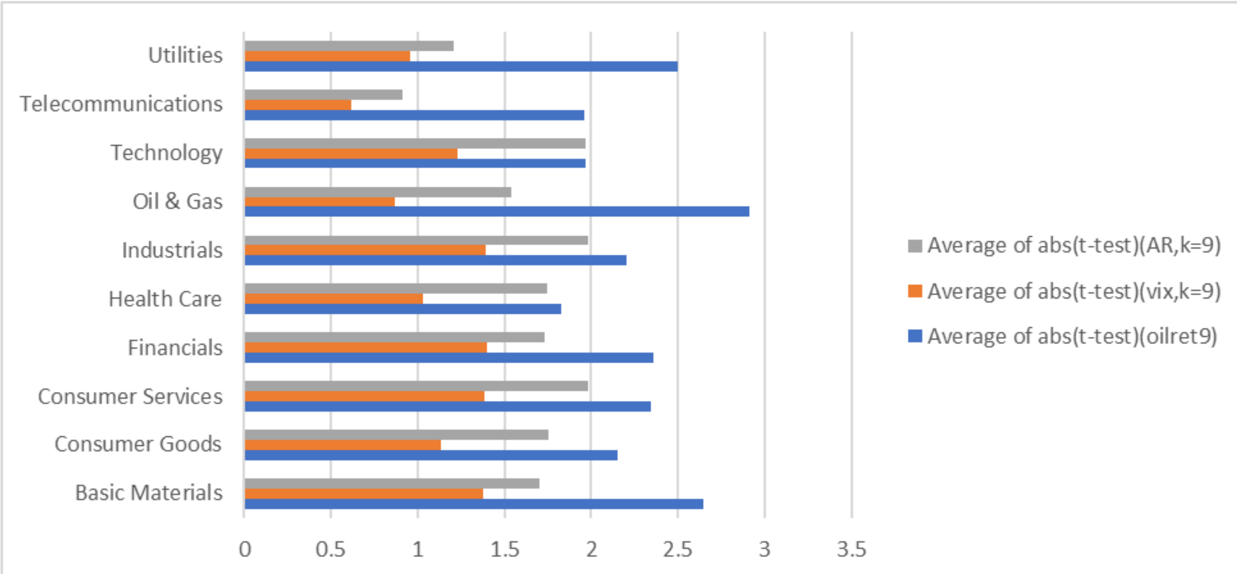
Average of abs(t-test)(AR,k=6)
Average of abs(t-test)(vix,k=6)
Average of abs(t-test)(oilret6)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Financials
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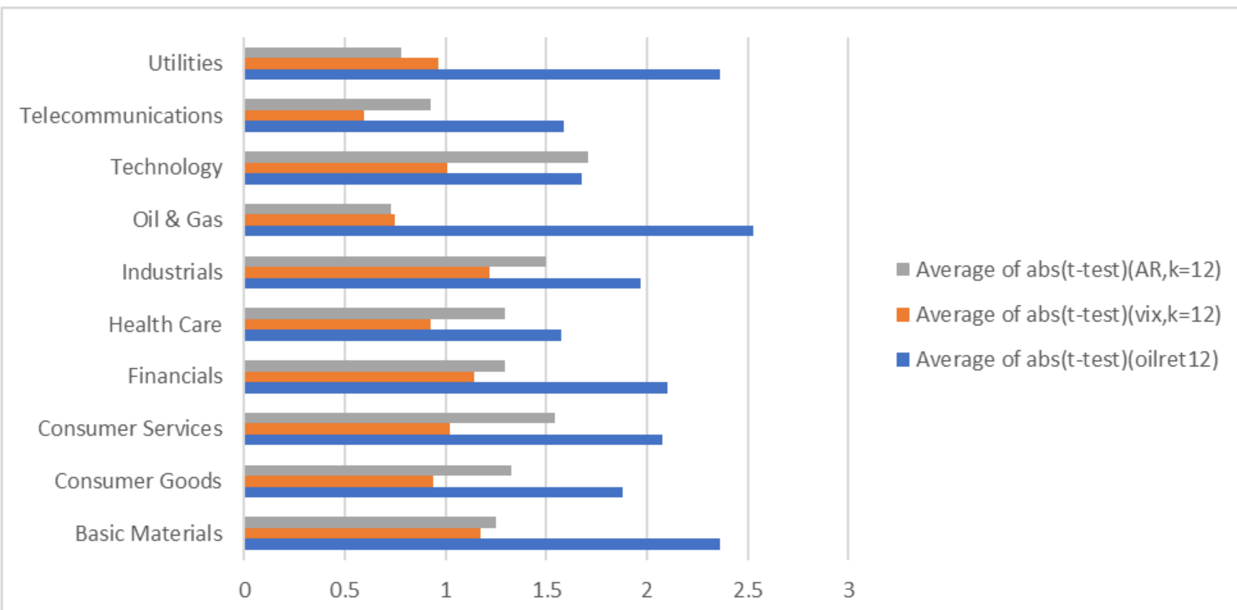
Average of abs(t-test)(AR,k=9)
Average of abs(t-test)(vix,k=9)
Average of abs(t-test)(oilret9)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2.5
3
Average of abs(t-test)(AR,k=12)
Average of abs(t-test)(vix,k=12)
Average of abs(t-test)(oilret12)

Table 1. Descriptive statistics

	SP500 RV	VIX	OIL RETURNS	OILRV	OILRET1	OILRET3	OILRET6	OILRET9	OILRET12
Mean	0.002	0.197	0.006	0.003	0.006	0.007	0.007	0.006	0.006
Median	0.001	0.177	0.010	0.001	0.003	0.003	0.003	0.002	0.002
Max.	0.049	0.626	0.458	0.045	0.146	0.183	0.192	0.077	0.087
Min.	0.000	0.108	-0.286	0.000	0.000	0.000	0.000	0.000	0.000
St. Dev.	0.004	0.076	0.086	0.005	0.011	0.014	0.014	0.010	0.010
Skew.	7.902	2.002	0.195	3.653	7.497	7.505	7.681	3.573	3.927
Kurt.	91.998	9.561	5.486	22.404	89.665	87.723	88.689	20.415	23.637

Table 2. Granger causality tests for the baseline SVAR model between stock market volatility and oil-related variables.

Panel A: Granger causality tests between SP500RV and oil related variables

Dependent variable	Independent variable	Chi-square	p-value
SP500RV	INVENT	13.55	0.14
SP500RV	GACT	4.27	0.89
SP500RV	OILPRICE	8.58	0.48
SP500RV	OILRV	7.83	0.55
SP500RV	OILRET3	51.03***	0.00

Panel B: Granger causality tests between oil related variables and SP500RV

Dependent variable	Independent variable	Chi-square	p-value
INVENT	SP500RV	7.17	0.62
GACT	SP500RV	42.67***	0.00
OILPRICE	SP500RV	30.97***	0.00
OILRV	SP500RV	28.94***	0.00
OILRET3	SP500RV	18.07**	0.03

Notes: This table shows the results of the Granger causality tests between the six endogenous variables of our baseline SVAR model (in which we use OILRET3 as our oil price uncertainty variable). The results of the Granger causality tests do not differentiate if we use OILRET1, OILRET6, OILRET9 or OILRET12 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.

Table 3. Forecasting S&P 500RV using oil price uncertainty (Jan 1990- Dec 2017 period)

Panel A

$$SP500RV_t = b_0 + b_1 OILR(K)_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.002***	6.318	0.034	1.299	1.0
3m	0.002***	6.679	0.046	1.180	3.0
6m	0.002***	6.468	0.052	1.207	4.2
9m	0.001***	6.533	0.102**	2.103	7.5
12m	0.001	6.525	0.091*	1.902	6.5

Panel B

$$SP500RV_t = b_0 + b_1 SP500RV_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.001***	4.667	0.633***	10.952	40.1
3m	0.001***	4.673	0.310***	6.366	9.6
6m	0.002***	4.986	0.167***	3.986	2.8
9m	0.002***	5.756	0.139	1.337	1.9
12m	0.002***	5.278	0.088	1.328	0.8

Panel C

$$SP500RV_t = b_0 + b_1 VIX_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.002***	-3.981	0.025***	5.418	30.3
3m	-0.001***	-2.663	0.015***	5.647	11.0
6m	0.001	0.261	0.010***	4.280	4.6
9m	0.0003	0.051	0.010**	2.318	4.8
12m	0.0004	0.712	0.008**	2.307	3.0

Notes: The *t*-statistics reported in the relevant columns are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Table 4. Volatility Forecasting in the equity market using realized variance and oil price uncertainty. (Jan 1990- Dec 2017 period)

Panel A

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + \varepsilon_t$$

Horizon (k)	b_1	*t-stat*(b_1)	b_2	*t-stat*(b_2)	*% Adj.* R^2
1m	0.526***	5.717	0.006***	2.624	40.7
3m	0.125**	2.236	0.011***	3.116	11.6
6m	-0.004	-0.082	0.010***	2.614	4.6
9m	-0.091	-1.229	0.014***	2.825	5.1
12m	-0.130**	-2.170	0.013***	2.688	3.7

Panel B

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + b_3 OILR(K)_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_1	t-stat(b_1)	b_2	t-stat(b_2)	b_3	t-stat(b_3)	*% Adj.* R^2
1m	0.528***	5.711	0.006***	2.843	-0.016***	-2.649	41.0
3m	0.102	1.382	0.011***	3.039	0.027	0.936	12.7
6m	-0.011	-0.222	0.009***	2.808	0.047	1.136	8.1
9m	-0.108	-1.471	0.013***	2.982	0.097**	2.145	11.9
12m	-0.127**	-2.051	0.012***	2.684	0.087*	1.859	9.6

Panel C

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + b_3 OILRV_{t-k} + \varepsilon_t$$

Horizon (k)	b_1	t-stat(b_1)	b_2	t-stat(b_2)	b_3	t-stat(b_3)	*% Adj.* R^2
1m	0.522***	6.011	0.006**	2.447	0.014	0.339	40.8
3m	0.123*	1.951	0.011***	3.303	0.008	0.181	11.6
6m	0.002	0.053	0.010***	2.763	-0.026	-0.800	4.7
9m	-0.070	-0.961	0.014***	3.079	-0.074***	-2.609	6.1
12m	-0.108*	-1.912	0.014***	2.962	-0.083***	-3.337	4.8

Notes: The t-statistics reported in the relevant columns are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. For brevity we do not report the constant terms.

Table 5. Forecasting stock market volatility (S&P 500 Realized Variance) using 1, 3, 6, 9 and 12-month forecasting horizon. (Jan 1990- Dec 2017 period).

The baseline regression equation is given below:

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + b_3 OILRV_{t-k} + b_4 OILRET(K)_{t-(k+1)} + b_5 OILRETURN_{t-k} + b_6 EPU_{t-k} + b_7 BAA_{t-k} + b_8 IPI_{t-k} + +b_9 INFL_{t-k} + b_{10} TERM_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=6***	***k=9***	***k=12***
CONST	Coef.	-0.001**	-0.003	-0.003*	-0.005**	-0.003*
	t-stat	(-2.081)	(-1.536)	(-1.899)	(-2.328)	(-1.731)
SP500RV	Coef.	0.532***	0.101	0.013	-0.062	-0.091
	t-stat	(5.853)	(1.549)	(0.221)	(-0.693)	(-1.327)
VIX	Coef.	0.004	0.011***	0.009***	0.015***	0.016***
	t-stat	(1.323)	(3.333)	(2.836)	(3.134)	(3.048)
OILRV	Coef.	-0.007	-0.014	-0.050	-0.111**	-0.087***
	t-stat	(-0.267)	(-0.355)	(-1.540)	(-2.181)	(-2.796)
OILRET(K)	Coef.	-0.012*	0.022	0.041	0.087**	0.072*
	t-stat	(-1.728)	(0.910)	(1.220)	(2.002)	(1.859)
OILRETURNS	Coef.	-0.002	-0.006	0.001	-0.002	0.002
	t-stat	(-1.220)	(-1.419)	(0.570)	(-1.384)	(1.129)
EPU	Coef.	0.002	-0.0002**	-0.0002**	0.0001	-0.0002
	t-stat	(0.254)	(-2.110)	(-2.110)	(0.513)	(-0.409)
BAA	Coef.	0.031	0.081	0.076	-0.021	-0.037
	t-stat	(1.451)	(1.474)	(0.904)	(-0.512)	(-0.675)
IPI	Coef.	0.0001	0.0002	0.0004**	0.0005***	0.0004**
	t-stat	(1.578)	(1.550)	(2.074)	(2.608)	(2.017)
INFL	Coef.	0.110	0.201	0.164*	0.174*	0.041
	t-stat	(1.558)	(1.335)	(1.900)	(1.752)	(0.805)
TERM	Coef.	-0.004	0.026	0.021	-0.020	-0.039**
	t-stat	(-0.455)	(0.978)	(0.897)	(-0.918)	(-2.404)
% adj. R^2		39.9	16.2	11.1	14.8	14.5

Notes: 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 oil-uncertainty shock corresponds to the squared oil price uncertainty residual having k-month forecasting horizon.

Table 6. Forecasting S&P 500RV using oil price uncertainty for the pre-financialization period (Jan 1990- Dec 2003 period)

Panel A

$$SP500RV_t = b_0 + b_1 OILR(K)_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.002***	6.862	0.006	0.724	0.1
3m	0.002***	6.897	0.002	0.444	0.1
6m	0.002***	6.667	0.004	0.829	0.2
9m	0.002***	6.964	0.002	0.642	0.3
12m	0.002***	6.517	0.001	0.432	0.2

Panel B

$$SP500RV_t = b_0 + b_1 SP500RV_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	0.000773***	5.259	0.615***	12.525	37.7
3m	0.00138***	4.615	0.317***	3.484	10.0
6m	0.00150***	4.792	0.255***	2.934	6.5
9m	0.00161***	5.590	0.207**	2.204	4.3
12m	0.00143***	5.720	0.241**	2.133	7.2

Panel C

$$SP500RV_t = b_0 + b_1 VIX_{t-k} + \varepsilon_t$$

Horizon (k)	b_0	*t-stat*(b_0)	b_1	*t-stat*(b_1)	*% adj.* R^2
1m	-0.00229***	-5.088	0.0212***	7.413	39.3
3m	-0.00052	-1.061	0.0125***	5.061	13.7
6m	-0.0004	-0.816	0.0120***	5.128	12.7
9m	-0.00097	-1.228	0.0148***	3.129	19.4
12m	-0.00076	-1.070	0.0139***	3.278	16.4

Notes: The *t*-statistics reported in the relevant columns are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Table 7. Volatility Forecasting in the equity market using realized variance and oil price uncertainty for the pre-financialization period (Jan 1990- Dec 2003 period)

Panel A

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + \varepsilon_t$$

Horizon (k)	b_1	*t-stat*(b_1)	b_2	*t-stat*(b_2)	*% Adj.* R^2
1m	0.409***	4.296	0.010***	3.855	44.4
3m	0.219	1.063	0.006	1.261	14.4
6m	0.037	0.292	0.011**	2.461	11.6
9m	-0.196	-1.114	0.020**	2.440	19.7
12m	0.021	0.125	0.013**	2.104	15.3

Panel B

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + b_3 OILR(K)_{t-k-1} + \varepsilon_t$$

Horizon (*k*)	b_1	*t*-stat(b_1)	b_2	*t*-stat(b_2)	b_3	*t*-stat(b_3)	*% Adj.* R^2
1m	0.406***	4.247	0.010***	4.000	-0.013***	-3.278	44.8
3m	0.219	1.068	0.006	1.281	-0.003	-0.580	13.9
6m	0.038	0.284	0.011**	2.355	0.0002	0.057	11.0
9m	-0.197	-1.126	0.020**	2.390	0.003	0.302	19.2
12m	0.021	0.123	0.013**	2.048	-0.012	-0.515	14.8

Panel C

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + b_3 OILRV_{t-k} + \varepsilon_t$$

Horizon (*k*)	b_1	*t*-stat(b_1)	b_2	*t*-stat(b_2)	b_3	*t*-stat(b_3)	*% Adj.* R^2
1m	0.381***	3.936	0.011***	4.249	-0.070**	-2.556	44.9
3m	0.204	0.967	0.007	1.361	-0.037	-1.241	14.0
6m	0.005	0.044	0.012***	3.060	-0.082***	-2.694	12.2
9m	-0.254	-1.521	0.023***	2.838	-0.147***	-2.905	22.6
12m	-0.021	-0.129	0.015**	2.516	-0.107**	-2.460	16.6

Notes: The *t*-statistics reported in the relevant columns are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. For brevity we do not report the constant terms.

Table 8. Forecasting stock market volatility (S&P 500 Realized Variance) using 1, 2, 3 and 6-month forecasting horizon for the pre-financialization period (Jan 1990- Dec 2003).

The baseline regression equation is given below:

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + b_3 OILRV_{t-k} + b_4 OILRET(K)_{t-(k+1)} + b_5 OILRETURN_{t-k} + b_6 EPU_{t-k} + b_7 BAA_{t-k} + b_8 IPI_{t-k} + +b_9 INFL_{t-k} + b_{10} TERM_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=6***	***k=9***	***k=12***
CONST	Coef.	-0.003**	-0.004*	-0.004	-0.009**	-0.005**
	t-stat	(-2.224)	(-1.804)	(-1.161)	(-2.410)	(-2.061)
SP500RV	Coef.	0.350***	0.125	-0.089	-0.270*	-0.068
	t-stat	(3.893)	(0.651)	(-0.618)	(-1.656)	(-0.447)
VIX	Coef.	0.008**	-0.001	0.005	0.011*	0.006
	t-stat	(2.400)	(-0.234)	(1.084)	(1.873)	(1.350)
OILRV	Coef.	-0.021	0.086	0.065	-0.052	0.010
	t-stat	(-0.649)	(1.449)	(1.327)	(-1.274)	(0.295)
OILRET(K)	Coef.	-0.015***	0.002	0.006	0.008	-0.026
	t-stat	(-3.420)	(0.456)	(1.301)	(0.465)	(-1.360)
OILRETURNS	Coef.	0.001	-0.0006	0.001	-0.004**	0.0002
	t-stat	(1.100)	(-0.416)	(0.689)	(-2.136)	(0.144)
EPU	Coef.	-0.0002	-0.0001	-0.0002**	0.0001	-0.0001
	t-stat	(-0.244)	(-1.119)	(-2.376)	(1.023)	(-0.027)
BAA	Coef.	0.028	0.047	0.065	-0.080	-0.023
	t-stat	(0.543)	(0.782)	(1.259)	(-1.473)	(-0.383)
IPI	Coef.	0.0003	0.0007**	0.0007*	0.0001***	0.0009***
	t-stat	(1.515)	(2.299)	(1.694)	(3.438)	(3.447)
INFL	Coef.	0.060	0.116	0.049	-0.011	-0.045
	t-stat	(0.939)	(1.215)	(0.461)	(-0.073)	(-0.299)
TERM	Coef.	-0.006	0.007	0.013	0.009	-0.005
	t-stat	(-0.357)	(0.232)	(0.412)	(0.487)	(-0.325)
% adj. R^2		46.1	27.8	27.3	34.1	28.5

Notes: 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 oil-uncertainty shock corresponds to the squared oil price uncertainty residual having k-month forecasting horizon.

Table 9. Forecasting S&P 500RV using oil price uncertainty (Jan 2004- Dec 2017 period)

Panel A

$$SP500RV_t = b_0 + b_1 OILR(K)_{t-k-1} + \varepsilon_t$$

Horizon (k)	*b_0*	*t-stat(b_0)*	*b_1*	*t-stat(b_1)*	*% adj. R^2*
1m	0.002***	3.950	0.093*	1.755	2.8
3m	0.001***	4.275	0.130**	2.148	9.9
6m	0.001***	4.071	0.143**	2.367	13.1
9m	0.001***	4.129	0.129**	2.549	10.9
12m	0.001***	4.176	0.111**	2.198	9.3

Panel B

$$SP500RV_t = b_0 + b_1 SP500RV_{t-k} + \varepsilon_t$$

Horizon (k)	*b_0*	*t-stat(b_0)*	*b_1*	*t-stat(b_1)*	*% adj. R^2*
1m	0.001***	2.933	0.629***	9.195	39.6
3m	0.001***	2.867	0.295***	6.236	8.7
6m	0.001***	2.968	0.138***	4.437	1.9
9m	0.002***	3.501	0.107	1.028	1.1
12m	0.002***	3.209	0.037	0.858	0.1

Panel C

$$SP500RV_t = b_0 + b_1 VIX_{t-k} + \varepsilon_t$$

Horizon (k)	*b_0*	*t-stat(b_0)*	*b_1*	*t-stat(b_1)*	*% adj. R^2*
1m	-0.003***	-3.689	0.028***	4.423	29.8
3m	-0.001***	-2.651	0.017***	4.275	11.1
6m	0.001	0.710	0.009**	2.539	3.1
9m	0.001	0.697	0.008	1.321	2.5
12m	0.001	1.329	0.006	1.312	1.3

Notes: The *t*-statistics reported in the relevant columns are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator.

Table 10. Volatility Forecasting in the equity market using realized variance and oil price uncertainty. For the post-financialization period (Jan 2004- Dec 2017 period).

Panel A

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + \varepsilon_t$$

Horizon (k)	b_1	*t-stat*(b_1)	b_2	*t-stat*(b_2)	*% Adj.* R^2
1m	0.545***	5.291	0.005*	1.817	38.8
3m	0.072	0.889	0.014**	2.122	9.5
6m	-0.014	-0.140	0.010	1.278	1.2
9m	-0.060	-0.822	0.011	1.412	0.7
12m	-0.165	-1.375	0.013	1.469	0.3

Panel B

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + b_3 OILR(K)_{t-k-1} + \varepsilon_t$$

Horizon (k)	b_1	t-stat(b_1)	b_2	t-stat(b_2)	b_3	t-stat(b_3)	*% Adj.* R^2
1m	0.553***	5.101	0.006*	1.862	-0.026	-1.300	38.9
3m	-0.028	-0.197	0.015*	1.938	0.100	1.501	14.6
6m	-0.096	-0.848	0.012*	1.689	0.142**	2.324	13.9
9m	-0.076	-1.139	0.011*	1.913	0.126***	2.698	11.2
12m	-0.147	-1.278	0.012	1.525	0.108**	2.208	9.2

Panel C

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + b_3 OILRV_{t-k} + \varepsilon_t$$

Horizon (k)	b_1	t-stat(b_1)	b_2	t-stat(b_2)	b_3	t-stat(b_3)	*% Adj.* R^2
1m	0.542***	5.313	0.004	1.598	0.024	0.468	38.9
3m	0.072	0.882	0.014**	2.158	-0.004	-0.129	9.5
6m	-0.008	-0.086	0.011	1.301	-0.044	-1.029	1.4
9m	-0.045	-0.597	0.013	1.529	-0.120	-1.385	2.5
12m	-0.148	-1.333	0.016	1.647	-0.143*	-1.778	2.8

Notes: The t-statistics reported in the relevant columns are corrected for autocorrelation and heteroscedasticity using the Newey-West (1987) estimator. For brevity we do not report the constant terms.

Table 11. Forecasting stock market volatility (S&P 500 Realized Variance) using 1, 2, 3 and 6-month forecasting horizon for the post-financialization period (Jan 2004- Dec 2017).

The baseline regression equation is given below:

$$SP500RV_t = a + b_1 SP500RV_{t-k} + b_2 VIX_{t-k} + b_3 OILRV_{t-k} + b_4 OILRET(K)_{t-(k+1)} + b_5 OILRETURN_{t-k} + b_6 EPU_{t-k} + b_7 BAA_{t-k} + b_8 IPI_{t-k} + +b_9 INFL_{t-k} + b_{10} TERM_{t-k} + \varepsilon_t$$

Horizon (k)		***k=1***	***k=3***	***k=6***	***k=9***	***k=12***
CONST	Coef.	0.006	-0.021	-0.025	-0.032	-0.028
	t-stat	(0.837)	(-1.156)	(-1.174)	(-1.453)	(-1.471)
SP500RV	Coef.	0.587***	-0.054	-0.058	-0.105	-0.268
	t-stat	(4.891)	(-0.358)	(-0.629)	(-1.220)	(-1.410)
VIX	Coef.	-0.002	0.022*	0.017**	0.027*	0.043*
	t-stat	(-0.352)	(1.852)	(2.206)	(1.957)	(1.795)
OILRV	Coef.	0.012	-0.078	-0.110	-0.149	-0.118**
	t-stat	(0.250)	(-1.409)	(-1.206)	(-1.503)	(-2.587)
OILRET(K)	Coef.	-0.028	0.084	0.110***	0.101***	0.066**
	t-stat	(-1.146)	(1.440)	(2.73)	(3.166)	(2.468)
OILRETURNS	Coef.	-0.008	-0.011	0.001	0.001	0.006
	t-stat	(-1.550)	(-1.479)	(0.422)	(0.562)	(1.174)
EPU	Coef.	0.00005	-0.0001	-0.0001	0.0001	-0.0001
	t-stat	(0.581)	(-1.392)	(-0.931)	(0.687)	(-0.077)
BAA	Coef.	0.056	0.066	0.074	-0.016	-0.129
	t-stat	(1.488)	(0.940)	(0.621)	(-0.222)	(-1.032)
IPI	Coef.	-0.006	0.0001	0.0002	0.0002	0.0002
	t-stat	(-0.269)	(0.365)	(1.101)	(0.144)	(0.014)
INFL	Coef.	0.166	0.380	0.184**	0.266**	0.107
	t-stat	(1.581)	(1.221)	(2.201)	(1.985)	(1.387)
TERM	Coef.	-0.008	0.053	0.055	-0.024	-0.048*
	t-stat	(-0.424)	(1.183)	(1.092)	(-0.657)	(-1.673)
% adj. R^2		38.4	17.6	13.8	16.7	17.6

Notes: 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 oil-uncertainty shock corresponds to the squared oil price uncertainty residual having k-month forecasting horizon.