Oil Jump Risk

Nima Ebrahimi

September 2, 2019

Abstract. We show that the risk associated with big upside jumps in oil market is a significant driver of the cross-section of stock returns, using a 28-year sample of data from 1986 to 2014. The risk associated with the small and continuous price changes- Variance Risk -is only a priced factor in the cross-section of stock returns when we do not control for jumps. The average monthly return for the high-low upside jump risk exposure portfolio is -0.5%. For the 2000-2008 sub-period, the average monthly returns of the portfolio decreases to -1.28%. The price of upside risk is much smaller after 2008, which can be due to Shale Revolution that increased US oil production considerably. We show that Geopolitical Risk Index is the only variable which can describe a part of variation in the time series of upside and downside jump risks. We also show that the innovation in the risk neutral jumps have a considerable predictive power for important economic indicators such as GDP growth, consumption growth, and total investment. In addition, we observe that the upside jump risk is a significant predictor of stock market index return and the returns of oil futures. Furthermore, the upside jump probability is a significant and relatively strong predictor for oil market fundamentals including inventory growth, demand growth, and OPEC's production growth.

I. Introduction

Large oil price spikes and drops have been the subject of a substantial amount of research in finance and economics during the recent decades. More recently, scholars have examined the effect of time variation in oil price volatility on asset prices. Ebrahimi and Pirrong (2018) have extended this research to quantify the effects of time variation in higher moments (skewness and kurtosis) on asset prices. In this article, we extend that inquiry by investigating how upward and downward jumps, which can affect skewness and kurtosis, affect asset returns, and whether these factors have predictive power over real variables (e.g., GDP growth) and measures of oil market fundamentals.

The main motivation is that our previous research shows that in a competition among variance, skewness and kurtosis, variance loses its significance in explaining cross-section of stock returns after controlling for skewness and kurtosis. In addition, we find that the kurtosis effect explains more of the the cross-section of stock returns and retains its significance through different sub-periods and different option maturities. Since upside and downside jumps in oil prices can affect skewness and kurtosis, in this article we attempt to provide a deeper understanding of what drives the explanatory power of higher oil return moments for the cross-section of stock returns.

There are several reasons why we are focusing on oil market in this paper. First, energy commodities are the most important type of commodities considering their impact on the economy: a series of articles stretching back decades have shown that oil price shocks have macroeconomic effects, and affect stock returns. (Hamilton (1983, 1996, 2003), Kilian (2009), Kilian and Vigfusson (2013, 2017), Kilian and Park (2009), Engemann *et al*(2011), etc.)

Second, options on crude oil futures are highly liquid, and therefore we can use them to construct reliable estimates of different measures of oil price risk. Among all the commodities, crude oil financial derivatives are the most liquid ones. In particular, we can use option prices to calculate variances, and estimates of the (risk neutral) probabilities of downward and upward jumps, but also we can estimate how each of these factors is priced by investors using options portfolios that are hedged against certain risks. For example the returns on an oil futures option portfolio that is hedged against variance risk measures the premium that investors demand to bear the upside and downside jumps.

The connection between oil market conditions, oil prices, and macroeconomic activity suggests that measures of oil price risk, and investor preferences regarding these risks, may have some power to predict oil market fundamentals and macroeconomic activity.(Gao *et al*(2017)). Furthermore, given this connection between oil market conditions and economic activity, and the connection between economic activity and equity risk premia, we also explore whether oil risk premia affect the cross-section of equity returns.(Christofferson and Pan (2017), Feuno et al (2017))

Looking at the relationship between oil price shocks and macroeconomic variables, we face a big technical problem which makes it hard for us to truly identify the causal relationship of oil market fluctuations and macroeconomic factors. As discussed by Alquist *et al* (2013), the real price of oil has been endogenous to the world's economic condition since 1974. This means that the changes in the real price of oil affects the economic condition of oil-importing economies like the United States. At the same time, the economic conditions of the oil-importing countries have a direct effect on the real price of oil. This is what makes it very hard to identify the causal relationship between the oil price and the macroeconomic conditions, in the case of industrialized, oil-importing economies. As proposed by Hamilton (2003), if we suppose that the major oil price fluctuations are the result of the disruptions in oil production which is mainly caused by exogenous geopolitical tensions in the Middle East like 1973 Yom Kippur War in 1973-1974, Iranian Revolation 1979, Persian Gulf War of 1990-1991 etc, we can perform the identification with no problem. However, as pointed out by different papers (e.g. Kilian (2014)) there is some evidence that the logic does not match with reality and the historical data. Barsky and Kilian (2002) shows that the flow demand is one of the main determinants of the real price of oil in the market.

A solution to the endogeneity problem is to disentangle the supply and demand effects and use the exogenous supply-driven component to see if it can predict the macroeconomic variables. The price of the out of the money options can be used as a proxy of the probability of jumps in oil prices. We can separate the probability associated with small and big jumps by choosing the moneyness of the option contracts we work with. If we choose the options with relatively short time to maturity (here, we use 60-day horizon) and we also choose far out of the money set of options, we can guarantee that the only factor which will be proxied by the changes in the prices of these options are exogenous supply shocks, which are represented by geopolitical events and supply disruptions. The logic behind this is that the time to maturity of the options is too short and the jump size is too big, so no demand-side shock can contribute to it, as it takes a long time (if possible at all) for a demand shock to cause such a huge increase in oil prices.

Our results fall into three categories. First, we show that the risk premia help explain the cross-section of equity returns. After controlling for the downside and upside risk premia, the variance risk premium is not a significant risk factor in the cross-section of stock returns. Moreover, the upside risk premium is the most significant factor and the high-low upside jump risk portfolio portfolio earns an average monthly return of -0.50%. The same pattern holds in sub-samples using different break points, with the major exception that the upside jump risk premium loses its explanatory power after 2008, but the variance risk premium is more significant in this period. This is the era of "shale revolution", during which the domestic oil production of the United States grew substantially.

Second, we evaluate power of variance, upside jump, and downside jump risk premia to predict important macroeconomic factors. We show that the risk premia and their lags are able to predict considerable amount of variation in GDP growth, consumption growth, investment growth, and equity index returns. The results show that the upside and downside risk premia are important predictors of macroeconomic variables and adding them to our model increases the predictive power of the model considerably.

Finally, we show that the premia have power to predict some of the salient measures of oil market fundamentals. The results show that downside and upside risk premia predict oil futures returns, oil inventory growth, and oil demand growth. We also observe that the upside jump premium predicts the aggregate OPEC[1]'s production growth.

II. Data and Methodology

The standard way to quantify the risk premia associated with various attributes of return distributions is by calculating the returns on options portfolios hedged against other attributes. For example, a delta hedged option portfolio is hedged against changes in prices, but exposed to changes in variance, and hence returns on this portfolio compensate investors for bearing variance risk. To be on the safe side, we would use the returns on a delta-gamma hedged portfolio of options instead of the return on delta-hedged portfolio of options, in order to capture the variance risk premium. The reason is that although a delta-hedged portfolio of options is not exposed to the price risk, but there are some other attributes of the distribution of returns which their risks are priced in returns of this portfolio. A delta-gamma hedged portfolio though, is only prone to the risk of variance (vega). In the same fashion, the returns of the delta-vega hedged portfolio of options represents the jump risk premia, as it is hedged against the risks of price (delta) and variance (vega).

There is a big literature on the non-linear relationship between oil prices and the macroeconomic variables.(Hamilton(2011), Mork (1989), Davis and Haltiwanger (2001), Herrera *et al*(2011)) The non-linearity of the relationship between oil and economic variables can be analyzed from two different angles. First, there might be a difference between the effect of big changes versus the effect of small changes. Also, there is a possibility that some specific size of upward jump will not have the same effect (in terms of magnitude) as a

[1]Organization of the Petroleum Exporting Countries

downward jump with the same size. What we do to investigate the non-linearity effect is to decouple the downside and upside jumps. This can be easily done by using options data. We use out of the money call (put) options to calculate the risk premium associated with upside(downside)jumps.

We utilize the approach similar to the one utilized by Cremers *et al* (2015) and Bali and Murray (2013) to quantify the variance risk premium ("VRP"), downside jump risk premium ("DRP"), and the upside risk premium ("URP") in oil markets using option contracts on crude oil futures. Specifically, we utilize prices for 60 days to maturity options on West Texas Intermediate crude oil futures options traded on the CME (formerly NYMEX) for the period 1986 to 2014. We first filter the data by deleting the at-the-money ("ATM") in-the-money ("ITM") option contracts. We also eliminate options which violate no-arbitrage conditions. Finally, we delete the option contracts with prices lower than \$0.05.[2]

The CME trades American options. However, the Cremers *et al* methodology relies on European options prices. To convert the observed American option prices into estimates of European options prices, we implement the conversion method of Bjerksund-Stensland (2002).

After implementing these data transformations, we construct three different portfolios of options to calculate VRP, DRP and URP. To calculate the VRP, we form a delta-vega neutral portfolio of two near the money straddles. On each day, we pick closest to at-the-money put and call option: call these P_1 and C_1 respectively. At the same day and with the same maturity, we select second pair of put and call options which are second-nearest to at-the-money: call these P_2 and C_2. We then form the two straddles based on the following two equations:

$$Straddle_1 = P_1 + aC_1 \tag{1}$$

$$Straddle_2 = P_2 + bC_2 \tag{2}$$

That is, the first straddle comprises one unit of P_1 and a units of C_1. Likewise, the second straddle consists of one unit of P_2 and b units of C_2. Next, we choose a and b to form a portfolio of the straddles on each day that is delta and gamma hedged. To form a delta hedged portfolio we solve the following system of linear equations:

[2] These are the filters used by Trolle and Schwartz (2010)

$$\Delta_{P1} + a\Delta_{C1} = 0 \tag{3}$$

$$\Delta_{P2} + b\Delta_{C2} = 0 \tag{4}$$

where Δ_X is the Black (1976) delta of option X. Solving these two equations produces $a = -\frac{\Delta_{P1}}{\Delta_{C1}}$ and $b = -\frac{\Delta_{P2}}{\Delta_{C2}}$. Replacing the solved parameters in equation 1, we the value of the two straddles is:

$$Straddle_1 = P_1 - \frac{\Delta_{P1}}{\Delta_{C1}} C_1 \tag{5}$$

$$Straddle_2 = P_2 - \frac{\Delta_{P2}}{\Delta_{C2}} C_2 \tag{6}$$

We next construct a gamma-neutral portfolio consisting of the two straddles. The gamma of each of the straddles is:

$$\Gamma_{Straddle1} = \Gamma_{P1} - \frac{\Delta_{P1}}{\Delta_{C1}} \Gamma_{C_1} \tag{7}$$

$$\Gamma_{Straddle2} = \Gamma_{P2} - \frac{\Delta_{P2}}{\Delta_{C2}} \Gamma_{C_2} \tag{8}$$

To form a gamma neutral portfolio of the straddles, we choose d to satisfy:

$$\Gamma_{Straddle1} + d\Gamma_{Straddle2} = 0 \Rightarrow d = -\frac{\Gamma_{Straddle1}}{\Gamma_{Straddle2}} \tag{9}$$

Now, we can calculate the value of the desired portfolio using the following equation:

$$Portfolioval_{Delta-Gamma} = Straddle_1 + d \times Straddle_2 \tag{10}$$

The delta-gamma hedged portfolio is exposed to variance risk, and hence its value incorporates compensation for bearing this risk.

To calculate the premium for downside jump risk, we construct portfolios that are exposed to this risk but are hedged against price and variance risk. We define a downward jump as a price movement that which is defined by the deepest out of the money put options in the sample. To construct a portfolio exposed to this risk, we choose three put options with lowest moneyness where the moneyness is defined by $\ln \frac{K}{F}$. Next, we solve the following system of linear equations to make sure that the portfolio is delta-vega hedged (and hence hedged against variance/volatility risk):

$$\Delta_{P1} + x\Delta_{P2} + y\Delta_{P3} = 0 \tag{11}$$

$$\Lambda_{P1} + x\Lambda_{P2} + y\Lambda_{P3} = 0 \tag{12}$$

where Δ and Λ are the Black (1976) delta and vega of the option. This produces:

$$x = \frac{-\Delta_{P1} - y\Delta_{P3}}{\Delta_{P2}}$$

and

$$y = \frac{\Lambda_{P2}\frac{\Delta_{P1}}{\Delta_{P2}} - \Lambda_{P1}}{\Lambda_{P3} - \frac{\Delta_{P3}}{\Delta_{P2}}}$$

Now, the value of the downside jump portfolio is:

$$DownPortfolioval_{Delta-Vega} = P_1 + xP_2 + yP_3 \tag{13}$$

To form the upside jump risk portfolio, we choose the three options with maximum moneyness. We then solve the following system of linear equations:

$$\Delta_{C1} + w\Delta_{C2} + z\Delta_{C3} = 0 \tag{14}$$

$$\Lambda_{C1} + w\Lambda_{C2} + z\Lambda_{C3} = 0 \tag{15}$$

Solving the system of equations produces

$$z = \frac{-\Delta_{C1} - y\Delta_{C3}}{\Delta_{C2}}$$

$$w = \frac{\Lambda_{C2}\frac{\Delta_{C1}}{\Delta_{C2}} - \Lambda_{C1}}{\Lambda_{C3} - \frac{\Delta_{C3}}{\Delta_{C2}}}$$

Using the solutions for y, w, and z, we calculate the value of the upside jump risk portfolio as:

$$UpPortfolioval_{Delta-Vega} = C_1 + wC_2 + zC_3 \tag{16}$$

In order to construct 60 day fixed-horizon portfolio values, we form each of the portfolios (10), (13) and (16) using options with maturities less than but closest to 60 days. We then construct the portfolios options with maturities greater than, but closest to, 60 days. Then we linearly interpolate these two values to derive the final value of the fixed-horizon portfolio.(Prokopczuk and Simen (2014))

The portfolios are designed to have exposures to variance risk, upside jump risk, and downside jump risk. Therefore, fluctuations in the values of these portfolios reflect changes in expectations of variance and jump probabilities in the equivalent $Q-$measure. The results of Ellwanger (2017) for oil futures options, and Bollerslev and Todorov (2011) demonstrate that jump probabilities in the physical $P-$measure do not exhibit strong time variation. Therefore, changes in $Q-$measure probabilities reflected in the changes in the values of the portfolios reflect primarily changes in risk premia. Reflecting this, we utilize the portfolio values to proxy for variance and jump risk premia.

Figure 1 depicts the implied (forward-looking) volatility, downside jump and upside jump. The implied volatility has been calculated based on Bakshi *et al*(2003) approach, using all OTM call and put options. The downside and upside jump probability are proxied using the average price of the options we chose at each day to form the downside and upside jump portfolios. There are some interesting facts that can be seen in the figure. First, We can see that the downside risk probability has a relatively low volatility between 1999 and 2009. It is after the energy crisis that the time series shows volatility again. More interestingly, the upside jump probability shows characteristics which we anticipated. It mainly reacts to the famous exogenous supply disruptions in oil market like the 2003 Invasion of Iraq by the US and the political turmoil in Libya in 2011. This shows that the upside risk can serve as the exogenous measure we hoped to find in order to capture the causal relationship between oil risk and macroeconomic variables.

We are interested in determining whether the risk premia are priced factors in the cross-section of stock returns. The ICAPM implies that *innovations* to these factors are relevant. (Chang *et al*(2013)). As seen visually in Figure 2, the portfolio values exhibit considerable persistence. Therefore, in order to determine innovations to these factors, we fit ARMA models to the time-series of the values each of the three portfolios in order to strip out time series predictability. We utilize the minimum-AIC to determine the optimal model specification. We run 100 combinations of models with from one to ten autoregressive lags, and one to ten moving average terms.

Figure 3 shows the autocorrelation function for residuals of the models mentioned. Based on the min-AIC we select ARMA (5,5), ARMA(9,6) and ARMA(3,1), for variance, downside jump risk, and upside jump risk portfolios, respectively. We then calculate the innovations in the portfolio values as follows:

$$VRP = Portfolioval_{Delta-Gamma} - \widehat{Portfolioval}_{Delta-Gamma} \tag{17}$$

$$URP = Upportfolioval_{Delta-Vega} - \widehat{Upportfolioval}_{Delta-Vega} \tag{18}$$

$$DRP = Downportfolioval_{Delta-Vega} - \widehat{Downportfolioval}_{Delta-Vega} \quad (19)$$

where $\widehat{Portfolioval}_{Delta-Gamma}$, $\widehat{Upportfolioval}_{Delta-Vega}$ and $\widehat{Downportfolioval}_{Delta-Vega}$ are the fitted values of the ARMA models fitted for each of the VRP, URP and DRP value portfolios respectively. The resulting premia are plotted in Figure 3. The “RP" notation refers to portfolio value, and risk premium, because as noted above, the innovations in portfolio values reflect unexpected changes in variance and jump risk premia.

III. Results

A. *Determinants of VRP, DRP and URP*

One natural question to ask is what are the macroeconomic and commodity-specific determinants of the variance, upside jump and downside jump risks in oil market? Looking at Figure 1 we can see that the time series of the portfolio value related to the three risks, especially portfolio values belong to DRP and URP, show spikes around some known geopolitical events. In the case of DRP, the spikes can be seen around the time that the oil market have been heading towards lower prices. Looking at the DRP's time series, we can see that there is one sub-period that the downside risk portfolio value is showing much more volatility. This sub-period is the 1986-1990 sub-period, during which the price of oil was in free-fall as a result of weakened demand which caused an oil glut. There also ware many problems inside OPEC, as a result of countries not abiding by the rules of the cartel. Also, Saudi Arabia left its role as a production swing and caused a huge oil glut in the market. In the case of URP, most of these geopolitical events are the ones that have resulted in supply disruption in crude oil market. There are some incidents that have not cause supply disruption but have increased the expected probability of supply disruptions in the future. The first and second Persian Gulf Wars in 1990 and 2003 respectively are two examples of geopolitical events that resulted in real supply disruption. The terrorist attack of 9/11 in 2001 and Israel-Hezbollah war in 2006 are two examples of geopolitical incidents that have affected the time-series of URP while it has no effect on the real supply flow of crude oil. These are clear graphical indications of the effect of geopolitical events that directly and indirectly affect the crude oil market.

The next step would be to investigate the determinants of the three risk premia using statistical methods. Tables I and II show the regressions of VRP, DRP and URP on some of the most relevant determinants of crude oil market risks in contemporaneous and predictive framework. The determinants we test here are total world crude oil supply growth, proxied by total world crude oil production growth, the index of geopolitical risk by Caldara and

Iacoviello (2018), total world crude oil demand growth, proxied by total OECD countries crude oil consumption growth and news uncertainty proxied by the news VIX index by Manela (2017). We can see in the first table that none of these variables have an statistically significant relationship with the VRP. We also are not able to detect any significance in the case of DRP. We can see that among the four variables, the geopolitical risk index is the only statistically significant determinant of the URP. As expected, the coefficient of the geopolitical risk index is positive. This means that by higher geopolitical tensions, the upside risk-neutral jump in crude oil market is going to be higher. Table II presents the predictive results using the first lag of variables, after controlling for the first lag of the premia. The results show that the VRP cannot be predicted using the lags of the four variables. The first lag of geopolitical risk index is significant in the case of DRP and URP. For DRP, the first lag of geopolitical risk index is statistically significant at the 90% confidence level. The model is also able to describe 4.3% of the variation in DRP. The first lag of geopolitical risk index is also strongly significant in the case of URP. The coefficient is still positive, as expected, and the model provides R-squared equal to 3.6%. Overall, we can conclude that the VRP in oil market cannot be explained, using any of these four factors. The DRP and URP cannot be explained by supply and demand and news uncertainty, but their variation can be explained (to some extent) by the geopolitical risk index. Among the two, the URP looks more responsive to geopolitical risk index, as it shows meaningful relationship with the index both in the contemporaneous and predictive frameworks.

B. *Oil Risk Premia and the Cross-Section of Stock returns*

In this section, we investigate if the three oil premia can be identified as drivers of the cross-section of stock returns. We implement the standard methodology adopted by many papers in this field before. First, we calculate the sensitivities of individual stock returns to the risk premium factors. We calculate these sensitivities both in uni-variate regressions, but also in regressions that include the other risk premia as controls. Then, we sort stocks into portfolios based on the estimated sensitivities. Third, we calculate the returns on these portfolios, and the return on a position consisting of a long position in the highest-sensitivity portfolio and a short position in the lowest-sensitivity portfolio. We then calculate the Jensen's α for the individual portfolios, and the long-short portfolio. We are looking after two signs of significance in this analysis. First, we want to see if moving from lowest to highest sensitivity portfolio we can spot a clear downward or upward trend in the return of the portfolios. Second, we want to know if the Carhart Alpha of the high-low portfolio is statistically significant. The presence of these two factors can be interpreted as a sign of the factors being priced in the cross-section of stock returns.

B.1. Sorting Based on Exposure to VRP

According to the ICAPM, if the premia are priced factors in the cross-section of stock returns, then the returns on stocks should depend on their sensitivities to the risk premia. In this section, we would test whether VRP is a priced factor. Ang, Hodrick, Zhing and Zhang(2006) shows that the higher is the sensitivity of a stock to innovations in market volatility, the lower is the average return of the stock, using the data in NYSE/AMEX/NASDAQ between 1990 to 2012. Our approach is related, but somewhat different, in that we use sensitivity to VRP in the oil market. Moreover, we control for sensitivities to URP and DRP of oil market when estimating the sensitivity to VRP, and show this has some impact on the results.

Following Chang, Christofferson and Jacobs (2013) and Christofferson and Pan (2015), we use daily returns on NYSE, AMEX and NASDAQ stocks and a 60-day estimation window in order to estimate time varying factor exposures. At the end of each month, we run one of the following three regressions for each of the stocks in the sample to get the sensitivity of the stock's return to VRP:

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{VRP} VRP + \varepsilon_{i,t} \tag{20}$$

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{VRP} VRP + \beta^i_{DRP} DRP + \varepsilon_{i,t} \tag{21}$$

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{VRP} VRP + \beta^i_{DRP} DRP_t + \beta^i_{URP_t} URP_t + \varepsilon_{i,t} \tag{22}$$

Note that (20) estimates β^i_{VRP} controlling only for the market return, while (21) and (22) control for DRP only and DRP and both URP, respectively.

At the end of each month, we sort all stocks in the data based on the estimated sensitivities to the VRP(measured by β^i_{VRP}). We then form five portfolios of the sorted stocks, portfolio one having the lowest and portfolio five having the highest exposure to VRP. We then calculate the time-series of post-ranking returns of each of these five portfolios during the following 30 days. Each month, we roll the window for one month and repeat this procedure through the sample period. This procedure produces daily returns for the five portfolios during the sample period.

We next estimate the following regression on the daily return data:

$$R_{p,t} - R_{f,t} = \alpha^p + \beta^p_{MKT}(R_{m,t} - R_{f,t}) + \beta^p_{SMB} SMB_t + \beta^p_{HML} HML_t + \beta^p_{UMD} UMD_t + \varepsilon_{p,t}$$

where $R_{p,t}$ is the return of each portfolio, SMB and HML are the Fama-French (1993) size and value factors respectively, and UMD is the momentum factor from Carhart (1997). Significance of the α^p implies that the factor is priced in the cross-section of stock returns.

Table III reports the average pre-ranking βs, the Jensen's α, and the average post-ranking monthly returns. In all the tables presented in this paper, we report the p-Value of Jensen's α calculated using Newey-West with 21 lags. Panels A, B and C present the results of the analysis based on regressions (20), (21) and (22). Columns 1 to 5 present the results for five sorted portfolios, portfolio 1 having the lowest and 5 having the highest exposure to VRP. We also report the average return and the Jensen's α for the portfolio that longs the highest exposure quintile portfolio and shorts the lowest exposure quintile of stocks. Results for this strategy are reported in column 5, labeled "5-1". The average monthly Jensen's α is the estimated intercept multiplied by 21 to report a monthly value.

Panel (A) shows that the difference between the Jensen's alpha of portfolio 5 and Jensen's alpha of portfolio 1 is -0.40%. Also, the average monthly difference between the return of portfolios 5 and 1 is -0.34 %. The Jensen's alpha of the high-low portfolio is statistically significant at the 95% confidence level. Overall we can say that oil VRP is a priced factor in the cross-section of stock returns before we control for DRP and URP.

The results for portfolios sorted on VRP after controlling for DRP, and DRP and URP, are presented in panels B and C respectively. These two panels exhibit a similar pattern for Jensen's alpha and average portfolio returns as seen in panel A. However, the Jensen's α show no statistical significance at the 90% confidence level in the two latter cases. Thus, the results provide no evidence that the innovations in oil VRP is a priced factor in the cross-section of stock returns after we control for downside and upside jump risk premia. In other words, the variance risk premium is only a significant driver of the cross-section of stock returns if we do not control for the jump risks.

Figure 4 depicts the average monthly return and monthly Jensen's alphas of the hedge portfolio through time, based on a 5-year rolling window. They also display the Newey-West t-stats and the 90% confidence level bounds. These diagrams shed light on how average return and Jensen's α are evolving through the sample period. Looking at the top two graphs we can see that the t-stats associated with average return of the high-low portfolio in the case of VRP are much closer to the confidence bounds during the two sub-periods of 1990-2000 and 2008-2014, in comparison to the period of 2000-2008.

The middle two graphs present the behavior of the α and the statistical significance after controlling for DRP, when estimating exposure to VRP. The graphs show that controlling for DRP makes the results weaker, as the t-stats get far from the confidence bounds after controlling for the new factor.

The bottom two figures present the results, controlling for URP and DRP when estimating VRP sensitivity. It demonstrates that after controlling for URP, VRP is clearly not a priced factor during any sub-period. This suggests that previous empirical findings in the literature that oil variance is a priced factor may reflect a specification error, namely, that variance risk estimates are affected by exposure to upside jump risk, and once this risk is controlled for, oil variance no longer has any power to explain the cross-sectional variation of stock returns.

B.2. Sorting Based on Exposure to DRP

We now evaluate the performance of stock portfolios stocks sorted based on their exposure to DRP. In addition, regression (20) is replaced by the following regression:

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{DRP_t} DRP + \varepsilon_{i,t} \tag{23}$$

Table IV presents the results. Focusing on Panel C, which shows the results for the case of sorting based on the exposure to DRP, after controlling for VRP and URP, there is no evident trend in average returns and Jensen's α's moving from least to most exposed portfolio, which is consistent with DRP not being a priced factor. The average monthly return of the high-low portfolio is -0.09% and the α of the high-low portfolio is -0.11% and neither is statistically significant. Thus, there is no evidence for DRP being a priced factor in the cross-section of stock returns.

Figure 5 reinforces this point. It presents the graphs of the time series of monthly returns and Jensen's α for portfolios formed based on the exposure to DRP. The top two graphs show the results for the case of sorting based on the DRP without controlling for VRP and URP. The t-statistics are far from the confidence bounds for most of the sample years. The middle and bottom two panels of this figure show that controlling for VRP and URP when calculating DRP's sensitivity, does not fundamentally change the results.

B.3. Sorting Based on Exposure to URP

We now present the results based on portfolios sorted on sensitivity to URP. In this analysis, regressions (20) and (21) are replaced by the following two regressions respectively:

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{URP} URP + \varepsilon_{i,t} \tag{24}$$

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{VRP} VRP + \beta^i_{URP_t} URP + \varepsilon_{i,t} \tag{25}$$

Table V reports the results. In panel A, the downward trend in average monthly returns as one moves from the low-sensitivity to high-sensitivity portfolios is very clear. The average monthly return for the case of sorting based on exposure to URP, without controlling for the other premia, is -0.55%. The Jensen's α associated with the high-low portfolio is -0.44% and its P-Value is 0.06 which indicates that the Jensen's alpha is statistically significant at the 90% confidence level. Panels B and C present the results when we also control for VRP and DRP. Controlling for the VRP and DRP has a slight effect on the magnitude of returns and Jensen's α, but the results are quite similar. As shown in panel C of this table, controlling for the latter two variables reduces the absolute value of the average monthly return of high-low portfolio to -0.5%, but the average monthly return is still high in absolute value. The table also shows a downward trend in average returns going from low to high sensitivity portfolio. Also, the high-low portfolio's Jensen's α remain statistically significant after controlling for these two additional factors.

Figure 6 presents the evolving average monthly returns, the Jensen's α and the t-statistics associated with them for the URP's high-low portfolio. The figure contains interesting information which shows how the significance of the factor has changed over time and along major events in the oil market. Moving from early 1990s to 2000, the average return of the high-low portfolio decreases from positive to negative returns. The bottom-right graph shows that in the time period of 2000-2008 the Jensen's α associated with high-low portfolio is statistically significant at the 90% confidence level.

The transition from significance to insignificance for Jensen's α occurs in 2008. After that time, the average returns and Jensen's α are small in absolute value and are not statistically significant at the 90% confidence level. The timing of this change is suggestive, given that 2011 also represents the time at which shale oil production in the US began its dramatic increase. Before 2008 and as a result of increasing growth in oil demand and lack of excess capacity, the price of oil was a place of concern for the oil importing economies, including US economy. As the shale revolution in the US showed its effect as a considerable increase in oil production inside the US, it seems the price of risk for the upside jump risk in oil market has been decreased. We will empirically investigate this phenomenon below.

In sum, whereas there is little evidence that VRP and DRP are priced factors, there is strong evidence that URP is a priced factor in the cross-section of stock returns, at least after 2008. Stock returns vary with exposure to URP, even after controlling for sensitivity to VRP and DRP. Moreover, greater exposure to URP is associated with lower stock returns.

IV. The sub-periods

As seen in the previous section, URP is a significant driver of the cross-section of stock returns. We know that the oil market has been experiencing continuous fluctuations from both supply and demand perspective. The period of 1986-2014 can be broken down into (at least) three sub-periods. looking at figure 6 can be very informative about the sub-periods. As we can see, the URP is no a priced risk factor in the cross-section of returns before 2000. The URP risk is statistically significant as a driver of the cross-section of stock returns from 2000 to 2008. After 2008, there is no significance for the URP again. This primary observation makes it worthwhile to look at each of these three sub-periods separately.

A. 1986-2000

Following the 1970s energy crisis, through which the energy price increased substantially, the demand for oil was in free fall at the beginning of 1980s. As a result, the so-called "Oil Glut" phenomenon showed itself in oil market. The increase in production of non-conventional oil resources (specially the ones from non-OPEC countries) exacerbated the situation in oil market. OPEC countries reduced their oil production with the hope that the lower supply would stabilize the oil prices. The only result of this action was that the OPEC countries lost a considerable amount of their market share from aggregate oil supply in the world. OPEC members could not reach an agreement for suppressing their oil production, which resulted in lower oil prices. Although there was some ups and downs in the price of oil as a consequence of changing supply-demand balance, there was no clear upward pressure from the demand side which could not be answered by the oil producers. It seems this lack of demand pressure has caused URP, as a factor which measures the importance of geopolitical events, insignificant through this sub-period.

Panels A,B and C of table VI show the results for VRP, DRP and URP during the first sub-period, 1986-2000. Panel A shows the result for the case of sorting based on exposure to VRP. Sub-Panel A1 is showing the result when we sort based on VRP without controlling for DRP and URP. We can see that a downward trend in average monthly returns can be seen moving from low to high exposure portfolio. The average monthly return of the high-low portfolio is -0.35%, and the Jensen's α associated with this portfolio is significant at the 90% confidence level. Sub-Panels A2 and A3 show that after controlling for DRP and URP, the average monthly return of the high-low portfolio is about the same as previous sub-panel. Also, the associated Jensen's α is not statistically significant in these cases. Overall, the evidence shows that VRP is a priced factor in the cross-section of stock returns for the sub-period 1986-2000.

Panel B presents the results in case of DRP. Sub-Panels B1, B2 show the results when sorting based on DRP without and with controlling for VRP , respectively. In both cases, there is a clear downward trend in average returns of the high-low portfolio (with one exception). The Jensen's α of high-low portfolio is not statistically significant at the 90% at the case of sorting based on DRP, without controlling for VRP and URP. Sub-Panels B2 and B3 shows that after controlling for VRP and URP, with one exception, there is still a downward trend in average monthly returns of the high-low portfolio. The Jensen's α is also statistically significant in this case, in contrast to previous two sub-panels. The average monthly return of the high-low portfolio in the case of controlling for VRP and URP is -0.21%.

Panel C and its sub-panels show the results for the case of sorting based on URP. Sub-Panels C1, C2 and C3 show that the average monthly returns of the high-low portfolio are very small in the case of controlling for no other variable than URP, controlling for VRP and controlling for VRP and DRP together, respectively. In neither of the three cases the Jensen's alpha is significant at the 90% confidence level. Overall, the results of this Panel show that the VRP and DRP are the significant factor in the cross-section of stock returns in the period 1986-2000. It also shows that URP is not a priced factor in this sub-period.

B. 2000-2008

After a short period of economic recessions in in Asian economies from 1997 to 1999, they started to revive very quickly. During the period 2000-2008 many of the commodity prices increased sharply. The phenomenon of sharp rise and fall of commodity prices within this sub-period is named the "Commodity Super-cycle". The rising demand from emerging markets, particularly china, was the main reason for the dramatic increase in commodity prices during this period. China was a net exporter of petroleum in the early 1990s. In late 1990s still the daily petroleum import of the country is less than 1 million barrel per day. By 2007 the net petroleum import of China was about 4 mbd, which made china one of the biggest oil importers in the world. The aggregate world demand for crude oil increased by 6% in 2003-2005 period. Although most of the scholars agree that during this period demand has played a big role in increase of oil prices, the natural question would be why this has never happened before the 2000s while the continuous growing demand of crud oil can be obviously detected, at least from early 1980s. The answer to this question can be very helpful for and relevant to our analysis. In fact, the reason for huge increase in the price of oil was not only demand growth but also supply growth being constrained and not be able to keep up with demand's. As an example, the amount of oil supplied in the first half of 2008 is not different from what was supplied in 2005, while there has been a huge increase in the aggregate demand level during these three years. In this very tight supply-demand framework, any supply disruptions or fear of supply disruption as a result of some energy-related geopolitical events can be very important in shaping the expectation of energy market participants and all the asset holders which their assets are impacted by shocks to energy markets. To investigate if this sub-period of 2000-2008 is different in terms of significance of oil risks as drivers of the cross-section of stock returns, we look at the result of analysis for this sub-period only. The results are shown in table VII.

Panels A,B and C of the table show the results for VRP, DRP and URP during this sub-period. Panel A shows the result for the case of sorting based on exposure to VRP. Sub-Panel A1 is showing the result when we sort based on VRP without controlling for DRP and URP. We can see that there is not clear downward (or upward) trend in the average monthly returns of high-low portfolio. The absolute value of the average monthly return of the hedge portfolio is very small and the Jensen's α associated with this portfolio is not significant at the 90% confidence level. Sub-Panels A2 and A3 show that after controlling for DRP and URP, the average monthly return of the high-low portfolio is much smaller and the associated Jensen's α is even less statistically significant. Overall, the evidence shows that VRP was not a priced factor in the cross-section of stock returns for the sub-period 2000-2008.

Panel B presents the results in case of DRP. Sub-Panels B1, B2 show the results when sorting based on DRP without and with controlling for VRP respectively. In both cases, there is not a downward trend in average returns of the high-low portfolio. The Jensen's α of high-low portfolio is not statistically significant at the 90% confidence level. Controlling for VRP reduces the magnitude of the average return. Sub-Panel B3 shows that after controlling for URP, with one exception, there is no trend in average monthly returns of the high-low portfolio. The Jensen's α is not statistically significant in this case, as in previous two sub-panels. This can be interpreted as no statistical significance for the DRP during this sub-period.

Panel C and its three sub-panels show the results for the case of sorting based on exposure to URP. Sub-panel C1 shows that the average monthly return of the portfolios has a clear downward trend moving from the least-exposed to most-exposed portfolio. The average monthly return of the high-low portfolio is -1.59%. Also, the Jensen's alpha is statistically significant at the 99% confidence level. Sub-panel C2 is showing the results for the case of sorting based on sensitivity to URP, controlling for VRP. The results show that the downward trend in average monthly return of the portfolios is even more evident than the previous case. the Jensen's alpha is also significant at the 99% confidence level. The last sub-panel shows the results for the case of sorting to exposure to URP, after controlling for VRP and DRP both. With one exception we can still observe the downward trend in average monthly returns of portfolios, moving from lowest to highest exposure portfolio. The average monthly returns of the high-low portfolio in this case is -1.28% and the Jensen's alpha is statistically significant at the 95% confidence level. Overall, there is convincing evidence which shows that URP in oil market is one of significant drivers of the cross-section of stock returns in the sub-period of 2000-2008.

C. 2009-2014

As we noted in the previous section, oil prices were experiencing a continuously increasing trend, beginning at the early 2000s and continuing to mid-2008. It was in July 2008 that the oil price reached the $145 per barrel as a result of the demand pressure and supply not being able to keep up with demand. This was caused by the very low spare capacity of the main oil-producing countries at that time. By the end of 2008 and as a result of the financial crisis and severe decrease in demand, the oil price plummeted to around $30 per barrel. As a result, OPEC slashed its production considerably and this action resulted the price of oil to be more than doubled between 2009 and 2011. But there was a different phenomenon developing during the same time period which changed the shape and dynamics (in terms of supply constraint and scarcity) of the oil market forever. The emergence of two oil drilling technologies, horizontal drilling and hydraulic fracturing, changed the dominance of cartels like OPEC in the supply side of the oil market. The so-called "Shale (fracking) Revolution" made U.S. oil production to start rising in 2009. The increasing trend in oil production in the U.S. has made the country the largest oil producer among all the oil-producing countries.

A brief look at Figure 6 shows that after 2008 the Jensen's alpha of the high-low portfolio in the case of sorting based on URP is getting far from the confidence bound in comparison to the 2000-2008 period. Figure 4 also shows that the Jensen's alpha for the case of sorting based on VRP is getting close to the confidence bound in comparison to the same period. From our understanding, having the substantial changes in the supply-demand framework and also having the change in the pattern of significance of upward jump and variance risks at the same period is more than a coincidence. It seems that the shale revolution has substantially decreased the fear of demand pressure and relative supply shortage. As an outcome, the URP which is tightly linked to geopolitical events that cause of supply disruption in oil-producing countries, is weakened in terms of its significance as a driver of the cross-section of stock returns. We will statistically investigate the validity of our argument in the following paragraphs.

Table VIII shows the results for the period 2009-2014. Looking at all the panels and sub-panels of this table, we can observe that VRP and DRP are not significantly priced factors in the cross-section of stock returns. Neither the decreasing (increasing) pattern in average monthly returns, nor the statistical significance of the Jensen's α can be detected for these two factors.

Panel C, which shows the results for URP, exhibits a different pattern. There is a clear downward trend in the average monthly returns of portfolios, moving from low to high exposure. Sub-Panel C3 shows that the average monthly returns for the portfolios in the case of sorting based on URP, after controlling for both VRP and DRP. The average portfolio return decreases from % 0.36 to % 0.27 moving from the lowest towards the highest exposure portfolios. Although we can detect the clear downward trend in the return of the portfolios, the Jensen's *alpha* associated with the high-low portfolio is not statistically significant. This can be due the fact that the absolute value of the average monthly return in this case is much lower in comparison to the ones from previous sub-periods. Overall, we can conclude that the URP is a significant driver of the cross-section of stock returns after 2008 but its associated price of risk is not as significant as it was during the 2000-2008 period.

These findings are intriguing. One possible explanation is that the greater flexibility of shale production reduced the potential for oil price spikes, but full explanation requires further research.

D. *Oil Risk Premia as Macroeconomic Predictors*

As pointed out before, there is a considerable number of papers which document connections between oil price shocks and the macroeconomy. The causality goes in two directions: from oil price shocks to macroeconomic activity, and from macroeconomic activity to oil prices. Given the connection between oil prices and macroeconomic activity, and the forward-looking nature of oil options prices, the oil price-macroeconomy linkage suggests that our risk premium measures might be able to predict various macroeconomic variables including GDP growth, consumption growth, and investment growth. Further, links between macroeconomic variables and equity returns, and between macro variables and our measures of oil price risk, raise the possibility that the oil risk measures may help predict the time-series of stock market index returns. We investigate these possibilities now.

We employ macroeconomic data obtained from Federal Reserve Economic Data (FRED) and the OECD[3]'s website. Specifically, we examine growth in: monthly NVIX; monthly

[3]Organization for Economic Co-operation and Development

US interest rate proxid by 3-month T-bill; monthly US unemployment rate ; monthly default premium proxied by the spread between Mooody's Aaa and Baa rates; monthly US consumption growth proxied by personal consumption expenditure growth; monthly US inflation proxied by changes in consumer price index ; monthly US total investment growth and quarterly US GDP growth. We regress these variables on contemporaneous and lagged risk premium measures to evaluate the predictive power of the latter.

Table IX reports the results for $\Delta \mathrm{NVIX_t}$. Regressions 1 to 4 show the AR(4) models to predict $\Delta \mathrm{NVIX_t}$ by the first four lags of VRP, DRP and URP respectively. The results show that VRP and DRP are not showing statistical significance both in terms of coefficients and adjusted R-squared. Column 3 shows that the results in the case of URP is different from two previous predictors. The second lag is showing statistical significance and our AR(4) model is able to describe 2% of variation in $\Delta \mathrm{NVIX_t}$. Also the positive coefficient is in-line with our expectation as higher implied jump is expected to be the source of higher level of uncertainty in financial markets.

The NVIX index is composed of some underlying factors which control for uncertainty in different sections and from different sources in the economy. One of these sub-indexes is $\Delta \mathrm{NVIX_{Securities}}$ which is a gauge of uncertainty in the financial markets. Table X shows the prediction power of our risk premia for this variable. The results presented in columns 1 and 2 show that there is not much of significance in the AR models based on VRP and DRP. Like the previous case, the results of model 3 is totally different from previous models. The second lag's coefficient of URP is statistically significant (and positive as expected) and the R-squared is 4.3%.

Table XI is presenting the results for predicting changes in 3-month T-bill, which is calculated as the first difference of the monthly rate. The results from columns 1 and 2 show that although we are detecting some statistical significance for a couple of lags' coefficients in the case of VRP and DRP, the R-squared generated by the model is so low that we cannot claim that there is any prediction power in the models built on lags of VRP and DRP. Like previous variables, URP is the only variable which is showing statistical power, in terms of R-squared, for predicting changes in the changes in the interest rate. As can be seen, the model provides R-squared equal to 2.2%.

The next macroeconomic variable of interest is the US unemployment growth rate. Table XII shows the result for predicting this variable. The very interesting thing here is that in contrast to previous cases where URP was the only significant factor in explaining macroeconomic variables, here the most important factor in predicting the growth in unemployment level is VRP. When looking to the determinants of the premia in previous sections, we found that VRP seems to be correlated with the demand of oil, while DRP and URP seem to be correlated with and driven by the supply side. This table is implying the same mechanism. The VRP (which is correlated with demand for oil, which itself is a function of the total demand in the economy) is a significant predictor of unemployment rate, with positive coefficient as expected, and provides R-squared equal to 1.5%. DRP is showing some significance but does a poor job in terms of the R-squared. The VRP is not showing any significance, neither in terms of coefficients nor the model's R-squared.

One of the other variables of interest is the Default Premium. The way we define the variable is the first difference of Moody's monthly (Aaa-Baa) rate. This variable is used as a gauge of financial disaster and recession risk in the economy. We expect that higher change of recession and financial problems will be translated into more negative default premium. We know from the literature that oil price spike has been blamed for recession, unemployment and many other macroeconomic problems. With the same logic we expect the risk-neutral jumps to be a determinant and predictor of default premium. Table XIII shows the result for the case of default premium. It is clear that VRP and DRP are not playing an important role in describing the variation in default premium change. Looking at regression 3 though, we can see that the first lag of the URP is statistically significant with a negative sign. This is in-line with our prior expectations. Also we can verify that the URP is playing a relatively important and strong role in predicting default premium change, providing 1.6% of R-squared.

One of the most important variables for researchers in different areas of finance and economics, especially asset pricing, is consumption (growth). The consumption is historically the most volatile component of GDP. As a result, we expect to detect a connection between the risk measures of oil market we calculating and consumption growth, as the relationship between oil and GDP is stablished in the literature. The variable here is proxied by growth in personal consumption expenditure in the United States. Table XIV presents the results for the case of predicting consumption growth, which is being measured as the growth in personal consumption expenditure in the US economy. Again, the VRP and DRP variables are showing weak results. Regression 3 though is showing that URP has a very interesting ability in predicting the future consumption growth. Lags 1,3 and 4 are statistically significant and negative as expected. This means higher implied jumps today predict lower consumption growth in the future. The AR(4) model consists of the lags of URP also is providing R-squared of 5.7%, which is a considerable level in comparison to the prediction power of other predictors.

The other component of GDP which grabs a lot of attention in macroeconomics and finance literature is total investment growth. Table XV is presenting the regression of the quarterly total investment in the US on the lags of the oil premia. It is an established fact in the literature that oil implied variance has the ability of predicting macroeconomic investment with negative sign. The results from the table verifies the previous findings in the literature. Column one is showing the results for the contemporaneous regression. Among the three variables, URP is showing statistical significance but the R-squared provided by the model is not considerable in terms of its magnitude. Columns two to 5 are showing the results for the models including 1st to 4th lags of the three risk premia respectively. in all the regressions, and in-line with the previous findings of the literature, VRP is the most important variable in terms of providing the highest R-squared. The other observation is that the coefficient of the VRP is consistently negative,, meaning that the higher is the variance risk premium, the lower will be the total investment growth.

Among all the macroeconomic indexes, GDP growth is the most important variable for both practitioners and academicians. Table XVI is presenting the result for the quarterly US GDP growth and the ability of the three premia from oil market in predicting this macroeconomic variable. As we showed before, the VRP and URP have the ability of predicting investment and consumption growth which are the most important components of GDP growth. So, we expected the two risk premia to have the ability of predicting GDP growth with the same signs they had in predicting its components.Column 1 shows the result for the contemporaneous regression analysis. As we can see, the URP has negative coefficients and the URP provides considerable R-squared of 8.7%. Columns 2 to 5 are showing the results for the models with 1st to 4th lags of the premia. The results validate the hypothesis of VRP and URP predicting GDP growth with negative sign. It can also be seen from column 2 that the first lag of DRP is also significant and negative.

E. Oil Risk Premia as Predictors of the Oil Market Fundamentals

In this section, we examine whether the risk premia predict various oil market metrics. The first variable is returns on front-month WTI crude oil futures. We regress the monthly return of the front month futures against the lagged risk premium measures which is the average daily risk premium of the month prior to the month in which the oil return is measured. The first lag is the average return of the front month contract during the last month, the second lag is the same measure for a month prior to last month, and so on.

The results are presented in table XVIII. VRP and DRP have no predictive power, so the table presents only results for URP. Columns 1 to 3 report the results of univariate regressions of oil return on the first, second, and third lagged URP, respectively. The second and third lags are significant at the 90% confidence level. The R-squared provided by these AR(2) and AR(3) models are 1.2% and 0.7% respectively. The coefficients of the two lags are negative as expected. Column 4 shows that the combination of these two lags provide evidence of some predictive power, as indicated by the R-squared of 2.2%. We can also see that the coefficient on both of the lags are negative in this model as well. Column 5 shows that controlling the first lagged futures returns decreases the significance level of the third lag of URP while the second lag's significance remains intact.

Table XVII presents the results of predictive regressions using oil inventory growth as the dependent variable. The VRP provides stronger evidence of predictive power than either DRP and URP. Whereas the R-squared values for DRP and URP are -0.6% and 0.7%, the R-squared in the case of VRP is substantially larger, at 1.5%. Also, we can see that the coefficients on the significant lags of VRP and URP are negative. Column 4 shows that the significance of VRP and URP lags which were significant stays intact after controlling for lags for the other predictors.

Table XIX presents results for the case of the oil demand growth. Based on theory, we expect higher uncertainty would result on demand to be higher in order to increase the inventory which works as a cushion for consumers of crude oil against the uncertainty in this market. As shown in the column 1 of the table, the second lag of VRP is significant with a positive coefficient as expected. The R-squared provided by the lags of VRP for forecasting demand growth is 1.6%. The DRP is not showing a considerable power in predicting demand growth and it provides a negative R-squared. Column 3 shows that the same logic that makes the coefficient positive holds in the case of URP as well. Logically, if the consumers expect some sort of upward jumps in the price of crude oil, they will increase their demand to increase the crude oil inventory level, which makes them capable of insuring themselves against the geopolitical risks that might cause disruption in supply of crude oil. The first lag of the URP is significant with positive coefficient. The R-squared of the model is 2.6%. All in all, it seems both VRP and URP are important in predicting oil demand growth but the URP is showing a higher predictive ability.

Tables XX and XXI investigate the power of the oil premia to predict the total crude oil supply growth and also OPEC's crude oil supply growth. Table XX shows the results for the case of world crude oil supply production. Earlier in the paper, we showed that the only factor which can describe and predict the variation in upside jump risk premia is geopolitical tensions risk. So, we would expect the upside risk premia to be the most relevant variable for predicting total oil supply growth. The table shows that among the three factors we extracted from oil securities the only significant predictor is the URP. The coefficient of the third lag of this variable is negative, as expected, and the R-squared provided by the lags of the URP is 1.8%.

Lastly, we examine the relationship between oil risk premia and OPEC production growth. The results, presented in table XXI, show that the R-squared in the regression using the third lag of URP equals to 3.7% and its coefficient is negative. The R-squared in the case of VRP is around 1.5% and the one associated with the DRP's regression is negligible. The significant lags in both of the cases of VRP and URP are negative. This again, shows that the URP is the most important predictor of the variables of interest in the oil market, among the three premia.

In sum, the URP and VRP have some power to predict oil market variables, including oil futures returns, inventory growth, and OPEC production growth, URP having greater effects than the VRP. The DRP has little or no predictive power.

V. Conclusion

In this article, we examine whether these risk premia are priced factors in the cross-section of stock returns. We also examine whether risk premia associated with upside and downside jumps in oil prices have power to predict macroeconomic variables and oil market fundamentals. We find that the risk premium associated with upward jumps is priced in the cross-section of stock returns for a large portion of our sample period, but the significance diminishes after 2008–which corresponds to the acceleration in the shale oil boom in the US. Premia associated with downside jumps are not priced throughout the entire period. Premia associated with variance risk are generally not priced too. Finally, we find that jump premia have predictive power for important macroeconomic variables (e.g., GDP growth) and oil market fundamentals (e.g., inventory growth).

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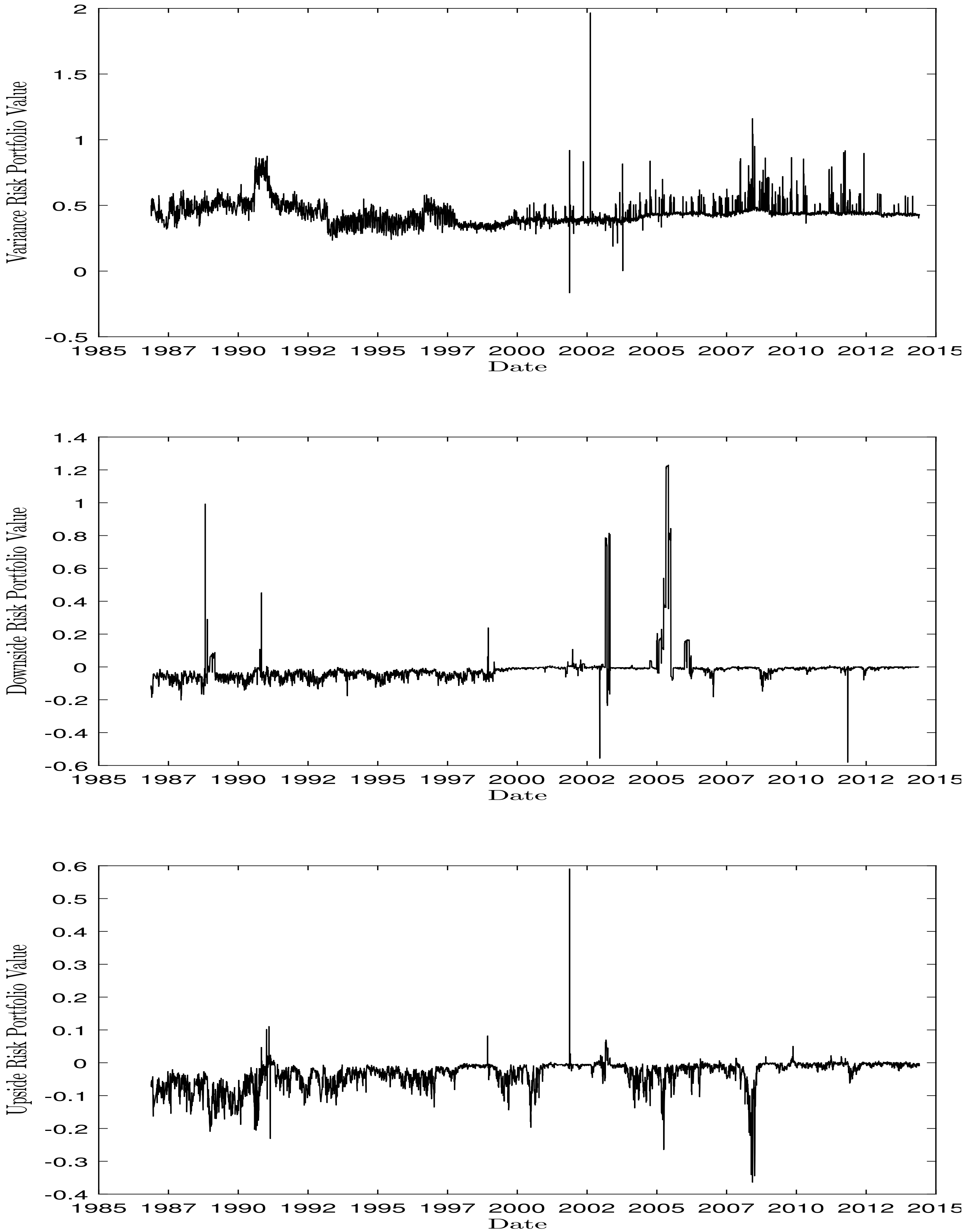

Figure 1.
This figure shows the time-series of the value of 60-days Variance Portfolio, Downside Jump Portfolio and Upside Jump Portfolio in oil market . The data ranges from 1996 to 2014.

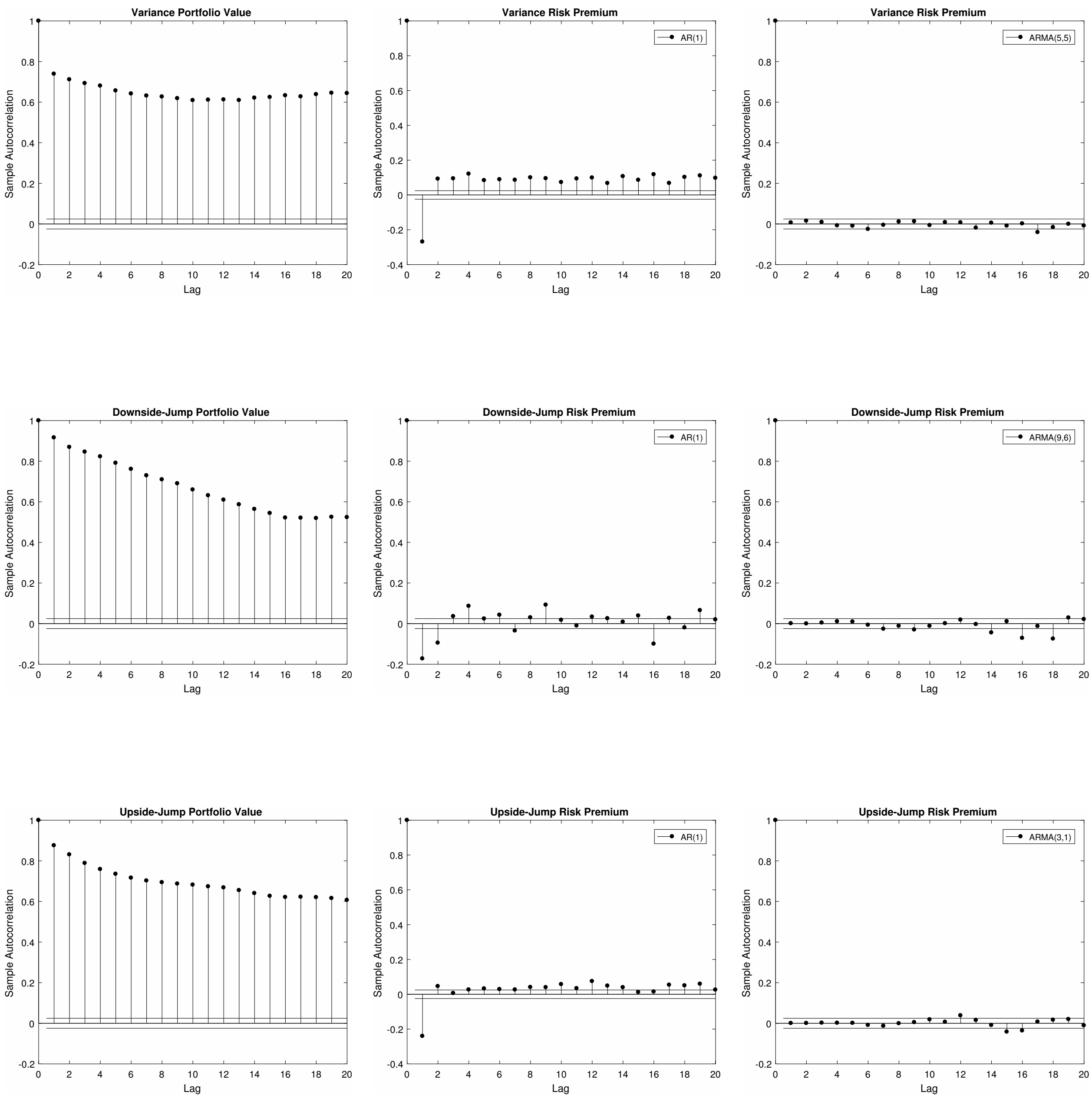

Figure 2. This figure shows the sample autocorrelation functions for different processes. The vertical axis is sample autocorrelation in all the graphs and the horizontal axis shows the number of lags. The top row, middle row and bottom row are showing autocorrelations for variance, Downside Jump and Upside Jump respectively. The graphs show Variance Portfolio Value, Variance Risk Premium based on AR(1), Variance Risk Premium based on ARMA(5,5), Downside-Jump Portfolio Value, Downside-Jump Risk Premium based on AR(1) model,Downside-Jump Risk Premium based on ARMA(9,6) model, Upside-Jump Portfolio Value , Upside-Jump Risk Premium based on AR(1) model and Upside-Jump Risk Premium based on ARMA(3,1) model in oil market.

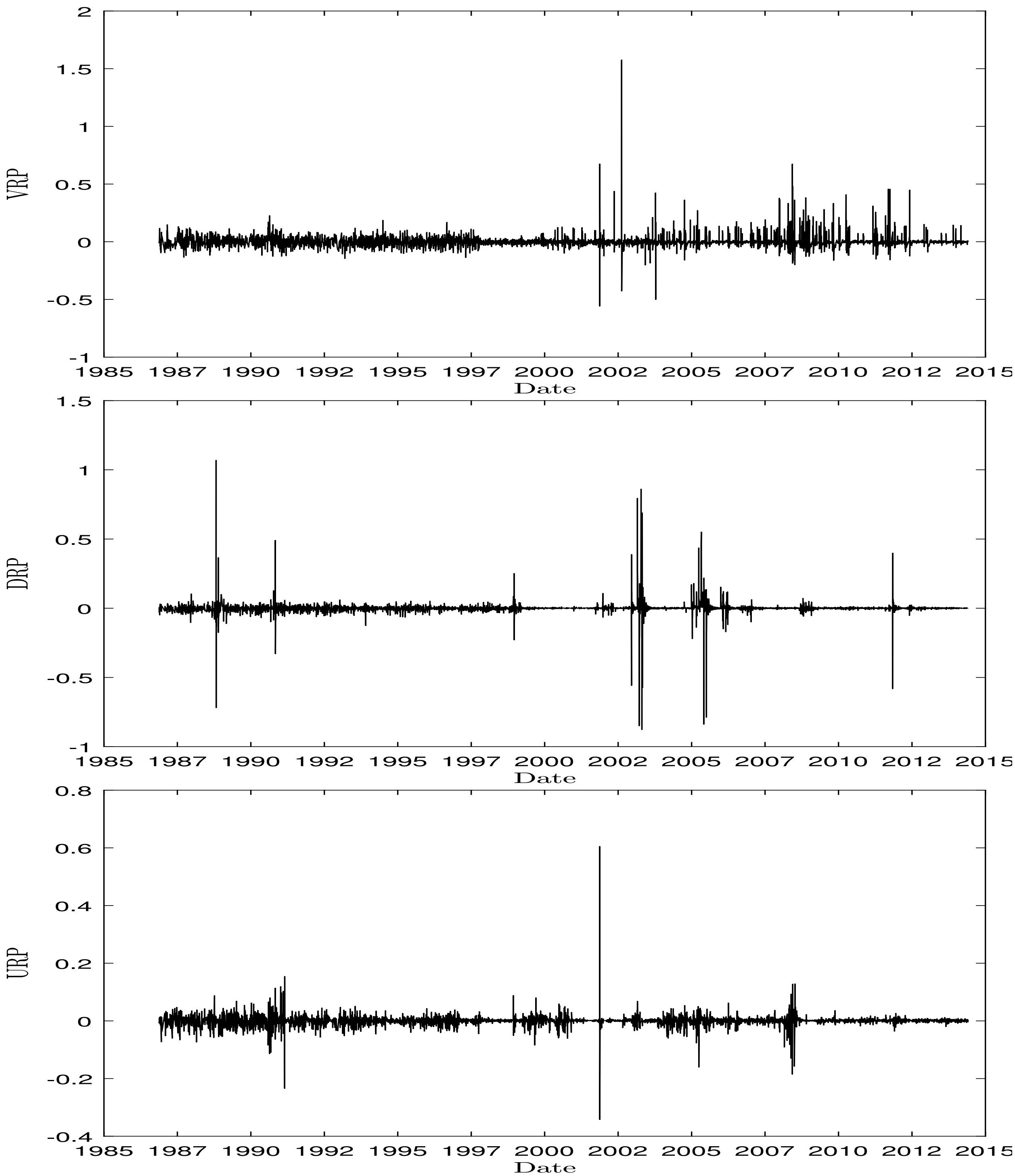

Figure 3. This figure shows the time-series of Variance Risk Premium, Downside-Jump Risk Premium and Upside-Jump Risk Premium in oil market. The chosen fitted models based on which we calculated the risk premia are ARMA(5,5), ARMA(9,6) and ARMA(3,1) for Variance, Downside and Upside jump premia respectively. The data range is from 1996 to 2014.

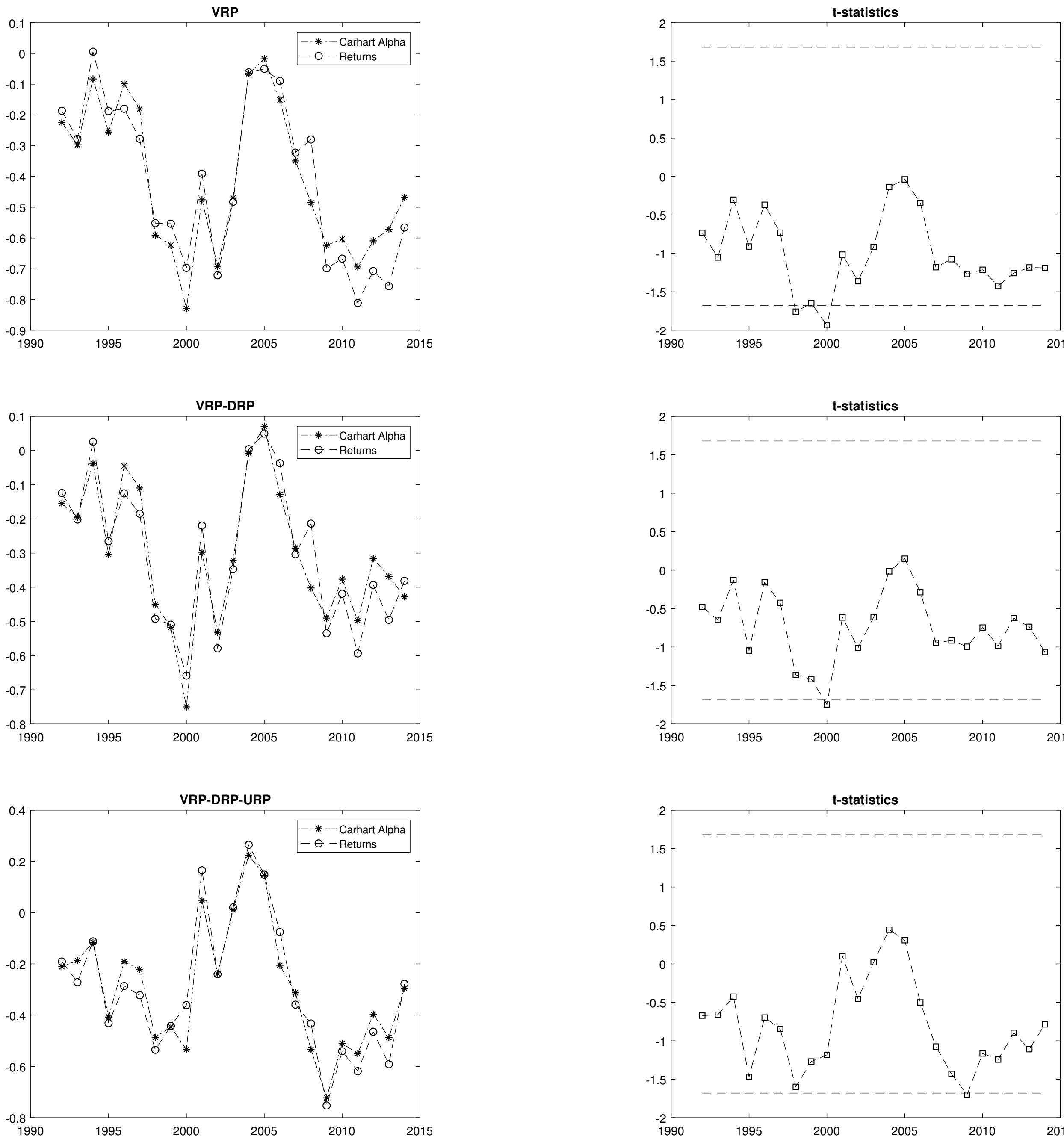

Figure 4. This Figure presents the evolution of average monthly returns and Jensen's Alpha of the hedge portfolio through the sample period in the case of sorting based on the exposure to VRP. The left column shows the average monthly returns and Jensen's Alpha of the hedge portfolio in case we form the portfolio based on VRP, based on VRP after controlling for DRP and based on VRP after controlling for DRP and URP respectively, moving from top to bottom. The second column shows the corresponding t-statistics for Jensen's alpha using Newey-West with 21 lags and confidence bounds associated with the 90% confidence level for each of the three cases. The returns and Jensen's alphas are computed based on a 10-year rolling window.

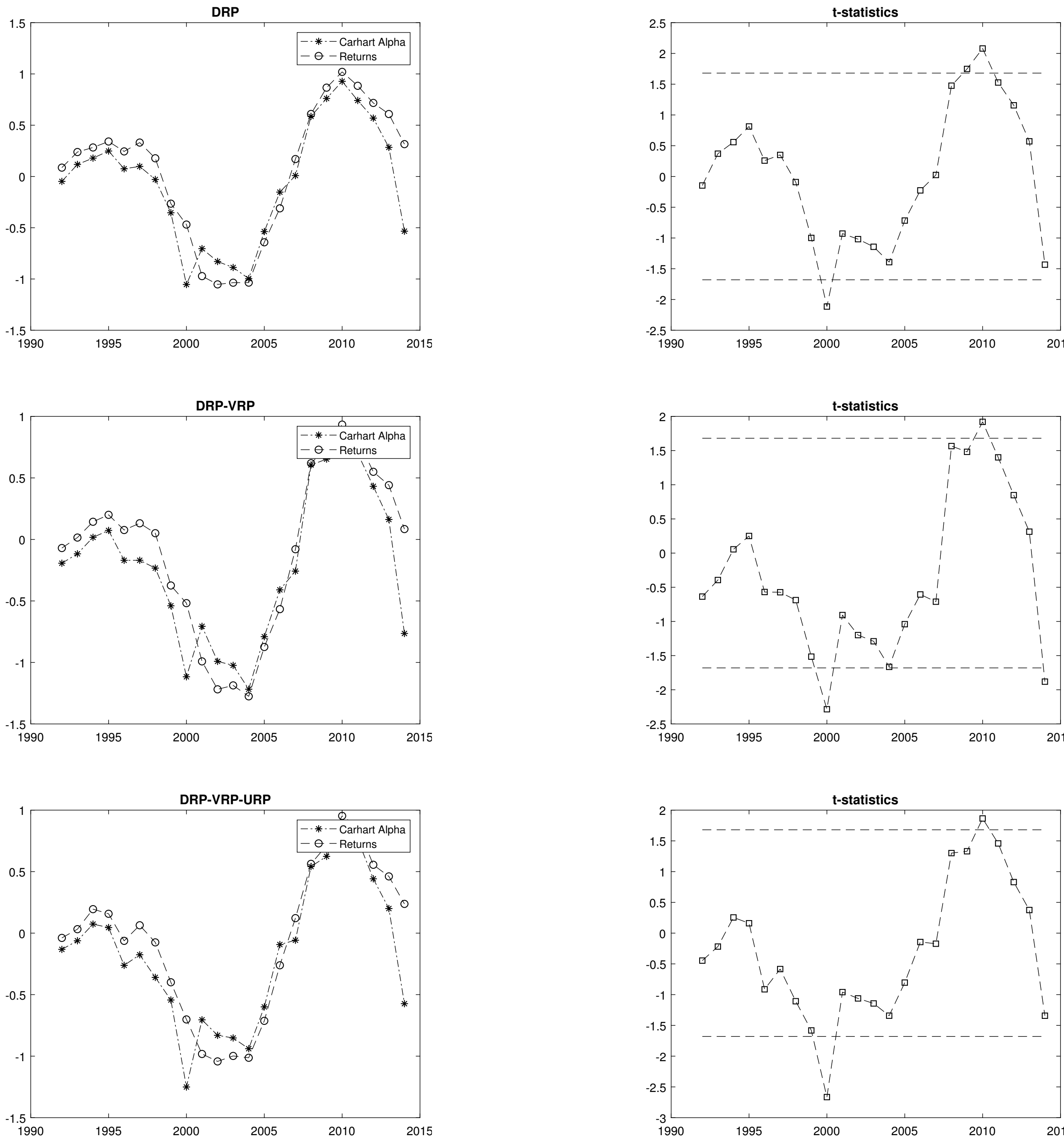

Figure 5. This Figure presents the evolution of average monthly returns and Jensen's Alpha of the hedge portfolio through the sample period in the case of sorting based on the exposure to DRP. The left column shows the average monthly returns and Jensen's Alpha of the hedge portfolio in case we form the portfolio based on DRP, based on DRP after controlling for VRP and based on DRP after controlling for VRP and URP respectively, moving from top to bottom. The second column shows the corresponding t-statistics for Jensen's alpha using Newey-West with 21 lags and confidence bounds associated with the 90% confidence level for each of the three cases. The returns and Jensen's alphas are computed based on a 10-year rolling window.

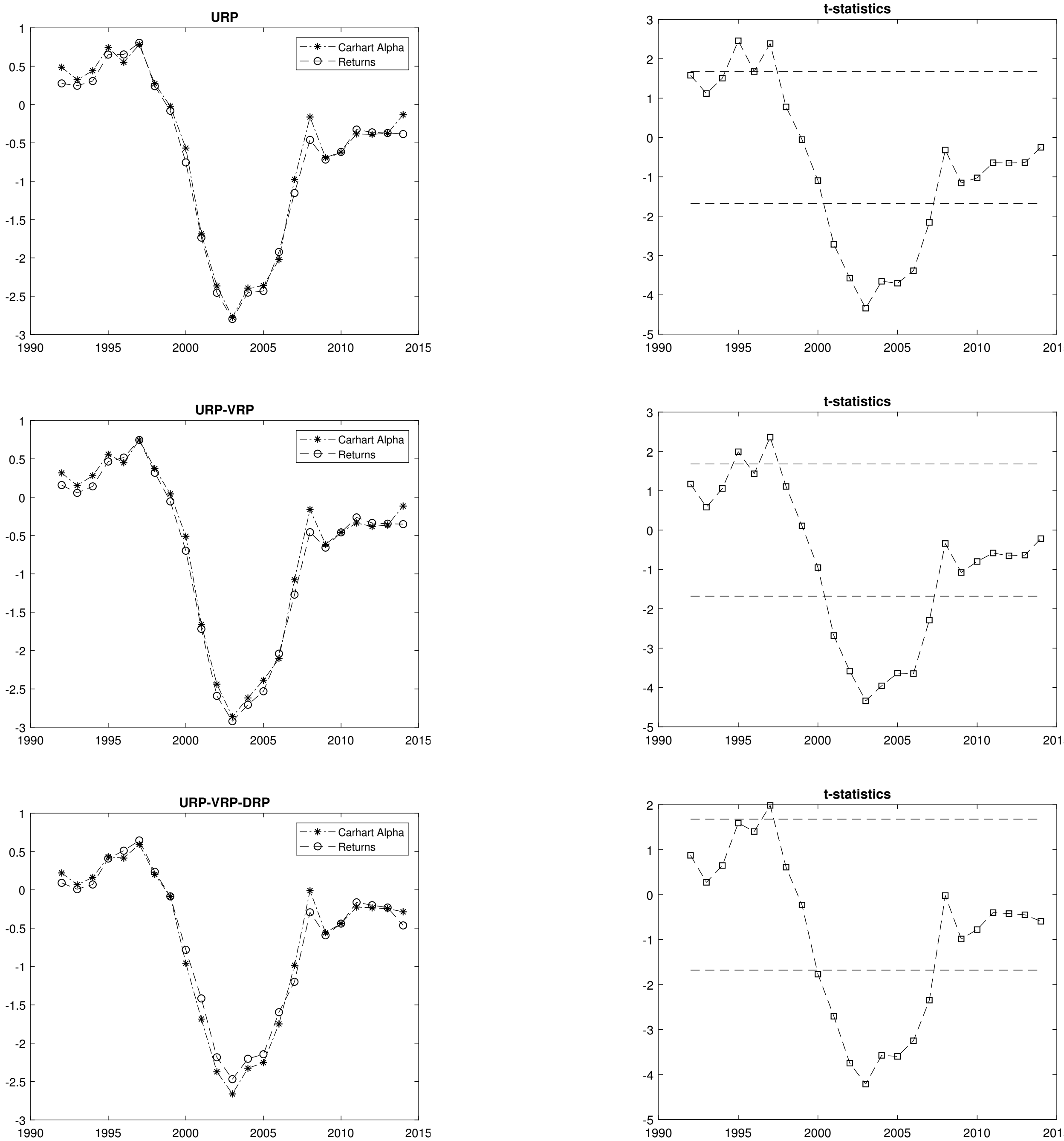

Figure 6. This Figure presents the evolution of average monthly returns and Jensen's Alpha of the hedge portfolio through the sample period in the case of sorting based on the exposure to URP. The left column shows the average monthly returns and Jensen's Alpha of the hedge portfolio in case we form the portfolio based on URP, based on URP after controlling for VRP and based on URP after controlling for VRP and DRP respectively, moving from top to bottom. The second column shows the corresponding t-statistics for Jensen's alpha using Newey-West with 21 lags and confidence bounds associated with the 90% confidence level for each of the three cases. The returns and Jensen's alphas are computed based on a 10-year rolling window.

	(1) VRP$_t$	(2) DRP$_t$	(3) URP$_t$
$\%\Delta$Supply$_t$	-0.403	0.174	-0.0748
	(0.873)	(0.640)	(0.872)
Geopolitical Risk$_t$	0.000169	0.000256	0.000167***
	(0.529)	(0.128)	(0.000)
$\%\Delta$Demand$_t$	0.0135	0.0127	-0.207
	(0.959)	(0.960)	(0.145)
ΔNVIX$_t$	0.00504	-0.00196	0.000738
	(0.170)	(0.156)	(0.568)
_cons	-0.0117	-0.0161	-0.0117*
	(0.505)	(0.472)	(0.039)
N	327	327	327
adj. R^2	-0.003	-0.001	0.017

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table I. Fundamental Determinants of Oil Premia

	(1) VRP$_t$	(2) DRP$_t$	(3) URP$_t$
$\%\Delta$Supply$_{t\text{-}1}$	0.721	0.0874	1.022
	(0.321)	(0.860)	(0.100)
Geopolitical Risk$_{t\text{-}1}$	-0.0000499	0.000264	0.000160***
	(0.651)	(0.076)	(0.000)
$\%\Delta$Demand$_{t\text{-}1}$	0.776	-0.534	-0.147
	(0.061)	(0.206)	(0.275)
ΔNVIX$_{t\text{-}1}$	0.00239	0.00233	0.000603
	(0.410)	(0.223)	(0.435)
VRP$_{t\text{-}1}$	-0.0818		
	(0.544)		
DRP$_{t\text{-}1}$		0.179	
		(0.480)	
URP$_{t\text{-}1}$			-0.133
			(0.165)
_cons	0.00403	-0.0166	-0.0121
	(0.834)	(0.366)	(0.062)
N	326	326	326
adj. R^2	0.008	0.043	0.036

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table II. Predicting Oil Premia Using Fundamentals

Factor: VRP						
Quintile Portfolio	1	2	3	4	5	5-1
Panel A						
Average Beta	-0.521	-0.126	-0.007	0.113	0.508	1.028
Average Returns	0.909	1.048	0.961	0.826	0.568	-0.341
Carhart Alpha	0.077	0.263	0.150	0.003	-0.323	-0.400
P-Value	0.524	**0.000**	**0.012**	0.966	**0.017**	**0.041**
Panel B						
Average Beta	-0.542	-0.130	-0.006	0.119	0.531	1.073
Average Returns	0.869	1.023	0.964	0.843	0.620	-0.249
Carhart Alpha	0.034	0.229	0.162	0.019	-0.264	-0.298
P-Value	0.783	**0.000**	**0.004**	0.784	**0.055**	0.131
Panel C						
Average Beta	-0.567	-0.136	-0.006	0.125	0.556	1.123
Average Returns	0.893	1.032	0.946	0.824	0.656	-0.237
Carhart Alpha	0.050	0.239	0.146	-0.005	-0.211	-0.261
P-Value	0.674	**0.000**	**0.017**	0.946	**0.089**	0.152

Table III. At the end of each month, we run the following regressions on daily returns in that month:

$$\begin{array}{ll} \text{(PanelA)} & R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{VRP} VRP_t + \varepsilon_{i,t} \\ \text{(PanelB)} & R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{VRP} VRP_t + \beta^i_{DRP} DRP_t + \varepsilon_{i,t} \\ \text{(PanelC)} & R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{VRP} VRP_t + \beta^i_{DRP} DRP_t + \beta^i_{URP} URP_t + \varepsilon_{i,t} \end{array}$$

We sort the stocks into 5 quintiles based on VRP regression coefficient,β_{VRP}, the first quintile having lowest and the fifth quintile having highest exposure. Then we form a Value-Weighted portfolio for each quintile, each stock having weight equal to its value on aggreate value of the stocks in that portfolio. Then we get the post-ranking daily returns of each of these 5 portfolios for the month following the portfolio-formation period. We roll the beta estimation period one month and keep doing the same procedure until we cover the whole sample.At the end of this procedure, we have the daily return of these five portfolios and monthly pre-rankingβ_{VRP} for all portfolios. This table reports the average pre-tanking beta and average monthly return for each of the five portfolios. We also compute Jensen's Alpha of the Carhart 4-Factor model by regressing daily returns on SMB,HML,UMD and Rm-Rf. The reported alphas are computed by multiplying daily alpha by 21. The reported numbers are in percent. We also report the P-Value of Carhart alpha. The boldfaced Alphas are the ones significant at 90% confidence level.

Factor: DRP						
Quintile Portfolio	1	2	3	4	5	5-1
Panel A						
Average Beta	-1.829	-0.376	0.074	0.531	2.003	3.833
Average Returns	0.942	0.835	0.895	0.863	0.919	-0.024
Carhart Alpha	0.102	0.027	0.085	0.033	0.076	-0.027
P-Value	0.476	0.725	**0.086**	0.676	0.594	0.909
Panel B						
Average Beta	-1.894	-0.383	0.084	0.558	2.085	3.979
Average Returns	1.004	0.854	0.852	0.919	0.846	-0.158
Carhart Alpha	0.158	0.056	0.036	0.084	-0.009	-0.167
P-Value	0.279	0.474	0.473	0.269	0.949	0.480
Panel C						
Average Beta	-2.003	-0.408	0.084	0.582	2.186	4.189
Average Returns	0.907	0.951	0.843	0.877	0.808	-0.099
Carhart Alpha	0.059	0.145	0.033	0.041	-0.052	-0.111
P-Value	0.680	**0.055**	0.552	0.600	0.708	0.630

Table IV. At the end of each month, we run the following regressions on daily returns in that month:

$$\begin{array}{ll}
\text{(PanelA)} & R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{DRP} DRP_t + \varepsilon_{i,t} \\
\text{(PanelB)} & R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{VRP} VRP_t + \beta^i_{DRP} DRP_t + \varepsilon_{i,t} \\
\text{(PanelC)} & R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{VRP} VRP_t + \beta^i_{DRP} DRP_t + \beta^i_{URP} URP_t + \varepsilon_{i,t}
\end{array}$$

We sort the stocks into 5 quintiles based on DRP regression coefficient,β_{DRP}, the first quintile having lowest and the fifth quintile having highest exposure. Then we form a Value-Weighted portfolio for each quintile, each stock having weight equal to its value on aggreate value of the stocks in that portfolio. Then we get the post-ranking daily returns of each of these 5 portfolios for the month following the portfolio-formation period. We roll the beta estimation period one month and keep doing the same procedure until we cover the whole sample.At the end of this procedure, we have the daily return of these five portfolios and monthly pre-rankingβ_{DRP} for all portfolios. This table reports the average pre-tanking beta and average monthly return for each of the five portfolios. We also compute Jensen's Alpha of the Carhart 4-Factor model by regressing daily returns on SMB,HML,UMD and Rm-Rf. The reported alphas are computed by multiplying daily alpha by 21. The reported numbers are in percent. We also report the P-Value of Carhart alpha. The bold Alphas are the ones significant at 90% confidence level.

Factor: URP						
Quintile Portfolio	1	2	3	4	5	5-1
Panel A						
Average Beta	-2.321	-0.595	-0.071	0.443	2.121	4.442
Average Returns	1.140	0.980	0.893	0.779	0.587	-0.553
Carhart Alpha	0.262	0.155	0.084	-0.032	-0.185	-0.447
P-Value	**0.082**	**0.047**	**0.094**	0.630	0.184	**0.066**
Panel B						
Average Beta	-2.400	-0.611	-0.066	0.472	2.227	4.627
Average Returns	1.133	0.990	0.889	0.833	0.534	-0.599
Carhart Alpha	0.258	0.171	0.072	0.026	-0.235	-0.493
P-Value	**0.091**	**0.017**	0.170	0.695	**0.094**	**0.041**
Panel C						
Average Beta	-2.514	-0.626	-0.054	0.509	2.350	4.864
Average Returns	1.054	1.012	0.882	0.792	0.550	-0.504
Carhart Alpha	0.201	0.196	0.075	-0.032	-0.261	-0.462
P-Value	0.180	**0.003**	0.169	0.636	**0.044**	**0.047**

Table V. At the end of each month, we run the following regressions on daily returns in that month:

$$\begin{array}{ll}
\text{(PanelA)} & R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{URP} URP_t + \varepsilon_{i,t} \\
\text{(PanelB)} & R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{VRP} VRP_t + \beta^i_{URP} URP_t + \varepsilon_{i,t} \\
\text{(PanelC)} & R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{VRP} VRP_t + \beta^i_{DRP} DRP_t + \beta^i_{URP} URP_t + \varepsilon_{i,t}
\end{array}$$

We sort the stocks into 5 quintiles based on URP regression coefficient,β_{URP}, the first quintile having lowest and the fifth quintile having highest exposure. Then we form a Value-Weighted portfolio for each quintile, each stock having weight equal to its value on aggreate value of the stocks in that portfolio. Then we get the post-ranking daily returns of each of these 5 portfolios for the month following the portfolio-formation period. We roll the beta estimation period one month and keep doing the same procedure until we cover the whole sample.At the end of this procedure, we have the daily return of these five portfolios and monthly pre-rankingβ_{URP} for all portfolios. This table reports the average pre-tanking beta and average monthly return for each of the five portfolios. We also compute Jensen's Alpha of the Carhart 4-Factor model by regressing daily returns on SMB,HML,UMD and Rm-Rf. The reported alphas are computed by multiplying daily alpha by 21. The reported numbers are in percent. We also report the P-Value of Carhart alpha. The bold Alphas are the ones significant at 90% confidence level.

Factor: VRP							
Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-0.521	-0.126	-0.007	0.113	0.508	1.028
	Average Returns	1.418	1.369	1.310	1.163	1.068	-0.350
	Carhart Alpha	0.122	0.123	0.096	-0.089	-0.289	-0.411
	P-Value	0.386	**0.098**	0.142	0.334	**0.081**	**0.083**
Sub-Panel A2	Average Beta	-0.542	-0.130	-0.006	0.119	0.531	1.073
	Average Returns	1.388	1.361	1.318	1.164	1.073	-0.314
	Carhart Alpha	0.094	0.107	0.114	-0.098	-0.240	-0.334
	P-Value	0.519	0.182	**0.052**	0.258	0.143	0.157
Sub-Panel A3	Average Beta	-0.567	-0.136	-0.006	0.125	0.556	1.123
	Average Returns	1.453	1.380	1.278	1.150	1.134	-0.319
	Carhart Alpha	0.161	0.135	0.064	-0.111	-0.178	-0.339
	P-Value	0.267	**0.078**	0.332	0.199	0.256	0.133
Factor: DRP							
Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-1.829	-0.376	0.074	0.531	2.003	3.833
	Average Returns	1.559	1.285	1.218	1.160	1.454	-0.105
	Carhart Alpha	0.302	0.061	0.008	-0.122	0.054	-0.248
	P-Value	**0.047**	0.492	0.893	0.139	0.743	0.301
Sub-Panel B2	Average Beta	-1.894	-0.383	0.084	0.558	2.085	3.979
	Average Returns	1.622	1.269	1.157	1.216	1.383	-0.239
	Carhart Alpha	0.400	0.045	-0.057	-0.075	-0.016	-0.416
	P-Value	**0.009**	0.593	0.372	0.353	0.916	**0.073**
Sub-Panel B3	Average Beta	-2.003	-0.408	0.084	0.582	2.186	4.189
	Average Returns	1.558	1.314	1.188	1.188	1.340	-0.218
	Carhart Alpha	0.331	0.097	-0.031	-0.101	-0.040	-0.371
	P-Value	**0.029**	0.196	0.655	0.198	0.792	**0.095**
Factor: URP							
Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-2.321	-0.595	-0.071	0.443	2.121	4.442
	Average Returns	1.352	1.199	1.281	1.279	1.459	0.108
	Carhart Alpha	-0.024	-0.062	0.067	0.030	0.226	0.251
	P-Value	0.876	0.473	0.304	0.701	0.169	0.334
Sub-Panel C2	Average Beta	-2.400	-0.611	-0.066	0.472	2.227	4.627
	Average Returns	1.365	1.216	1.259	1.331	1.417	0.052
	Carhart Alpha	-0.005	-0.069	0.036	0.118	0.181	0.186
	P-Value	0.976	0.385	0.566	0.155	0.246	0.438
Sub-Panel C3	Average Beta	-2.514	-0.626	-0.054	0.509	2.350	4.864
	Average Returns	1.346	1.286	1.213	1.322	1.379	0.034
	Carhart Alpha	0.018	0.012	-0.002	0.086	0.116	0.098
	P-Value	0.909	0.875	0.976	0.252	0.457	0.676

Table VI . This table shows the analysis for period 1986-2000 using 60-day maturity innovations. Panel A,B and C show the analysis for VRP, DRP and URP respectively. Sub-Panels A1,A2 and A3 present the results for regressions (15),(16) and (17). Sub-panels B1, B2 and B3 present the results for regressions (18), (16) and (17). sub-panels C1,C2 and C3 present the results for regressions (19),(20) and (17).

Factor: VRP Panel A	Quintile Portfolio	1	2	3	4	5	5-1
	Average Beta	-0.521	-0.126	-0.007	0.113	0.508	1.028
Sub-Panel A1	Average Returns	-0.405	0.222	0.202	0.084	-0.622	-0.217
	Carhart Alpha	-0.041	0.394	0.220	0.241	-0.241	-0.200
	P-Value	0.864	**0.002**	**0.080**	**0.056**	0.383	0.627
	Average Beta	-0.542	-0.130	-0.006	0.119	0.531	1.073
Sub-Panel A2	Average Returns	-0.443	0.168	0.218	0.107	-0.540	-0.097
	Carhart Alpha	-0.100	0.317	0.268	0.254	-0.160	-0.059
	P-Value	0.697	**0.011**	**0.032**	**0.078**	0.566	0.888
	Average Beta	-0.567	-0.136	-0.006	0.125	0.556	1.123
Sub-Panel A3	Average Returns	-0.412	0.163	0.188	0.104	-0.531	-0.119
	Carhart Alpha	-0.053	0.319	0.232	0.237	-0.144	-0.091
	P-Value	0.831	**0.018**	**0.083**	**0.089**	0.560	0.813
Factor: DRP Panel A	Quintile Portfolio	1	2	3	4	5	5-1
	Average Beta	-1.829	-0.376	0.074	0.531	2.003	3.833
Sub-Panel B1	Average Returns	-0.191	-0.092	0.074	0.039	-0.266	-0.075
	Carhart Alpha	0.059	-0.036	0.118	0.252	0.216	0.157
	P-Value	0.860	0.826	0.275	0.138	0.462	0.774
	Average Beta	-1.894	-0.383	0.084	0.558	2.085	3.979
Sub-Panel B2	Average Returns	-0.201	0.024	0.022	0.119	-0.353	-0.152
	Carhart Alpha	0.005	0.104	0.067	0.308	0.080	0.075
	P-Value	0.988	0.541	0.506	**0.066**	0.791	0.893
	Average Beta	-2.003	-0.408	0.084	0.582	2.186	4.189
Sub-Panel B3	Average Returns	-0.338	0.224	-0.025	0.037	-0.435	-0.097
	Carhart Alpha	-0.120	0.263	0.050	0.195	0.018	0.138
	P-Value	0.719	0.108	0.680	0.268	0.952	0.803
Factor: URP Panel A	Quintile Portfolio	1	2	3	4	5	5-1
	Average Beta	-2.321	-0.595	-0.071	0.443	2.121	4.442
Sub-Panel C1	Average Returns	0.521	0.273	0.030	-0.244	-1.073	-1.594
	Carhart Alpha	0.842	0.427	0.101	-0.109	-0.618	-1.460
	P-Value	**0.011**	**0.012**	0.332	0.481	**0.038**	**0.006**
	Average Beta	-2.400	-0.611	-0.066	0.472	2.227	4.627
Sub-Panel C2	Average Returns	0.498	0.323	0.034	-0.191	-1.174	-1.672
	Carhart Alpha	0.790	0.496	0.059	-0.061	-0.666	-1.456
	P-Value	**0.018**	**0.001**	0.616	0.665	**0.036**	**0.007**
	Average Beta	-2.514	-0.626	-0.054	0.509	2.350	4.864
Sub-Panel C3	Average Returns	0.210	0.291	0.086	-0.289	-1.070	-1.280
	Carhart Alpha	0.572	0.477	0.145	-0.219	-0.692	-1.264
	P-Value	**0.085**	**0.001**	0.217	0.156	**0.014**	**0.017**

Table VII . This table shows the analysis for period 2000-2008 using 60-day maturity innovations. Panel A,B and C show the analysis for VRP, DRP and URP respectively. Sub-Panels A1,A2 and A3 present the results for regressions (15),(16) and (17). Sub-panels B1, B2 and B3 present the results for regressions (18), (16) and (17). sub-panels C1,C2 and C3 present the results for regressions (19),(20) and (17).

Factor: VRP Panel A	Quintile Portfolio	1	2	3	4	5	5-1
	Average Beta	-0.521	-0.126	-0.007	0.113	0.508	1.028
Sub-Panel A1	Average Returns	0.389	0.341	0.287	0.259	0.283	-0.106
	Carhart Alpha	0.164	0.205	0.026	-0.179	-0.304	-0.468
	P-Value	0.496	**0.073**	0.786	0.197	0.221	0.234
	Average Beta	-0.542	-0.130	-0.006	0.119	0.531	1.073
Sub-Panel A2	Average Returns	0.376	0.337	0.281	0.269	0.304	-0.072
	Carhart Alpha	0.168	0.212	0.015	-0.161	-0.260	-0.428
	P-Value	0.470	0.120	0.868	0.274	0.322	0.287
	Average Beta	-0.567	-0.136	-0.006	0.125	0.556	1.123
Sub-Panel A3	Average Returns	0.359	0.338	0.291	0.257	0.309	-0.050
	Carhart Alpha	0.087	0.201	0.058	-0.206	-0.207	-0.295
	P-Value	0.686	0.141	0.491	0.165	0.399	0.432

Factor: DRP Panel B	Quintile Portfolio	1	2	3	4	5	5-1
	Average Beta	-1.829	-0.376	0.074	0.531	2.003	3.833
Sub-Panel B1	Average Returns	0.285	0.272	0.307	0.312	0.335	0.050
	Carhart Alpha	0.150	0.113	0.091	-0.138	-0.384	-0.534
	P-Value	0.500	0.366	0.332	0.280	0.127	0.152
	Average Beta	-1.894	-0.383	0.084	0.558	2.085	3.979
Sub-Panel B2	Average Returns	0.321	0.259	0.310	0.316	0.325	0.004
	Carhart Alpha	0.331	0.053	0.103	-0.108	-0.434	-0.764
	P-Value	0.195	0.686	0.258	0.372	**0.094**	**0.060**
	Average Beta	-2.003	-0.408	0.084	0.582	2.186	4.189
Sub-Panel B3	Average Returns	0.300	0.268	0.302	0.315	0.334	0.035
	Carhart Alpha	0.215	0.088	0.060	-0.092	-0.358	-0.573
	P-Value	0.395	0.491	0.480	0.469	0.190	0.180

Factor: URP Panel C	Quintile Portfolio	1	2	3	4	5	5-1
	Average Beta	-2.321	-0.595	-0.071	0.443	2.121	4.442
Sub-Panel C1	Average Returns	0.340	0.334	0.291	0.269	0.271	-0.068
	Carhart Alpha	-0.109	0.139	0.034	-0.072	-0.242	-0.133
	P-Value	0.735	0.359	0.687	0.555	0.404	0.803
	Average Beta	-2.400	-0.611	-0.066	0.472	2.227	4.627
Sub-Panel C2	Average Returns	0.334	0.319	0.295	0.281	0.272	-0.062
	Carhart Alpha	-0.100	0.081	0.058	-0.040	-0.216	-0.115
	P-Value	0.760	0.578	0.470	0.746	0.439	0.828
	Average Beta	-2.514	-0.626	-0.054	0.509	2.350	4.864
Sub-Panel C3	Average Returns	**0.361**	**0.319**	**0.292**	**0.277**	**0.270**	**-0.091**
	Carhart Alpha	0.028	0.092	0.048	-0.060	-0.258	-0.286
	P-Value	0.930	0.537	0.563	0.640	0.294	0.553

Table VIII . This table shows the analysis for period 2009-2014 using 60-day maturity innovations, for the case of ommiting oil and gas companies. Panel A,B and C show the analysis for VRP, DRP and URP respectively. Sub-Panels A1,A2 and A3 present the results for regressions (15),(16) and (17). Sub-panels B1, B2 and B3 present the results for regressions (18), (16) and (17). sub-panels C1,C2 and C3 present the results for regressions (19),(20) and (21).

	(1)	(2)	(3)	(4)
	ΔNVIX$_t$	ΔNVIX$_t$	ΔNVIX$_t$	ΔNVIX$_t$
VRP$_{t-1}$	-0.621			-0.584
	(0.455)			(0.497)
VRP$_{t-2}$	-0.960			-0.869
	(0.262)			(0.348)
VRP$_{t-3}$	0.871			0.952
	(0.277)			(0.159)
VRP$_{t-4}$	0.819			0.540
	(0.293)			(0.485)
DRP$_{t-1}$		0.0786		0.156
		(0.883)		(0.749)
DRP$_{t-2}$		-0.565		-0.931*
		(0.326)		(0.049)
DRP$_{t-3}$		0.0794		-0.0684
		(0.862)		(0.920)
DRP$_{t-4}$		0.0664		0.167
		(0.867)		(0.576)
URP$_{t-1}$			-2.612	-2.845
			(0.235)	(0.177)
URP$_{t-2}$			6.087*	5.784**
			(0.016)	(0.007)
URP$_{t-3}$			2.102	2.138
			(0.404)	(0.417)
URP$_{t-4}$			-4.468	-4.707
			(0.100)	(0.072)
_cons	0.00655	0.00765	0.00573	0.00799
	(0.948)	(0.933)	(0.966)	(0.929)
N	324	324	324	324
adj. R^2	-0.002	-0.012	0.020	0.006

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table IX. Predicting Changes in ΔNVIX Using Oil Premia

	(1) $\Delta\text{NVIX}_{\text{Securities}}$	(2) $\Delta\text{NVIX}_{\text{Securities}}$	(3) $\Delta\text{NVIX}_{\text{Securities}}$	(4) $\Delta\text{NVIX}_{\text{Securities}}$
$\text{VRP}_{\text{t-1}}$	-0.138			-0.125
	(0.507)			(0.495)
$\text{VRP}_{\text{t-2}}$	-0.257			-0.215
	(0.387)			(0.488)
$\text{VRP}_{\text{t-3}}$	0.218			0.228
	(0.443)			(0.381)
$\text{VRP}_{\text{t-4}}$	0.259			0.202
	(0.338)			(0.410)
$\text{DRP}_{\text{t-1}}$		0.176		0.128
		(0.085)		(0.365)
$\text{DRP}_{\text{t-2}}$		-0.129		-0.117
		(0.226)		(0.344)
$\text{DRP}_{\text{t-3}}$		0.250*		0.218
		(0.025)		(0.202)
$\text{DRP}_{\text{t-4}}$		-0.359***		-0.344***
		(0.000)		(0.000)
$\text{URP}_{\text{t-1}}$			-0.672	-0.783
			(0.144)	(0.051)
$\text{URP}_{\text{t-2}}$			1.950*	1.806*
			(0.026)	(0.046)
$\text{URP}_{\text{t-3}}$			-0.857	-0.780
			(0.233)	(0.304)
$\text{URP}_{\text{t-4}}$			0.314	0.354
			(0.664)	(0.637)
_cons	-0.00732	-0.00713	-0.00680	-0.00646
	(0.601)	(0.601)	(0.608)	(0.645)
N	324	324	324	324
adj. R^2	0.003	-0.002	0.043	0.040

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table X. Predicting $\Delta\text{NVIX}_{\text{Securities}}$ Using Oil Premia

	(1)	(2)	(3)	(4)
	$\Delta R3_t$	$\Delta R3_t$	$\Delta R3_t$	$\Delta R3_t$
VRP_{t-1}	0.00816			-0.0157
	(0.873)			(0.782)
VRP_{t-2}	0.00567			-0.0142
	(0.897)			(0.759)
VRP_{t-3}	-0.0901*			-0.0952*
	(0.025)			(0.014)
VRP_{t-4}	-0.0608			-0.0609
	(0.253)			(0.168)
DRP_{t-1}		0.0520		0.0363
		(0.088)		(0.205)
DRP_{t-2}		0.0803***		0.0919***
		(0.000)		(0.000)
DRP_{t-3}		0.0804***		0.0999***
		(0.000)		(0.000)
DRP_{t-4}		-0.00116		0.00694
		(0.963)		(0.754)
URP_{t-1}			-0.286*	-0.293*
			(0.037)	(0.015)
URP_{t-2}			-0.306*	-0.331
			(0.044)	(0.058)
URP_{t-3}			-0.292	-0.331*
			(0.077)	(0.045)
URP_{t-4}			-0.150	-0.157
			(0.268)	(0.221)
_cons	-0.0176	-0.0182	-0.0174	-0.0181
	(0.475)	(0.432)	(0.355)	(0.423)
N	326	326	326	326
adj. R^2	0.001	0.002	0.022	0.030

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XI. Predict Interest Rate Growth Using Oil Premia

	(1)	(2)	(3)	(4)
	$\%\Delta \mathrm{UN}_{\mathrm{t}}$	$\%\Delta \mathrm{UN}_{\mathrm{t}}$	$\%\Delta \mathrm{UN}_{\mathrm{t}}$	$\%\Delta \mathrm{UN}_{\mathrm{t}}$
$\mathrm{VRP}_{\text{t-1}}$	0.00402			0.00449
	(0.382)			(0.300)
$\mathrm{VRP}_{\text{t-2}}$	0.00864			0.00986
	(0.133)			(0.091)
$\mathrm{VRP}_{\text{t-3}}$	0.0182^{**}			0.0198^{**}
	(0.002)			(0.002)
$\mathrm{VRP}_{\text{t-4}}$	0.00433			0.00504
	(0.285)			(0.254)
$\mathrm{DRP}_{\text{t-1}}$		-0.0105^{*}		-0.00936^{*}
		(0.012)		(0.033)
$\mathrm{DRP}_{\text{t-2}}$		0.00471		0.00714
		(0.176)		(0.052)
$\mathrm{DRP}_{\text{t-3}}$		-0.00933^{*}		-0.0101^{*}
		(0.042)		(0.049)
$\mathrm{URP}_{\text{t-4}}$		0.00639^{*}		0.00428
		(0.031)		(0.163)
$\mathrm{URP}_{\text{t-1}}$			-0.00376	-0.00707
			(0.864)	(0.720)
$\mathrm{URP}_{\text{t-2}}$			-0.00523	-0.00215
			(0.802)	(0.918)
$\mathrm{URP}_{\text{t-3}}$			0.0137	0.0193
			(0.517)	(0.338)
$\mathrm{URP}_{\text{t-4}}$			0.0270	0.0342
			(0.210)	(0.097)
_cons	0.000182	0.000233	0.000209	0.000213
	(0.948)	(0.937)	(0.943)	(0.939)
N	326	326	326	326
adj. R^2	0.015	-0.002	-0.005	0.012

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XII. Predicting Unemployment Growth Using Oil Premia

	(1)	(2)	(3)	(4)
	ΔDefault Premium$_t$	ΔDefault Premium$_t$	ΔDefault Premium$_t$	ΔDefault Premium$_t$
VRP_{t-1}	-0.00797			-0.0188
	(0.787)			(0.612)
VRP_{t-2}	-0.0501*			-0.0586*
	(0.037)			(0.045)
VRP_{t-3}	-0.00469			-0.00363
	(0.796)			(0.838)
VRP_{t-4}	-0.00982			-0.0106
	(0.600)			(0.689)
DRP_{t-1}		-0.00814		-0.0154
		(0.757)		(0.536)
DRP_{t-2}		-0.00853		-0.00308
		(0.402)		(0.777)
DRP_{t-3}		0.0160		0.0248
		(0.173)		(0.083)
DRP_{t-4}		-0.0315*		-0.0297**
		(0.022)		(0.008)
URP_{t-1}			-0.194**	-0.199**
			(0.002)	(0.008)
URP_{t-2}			-0.0988	-0.116
			(0.190)	(0.377)
URP_{t-3}			-0.110	-0.128
			(0.246)	(0.326)
URP_{t-4}			-0.0612	-0.0781
			(0.557)	(0.529)
_cons	0.00205	0.00210	0.00205	0.00223
	(0.788)	(0.723)	(0.747)	(0.771)
N	326	326	326	326
adj. R^2	-0.002	-0.009	0.016	0.010

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XIII. Predicting Default Premium Growth Using Oil Premia

	(1) $\%\Delta PCE_t$	(2) $\%\Delta PCE_t$	(3) $\%\Delta PCE_t$	(4) $\%\Delta PCE_t$
VRP_{t-1}	-0.0000134			-0.000758
	(0.987)			(0.438)
VRP_{t-2}	-0.00161*			-0.00211*
	(0.033)			(0.028)
VRP_{t-3}	-0.00138			-0.00144
	(0.056)			(0.104)
VRP_{t-4}	-0.00175*			-0.00197*
	(0.021)			(0.025)
DRP_{t-1}		0.000269		-0.000207
		(0.823)		(0.873)
DRP_{t-2}		0.00259*		0.00280***
		(0.011)		(0.001)
DRP_{t-3}		-0.00118*		-0.000682
		(0.028)		(0.404)
DRP_{t-4}		0.000410		0.000640
		(0.549)		(0.490)
URP_{t-1}			-0.0106***	-0.0111***
			(0.000)	(0.000)
URP_{t-2}			-0.00516	-0.00563
			(0.093)	(0.072)
URP_{t-3}			-0.00758*	-0.00869*
			(0.028)	(0.021)
URP_{t-4}			-0.00653*	-0.00695
			(0.047)	(0.052)
_cons	0.00419***	0.00419***	0.00419***	0.00419***
	(0.000)	(0.000)	(0.000)	(0.000)
N	326	326	326	326
adj. R^2	0.006	-0.001	0.057	0.073

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XIV. Predicting Consumption Growth Using Oil Premia

	(1) %ΔInvestment$_t$	(2) %ΔInvestment$_t$	(3) %ΔInvestment$_t$	(4) %ΔInvestment$_t$	(5) %ΔInvestment$_t$
VRP_t	-0.00619				
	(0.474)				
DRP_t	-0.000957				
	(0.776)				
URP_t	-0.0499**				
	(0.004)				
VRP_{t-1}		-0.0223***			
		(0.000)			
DRP_{t-1}		0.00456			
		(0.149)			
URP_{t-1}		-0.0268			
		(0.179)			
VRP_{t-2}			-0.0247**		
			(0.004)		
DRP_{t-2}			0.0124***		
			(0.000)		
URP_{t-2}			-0.0430		
			(0.071)		
VRP_{t-3}				-0.0118	
				(0.274)	
DRP_{t-3}				0.00360	
				(0.400)	
URP_{t-3}				0.0293	
				(0.402)	
VRP_{t-4}					-0.00916
					(0.238)
DRP_{t-4}					-0.00347
					(0.452)
URP_{t-4}					0.000865
					(0.979)
_cons	0.0102*	0.0104**	0.0103*	0.0102**	0.0105*
	(0.029)	(0.010)	(0.016)	(0.007)	(0.010)
N	95	94	93	92	91
adj. R^2	0.009	0.028	0.062	0.016	-0.021

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XV. Predicting Investment Growth Using Oil Premia

	(1)	(2)	(3)	(4)	(5)
	$\%\Delta\mathrm{GDP_t}$	$\%\Delta\mathrm{GDP_t}$	$\%\Delta\mathrm{GDP_t}$	$\%\Delta\mathrm{GDP_t}$	$\%\Delta\mathrm{GDP_t}$
$\mathrm{VRP_t}$	-0.00159				
	(0.178)				
$\mathrm{DRP_t}$	0.000396				
	(0.715)				
$\mathrm{URP_t}$	-0.0181***				
	(0.000)				
$\mathrm{VRP_{t\text{-}1}}$		-0.00434*			
		(0.017)			
$\mathrm{DRP_{t\text{-}1}}$		0.00199*			
		(0.044)			
$\mathrm{URP_{t\text{-}1}}$		-0.00958			
		(0.150)			
$\mathrm{VRP_{t\text{-}2}}$			-0.00479*		
			(0.012)		
$\mathrm{DRP_{t\text{-}2}}$			0.000949		
			(0.230)		
$\mathrm{URP_{t\text{-}2}}$			-0.00929*		
			(0.018)		
$\mathrm{VRP_{t\text{-}3}}$				-0.000678	
				(0.653)	
$\mathrm{DRP_{t\text{-}3}}$				0.00160	
				(0.081)	
$\mathrm{URP_{t\text{-}3}}$				0.00247	
				(0.665)	
$\mathrm{VRP_{t\text{-}4}}$					-0.00267
					(0.134)
$\mathrm{DRP_{t\text{-}4}}$					-0.000398
					(0.750)
$\mathrm{URP_{t\text{-}4}}$					-0.00732
					(0.118)
_cons	0.0123***	0.0123***	0.0123***	0.0122***	0.0121***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	94	94	93	92	91
adj. R^2	0.087	0.038	0.039	-0.020	-0.003

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XVI. Predicting GDP Growth Using Oil Premia

	(1)	(2)	(3)	(4)	(5)
	fret	fret	fret	fret	fret
$\text{URP}_{\text{t-1}}$	-0.0174				
	(0.0912)				
$\text{URP}_{\text{t-2}}$		-0.138		-0.154*	-0.150*
		(0.0705)		(0.0703)	(0.0676)
$\text{URP}_{\text{t-3}}$			-0.112	-0.130*	-0.113
			(0.0594)	(0.0606)	(0.0626)
$\text{fret}_{\text{t-1}}$					0.117*
					(0.0587)
_cons	0.00648	0.00603	0.00593	0.00590	0.00521
	(0.00489)	(0.00471)	(0.00478)	(0.00463)	(0.00427)
N	330	329	328	328	328
adj. R^2	-0.002	0.012	0.007	0.022	0.033

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XVII . The table reports predictability results for oil future returns by oil VRP, oil DRP and oil URP and their lags and also lagged future returns during the period 1986-2014. Newey-West Standard errors are reported in parentheses.

	(1) $\%\Delta\mathrm{INV_t}$	(2) $\%\Delta\mathrm{INV_t}$	(3) $\%\Delta\mathrm{INV_t}$	(4) $\%\Delta\mathrm{INV_t}$
$\mathrm{VRP_{t-1}}$	0.00250			0.00179
	(0.164)			(0.308)
$\mathrm{VRP_{t-2}}$	-0.00633**			-0.00685***
	(0.002)			(0.001)
$\mathrm{VRP_{t-3}}$	-0.00318			-0.00303
	(0.242)			(0.242)
$\mathrm{VRP_{t-4}}$	0.000104			0.000229
	(0.959)			(0.896)
$\mathrm{DRP_{t-1}}$		0.00465		0.00480
		(0.126)		(0.057)
$\mathrm{DRP_{t-2}}$		0.0000845		0.000675
		(0.977)		(0.806)
$\mathrm{DRP_{t-3}}$		-0.000175		0.000357
		(0.940)		(0.861)
$\mathrm{DRP_{t-4}}$		0.00113		0.000646
		(0.519)		(0.740)
$\mathrm{URP_{t-1}}$			-0.0161*	-0.0164*
			(0.018)	(0.021)
$\mathrm{URP_{t-2}}$			-0.00972	-0.0114*
			(0.089)	(0.048)
$\mathrm{URP_{t-3}}$			-0.00202	-0.00228
			(0.816)	(0.802)
$\mathrm{URP_{t-4}}$			-0.0000491	-0.00125
			(0.994)	(0.831)
_cons	0.000526	0.000481	0.000525	0.000517
	(0.241)	(0.385)	(0.344)	(0.229)
N	317	317	317	317
adj. R^2	0.015	-0.006	0.007	0.019

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XVIII. Predicting Crude Oil Inventory Growth Using Oil Premia

	(1)	(2)	(3)	(4)
	%ΔDemand$_t$	%ΔDemand$_t$	%ΔDemand$_t$	%ΔDemand$_t$
VRP$_{t-1}$	-0.0140			-0.0128
	(0.114)			(0.172)
VRP$_{t-2}$	0.0192***			0.0190**
	(0.000)			(0.001)
VRP$_{t-3}$	-0.00293			-0.00540
	(0.650)			(0.408)
VRP$_{t-4}$	0.00225			0.00311
	(0.750)			(0.658)
DRP$_{t-1}$		-0.0114		-0.0148
		(0.258)		(0.069)
DRP$_{t-2}$		0.0107		0.00976
		(0.242)		(0.273)
DRP$_{t-3}$		-0.00209		-0.00153
		(0.847)		(0.878)
DRP$_{t-4}$		-0.00973*		-0.00671
		(0.013)		(0.116)
URP$_{t-1}$			0.0767**	0.0759*
			(0.003)	(0.014)
URP$_{t-2}$			-0.00555	-0.00430
			(0.768)	(0.829)
URP$_{t-3}$			-0.0317	-0.0361
			(0.052)	(0.064)
URP$_{t-4}$			0.0183	0.0220
			(0.344)	(0.378)
_cons	0.000867	0.000903	0.000860	0.000918
	(0.161)	(0.205)	(0.246)	(0.177)
N	326	326	326	326
adj. R^2	0.016	-0.005	0.026	0.039

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XIX. Predicting Crude Oil Demand Growth Using Oil Premia

	(1)	(2)	(3)	(4)
	$\%\Delta\text{Supply}_{\text{t}}$	$\%\Delta\text{Supply}_{\text{t}}$	$\%\Delta\text{Supply}_{\text{t}}$	$\%\Delta\text{Supply}_{\text{t}}$
$\text{VRP}_{\text{t-1}}$	0.00418			0.00391
	(0.302)			(0.318)
$\text{VRP}_{\text{t-2}}$	0.00101			0.000332
	(0.672)			(0.894)
$\text{VRP}_{\text{t-3}}$	0.00202			0.00120
	(0.446)			(0.617)
$\text{VRP}_{\text{t-4}}$	-0.00341			-0.00304
	(0.156)			(0.177)
$\text{DRP}_{\text{t-1}}$		-0.00122		-0.00269
		(0.650)		(0.452)
$\text{DRP}_{\text{t-2}}$		-0.00161		-0.00161
		(0.625)		(0.683)
$\text{DRP}_{\text{t-3}}$		0.000137		0.00115
		(0.919)		(0.444)
$\text{DRP}_{\text{t-4}}$		-0.00293*		-0.00246
		(0.027)		(0.112)
$\text{URP}_{\text{t-1}}$			0.0118	0.0126
			(0.293)	(0.267)
$\text{URP}_{\text{t-2}}$			-0.0125	-0.0108
			(0.266)	(0.294)
$\text{URP}_{\text{t-3}}$			-0.0168**	-0.0161**
			(0.001)	(0.009)
$\text{URP}_{\text{t-4}}$			-0.00124	-0.00176
			(0.882)	(0.837)
_cons	0.00112*	0.00115**	0.00114***	0.00115**
	(0.011)	(0.002)	(0.001)	(0.003)
N	326	326	326	326
adj. R^2	0.003	-0.008	0.018	0.010

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XX. Predicting Crude Oil Supply Growth Using Oil Premia

	(1)	(2)	(3)	(4)
	%ΔSupply$_{\text{OPEC}}$	%ΔSupply$_{\text{OPEC}}$	%ΔSupply$_{\text{OPEC}}$	%ΔSupply$_{\text{OPEC}}$
VRP$_{\text{t-1}}$	0.0112			0.00999
	(0.268)			(0.323)
VRP$_{\text{t-2}}$	-0.00301			-0.00511
	(0.641)			(0.446)
VRP$_{\text{t-3}}$	0.00400			0.00129
	(0.497)			(0.786)
VRP$_{\text{t-4}}$	-0.0112*			-0.0103
	(0.036)			(0.051)
DRP$_{\text{t-1}}$		0.00232		-0.00205
		(0.670)		(0.799)
DRP$_{\text{t-2}}$		-0.00397		-0.00454
		(0.556)		(0.598)
DRP$_{\text{t-3}}$		-0.00167		0.00145
		(0.655)		(0.703)
DRP$_{\text{t-4}}$		0.00265		0.00425
		(0.395)		(0.169)
URP$_{\text{t-1}}$			0.0322	0.0345
			(0.282)	(0.218)
URP$_{\text{t-2}}$			-0.0347	-0.0313
			(0.165)	(0.163)
URP$_{\text{t-3}}$			-0.0466***	-0.0465**
			(0.001)	(0.002)
URP$_{\text{t-4}}$			-0.0111	-0.0151
			(0.414)	(0.317)
_cons	0.00250*	0.00252*	0.00253**	0.00251**
	(0.012)	(0.015)	(0.005)	(0.009)
N	326	326	326	326
adj. R^2	0.015	-0.011	0.037	0.039

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XXI Predicting OPEC's Production Growth Using Oil Premia