UNIVERSITY OF HOUSTON

DOCTORAL THESIS

Essays on Oil Risk and Financial Markets

Author:
Nima Ebrahimi

Supervisor:
Prof. Craig Pirrong

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

in the

Finance Department
Bauer College of Business

Wednesday 8th May, 2019

Acknowledgements

Firstly, I would like to express my sincere gratitude to my advisor Prof. Craig Pirrong for the continuous support of my Ph.D study and related research, for his patience, motivation, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and mentor for my Ph.D study.

Besides my advisor, I would like to thank the rest of my thesis committee: Prof. Kris Jacobs, Dr. Raul Susmel, and Prof. David Papell, for their insightful comments and encouragement.

Last but not the least, I would like to thank my family: my lovely wife Tanya, my mother Roya, my father Bahman, my sister Ayda and my brother Pouya for supporting me spiritually throughout writing this thesis and my life in general.

UNIVERSITY OF HOUSTON

Abstract

Prof. Craig Pirrong
Bauer College of Business

Doctor of Philosophy

Essays on Oil Risk and Financial Markets

by Nima EBRAHIMI

The effects of oil price risk has always been one of the widely discussed topics in finance and macroeconomics. There is also some recent work which concentrate on the implications of higher moments risk premium in oil market for financial markets. All the previous work on oil risk has concentrated on the normal characteristics of distribution of the returns. The main questions we ask through this thesis is how can we extract and disentangle the normal and non-normal risks in the oil market, using the highly liquid options contracts data available for the oil market. Also, after calculating the premia, we answer to the question of how important these risks are as a driver of the cross-section of stock returns and major macroeconomic indices. Finally, we ask if it is possible to describe the variation in the time-series of these risk premia using some widely-known fundamental factors of oil market (e.g. Supply, Demand and Inventory Growth), macroeconomic factors(e.g. GDP growth, Consumption Growth and Inflation) and geopolitical tension index.

The results show that the non-normal characteristics of the distribution (upside and downside jumps) are playing more important role in driving the cross-section of stock returns than the normal characteristics (variance). The second moment risk effect fades after we control for the jumps. Also, we can clearly see that among the risks of upside price jumps and downside price jumps, the upside risk has much more important and robust power as a driver of the cross-section of stock returns. We also show that the upside and downside risk in oil market has higher power in predicting macroeconomic indices and fundamentals of oil market in comparison with variance. We can also verify the results we got using a different approach. We investigate the importance of the risk-neutral moments derived from oil option contracts and we can verify that among the three moments, skewness and kurtosis (non-normal moments) has much stronger and robust implications for the cross-section of stock returns than variance(the normal moment).

We also investigate the commodity-specific and macroeconomic determinants of variance and skewness risk premia in the oil market. The results show that macroeconomic variables has more power than commodity-specific variables as determinants of the premia. We can also see that supply shocks from the middle east countries and geopolitical tensions have a considerable power to describe the variation in the premia. While the macroeconomic variables are significant in both cases of variance and skewness, geopolitical tensions is only a significant determinant in the case of skewness risk premium.

Contents

List of Tables

List of Figures

Chapter 1

Oil Jump Risk

1.1 Introduction

Oil price jumps and drops have been the core of substantial amount of research in finance and economics during the recent decades. The history of finance and financial derivatives has recorded a substantial amount of time variation in implied variance and implied jumps in the oil market. In this paper, we would use a technique which makes us able to decouple the normal and the non-normal characteristics of the distribution of oil future returns, in terms of probability and the way the probabilities are being priced by investors. The main motivation to do this is our previous paper which shows in a competition among variance, Skewness and Kurtosis to see which one has significant effects on stock market returns, the variance loses its significance after controlling for skewness and kurtosis. In addition, we can see that kurtosis effect is more statistically significant in the cross-section of stock returns and keeps its significance through different sub-periods and different option maturities. This reason for us to not only concentrate on jumps versus variance, but also to pay attention to small jumps versus big jumps. One of the other methodological advances in our work, would be to disentangle the upside and downside jumps and calculate the pricing value of each of them separately.

There are many reasons why we are focusing on oil market in this paper. Among these reasons, we can highlight a couple which are the most important. First, energy commodities are the most important type of commodities considering their impact on the economy. Secondly, we need to have a market which is highly liquid because the tools we are using in order to characterize the risk premia are the options on the crude oil futures. Among all the commodities, crude oil financial derivatives are the most liquid ones. The previously mentioned technique makes us able to exploit a very interesting index out of the options data. Not only we can look at the implied probabilities of variance, downward and upward jumps, but also we can extract the way each of these factors are priced by investors in the oil market. In other words, we would use Delta-Vega and Delta-Gamma hedging to calculate the Variance Risk Premium (Henceforth VRP), Downside Jump Risk Premium (Henceforth DRP) and Upside Jump Risk Premium (Henceforth URP) .

The results we got can be classified into three groups. First, we take a look at the prediction power of the three premia we calculated and their

lags to predict important macroeconomic factors. The results show that the variables of interest and their lags are able to predict considerable amount of variation in gdp growth, consumption growth, investment growth and stock market index returns. The results show that the upside and downside risk premia are important predictors of macroeconomic variables and adding them to our model would increase the prediction power of the model considerably. The next class of results are the ones which present the prediction power of the premia for predicting some of the most important variables associated with the fundamentals of the oil market. The results show that the role of downside and upside risk premia is very important in case of predicting oil futures returns, oil inventory growth and oil demand growth. We can also observe that the upside jump premium has a big power for predicting the aggregate OPEC's production growth. The last class of results, are the ones which investigates the role of the calculated premia as a priced factor in the cross-section of stock returns. We can clearly see that 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 anymore. Among the three, the upside risk premium is the most significant factor and the high-low portfolio, sorting based on exposure to URP, can yield the average monthly return of -0.94%. We can see the same pattern when we split the sample based on sub-samples using different break points. The last major result we get from the analysis is that URP's effect vanishes after 2011 and it is replaced by the effect of VRP. This is the year of "shale revolution", during which the domestic oil production of the united states started to grow substantially and the country started moving toward energy independence. The energy independence and being secure against the supply side risks can be a reason for this phenomenon.

1.2 Data and Methodology

1.2.1 Macroeconomic and Oil Fundamentals Data

The macroeconomic data we use are all downloaded from the OECD website. In the case we have access to monthly and quarterly data, we just use the United States data, as we are more interested in the US's economy than the other economies. In case we do not have access to monthly and quarterly data, we would use the panel of yearly data of all OECD countries. We use gross fixed capital formation data as the measure of investment. We also use the household spending as a proxy for the consumption. We also collect the fundamental variables of the oil market from U.S. Energy Information Administration (EAI). We would use the aggregate demand growth for crude oil in OECD countries as a proxy for world's aggregate demand, aggregate growth of the crude oil stocks by OECD countries as a proxy for world's inventory growth and we also use OPEC members' aggregate production growth to check the effect of the premia on the oil market fundamentals. We

calculate the variable growth as $Growth_t = \frac{Var_t - Var_{t-1}}{Var_{t-1}}$ where $Growth_t$ is the variable growth and Var_t is the value of each of the variables at time t.

1.2.2 Estimation of the Oil Premia

We would use the approach introduced and used by Cremers et al. (2015) to quantify the VRP, DRP and URP in oil markets using the option contracts on crude oil futures. We would construct a 60-day fixed-horizon measure of oil risk premia, which is forward-looking measure. We use the options data from CME (formerly NYMEX) for the period 1986 to 2014. We would start filtering the data by deleting the ATM (at-the-money) and ITM(in-the-money) option contracts. We also filter the option contracts which violate the no-arbitrage conditions. Lastly, we would delete the option contracts with prices lower than 0.05 $. These are the filters used by Trolle and Schwartz (2010). The next challenge we face is that the option contracts data that we got from CME are American Options. But our methodology works based on the European option prices. So we would need to transfer the American option prices into Europeans and then compute the implied volatility. We do the conversion based on Bjerksund-Stensland (2002) approach. Figure 1.1 shows implied volatility, downside jump probability and upside jump probability respectively.

We would compose three different portfolio of options based on which we can calculate the VRP, DRP and URP. For calculating the VRP, we would form a portfolio of two near the money straddles. On each day, we pick closest to at the money put and call option and we call them P_1 and C_1 respectively. At the same day and with the same maturity, we would select second pair of put and call options which are second-nearest to at the money options, and we call them P_2 and C_2. having two sets of options we would form two straddles by combining puts and calls together. We would form the two straddles based on the following two equations:

$$\begin{cases} Straddle_1 = P_1 + aC_1 \\ Straddle_2 = P_2 + bC_2 \end{cases} \tag{1.1}$$

Based on these two equations, the first straddle comprises one unit of P_1 and a units of C_1. Likewise, the second straddle would be made using one unit of P_2 and b units of C_2. We would calculate the exact amount of the parameters (a and b) by solving some equations in order to guarantee that our portfolios have some specific characteristics. In the case of VRP, we would like to form a portfolio of options on each day which is delta-gamma hedged. In order to do that, we would solve the following system of linear equations to make sure that the each of the two straddles are delta-hedged:

$$\begin{cases} \Delta_{P1} + a\Delta_{C1} = 0 \\ \Delta_{P2} + b\Delta_{C2} = 0 \end{cases} \tag{1.2}$$

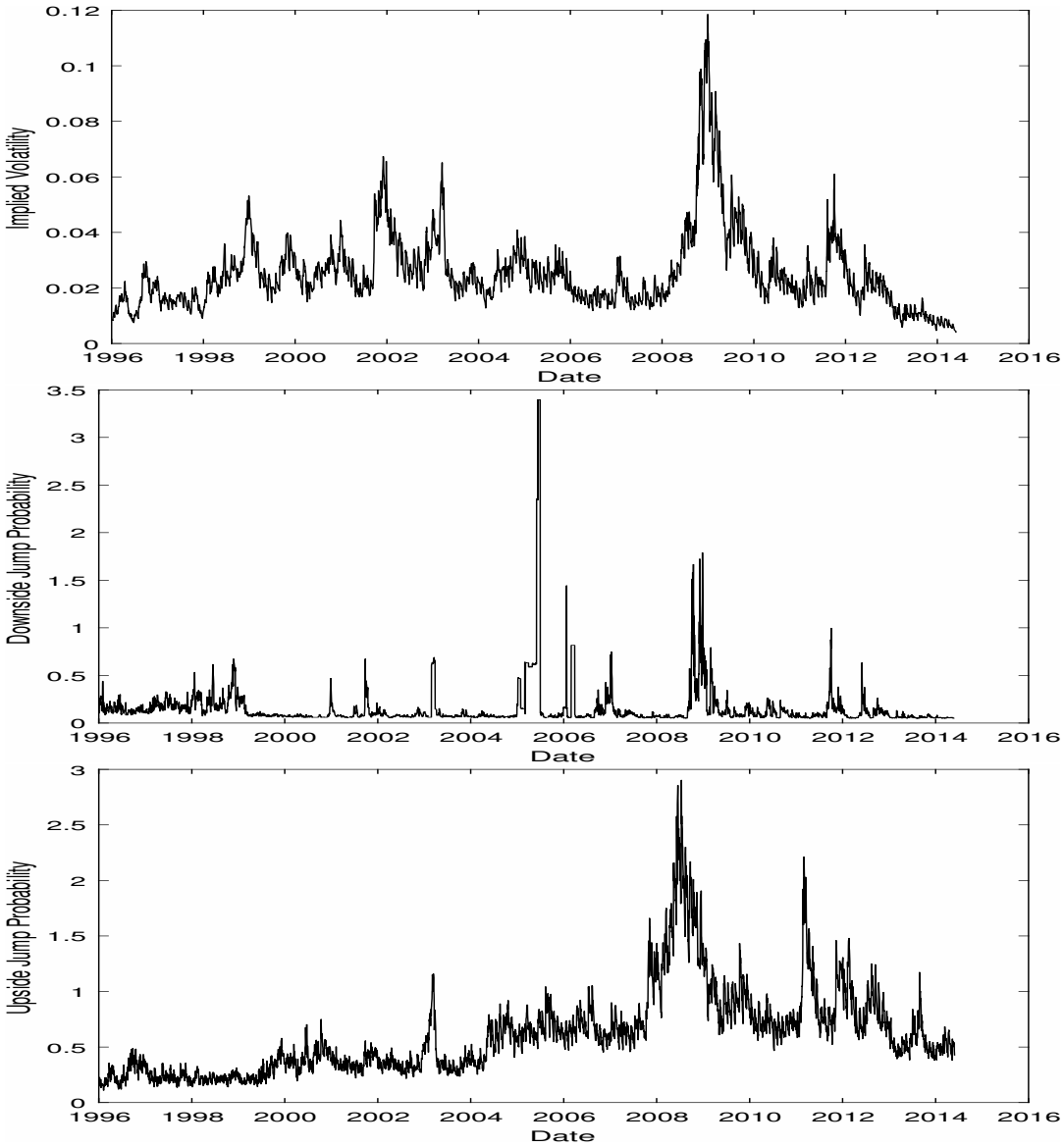

FIGURE 1.1: This figure shows the time-series of the value of 60-days Variance Portfolio, Downside Jump Portfolio and Upside Jump Portfolio in oil market . The data ranges from 1996 to 2014.

Where δ is the black (1976) delta of the option. Solving these two equations we would get $a = -\frac{\Delta_{P1}}{\Delta_{C1}}$ and $b = -\frac{\Delta_{P2}}{\Delta_{C2}}$. Replacing the solved parameters in equation 1, we would get the value of the two straddles as:

$$\begin{cases} Straddle_1 = P_1 - \frac{\Delta_{P1}}{\Delta_{C1}} C_1 \\ Straddle_2 = P_2 - \frac{\Delta_{P2}}{\Delta_{C2}} C_2 \end{cases} \tag{1.3}$$

Now that the straddles are formed and we have guaranteed that both of the straddles are delta-hedged, the next move would be to make a gamma-neutral portfolio consisting of the two straddles. The gamma of each of the straddles would be calculated based on the following equations:

$$\begin{cases} \Gamma_{Straddle1} = \Gamma_{P1} - \frac{\Delta_{P1}}{\Delta_{C1}}\Gamma_{C_1} \\ \Gamma_{Straddle2} = \Gamma_{P2} - \frac{\Delta_{P2}}{\Delta_{C2}}\Gamma_{C_2} \end{cases} \tag{1.4}$$

Then, in order to form a portfolio of straddles which is delta-neutral and gamma-neutral, we would calculate the following linear equation:

$$\Gamma_{Straddle1} + d\Gamma_{Straddle2} = 0 \Rightarrow d = -\frac{\Gamma_{Straddle1}}{\Gamma_{Straddle2}} \tag{1.5}$$

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

$$Portfolioval_{Delta-Gamma} = Straddle_1 + d \times Straddle_2 \tag{1.6}$$

Where d is calculated based on equation (1.5).

After VRP's portfolio, it is time for us to calculate the DRP's and the URP's as well. We would go through the calculations of the DRP's portfolio. Calculating URP's would be similar to the one for DRP's. We choose three put options which their moneyness (which we define as $\ln(\frac{K}{F})$) is closest to $-6 \times \sigma \times \sqrt{T-t}$. Next, we would solve the following system of linear equations to make sure that the portfolio is delta-vega hedged:

$$\begin{cases} \Delta_{P1} + x\Delta_{P2} + y\Delta_{P3} = 0 \\ \nu_{P1} + x\nu_{P2} + y\nu_{P3} = 0 \end{cases} \tag{1.7}$$

Where Δ and ν are the Black (1976) delta and vega of the option. This would give us $x = \frac{(-\Delta_{P1} - y\Delta_{P3})}{\Delta_{P2}}$ and $y = \frac{(\nu_{P2} \times (\frac{\Delta_{P1}}{\Delta_{P2}}) - \nu_{P1})}{(\nu_{P3} - (\frac{\Delta_{P3}}{\Delta_{P2}}))}$.

Now, we would have the value of the downside portfolio as:

$$Downportfolioval_{Delta-Vega} = P_1 + xP_2 + yP_3 \tag{1.8}$$

We also choose three call options which their moneyness is closest to $6 \times \sigma \times \sqrt{T-t}$. We then solve the following system of linear equations:

$$\begin{cases} \Delta_{C1} + w\Delta_{C2} + z\Delta_{C3} = 0 \\ \nu_{C1} + w\nu_{C2} + z\nu_{C3} = 0 \end{cases} \tag{1.9}$$

Solving the system of equations, we would get $z = \frac{(-\Delta_{C1} - y\Delta_{C3})}{\Delta_{C2}}$ and $w = \frac{(\nu_{C2} \times (\frac{\Delta_{C1}}{\Delta_{C2}}) - \nu_{C1})}{(\nu_{C3} - (\frac{\Delta_{C3}}{\Delta_{C2}}))}$. Using the solutions calculated from equation 9, we would be able to calculate the value of the upside portfolio as:

$$Upportfolioval_{Delta-Vega} = C_1 + wC_2 + zC_3 \tag{1.10}$$

In order to make sure that we are as close as we can to the 60-days , fixed-horizon portfolio values, we calculate each of the variance, downside jump and upside jump portfolios for closest maturity less than 60-day and the closest maturity greater than 60-days. Then, we get the value of the 60-day portfolio for each of the risks by linearly interpolating the two values. The resulting time-series of the value of each of the three portfolios is presented in figure 1.2.

As we have already noted, we need to calculate the VRP, DRP and URP of the oil market. In order to get the premia , we fit the appropriate ARMA model to time-series of the value of the each three portfolios we have already formed. The criteria we would use in order to select the best ARMA model is AIC (Akaike Information Criterion) . We run all the combinations of models (100 models), (ARMA(AR:i=1 to 10,MA:j=1 to 10)). The intuition behind this move is to remove the auto-correlation from the time-series of the value portfolios. We have also done all of the analyses using AR(1) and AR(1,1) to compare the models used in the literature and the model we choose based on our criteria. Figure 3 shows the autocorrelation function for residuals of the models mentioned. We can see that among all these models ARMA (5,5),ARMA(9,6) and ARMA(3,1), which have been selected based on minimum-AIC criteria, are able to remove most of the auto-correlation and is able to give us VRP, DRP and URP respectively.
The VRP, URP and DRP are calculated using the following three equations respectively:

$$VRP = Portfolioval_{Delta-Gamma} - \widehat{Portfolioval}_{Delta-Gamma} \tag{1.11}$$

$$URP = Upportfolioval_{Delta-Vega} - \widehat{Upportfolioval}_{Delta-Vega} \tag{1.12}$$

$$DRP = Downportfolioval_{Delta-Vega} - \widehat{Downportfolioval}_{Delta-Vega} \tag{1.13}$$

where $\widehat{Portfolioval}_{Delta-Gamma}$, $\widehat{Upportfolioval}_{Delta-Vega}$ and $\widehat{Downportfolioval}_{Delta-Vega}$ are the fitted value of the ARMA models fitted for each of the VRP, URP and DRP value portfolios respectively. The resulting premia that we use all through this paper are plotted in Figure 1.3.

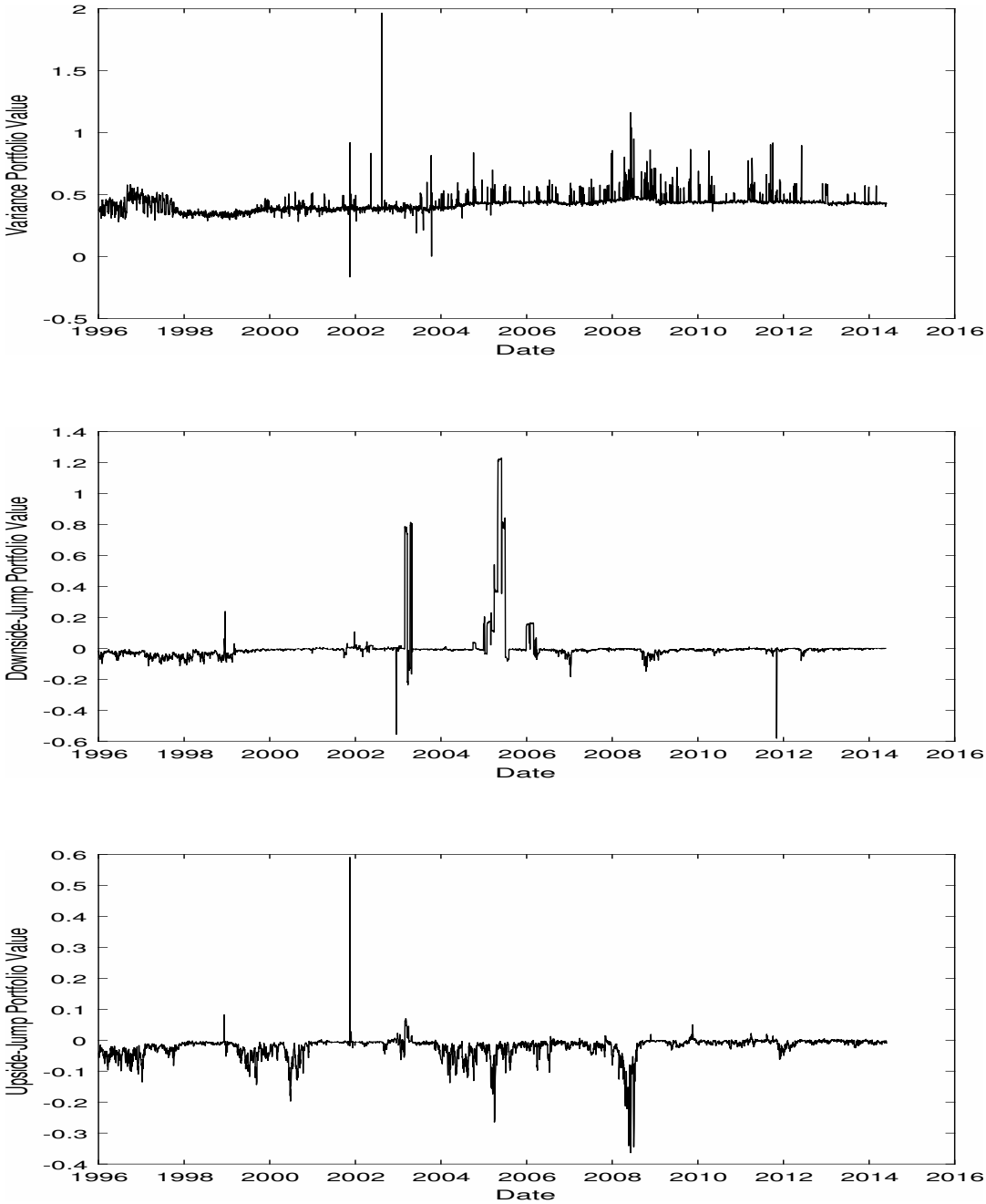

FIGURE 1.2: This figure shows the time-series of the value of 60-days Variance Portfolio, Downside Jump Portfolio and Upside Jump Portfolio in oil market . The data ranges from 1996 to 2014.

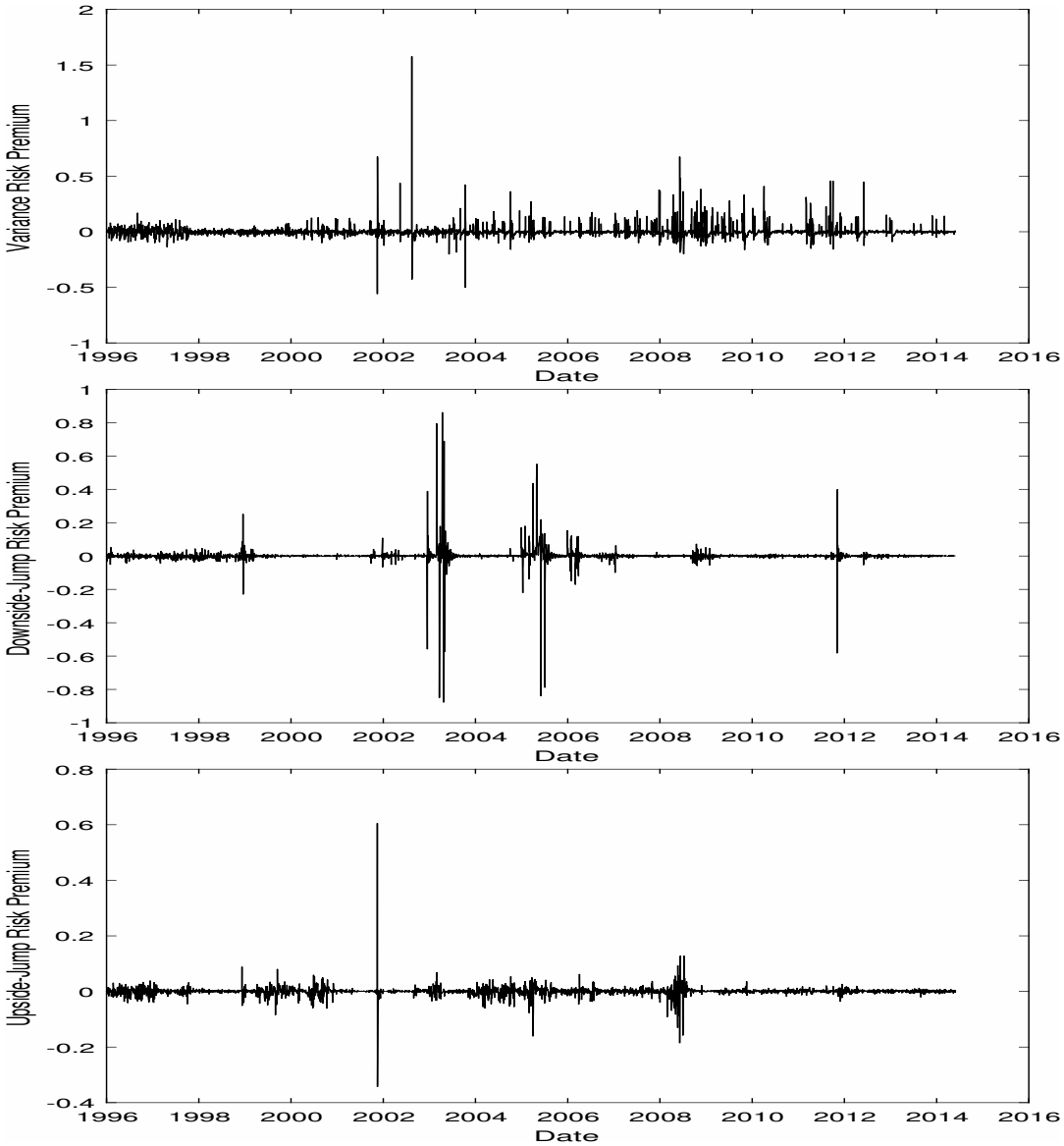

FIGURE 1.3: This figure shows the time-series of Variance Risk Premium, Downside-Jump Risk Premium and Upside-Jump Risk Premium in oil market. The chosen fitted models based on which we calculated the risk premia are ARMA(5,5), ARMA(9,6) and ARMA(3,1) for Variance, Downside and Upside jump premia respectively. The data range is from 1996 to 2014.

1.3 Results

1.3.1 Oil Risk Premia as Macroeconomic Predictors

Looking at table 1.1 , we can see that the URP is a significant predictor of the gdp growth in the united states. The table shows that the loading on this variable for the lags zero, one and two are negative. In terms of statistical significance, lags two and zero are statistically significant at the 95% confidence level. We can also see that the lag zero and lag two of the URP are explaining 1.8% and 1.5% of the variation inside the gdp growth respectively. In column 4, we can also see that the URP is still a significant player after controlling for the first lag of the gdp growth.

Table 1.2 is showing the results for the case of predicting consumption growth, using a yearly panel data set of the consumption growth from OECD countries. We can see that the only variable which all its lags (0 to 3) are statistically significant is URP. the VRP and DRP show significance for three lags (1 to 3). The loading on the VRP is consistently negative for all lags, while in the case of the URP, the sign changes every other lag and the DRP loading changes from positive to negative for the last lag. The R-squared in the case of VRP, URP and DRP are 4.3%, 3% and 3.1% respectively.

We do the same analysis for the investment growth and we present the results in table 1.3. The results and significance of the three classes of variables stay the same as the case of consumption. The only change is that the URP's lag zero is significant in this case while it was not in the previous case. The R-squared for the case of VRP, URP and DRP are equal to 5.3%, 3% and 3.4% respectively.

Table 1.4 looks at the predictive power of the URP for the value-weighted stock market index return in the United States. We have omitted the VRP and DRP here, as they have not shown any significance in the regressions. The results show that lag one of the URP has a positive loading and the R-squared of the uni-variate regression is 0.7%. We can also see that the URP's first lag keeps its significance after controlling for the first lag of the index return. Column 3 also, shows that adding the first lag of the VRP and the DRP does not make the first lag of URP insignificant. It is also clear that adding DRP and VRP does not add anything to prediction power of the model, in terms of R-squared.

1.3.2 Oil Risk Premia as Predictors of the Oil Market

In this section, we would take a look at the predictive power of the VRP, DRP and URP for some of the most important variables related to oil market. The first variable is the future returns. The results are presented in table 1.5. The regressions we have done, shows that the VRP and DRP do not have any implications and predicting power. That's why the URP is the only premium among the three premia, that we would consider in the predictive regressions. We initially do the uni-variate regressions using the first second and third lags of the URP as predictors and we present the results in columns

TABLE 1.1: Predicting GDP growth using Oil Premia

	(1) gdpgrowth	(2) gdpgrowth	(3) gdpgrowth	(4) gdpgrowth
VRP	0.745			
	(1.485)			
URP	-8.649*			-6.632**
	(3.733)			(2.182)
DRP	-0.932			
	(0.867)			
VRP_{t-1}		0.0687		
		(0.965)		
URP_{t-1}		-3.184		
		(2.935)		
DRP_{t-1}		-0.337		
		(0.753)		
VRP_{t-2}			-0.148	
			(0.984)	
URP_{t-2}			-8.612*	-5.901
			(3.880)	(3.453)
DRP_{t-2}			-1.482	
			(0.814)	
$gdpgrowth_{t-1}$				0.395**
				(0.121)
_cons	0.614***	0.631***	0.616***	0.345**
	(0.113)	(0.110)	(0.110)	(0.127)
N	108	107	106	106
adj. R^2	0.018	-0.023	0.015	0.211

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

1 to 3. As we can see, the URP's second and third lags are significant at the 90% confidence level. Column 4 shows that the combination of the two mentioned lags provide the R-squared equal to 2.2%. We can also see that the loading on both of the lags are negative. Column 5 shows that controlling for lag one of the futures returns decrease the significance level of the second lag of URP while the first lags significance remains intact.

Table 1.6 presents the results for the case of predicting oil inventory growth. The results show that VRP and DRP show much lower predictive power than the URP for oil inventory growth. While the VRP and DRP are only able to provide R-squared equal to 0.4%, the R-squared in the case of URP is 4.5%.

TABLE 1.2: Predicting Consumption Growth using Oil Premia

	(1) consgrowth	(2) consgrowth	(3) consgrowth	(4) consgrowth
VRP	0.243			0.161
	(0.133)			(0.133)
VRP_{t-1}	-0.531***			-0.158
	(0.132)			(0.154)
VRP_{t-2}	-0.500***			-0.397***
	(0.131)			(0.116)
VRP_{t-3}	-0.347**			0.00504
	(0.131)			(0.116)
URP		-4.125***		-5.262***
		(0.765)		(0.929)
URP_{t-1}		1.867**		4.109***
		(0.645)		(0.735)
URP_{t-2}		-2.765***		-3.233***
		(0.638)		(0.590)
URP_{t-3}		2.039**		2.084**
		(0.651)		(0.784)
DRP			0.141	-0.0912
			(0.117)	(0.121)
DRP_{t-1}			0.433***	0.582***
			(0.117)	(0.102)
DRP_{t-2}			0.341**	0.242*
			(0.116)	(0.102)
DRP_{t-3}			-0.429***	-0.857***
			(0.114)	(0.125)
$consgrowth_{t-1}$				0.500***
				(0.0261)
_cons	2.771***	2.998***	2.728***	1.542***
	(0.102)	(0.109)	(0.105)	(0.122)
N	1023	1023	1023	1023
adj. R^2	0.043	0.030	0.031	0.354

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

We can see that the loading on the significant lags of VRP and DRP are negative and positive respectively, while the loading on URP's lag zero is positive and the loading for lag one is negative. All the significant lags of the

TABLE 1.3: Predicting Investment Growth using Oil Premia

	(1) investment	(2) investment	(3) investment	(4) investment
VRP	1.014**			0.402
	(0.359)			(0.401)
VRP_{t-1}	-1.505***			-0.804
	(0.355)			(0.463)
VRP_{t-2}	-1.839***			-1.926***
	(0.356)			(0.354)
VRP_{t-3}	-0.798*			-0.000338
	(0.355)			(0.354)
URP		-12.17***		-13.52***
		(2.093)		(2.819)
URP_{t-1}		6.927***		10.34***
		(1.763)		(2.219)
URP_{t-2}		-7.790***		-9.992***
		(1.743)		(1.792)
URP_{t-3}		7.170***		3.949
		(1.777)		(2.381)
DRP			0.449	0.00661
			(0.322)	(0.370)
DRP_{t-1}			1.280***	1.755***
			(0.323)	(0.313)
DRP_{t-2}			1.153***	0.983**
			(0.320)	(0.313)
DRP_{t-3}			-0.718*	-1.609***
			(0.311)	(0.378)
$investment_{t-1}$				0.288***
				(0.0282)
_cons	3.576***	4.177***	3.361***	2.861***
	(0.278)	(0.299)	(0.286)	(0.315)
N	1084	1084	1084	1084
adj. R^2	0.053	0.030	0.034	0.202

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

three predictors keep their significance after controlling for lagged inventory growth.

Table 1.7 is showing the results for the case of the oil demand growth.

TABLE 1.4: Predicting Value Weighted Index Return using Oil Premia

	(1) indexret	(2) indexret	(3) indexret
upsidejp $_{t-1}$	0.0610*	0.0633*	0.0620*
	(0.0289)	(0.0272)	(0.0267)
indexret$_{t-1}$		0.0811	0.0793
		(0.0714)	(0.0714)
VRP$_{t-1}$			-0.00895
			(0.00973)
DRP$_{t-1}$			-0.000104
			(0.00303)
_cons	0.000418**	0.000384**	0.000383**
	(0.000133)	(0.000140)	(0.000140)
N	292	292	292
adj. R^2	0.007	0.01	0.005

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

TABLE 1.5: Predicitng Oil Future Returns using Oil Premia

	(1) fret	(2) fret	(3) fret	(4) fret	(5) fret
URP$_{t-1}$	-0.0174				
	(0.0912)				
URP$_{t-2}$		-0.138		-0.154*	-0.150*
		(0.0705)		(0.0703)	(0.0676)
URP$_{t-3}$			-0.112	-0.130*	-0.113
			(0.0594)	(0.0606)	(0.0626)
fret$_{t-1}$					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
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The second lag of VRP is significant with positive loading and the R-squared provided by it is 0.6%. The DRP's first lag is significant with negative loading and the R-squared associated with it is 0.2%. The URP's first and third lags are significant with positive and negative signs respectively. The R-squared provided by URP is much higher than the other two predictors and it is equal

TABLE 1.6: Predicting Oil Inventory Growth Using Oil Premia

	(1) invgrowth	(2) invgrowth	(3) invgrowth	(4) invgrowth
VRP	-0.0244			
	(0.0342)			
VRP_{t-1}	0.0362			
	(0.0492)			
VRP_{t-2}	-0.112*			-0.147***
	(0.0484)			(0.0436)
VRP_{t-3}	-0.0563			
	(0.0540)			
URP		0.489***		0.477***
		(0.141)		(0.126)
URP_{t-1}		-0.278*		-0.322**
		(0.112)		(0.120)
URP_{t-2}		-0.168		
		(0.0854)		
URP_{t-3}		-0.0696		
		(0.143)		
DRP			-0.0134	
			(0.0251)	
DRP_{t-1}			0.0713***	0.0507**
			(0.0146)	(0.0176)
DRP_{t-2}			0.0142	
			(0.0182)	
DRP_{t-3}			0.0405	
			(0.0206)	
$invgrowth_{t-1}$				0.0936
				(0.0504)
_cons	0.000519	0.000504	0.000521	0.000485
	(0.000419)	(0.000405)	(0.000420)	(0.000398)
N	317	317	317	316
adj. R^2	0.009	0.045	0.004	0.075

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

to 3.8%. This is inline with the previous regressions' results.

The last variable we look at, is OPEC's production growth. The results,presented in table 1.8 show that URP's third lag is able to provide R-squared equal to

TABLE 1.7: Predicting Demand Growth Using Oil Premia

	(1) demandgrowth	(2) demandgrowth	(3) demandgrowth	(4) demandgrowth
VRP	0.0167			
	(0.148)			
VRP_{t-1}	-0.231			
	(0.221)			
VRP_{t-2}	0.291			0.290*
	(0.169)			(0.133)
VRP_{t-3}	0.00295			
	(0.141)			
URP		-0.502		
		(0.556)		
URP_{t-1}		1.547**		1.400**
		(0.515)		(0.449)
URP_{t-2}		-0.378		
		(0.374)		
URP_{t-3}		-0.565		-0.642
		(0.299)		(0.340)
DRP			-0.106	
			(0.118)	
DRP_{t-1}			-0.201*	-0.221***
			(0.0853)	(0.0652)
DRP_{t-2}			0.0555	
			(0.0730)	
DRP_{t-3}			-0.0473	
			(0.0714)	
$demandgrowth_{t-3}$				-0.307***
				(0.0345)
_cons	0.000854	0.000766	0.000751	0.00109
	(0.000642)	(0.000637)	(0.000640)	(0.000775)
N	328	328	328	328
adj. R^2	0.006	0.038	0.002	0.145

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

3% and its loading is negative. The R-squared in the case of VRP and DRP are less than 1%. This again, shows that the URP is the most important predictor of the variables of interest in the oil market, among the three premia.

TABLE 1.8: Predicting OPEC Production Growth Using Oil Premia

	(1) OPECprodg	(2) OPECprodg	(3) OPECprodg	(4) OPECprodg
VRP	-0.182			-0.183
	(0.242)			(0.229)
VRP_{t-1}	0.181			0.167
	(0.182)			(0.158)
VRP_{t-2}	-0.0822			
	(0.151)			
VRP_{t-3}	0.0568			
	(0.164)			
URP		-0.552		
		(0.352)		
URP_{t-1}		0.406		
		(0.569)		
URP_{t-2}		-0.654		
		(0.477)		
URP_{t-3}		-0.603*		-0.490
		(0.236)		(0.258)
DRP			0.153	
			(0.137)	
DRP_{t-1}			-0.0848*	-0.0483
			(0.0343)	(0.0346)
DRP_{t-2}			0.0640	0.0311
			(0.0378)	(0.0393)
DRP_{t-3}			-0.137	
			(0.111)	
$OPEC_{t-1}$				-0.00757
				(0.122)
_cons	0.00228*	0.00217**	0.00227*	0.00227**
	(0.000911)	(0.000812)	(0.000918)	(0.000829)
N	328	328	328	328
adj. R^2	0.008	0.03	0.008	0.009

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

1.3.3 Oil Risk Premia and the Cross-Secction of Stock returns

In this section, we present the results of the analysis, which investigates the role of the three oil premia in the cross-section of stock returns. In each case,

we would sort the stocks into quintiles based on the sensitivity of the stocks' return toward each of the premia.

Sorting Based on Exposure to VRP

Based on what we have learned from ICAPM , we would expect the stocks with different sensitivities toward each of the oil premia to have different average returns, if the premia are priced factors in the cross-section of stock returns. In this section, we would test to see if this holds for oil VRP. The way we would do this task is to sort stocks and form portfolios based on the sensitivities of the stock returns to oil VRP and after that, we compare the average returns and Jensen's Alphas of the portfolios both visually and statistically. To the best of our knowledge, our paper is the first which is decomposing the preferences in oil market to downside, upside and variance risk premia and investigates the effect of the exposure level towards these variables on the average returns of the stocks. Ang,Hodrick,Zhing and Zhang(2006) and Christofferson and Pan (2015) have shown that the higher is the sensitivity of a stock to innovations in market and oil volatility, the lower is the average return of the stock, using the data in NYSE/AMEX/NASDAQ between 1990 to 2012. The difference that this paper makes is that it does the same analysis with replacing the implied moments in oil market with their associated premia, which are the way the implied moments and probabilities are priced into the return of financial assets. Following Chang,Christofferson and Jacobs (2013) and Christofferson and Pan (2015), we are using daily data on return and a 60-day window in order to grasp the conditional nature of 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:

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{VRP}VRP + \varepsilon_{i,t} \tag{1.14}$$

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{VRP}VRP + \beta^i_{DRP}DRP + \varepsilon_{i,t} \tag{1.15}$$

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{VRP}VRP + \beta^i_{DRP}DRP_t + \beta^i_{URP_t}URP_t + \varepsilon_{i,t} \tag{1.16}$$

At the end of each month, we sort all stocks in the data based on the sensitivity we got in the previous step (based on the regression's beta). 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 form the time-series of so-called "post-ranking" returns of each of these five portfolios during the following 30 days. Each time, we roll the window for one month and keep doing this procedure to cover the whole sample period. At the end

TABLE 1.9: VRP and the Cross-Section of Stock Returns

Factor: Variance Risk Premium						
Quintile Portfolio	1	2	3	4	5	5-1
Panel A						
Average Beta	-0.659	-0.157	-0.011	0.137	0.635	1.294
Average Returns	0.830	0.995	0.930	0.811	0.410	-0.420
Carhart Alpha	0.046	0.261	0.184	0.047	-0.432	-0.478
P-Value	0.786	**0.002**	**0.015**	0.592	**0.019**	**0.086**
Panel B						
Average Beta	-0.720	-0.161	-0.008	0.144	0.665	1.349
Average Returns	0.678	0.988	0.940	0.846	0.512	-0.166
Carhart Alpha	-0.114	0.254	0.196	0.083	-0.331	-0.217
P-Value	0.517	**0.002**	**0.010**	0.362	**0.079**	0.426
Panel B						
Average Beta	0.000	-0.168	-0.009	0.151	0.698	0.698
Average Returns	0.722	1.019	0.940	0.777	0.569	-0.153
Carhart Alpha	-0.071	0.286	0.195	0.010	-0.251	-0.180
P-Value	0.678	**0.001**	**0.014**	0.915	0.146	0.475

of this procedure we would have daily returns for the five portfolios during the sample period.

The next move would be to run the following regression with the daily returns data we have in hand:

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

Where $R_{p,t}$ is the return of each portfolio, SMB and HML are showing size and value respectively from Fama and French (1993), and UMD is momentum from Carhart (1997). In order to see if the effect of VRP persists after we control for other factors like market excess return, momentum, book-to-market and size, we also use the Carhart 4-factor model to compute the Jensen's Alpha. Significance of the Jensen's Alpha would show that the factor we are looking at is priced in the cross-section of stock returns. For each of the quintile portfolios, table IX reports the average pre-ranking beta plus the Jensen's Alpha and the average post-ranking monthly returns. In all the tables presented in this paper, we report the P-Value of Jensen's Alpha using Newey-West with 21 lags.

Panels A, B and C are showing the results of the analysis based on regressions (1.14) , (1.15) and (1.16). The columns 1 to 5 are the ones presenting the analysis results for five sorted portfolios, number 1 being the lowest and 5 being the highest exposure portfolio. We also have the average return and the Jensen's alpha for the portfolio that longs the highest exposure quntile and shorts the lowest exposure quintile of stocks. This would be the last column, with label "5-1". The average monthly Jensen's Alpha would be the daily alpha multiplied by 21. If the VRP of the oil market is a factor which is priced, we would see a monotonic (decreasing or increasing) trend in average

returns of the portfolio of stocks going from the lowest exposure portfolio to the highest exposure portfolio toward oil variance premium. We would also test the significance of the Jensen's Alpha and average return for the high-low portfolio. Looking at table 1.9, Panel (A) shows that the difference between the Jensen's alpha of portfolio 5 and Jensen's alpha of portfolio 1 is -0.47%. Also, the average monthly difference between the return of portfolios 5 and 1 is -0.42 %. Again, we can see that there is no monotonic trend in average monthly returns, moving from portfolio 1 towards portfolio 5. The Jensen's alpha of the high-low portfolio is statistically significant at the 90% confidence level. The results for portfolios sorted on VRP after controlling for DRP and URP are presented in panels B and C. These two panels show that a similar pattern for Jensen's alpha and average portfolio returns as the one saw in panel A, can be seen here too. We can see that the Jensen's alpha in none of the later two panels (B and C) is showing any statistical significance at the 90% confidence level. Overall, the results we got do not show that innovations in oil VRP is a priced factor in the cross-section of stock returns after we control for downside and upside risk premia.

Figure 1.4 demonstrate the average monthly return and monthly Jensen's alphas of the hedge portfolio through time. They also demonstrate the Newey-West t-statistics and the 90% confidence level bounds to show the result of significance test. The diagrams would give us the chance to understand how average return and Jensen's alphas are evolving through the sample period. Looking at the top two graphs we can see that the average return of the high-low portfolio in the case of VRP are statistically significant for two sub-periods of 1996-2000 and 2011-2014, while in the 2000-2011 period the return of the high-low portfolio is not highly negative and not statistically significant. The middle two graphs are presenting the results for the case of VRP , when we control for DRP as well. The graphs show that controlling for DRP makes the results weaker in terms of statistical significance, as the t-stat values depart form the confidence bounds. The bottom two figures can clearly show us the effect of controlling for URP on the significance of VRP exposure. Controlling for URP leads to see an upward shift in average returns and Jensen's alphas. Looking at bottom-right graph, we can clearly see that the t-stats in the two sub-periods, before 2000 and after 2011, which used to be close to confidence bounds or even beyond the bounds are now clearly moving away from the confidence bounds. This is a clear indication of the fact that after controlling for URP, there is no significant effect left for the VRP in the cross-section of stock returns. This is inline with the results we already got from regression analysis.

Sorting Based on Exposure to DRP

We do the same analysis that we did in the last section for the oil DRP by sorting the stocks based on their exposure to DRP. In addition, regression (1.14) is replaced by the following regression:

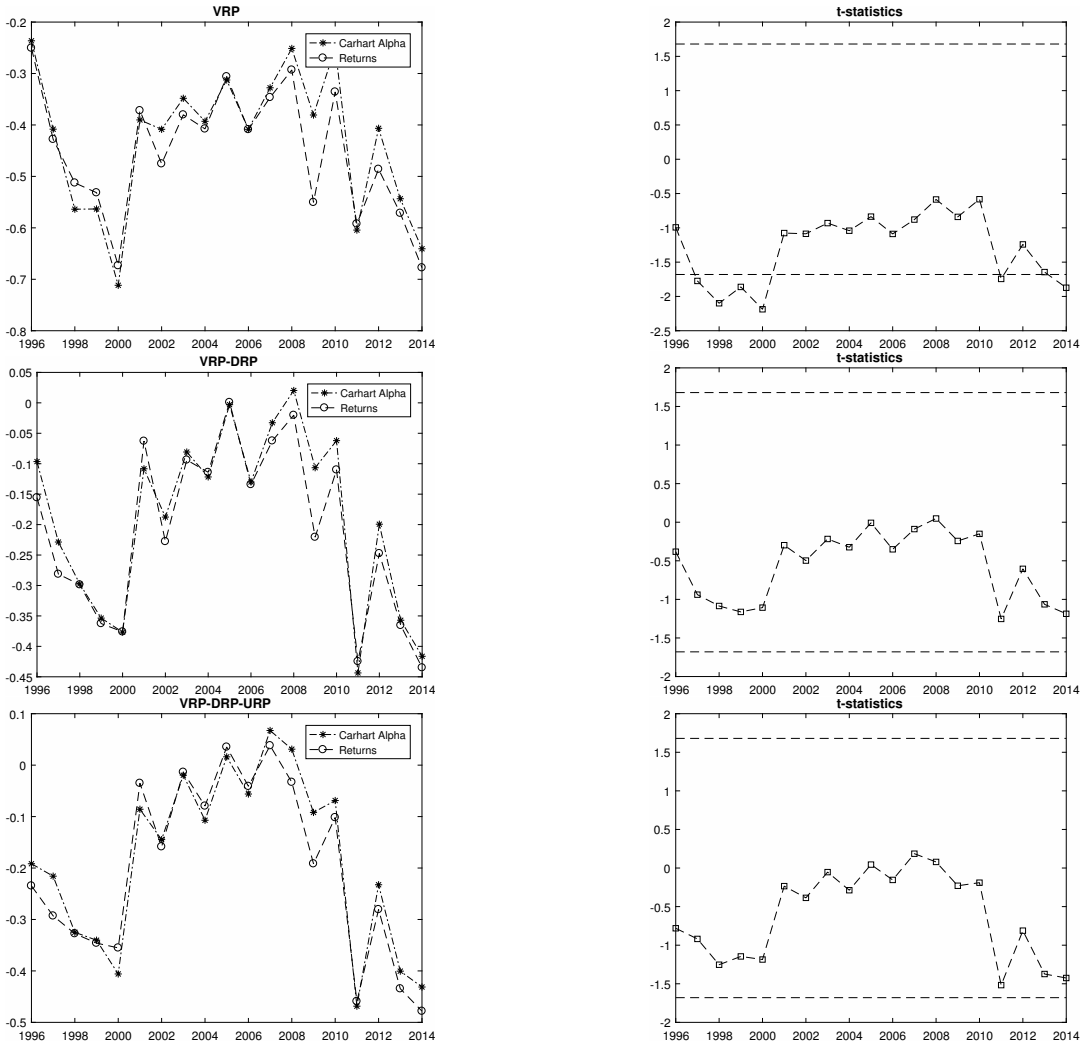

FIGURE 1.4: This Figure presents the evolution of average monthly returns and Jensen's Alpha of the hedge portfolio through the sample period in the case of sorting based on the exposure to VRP. The left column shows the average monthly returns and Jensen's Alpha of the hedge portfolio in case we form 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.

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{DRP_t} DRP + \varepsilon_{i,t} \tag{1.17}$$

The results we got from the analysis in this section are reported in Table 1.10. Panel C of table X shows the results for the case of sorting based on the exposure to DRP, after controlling for VRP and URP. As we can see, with one exception, the downward trend in average returns and Jensen's alphas are

TABLE 1.10: DRP and the Cross-Section of Stock Returns

Factor: Downside-Jump Risk Premium						
Quintile Portfolio	1	2	3	4	5	5-1
Panel A						
Average Beta	-2.554	-0.515	0.106	0.736	2.810	5.364
Average Returns	0.861	0.850	0.825	0.831	0.728	-0.133
Carhart Alpha	0.073	0.108	0.071	0.056	-0.055	-0.127
P-Value	0.707	0.277	0.266	0.598	0.767	0.683
Panel B						
Average Beta	-2.654	-0.526	0.118	0.771	2.926	5.580
Average Returns	0.932	0.846	0.819	0.868	0.755	-0.177
Carhart Alpha	0.126	0.110	0.059	0.090	-0.037	-0.163
P-Value	0.528	0.282	0.366	0.370	0.846	0.610
Panel C						
Average Beta	-2.846	-0.568	0.117	0.809	3.100	5.946
Average Returns	0.801	0.981	0.778	0.811	0.671	-0.131
Carhart Alpha	-0.009	0.245	0.023	0.032	-0.136	-0.127
P-Value	0.962	**0.014**	0.745	0.762	0.462	0.678

evident. The average monthly return of the high-low portfolio is -0.13%. The Jensen's alpha of the high-low portfolio is -0.12%. Although we can see the trend in the average returns and Jensen's alphas, as the size of the average returns and Jensen's alphas are small, we cannot find any statistical significance for the two variables. Overall, there is not enough solid statistical evidence for the risk of exposure to DRP to be a priced factor in the cross-section of stock returns. Appendix B shows the graphs which present the evolving average monthly returns and Jensen's alpha for the hedge portfolio through the sample period, in case we form the portfolios 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. As we can see the t-stats are far away from the confidence bounds and we cannot see any significance for the Jensen's alphas overall. The middle and bottom two panels of Figure 6 are showing that controlling for VRP and URP does not fundamentally change the size and the statistical significance of returns and Jensen's alphas in the case of forming portfolios based on DRP.

Sorting Based on Exposure to URP

In this section, we do the same analysis as two last parts. The only difference is that this time, we sort the stocks based on their exposure to URP. In addition, regressions 14 and 15 are replaced by the following two regressions respectively:

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{URP} URP + \varepsilon_{i,t} \tag{1.18}$$

TABLE 1.11: URP and the Cross-Section of Stock Returns

Factor: Upside-Jump Risk Premium Quintile Portfolio	1	2	3	4	5	5-1
Panel A						
Average Beta	-3.178	-0.807	-0.108	0.575	2.875	6.053
Average Returns	1.324	1.051	0.860	0.606	0.197	-1.127
Carhart Alpha	0.493	0.292	0.102	-0.135	-0.530	-1.023
P-Value	**0.017**	**0.005**	0.126	0.134	**0.005**	**0.003**
Panel B						
Average Beta	-3.290	-0.825	-0.098	0.618	-0.018	3.272
Average Returns	1.206	1.126	0.842	0.652	0.160	-1.046
Carhart Alpha	0.379	0.372	0.083	-0.092	-0.560	-0.940
P-Value	**0.066**	**0.000**	0.209	0.297	**0.002**	**0.004**
Panel C						
Average Beta	-3.473	-0.849	-0.082	0.672	3.230	6.703
Average Returns	1.170	1.089	0.853	0.624	0.228	-0.942
Carhart Alpha	0.375	0.339	0.103	-0.139	-0.527	-0.902
P-Value	**0.063**	**0.000**	0.141	0.133	**0.002**	**0.004**

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{VRP}VRP + \beta^i_{URP_t}URP + \varepsilon_{i,t} \quad (1.19)$$

The results we got from the analysis in this section is reported in 1.11. Starting from panel A, the downward trend in average monthly returns is very clear, moving from low exposure toward the high exposure portfolio. The average monthly return for the case of sorting based on exposure to URP, without controlling for VRP and DRP, is -1.12%. The Jensen's alpha associated with the high-low portfolio is -1.02% and its P-Value is 0.003 which indicates that the Jensen's alpha is statistically significant at the 99% confidence level. Panels B and C are showing the results when we also control for VRP and DRP. As we can see, controlling for the VRP and DRP has a slight effect on the magnitude of returns and Jensen's alphas. As shown by panel C of this table, controlling for the later two variables reduces the absolute value of the average monthly return of high-low portfolio to -0.94%, but the average monthly returns is still considerably high. It also shows that the downward trend in average returns and the statistical significance of the high-low portfolio's Jensen's alphas do not change as a result of controlling for these two additional factors.

Figure 1.5 demonstrates the evolving average monthly returns and Jensen's alphas and the t-statistics associated with them, for the case of sorting based on URP of the oil market. The figure contains interesting information which shows how the significance of the factor is changing with time and major events in the oil market. As we can see, moving from late 1990s to 2000, the average return of the high-low portfolio gets bigger and bigger in terms of absolute value, but with negative sign. The bottom-right graph shows that in the time period of 2000-2011 the Jensen's alpha associated with high-low portfolio is statistically significant at the 90% confidence level. As we can see,

the average monthly return and Jensen's alphas are showing a monotonically decreasing trend between 2000-2007 which is the time energy crisis happens. After the crisis, the average return and Jensen's alpha are getting toward being smaller in terms of absolute value, and being less significant. The point which is the point of transition from significance to insignificance for Jensen's alphas is 2011. Since 2011, the average returns and Jensen's alphas are small in absolute value and are not statistically significant at the 90% confidence level. This can be related to the shale revolution in united states which has led to US's energy independence. Overall, we can clearly see the pattern and persistence in the average monthly returns and Jensen's alphas in the case of VRP.

1.3.4 Financialization Effect

The financialization of commodity market and its effect on the economy has been the subject of a substantial amount of research and discussion in the realm of commodities. Most of the authors believe that the financialization has happened some time between 2004 and 2005. In this section, we follow the literature and split the whole sample period into two sub-periods one of which covering 1996-2004 and the other one covers 2005-2014. We report the results of the analysis for these two sub-periods in tables 1.12 and 1.13.

Panels A,B and C of table 1.12 show the results for the case of VRP, DRP and URP during the first sub-period. Panel A shows the result for the case of sorting based on exposure to oil VRP. Sub-Panel A1 is showing the result when we sort based on VRP without controlling for DRP and URP. We can see that with one exception, 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 -0.40%, but the Jensen's alpha associated with this portfolio is totally insignificant 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 goes positive and the associated Jensen's alpha is less statistically significant. Overall, there is enough empirical evidence that VRP is not a priced factor in the cross-section of stock returns for the sub-period 1996-2004. Panel B is presenting the results in case of DRP. Sub-Panels B1, B2 show the results for the case of 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. The Jensen's alpha 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 still a downward trend in average monthly returns of the high-low portfolio. The Jensen's alpha is not statistically significant in this case similar to the last two sub-panels. Overall, we can see that DRP is a priced factor in the cross-section of stock returns in this sub-period, but we cannot provide any solid statistical significance for the fact, in terms of carhart 4-factor model. Panel C and its sub-panels show the results for the

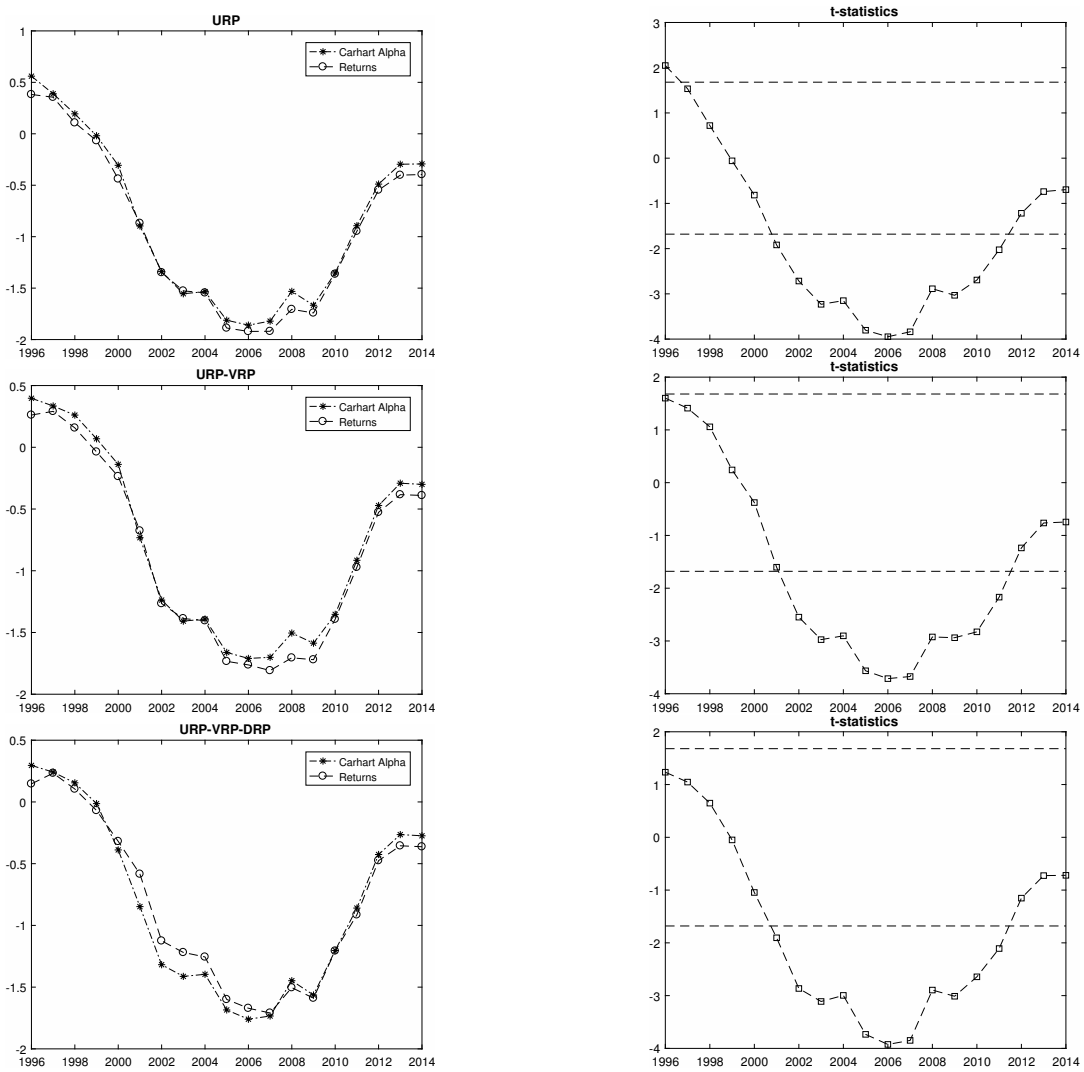

FIGURE 1.5: This Figure presents the evolution of average monthly returns and Jensen's Alpha of the hedge portfolio through the sample period in the case of sorting based on the exposure to URP. The left column shows the average monthly returns and Jensen's Alpha of the hedge portfolio in case we form 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.

case of sorting based on URP. Sub-Panels C1, C2 and C3 show that the average monthly returns of the high-low portfolio are -2.12%, -1.95% and -1.71% in the case of controlling for no other variable than URP, controlling for VRP and controlling for VRP and DRP together, respectively. In all three cases, the average monthly returns of the portfolios is decreasing, moving from low exposure to high exposure portfolios. The Jensen's alphas for all three cases are statistically significant at the 99% confidence level. Overall, the results of this

Panel shows that the URP is highly significant in the cross-section of stock returns for the sub-period 1996-2004.

TABLE 1.12: Oil Risk and Cross-Section of Stock Returns before 2004

Factor: VRP Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-0.814	-0.172	0.013	0.202	0.848	1.663
	Average Returns	0.600	1.013	1.147	0.891	0.193	-0.407
	Carhart Alpha	-0.118	0.239	0.305	0.076	-0.497	-0.379
	P-Value	0.664	0.129	**0.028**	0.595	**0.095**	0.399
Sub-Panel A2	Average Beta	-0.903	-0.179	0.014	0.210	0.885	1.736
	Average Returns	0.360	1.045	1.158	0.956	0.309	-0.052
	Carhart Alpha	-0.371	0.297	0.314	0.118	-0.377	-0.006
	P-Value	0.200	**0.042**	**0.019**	0.427	0.208	0.990
Sub-Panel A3	Average Beta	0.000	-0.190	0.013	0.219	0.932	0.932
	Average Returns	0.440	1.122	1.043	0.906	0.502	0.062
	Carhart Alpha	-0.244	0.393	0.193	0.048	-0.166	0.078
	P-Value	0.404	**0.010**	0.205	0.761	0.575	0.861
Factor: DRP Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-3.531	-0.811	-0.006	0.794	3.487	7.018
	Average Returns	1.252	0.989	0.906	0.695	0.388	-0.865
	Carhart Alpha	0.498	0.152	0.028	-0.116	-0.199	-0.697
	P-Value	0.226	0.419	0.797	0.564	0.549	0.283
Sub-Panel B2	Average Beta	-3.681	-0.837	-0.004	0.827	3.622	7.303
	Average Returns	1.265	0.984	0.885	0.855	0.427	-0.837
	Carhart Alpha	0.495	0.147	-0.017	0.046	-0.157	-0.652
	P-Value	0.231	0.437	0.882	0.816	0.637	0.319
Sub-Panel B3	Average Beta	-4.012	-0.908	-0.005	0.888	3.916	7.927
	Average Returns	1.016	1.237	0.835	0.705	0.269	-0.747
	Carhart Alpha	0.229	0.401	-0.024	-0.130	-0.344	-0.572
	P-Value	0.562	**0.034**	0.853	0.547	0.269	0.349
Factor: URP Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-4.255	-0.984	-0.044	0.887	4.160	8.415
	Average Returns	1.812	1.238	0.973	0.416	-0.314	-2.126
	Carhart Alpha	1.241	0.530	0.048	-0.415	-0.935	-2.177
	P-Value	**0.000**	**0.006**	0.699	**0.019**	**0.010**	**0.000**
Sub-Panel C2	Average Beta	-4.347	-0.968	-0.002	0.970	0.012	4.360
	Average Returns	1.572	1.364	0.927	0.471	-0.387	-1.958
	Carhart Alpha	1.010	0.661	-0.003	-0.370	-0.987	-1.997
	P-Value	**0.002**	**0.001**	0.979	**0.026**	**0.004**	**0.000**
Sub-Panel C3	Average Beta	-4.736	-1.069	-0.031	1.006	4.686	9.422
	Average Returns	1.459	1.325	0.926	0.440	-0.258	-1.717
	Carhart Alpha	1.018	0.635	0.023	-0.440	-0.975	-1.993
	P-Value	**0.002**	**0.000**	0.858	**0.013**	**0.003**	**0.000**

Table 1.13 is presenting the results for the post-financialization sub-period.

Panel A shows that even in this sub-period VRP is not a priced factor in the cross-section of stock returns. What is interesting, is that in this sub-period, the DRP is a priced factor in the cross-section of stock returns. The downward trend and statistical significance can be seen in all the sub-panels of panel B. As we can see, more exposure to the DRP is translated into having higher monthly average returns. Sub-Panel B3 which shows the result for the case we sort based on DRP, but we also control for VRP and URP, shows that the high-low portfolio's average monthly return is 0.76% and the Jensen's alpha associated with the portfolio is statistically significant at the 90% confidence level. The last observation from this table is that exposure to URP is still causing the stock to have lower average monthly returns. Although the Jensen's alphas are not statistically significant in any of sub-panels of panel C, we can see a clear downward trend in the average returns of the portfolios, starting from lowest-exposure and moving toward the highest-exposure portfolio. Overall, we can see that the post-financialization period is the period during which, URP and DRP are both priced factor in the cross-section of stock returns.

1.3.5 Dramatic Price Run-Up in 2007-2008

Oil is just one of the numerous commodities across different commodity classes (e.g. metal and agricultural and energy), which experienced a huge price increase in 2007-2008 period. The reason for such price increase in commodities has been the topic of numerous academic and policy-making debates through the recent years. One of the suggested theories for explaining this phenomenon is the price distortion cause by financialization. There has also been a theory based on which, the financialization has caused a difference in information discovery mechanism in commodity markets. (Among all, Kilian and Murphy (2013), Pindyck (2013), Singleton (2012) and Sockin and Xiong (2012)).
The huge volume of the mentioned literature makes this interesting to take a look at the performance of our measures after the price boom of 2007-2008. Performing Wald and Likelihood-Ratio tests, we can detect a single point of structural break during October of 2008 for the three implied moments in oil market. To be precise, the day on which the break has been detected is 14 oct 2008. Tables 1.14 and 1.15 are presenting the results of the analysis for the two sub-periods 1996 to 14-oct-2008 and 14-oct -2008 to 2014. Table 1.14 is showing the results for the first sub-period. Looking at panel A, we can observe that there is no evidence for the VRP to be a priced factor in the cross-section of stock returns. The return for average monthly portfolio return in sub-panel A3 is -0.03% which is infinitesimal. The Jensen's alpha associated with the portfolio also does not show any statistical significance. A look at panel B shows that there is also no evidence for having DRP as a significantly priced factor in the cross-section of returns. Looking at the significance tests for the Jensen's alphas is a way to validate this finding. Panel C of the table is showing the results for the case of URP. Sub-Panel C3 shows that there is a clear decreasing trend in the average monthly portfolio returns moving from

TABLE 1.13: Oil Risk and Cross-Section of Stock Returns after 2004

Factor: VRP Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-0.492	-0.127	-0.017	0.091	0.448	0.940
	Average Returns	0.846	0.855	0.563	0.555	0.320	-0.526
	Carhart Alpha	0.426	0.416	0.118	0.110	-0.203	-0.629
	P-Value	0.125	**0.003**	0.238	0.412	0.556	0.215
Sub-Panel A2	Average Beta	-0.528	-0.124	-0.009	0.104	0.473	0.973
	Average Returns	0.682	0.816	0.561	0.581	0.451	-0.231
	Carhart Alpha	0.260	0.380	0.114	0.136	-0.070	-0.330
	P-Value	0.345	**0.006**	0.236	0.339	0.842	0.523
Sub-Panel A3	Average Beta	0.000	-0.132	-0.012	0.106	0.493	0.493
	Average Returns	0.694	0.778	0.709	0.467	0.435	-0.260
	Carhart Alpha	0.292	0.340	0.259	0.024	-0.099	-0.392
	P-Value	0.267	**0.019**	**0.003**	0.844	0.734	0.379
Factor: DRP Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-1.717	-0.278	0.198	0.695	2.214	3.931
	Average Returns	0.183	0.458	0.484	0.892	1.080	0.897
	Carhart Alpha	-0.300	0.009	0.043	0.438	0.664	0.964
	P-Value	0.256	0.956	0.643	**0.005**	**0.039**	**0.034**
Sub-Panel B2	Average Beta	-1.775	-0.279	0.216	0.729	2.301	4.076
	Average Returns	0.308	0.445	0.525	0.755	1.161	0.853
	Carhart Alpha	-0.180	0.003	0.083	0.304	0.735	0.914
	P-Value	0.529	0.987	0.342	**0.041**	**0.018**	**0.045**
Sub-Panel B3	Average Beta	-1.842	-0.299	0.213	0.743	2.353	4.195
	Average Returns	0.293	0.500	0.486	0.798	1.061	0.768
	Carhart Alpha	-0.189	0.064	0.034	0.342	0.637	0.826
	P-Value	0.503	0.687	0.746	**0.019**	**0.055**	**0.084**
Factor: URP Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-2.646	-0.765	-0.167	0.404	2.171	4.817
	Average Returns	1.032	0.638	0.541	0.548	0.414	-0.618
	Carhart Alpha	0.595	0.216	0.101	0.102	-0.100	-0.695
	P-Value	0.158	0.201	0.244	0.401	0.735	0.264
Sub-Panel C2	Average Beta	-2.765	-0.815	-0.191	0.405	-0.022	2.743
	Average Returns	0.916	0.699	0.540	0.644	0.428	-0.487
	Carhart Alpha	0.502	0.273	0.092	0.198	-0.074	-0.576
	P-Value	0.205	**0.067**	0.300	0.077	0.803	0.330
Sub-PAnel C3	Average Beta	-2.791	-0.780	-0.135	0.482	2.371	5.162
	Average Returns	0.942	0.636	0.551	0.638	0.452	-0.490
	Carhart Alpha	0.514	0.208	0.114	0.174	-0.032	-0.546
	P-Value	0.193	0.173	0.226	0.156	0.905	0.339

lowest toward highest exposure portfolios. The average monthly returns of the high-low portfolio is equal to -1.30%. The Jensen's alpha associated with this portfolio is statistically significant at the 99% confidence level.

Table 1.15 is presenting the results for the sub-period after 2008. Panel

TABLE 1.14: Oil Risk and the Cross-Section of Stock Returns before 2008

Factor: VRP Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-0.710	-0.161	-0.000	0.163	0.714	1.423
	Average Returns	0.752	0.987	1.080	0.908	0.426	-0.326
	Carhart Alpha	0.006	0.182	0.244	0.084	-0.315	-0.321
	P-Value	0.976	**0.096**	**0.012**	0.416	0.155	0.316
Sub-Panel A2	Average Beta	-0.782	-0.167	0.001	0.169	0.744	1.484
	Average Returns	0.574	1.007	1.118	0.941	0.493	-0.080
	Carhart Alpha	-0.184	0.219	0.276	0.101	-0.232	-0.048
	P-Value	0.359	**0.032**	**0.004**	0.340	0.295	0.880
Sub-Panel A3	Average Beta	0.000	-0.175	-0.000	0.178	0.784	0.784
	Average Returns	0.643	1.073	1.031	0.907	0.611	-0.032
	Carhart Alpha	-0.095	0.287	0.185	0.068	-0.095	-0.001
	P-Value	0.642	**0.007**	**0.080**	0.538	0.657	0.998
Factor: DRP Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-2.854	-0.663	-0.007	0.646	2.819	5.673
	Average Returns	1.120	0.996	0.869	0.839	0.644	-0.476
	Carhart Alpha	0.334	0.158	0.005	0.030	-0.021	-0.355
	P-Value	0.236	0.218	0.949	0.826	0.929	0.429
Sub-Panel B2	Average Beta	-2.975	-0.687	-0.008	0.671	2.933	5.907
	Average Returns	1.149	1.006	0.870	0.895	0.661	-0.487
	Carhart Alpha	0.353	0.168	-0.009	0.084	-0.000	-0.353
	P-Value	0.212	0.196	0.907	0.535	0.999	0.432
Sub-Panel B3	Average Beta	-3.214	-0.738	-0.007	0.719	3.153	6.368
	Average Returns	0.971	1.176	0.844	0.788	0.576	-0.395
	Carhart Alpha	0.177	0.337	-0.012	-0.037	-0.109	-0.286
	P-Value	0.513	**0.009**	0.893	0.803	0.629	0.501
Factor: URP Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-3.174	-0.746	-0.044	0.649	3.057	6.231
	Average Returns	1.598	1.151	0.947	0.613	0.050	-1.548
	Carhart Alpha	0.867	0.377	0.070	-0.196	-0.602	-1.469
	P-Value	**0.000**	**0.006**	0.426	0.120	**0.017**	**0.000**
Sub-Panel C2	Average Beta	-3.254	-0.741	-0.017	0.707	-0.005	3.249
	Average Returns	1.461	1.239	0.928	0.625	0.022	-1.439
	Carhart Alpha	0.741	0.464	0.051	-0.191	-0.609	-1.350
	P-Value	**0.003**	**0.001**	0.571	0.105	**0.012**	**0.001**
Sub-Panel C3	Average Beta	-3.527	-0.813	-0.038	0.733	3.431	6.958
	Average Returns	1.389	1.217	0.945	0.600	0.081	-1.307
	Carhart Alpha	0.749	0.447	0.085	-0.244	-0.623	-1.372
	P-Value	**0.002**	**0.000**	0.357	**0.049**	**0.007**	**0.001**

A shows that the decreasing trend in the average monthly returns of the portfolios sorted based on VRP is more evident in this sub-period in comparison to the post-financialization (2005-2014) period. Although there is no statistical evidence to show the significance of alphas in the carhart 4-factor

model framework, the decreasing trend in all three sub-periods shows that by switching to this sub-period, the significance of the VRP as a priced factor in the cross-section of stock returns gets more clear. Panel B is showing the results for the case of DRP. All the sub-panels of the Panel show that the effect of DRP, in terms of both average monthly returns and Jensen's alpha's significance is not as big as the case of pre-financialization period. The average monthly return of the high-low portfolio of the sub-panel B3 is 0.16% and the Jensen's alpha is not statistically significant at the 90% confidence level. The results show that the DRP is not a priced factor in the cross-section of stock returns in the post-financialization. The last panel of this table, panel C, is presenting the results for the case of URP in this sub-period. Sub-panel C3 shows that a decreasing trend can be clearly seen in the average monthly returns of the portfolios going from lowest toward the highest exposure portfolio. The average monthly returns of the high-low portfolio is -0.36% and the Jensen's alpha associated with the portfolio is not significant at the 90% confidence level. This shows the closer we get to the end of our sample, especially 2011, the less is the significance of URP in the cross-section of stock returns.

1.3.6 The Shale Revolution

As we saw in the previous sections, by splitting our sample period into different sub-samples, we see that the significance of each of the three factors changes. Looking at figures 1.4 and 1.5, we can clearly see that there is a break in the pattern of the significance of VRP and URP in the cross-section of stocks, around 2011. Going past 2011, the t-statistics in the case of VRP (figure 1.4) gets more and more negative and closer to the confidence bound, towards being statistical significant. Figure 1.5 shows that moving past 2011, the t-statistics of the Jensen's alphas get closer to zero and get insignificant for the case of URP. The first thing that comes to mind as the main reason for such a change is the "shale revolution", which is a technological change that substantially increased the domestic crude oil production of the United States. The shale revolution has happened somewhere near 2011 and the domestic production of crude oil has been increased since that time. As a result, the dependence of the united states to the oil, which is imported from outside of the country, has been decreasing since 2011.

Table 1.16 shows the results for the period 1996-2011. Looking at all the panels and sub-panels of this table, we can find out 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 alphas cannot be seen in the case of these two factors. Panel C which shows the results for URP, has different indications. There is a clear downward trend in the average monthly returns of portfolios and all the alphas are significant at the 99% confidence level. Sub-Panel C3 shows that the average monthly returns for the high-low portfolio is -1.13% and the associated alpha is statistically significant at the 99% confidence level. There is enough evidence to conclude that the URP is a priced factor in the cross-section of stock returns.

TABLE 1.15: Oil Risk and the Cross-Section of Stock Returns after 2008

Factor: VRP Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-0.604	-0.153	-0.025	0.101	0.536	1.140
	Average Returns	1.948	1.721	1.423	1.355	1.359	-0.589
	Carhart Alpha	0.128	0.202	0.024	-0.095	-0.315	-0.443
	P-Value	0.610	**0.090**	0.811	0.508	0.218	0.297
Sub-Panel A2	Average Beta	-0.645	-0.155	-0.021	0.111	0.566	1.191
	Average Returns	1.859	1.708	1.383	1.378	1.508	-0.350
	Carhart Alpha	0.108	0.209	-0.003	-0.094	-0.245	-0.353
	P-Value	0.667	0.125	0.974	0.520	0.361	0.410
Sub-Panel A3	Average Beta	0.000	-0.158	-0.020	0.116	0.587	0.587
	Average Returns	1.777	1.709	1.453	1.271	1.574	-0.203
	Carhart Alpha	0.038	0.202	0.052	-0.187	-0.163	-0.201
	P-Value	0.869	0.125	0.544	0.196	0.513	0.609
Factor: DRP Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-1.813	-0.148	0.369	0.914	2.716	4.529
	Average Returns	1.392	1.410	1.526	1.561	1.652	0.260
	Carhart Alpha	0.119	0.172	0.094	-0.132	-0.444	-0.562
	P-Value	0.585	0.187	0.335	0.310	**0.084**	0.135
Sub-Panel B2	Average Beta	-1.877	-0.129	0.412	0.980	2.854	4.731
	Average Returns	1.590	1.363	1.536	1.555	1.659	0.069
	Carhart Alpha	0.286	0.131	0.100	-0.129	-0.421	-0.707
	P-Value	0.268	0.363	0.291	0.286	0.106	**0.081**
Sub-Panel B3	Average Beta	-1.964	-0.142	0.419	1.007	2.946	4.910
	Average Returns	1.531	1.418	1.465	1.591	1.694	0.163
	Carhart Alpha	0.200	0.155	0.026	-0.067	-0.345	-0.545
	P-Value	0.428	0.214	0.782	0.613	0.195	0.194
Factor: URP Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-3.419	-0.985	-0.245	0.463	2.720	6.138
	Average Returns	1.700	1.671	1.465	1.340	1.365	-0.336
	Carhart Alpha	-0.001	0.194	0.049	-0.107	-0.322	-0.321
	P-Value	0.997	0.225	0.559	0.380	0.287	0.565
Sub-Panel C2	Average Beta	-3.551	-1.014	-0.238	0.506	-0.040	3.510
	Average Returns	1.667	1.637	1.447	1.405	1.388	-0.279
	Carhart Alpha	-0.013	0.166	0.042	-0.073	-0.265	-0.252
	P-Value	0.969	0.280	0.611	0.573	0.336	0.643
Sub-Panel C3	Average Beta	-3.564	-0.939	-0.142	0.626	3.089	6.653
	Average Returns	1.732	1.660	1.424	1.406	1.366	-0.365
	Carhart Alpha	0.039	0.193	0.015	-0.078	-0.307	-0.347
	P-Value	0.903	0.214	0.859	0.540	0.222	0.484

Table 1.17 shows what happens after 2011. The table shows that this period is the period during which, the VRP is a priced factor while the URP lose its significance. Sub-Panel A3 of panel A shows that there is clear downward trend in average portfolio returns going from lowest exposure portfolio

TABLE 1.16: Oil Risk and the Cross-Section of Stock Returns before 2011

Factor: VRP Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-0.662	-0.151	-0.001	0.150	0.659	1.321
	Average Returns	0.694	0.927	0.883	0.769	0.317	-0.378
	Carhart Alpha	0.027	0.307	0.240	0.115	-0.413	-0.440
	P-Value	0.896	**0.002**	**0.007**	0.249	**0.059**	0.191
Sub-Panel A2	Average Beta	-0.725	-0.154	0.002	0.159	0.690	1.376
	Average Returns	0.507	0.929	0.899	0.806	0.418	-0.089
	Carhart Alpha	-0.171	0.312	0.259	0.149	-0.314	-0.143
	P-Value	0.418	**0.001**	**0.004**	0.149	0.155	0.663
Sub-Panel A3	Average Beta	0.000	-0.163	0.001	0.165	0.724	0.724
	Average Returns	0.566	0.960	0.898	0.729	0.504	-0.062
	Carhart Alpha	-0.109	0.342	0.255	0.069	-0.202	-0.093
	P-Value	0.595	**0.001**	**0.007**	0.502	0.312	0.759
Factor: DRP Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-2.732	-0.583	0.075	0.738	2.904	5.636
	Average Returns	0.808	0.763	0.722	0.796	0.704	-0.105
	Carhart Alpha	0.115	0.120	0.070	0.143	0.063	-0.052
	P-Value	0.612	0.308	0.346	0.247	0.773	0.887
Sub-Panel B2	Average Beta	-2.841	-0.599	0.083	0.771	3.023	5.865
	Average Returns	0.877	0.767	0.721	0.819	0.739	-0.139
	Carhart Alpha	0.164	0.131	0.065	0.161	0.084	-0.080
	P-Value	0.484	0.275	0.389	0.166	0.701	0.832
Sub-Panel B3	Average Beta	-3.052	-0.645	0.083	0.814	3.215	6.267
	Average Returns	0.723	0.918	0.696	0.747	0.606	-0.117
	Carhart Alpha	0.007	0.281	0.046	0.086	-0.064	-0.072
	P-Value	0.975	**0.017**	0.588	0.487	0.766	0.842
Factor: URP Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-3.358	-0.837	-0.090	0.641	3.112	6.470
	Average Returns	1.436	0.983	0.786	0.496	0.043	-1.393
	Carhart Alpha	0.720	0.342	0.131	-0.138	-0.568	-1.288
	P-Value	**0.003**	**0.006**	**0.097**	0.199	**0.014**	**0.002**
Sub-Panel C2	Average Beta	-3.456	-0.848	-0.077	0.686	-0.007	3.449
	Average Returns	1.268	1.072	0.758	0.565	0.014	-1.254
	Carhart Alpha	0.556	0.435	0.099	-0.068	-0.585	-1.141
	P-Value	**0.022**	**0.000**	0.208	0.508	**0.008**	**0.004**
Sub-Panel C3	Average Beta	-3.676	-0.890	-0.071	0.736	3.474	7.150
	Average Returns	1.217	1.017	0.779	0.541	0.080	-1.137
	Carhart Alpha	0.546	0.385	0.131	-0.117	-0.561	-1.107
	P-Value	**0.021**	**0.001**	0.113	0.288	**0.007**	**0.004**

toward highest exposure portfolio. The average monthly returns of the high-low portfolio is -057% and the Jensen's alpha is showing significance at the 90% confidence level. In contrast, neither the decreasing pattern in the returns, nor the significance of the Jensen's alphas can be seen in the case of URP in this sub-period.

TABLE 1.17: Oil Risk and the Cross-Section of Stock Returns after 2011

Factor: VRP Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-0.637	-0.181	-0.051	0.076	0.518	1.155
	Average Returns	1.429	1.282	1.116	0.962	0.809	-0.620
	Carhart Alpha	0.173	0.070	-0.047	-0.281	-0.497	-0.670
	P-Value	0.422	0.587	0.654	0.113	0.022	**0.041**
Sub-Panel A2	Average Beta	-0.687	-0.191	-0.056	0.076	0.540	1.208
	Average Returns	1.430	1.234	1.090	0.993	0.919	-0.512
	Carhart Alpha	0.159	0.006	-0.078	-0.225	-0.370	-0.529
	P-Value	0.461	0.963	0.410	0.203	0.142	0.124
Sub-Panel A3	Average Beta	0.000	-0.192	-0.052	0.084	0.566	0.566
	Average Returns	1.407	1.272	1.092	0.954	0.833	-0.575
	Carhart Alpha	0.140	0.040	-0.071	-0.270	-0.454	-0.594
	P-Value	0.443	0.791	0.472	0.138	**0.082**	**0.072**
Factor: DRP Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-1.764	-0.212	0.251	0.735	2.401	4.165
	Average Returns	1.051	1.207	1.266	0.951	0.863	-0.188
	Carhart Alpha	-0.069	0.072	0.090	-0.351	-0.558	-0.490
	P-Value	0.776	0.554	0.422	**0.028**	**0.050**	0.244
Sub-Panel B2	Average Beta	-1.825	-0.198	0.279	0.779	2.506	4.330
	Average Returns	1.134	1.161	1.243	1.057	0.837	-0.296
	Carhart Alpha	-0.003	0.042	0.056	-0.251	-0.567	-0.565
	P-Value	0.992	0.777	0.630	**0.090**	**0.075**	0.217
Sub-Panel B3	Average Beta	-1.928	-0.222	0.271	0.784	2.572	4.500
	Average Returns	1.146	1.228	1.140	1.054	0.925	-0.221
	Carhart Alpha	-0.015	0.104	-0.055	-0.236	-0.469	-0.454
	P-Value	0.953	0.459	0.597	0.156	0.142	0.334
Factor: URP Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-2.419	-0.688	-0.194	0.280	1.841	4.260
	Average Returns	0.854	1.342	1.146	1.071	0.832	-0.022
	Carhart Alpha	-0.442	0.104	-0.023	-0.119	-0.452	-0.010
	P-Value	0.103	0.411	0.803	0.370	**0.029**	0.975
Sub-Panel C2	Average Beta	-2.594	-0.733	-0.198	0.319	-0.067	2.526
	Average Returns	0.956	1.355	1.162	1.022	0.761	-0.195
	Carhart Alpha	-0.325	0.135	-0.006	-0.199	-0.506	-0.182
	P-Value	0.241	0.259	0.943	0.169	**0.012**	0.589
Sub-Panel C3	Average Beta	-2.603	-0.678	-0.136	0.387	2.156	4.759
	Average Returns	0.974	1.394	1.151	0.950	0.873	-0.100
	Carhart Alpha	-0.341	0.187	-0.013	-0.273	-0.396	-0.056
	P-Value	0.202	0.133	0.892	**0.023**	**0.021**	0.845

1.4 Conclusion

In this paper, we investigated the effects and significance of adding the risk premia associated with expected big upside and downside jumps in oil prices to the macroeconomic predictive models. We also test the ability of the premia to predict oil market important fundamental variables along with the extent to which the premia are priced in the cross-section of stock returns. Using a 30-year time series of options and futures contract of crude oil, we use delta-vega hedging and delta-gamma hedging to calculate the upside and downside jump premia and the variance risk premium respectively. We can classify our results into three different categories. The first category is related to the prediction power of the jump premia for a group of the most important macroeconomic indicators. The results Show that adding the jump premia to our model would substantially increase the ability of the model to predict the variation in macroeconomic variables. The second category of the results are the ones which present the prediction power of the jump premia for some important variables related to fundamentals of the the oil market. The results show that the jump premia have a substantial ability to describe the variation in oil inventory growth, oil demand growth and oil future returns. Also, the upside jump risk premium is having strong predictive power for OPEC's aggregate production growth. The last group of results is the one through which we show if the variance, downside jump and upside jump risk premia are priced factors in the cross-section of stock returns. The results we got show that among the three, the upside jump risk premium is the most important variable and is significantly priced in the cross-section of stock returns. The significance of the upside risk premium is intact after considering different break points and splitting the sample into different subsamples. One of the most interesting findings is that after 2011, the upside risk premia's significance is vanished and it is replaced by variance risk premium. The year 2011 is the time which is unanimously known as the " Shale Revolution" year, during which the technological progress made the united states to increase its domestic crude production substantially. The shale revolution is a big step for the united states toward having energy independence. This is the change that reduces the worry about big swings in oil prices as it saves the united states' economy against adverse supply shocks to the oil market by foreign countries. As a result the upside jump premium in oil market is not a significantly priced factor in the cross-section of stock returns after 2011.

Chapter 2

The Risks of Skewness and Kurtosis in Oil Market and the Cross-Section of Stock Returns

2.1 Introduction

Oil price jumps and drops have been the core of substantial amount of research in finance and economics during the recent decades. Most of the work has been done about oil's impact on economy is restrained to changes in the first moment. But there are other risks in oil market that the market participants would face. The history of finance and financial derivatives has recorded a substantial amount of time variation in implied variance, skewness and kurtosis in the oil market. Considering this , we would like to investigate the effect of the innovations in implied volatility, skewness and kurtosis of oil on the cross section of stock returns. There are many reasons why we are focusing on oil market in this paper. Among these reasons, we can highlight a couple which are the most important. First, energy commodities are the most important type of commodities considering their impact on the economy.Secondly, we need to have a market which is highly liquid because the tools we are using in order to characterize the innovations in implied moments are the options on the asset (here, oil futures). Among all the commodities, crude oil financial derivatives are the most liquid ones.

We can classify the main findings of our paper in five different categories. First, our results show a significant contribution from the innovations in implied skewness and kurtosis of oil for cross section of stocks and it also does not show any role and significance for the volatility after controlling for skewness and kurtosis. Second, we show that the results that we are getting is different and separate from the market moments. The magnitude and significance of our results get even bigger when we orthogonalize oil moment innovations with counterpart market moment innovations. This can be a strong evidence for the fact that what we have found in this paper is different from the findings in previous academic work which have concentrated on market moments and their implications for cross section of stock returns. The third category is the category of term structure effects. The previous works have concentrated on a single maturity for analyzing the effects,

but we are looking at 30-day, 60-day and 90-day maturities and did the analysis for all of them. Overall, The only class of innovations which is robust to switching across different maturities is innovation in oil kurtosis. We are also investigating the effect of Financialization in commodity market in this paper. There is a unanimity in the literature of the commodity financial markets to pick 2004-2005 as the time at which financialization has been taken place in commodity markets (e.g. Hamilton and Wu (2013), Baker (2012). We can summarize the implications of financialization in commodity market by a sharp increase in the trading volume of financial instruments of the commodity futures and options. The effects of financialization in commodity market on economy has been a place for constant academic and policy-making debates since 2004-2005. (Among all, Irwin and Sanders(2012) , Whaley (2010) and Krugman (2008)). As a result, we would consider two sub-periods to do the analysis. We would call these sub-periods Pre-Financialization and Post-Financialization period, the first one covering 1996-2004 and the second one covering 2005-2014. We find out that when we sort the stocks into portfolios based on their exposure to innovations in oil implied volatility, we can see hat there is no significant trend in average returns of the sorted portfolios and there is no statistically significant Jansen's Alpha when we control for skewness and kurtosis. When we switch from variance to skewness, we can see that the difference between returns of high and low exposure portfolios is -0.28% and there is a decreasing trend in portfolio returns moving from low to high exposure portfolios. We can also see that the Jensen's Alpha of the high-low portfolio is (almost) statistically significant at 90% confidence level. We can also spot the decreasing trend of the average portfolio returns moving from the lowest exposure to highest exposure portfolios , sorted on innovations in implied kurtosis in oil market. Looking at the sub-periods, we find out that the only factor which has a persistent and expectation-consistent (we expected to see the higher the exposure to the oil market innovations, the lower is the average returns of the stock) effect is innovation in kurtosis of the oil market. Innovations in volatility of oil market also is showing a trend in pre-financialization period which is in contrast to our expectation. The higher is the exposure to volatility innovations, the higher is the return. As we noted before, the story of kurtosis is different from volatility and skewness. In the pre-financialization period we get a decreasing trend in average returns, moving from low to high exposure portfolios. The average return of the high-low portfolio is -0.34%. in the post-financialization period, the average returns for the high-low portfolio is still around -0.34%. The decreasing trend in returns can be seen in this period too. Kurtosis is also the only factor which shows stability through the term structure effects. The innovations of oil kurtosis is the only of the three innovations which is showing decreasing trend and statistical significance for Carhart alpha (with only one exception of 90-day maturity case), looking at from 30-day,60-day and 90-day maturity. The next thing we investigate is to see if there is any value-added for the innovations of oil market after orthogonalizing these moments by their market counterparts. The results show that skewness and kurtosis pass the test of

significance after orthogonalization. The orthogonalized moments are showing a decreasing trend in average returns of the portfolios moving from low to high exposure and the average monthly returns for the high-low portfolio is around -0.43% and -0.42% for cases of skewness and kurtosis respectively. Lastly, we took a look at the potentially different implication of oil market moments before and after the dramatic oil price run-up of 2007-2008. The results show that the only moments which has implications both before and after the energy crisis is kurtosis.

2.2 Estimating Risk-Neutral Moments in Oil Market

We would use The approach introduced and used by Bakshi, Kapadia and Madan (2003) (henceforth BKM) , Bakshi and Madan (2001) and Carr and Madan (2000) to quantify the risk-neutral moments of oil markets using the option contracts on crude oil futures. We would construct a fixed-horizon measure of oil volatility, skewness and kurtosis which is forward-looking. We do this calculations of moments for three different 30-day, 60-day and 90-day horizons. We would use the options data from CME (formerly NYMEX) for the period 1996 to 2014. We begin our analysis in 1996 to be able to compare our analysis to the main papers in the area of the relationship between market implied moments and the cross section of stock returns (The main milestone would be the paper by Chang, Christofferson and Jacobs (2013)). We would start filtering the data by deleting the ATM (at-the-money) and ITM(in-the-money) option contracts. We also filter the option contracts which violate the no-arbitrage conditions. Lastly, we would delete the option contracts with prices lower than 0.05 $. These are the filters used by Trolle and Schwartz (2010). The next challenge we face is that the option contracts data that we got from CME are American Options. But the BKM methodology works based on the European option prices. So we would need to transfer the American option prices into Europeans and then compute the implied volatility. We do the conversion based on Bjerksund-Stensland (2002) approach. BKM states that we need to calculate the following integrals:

$$V = \int_{F}^{\infty} \frac{2(1-\ln(\frac{K}{F}))}{K^2} C(K)dK + \int_{0}^{F} \frac{2(1+\ln(\frac{F}{K}))}{K^2} P(K)dK \tag{2.1}$$

$$W = \int_{F}^{\infty} \frac{3\ln(\frac{K}{F})(1-2\ln(\frac{K}{F}))}{K^2} C(K)dK - \int_{0}^{F} \frac{3\ln(\frac{F}{K})(1+2\ln(\frac{F}{K}))}{K^2} P(K)dK \tag{2.2}$$

$$X = \int_{F}^{\infty} \frac{4\ln^2(\frac{K}{F})(3-\ln(\frac{K}{F}))}{K^2} C(K)dK - \int_{0}^{F} \frac{4\ln^2(\frac{F}{K})(3+\ln(\frac{F}{K}))}{K^2} P(K)dK \quad (2.3)$$

$$\mu \equiv E_Q \ln(\frac{F(\tau)}{F_0}) \approx e^{r\tau}(1 - e^{-r\tau} - \frac{V}{2} - \frac{W}{6} - \frac{X}{24}) \quad (2.4)$$

In these equations, K is the option strike, F is futures price, P is the price of European put option and C is price of the European call option. We would calculate the numerical counterpart of these integrals (so-called "Trapezoidal" inetgral). For an option with strike K,having the log-normality assumption of Black (1976), moneyness would be calculated as:

$$d = \frac{\log(K/F(t,T_1))}{\sigma\sqrt{(T-t)}} \quad (2.5)$$

In equation (2.5), t is the date at which we are evaluating the options, T is the expiration date of the option, T_1 is the delivery date of the corresponding futures contract and σ is the Black (1976) implied volatility of the closest option to at-the-money. We truncate at the strikes corresponding to d=-10 and d=10: $K_{\min} = F(t,T_1)e^{-10\sigma\sqrt{(T-t)}}$ and $K_{\max} = F(t,T_1)e^{10\sigma\sqrt{(T-t)}}$ respectively.The problem here is that we do not have a continuum of implied volatilities. To tackle this problem, we use linear interpolation to get a continuum of implied volatilities. The next stage would be to go from continuum of implied volatilities to continuum of prices. This again would be done using Black (1976) model. For the strikes lower than $K_{\min}$ and higher than $K_{\max}$, we use flat extrapolation ,meaning that we put the implied volatility of these points as equal to the implied volatility of the $K_{\min}$ and $K_{\max}$ strikes for strikes lower than $K_{\min}$ and higher than $K_{\max}$ respectively.

Then we would calculate the risk-neutral moments as:

$$Vol^{BKM} \equiv \sqrt{\frac{E_Q(R^2) - E_Q^2(R)}{\tau}} = \sqrt{\frac{e^{r\tau}V - \mu^2}{\tau}} \quad (2.6)$$

$$Skew^{BKM} \equiv \frac{E_Q(R^3) - 3E_Q(R)E_Q(R^2) + 2E_Q^3(R)}{(E_Q(R^2) - E_Q^2(R))^{3/2}} = \frac{e^{r\tau}W - 3e^{r\tau}\mu V + 2\mu^3}{(e^{r\tau}V - \mu^2)^{3/2}} \quad (2.7)$$

$$Kurt^{BKM} \equiv \frac{E_Q(R^4) - 4E_Q(R)E_Q(R^3) + 6E_Q^2(R)E_Q(R^2) - E_Q^4(R)}{\left(E_Q(R^2) - E_Q^2(R)\right)^2}$$
$$= \frac{e^{r\tau}X - 4e^{r\tau}\mu W + 6e^{r\tau}\mu^2 V - 3\mu^4}{\left(e^{r\tau}V - \mu^2\right)^2} \quad (2.8)$$

Figure2.1 shows the time series of Implied Volatility (henceforth IVOil), Implied Skewness (henceforth ISOil) and Implied Kurtosis (henceforth IKOil) in oil market.

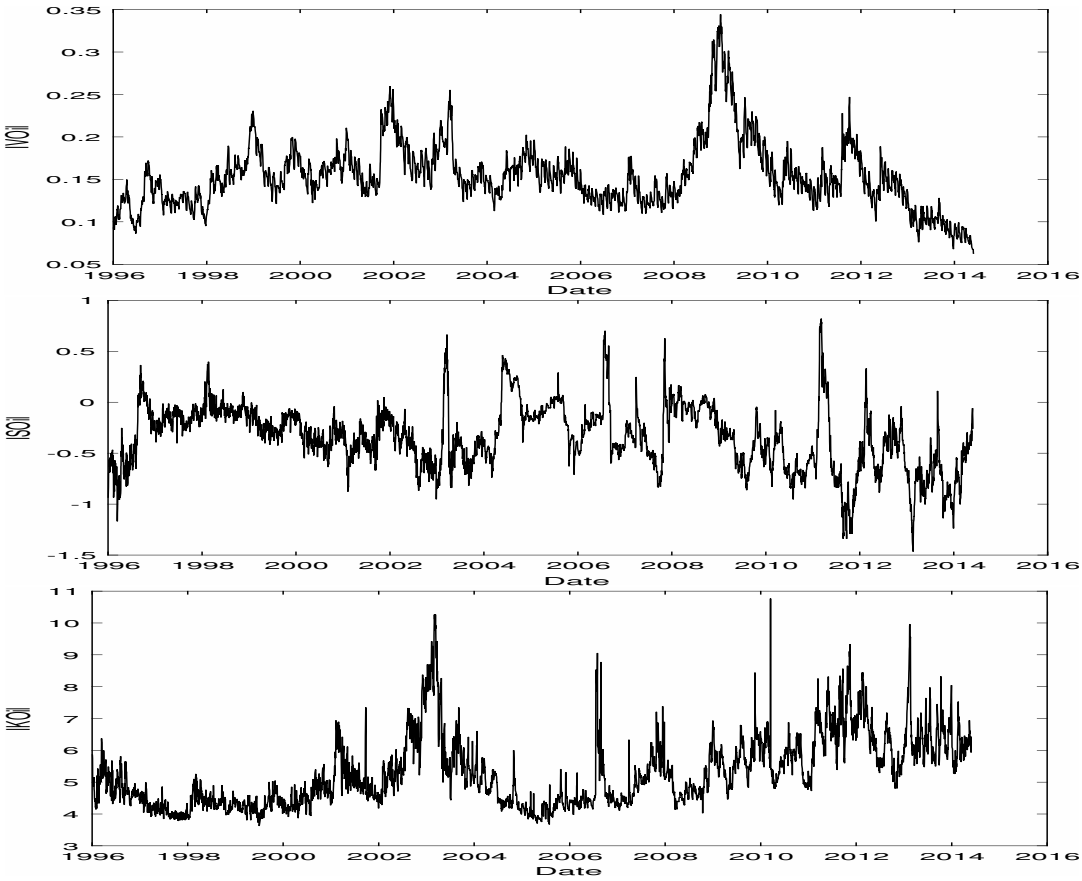

FIGURE 2.1:
This figure shows the time-series of 60-days Implied Variance (IVOil), Implied Skewness(ISOil) and Implied Kurtosis(IKOil) in oil market . The data ranges from 1996 to 2014.

As we have already noted, we need to calculate the innovations in implied variance, skewness and kurtosis of the oil market. In order to get the innovations for each of the three moments, we fit the appropriate ARMA model to time-series of each moment. The criteria we would use in order to select the best ARMA model is AIC (Akaike Information Criterion) in cases of skewness and kurtosis. We run all the combinations of models (25 models) (ARMA(i=1 to 5,j=1 to 5)). Among these models we choose the one with minimum AIC. In contrast to Christofferson and Pan (2015) which uses the

an auto-regressive model with one lag (AR(1)), we would choose the models for all the three implied moments and we choose the models based on our criteria. The reason for doing that is that as we will show, the AR(1) model is not able to remove the autocorrelation from the time series of implied volatility as perfectly as a higher order ARMA model. We have also done all of the analyses using AR(1) model for implied volatility. The results (which are not reported here) show that under that assumption the results can be overestimated and as a result they might be misleading. Figures 2 to 9 show the autocorrelation function for residuals of the models mentioned. We can see that among all these models ARMA (2,3),ARMA(1,1) and ARMA(2,3), which have been selected based on minimum-AIC, are able to remove most of the autocorrelation among the innovations of implied volatility, implied skewness and implied kurtosis respectively.
The resulting innovations that we use all through this paper are plotted in Figure 10.
The time-series of innovations in implied volatility, skewness and kurtosis are all obtained using the following three equations respectively:

$$\Delta IVOil_t = IVOil_t - 1.7947 \times IVOil_{t-1} + 0.7955 \times IVOil_{t-2} + 0.5269 \times \Delta IVOil_{t-1} + 0.2428 \times \Delta IVOil_{t-2} - 0.0743 \times \Delta IVOil_{t-3} \tag{2.9}$$

$$\Delta ISOil_t = ISOil_t - 0.9816 \times ISOil_{t-1} + 0.1305 \times \Delta ISOil_{t-1} \tag{2.10}$$

$$\Delta IKOil_t = IKOil_t - 1.8882 \times IKOil_{t-1} + 0.8886 \times IKOil_{t-2} + 1.1319 \times \Delta IKOil_{t-1} - 0.1194 \times \Delta IKOil_{t-2} - 0.0458 \times \Delta IKOil_{t-3} \tag{2.11}$$

$IVOil_t$,$ISOil_t$ and $IKOil_t$ are implied volatility, implied skewness and implied kurtosis at time t respectively in equations (2.9),(2.10) and (2.11). $\Delta IVOil_t$,$\Delta ISOil_t$ and $\Delta IKOil_t$ are the time-t innovations in implied volatility, implied skewness and implied kurtosis respectively.
We would do the same practice in the case of moments of market and calculate innovations in implied volatility ,skewness and kurtosis using the following three equations respectively:

$$\Delta IVM = IVM_t - IVM_{t-1} \tag{2.12}$$

$$\Delta ISM = ISM_t - 1.8507 \times ISM_{t-1} + 0.8512 \times ISM_{t-2} - 0.2931 \times \Delta ISM_{t-1} - 0.0276 \times \Delta ISM_{t-2} \tag{2.13}$$

$$\Delta IKM_t = IKM_t - 0.9129 \times IKM_{t-1} - 0.0017 \times IKM_{t-2} - 0.9712 \times IKM_{t-3} + 0.3902 \times \Delta IKM_{t-1} + 0.0774 \times \Delta IKM_{t-2} + 0.9543 \times \Delta IKM_{t-3} - 0.3928 \times \Delta IKM_{t-4} - 0.0575 \times \Delta IKM_{t-5} \tag{2.14}$$

IVM_t,ISM_t and IKM_t are implied volatility, implied skewness and implied kurtosis at time t respectively in equations (2.12),(2.13) and (2.14). These three implied moments have been calculated with the same methodology that we used to calculate the oil moments, by using the options on S&P 500 instead of options of oil futures. The models we have used for implied volatility, skewness and kurtosis in market are AR(1), ARMA(2,2) and ARMA(3,5) respectively. These models have been chosen by the same index we chose to model implied moments in oil market (AIC) . ΔIVM_t, ΔISM_t and ΔIKM_t are the time-t innovations in implied volatility, implied skewness and implied kurtosis of stock market respectively.

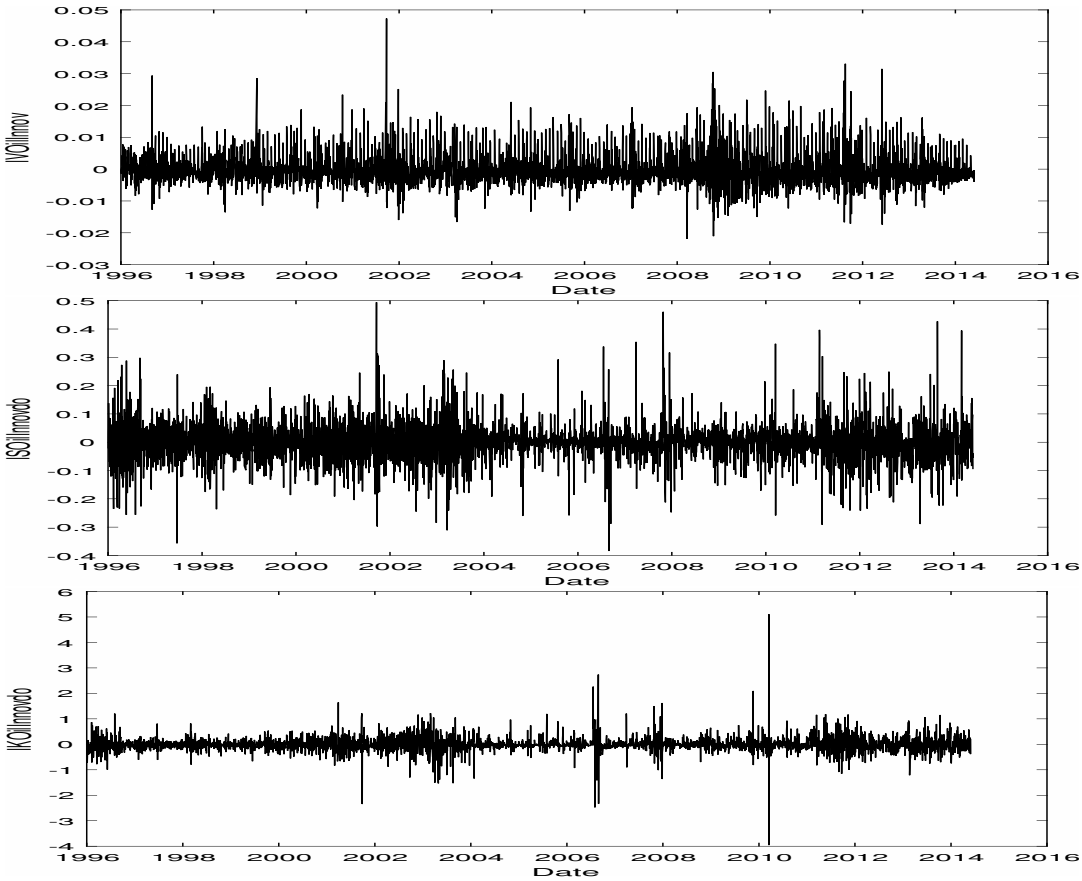

FIGURE 2.2: This figure shows the time-series of Innovations in oil implied volatility, Innovations in oil implied skewness and Innovations in oil implied kurtosis. The chosen fitted models based on which we calculated the innovations are ARMA(2,3),ARMA(1,1) and ARMA(2,3) for volatility, skewness and kurtosis respectively. The data range is from 1996 to 2014.

2.3 Portfolio Sorts on Exposure to Oil Moment Innovations

In this section, we present the results of the analysis when we do the sorting based on the innovations in volatility, skewness and kurtosis of oil market. In any of the three cases we do sort the cross section of stock returns into quintiles based on the sensitivity of the stocks to innovations in different oil moments. First we sort based on the innovations in oil volatility. Second we sort based on the skewness and finally we sort based on innovations in oil kurtosis.

2.3.1 Sorting Based on Exposure to Innovations in Oil Implied Volatility

Based on what we have learned from ICAPM , we would expect the stocks with different sensitivities toward innovations in different oil moments to have different average returns. In this section, we would test to see if this holds for oil volatility. The way we would do this task, is to sort stocks and form portfolios based on the sensitivities of the stocks to $\Delta IVOil$ and after that we compare the average returns and Jensen's Alphas of the portfolios. There is an extensive amount of work on the relationship between the volatility in stock market and cross-section of stock returns (Among all Ang,Hodrick,Zhing and Zhang (2006)). Chang Christofferson and Jacobs (2013) has extended the work to the other moments of market by adding the analysis based on skewness and kurtosis. Christofferson and Pan (2015) has done the analysis for innovations in oil volatility. To the best of our knowledge, our paper is the first which incorporates skewness and kurtosis to this analysis and shows the importance and significance of adding third and fourth moments of the oil market. Ang,Hodrick,Zhing and Zhang(2006) and Christofferson and Pan (2015) have shown that the higher is the sensitivity of a stock to innovations in market and oil volatility, the lower is the average return of the stock, using the data in NYSE/AMEX/NASDAQ between 1990 to 2012. We would control for skewness and kurtosis to see if the effect of the volatility persists after controlling for the other moments, using the same data they have used for stock returns in 1996-2014 time period. We would also look at the effect of the third and fourth moment in the oil market. Following Chang,Christofferson and Jacobs (2013) and Christofferson and Pan (2015), we are using daily data on return and a 60-day window in order to grasp the conditional nature of 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 return to $\Delta IVOil$ which is named $\beta^i_{\Delta IVOil}$:

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{\Delta IVOil}\Delta IVOil + \varepsilon_{i,t} \tag{2.15}$$

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{\Delta IVOil}\Delta IVOil + \beta^i_{\Delta ISOil_t}\Delta ISOil + \varepsilon_{i,t} \tag{2.16}$$

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{\Delta IVOil}\Delta IVOil + \beta^i_{\Delta ISOil_t}\Delta ISOil_t + \beta^i_{\Delta IKOil_t}\Delta IKOil_t + \varepsilon_{i,t} \tag{2.17}$$

At the end of each month, we sort all stocks in the data based on the sensitivity we got already. We then form five portfolios of the sorted stocks, portfolio one having the lowest and portfolio five having the highest exposure to $\Delta IVOil$. We then form the time-series of so-called "post-ranking" returns of each of these five portfolios during the following 30 days. Each time, we roll the window for one month and keep doing this procedure to cover the whole sample period. At the end of this procedure we would have daily returns for the five portfolios during the sample period.

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

Where $R_{p,t}$ is the return of each portfolio, SMB and HML are showing size and value respectively from Fama and French (1993), and UMD is momentum from Carhart (1997).

In order to see if the effect of $\Delta IVOil$ persists after we control for other factors like market excess return, momentum, book-to-market and size, we also use the Carhart 4-factor model to compute the Jensen's Alpha. Significance of the Jensen's Alpha would show that the factor we are looking at is priced in the cross-section of stock returns. For each of the quintile portfolios , Table 2.1 reports the average pre-ranking $\beta_{\Delta VOL}$ plus the Jensen's Alpha and the average post-ranking monthly returns. In all the tables presented in this paper, we report the P-Value of Jensen's Alpha using Newey-West with 21 lags.

TABLE 2.1: Oil Implied Volatility and the Cross-Section of Stock Returns

Factor: $\Delta IVOil$						
Quintile Portfolio	1	2	3	4	5	5-1
Panel A						
Average Beta	-4.689	-1.063	-0.143	0.767	4.428	9.117
Average Returns	1.268	1.067	0.920	0.982	0.850	-0.418
Carhart Alpha	0.267	0.140	0.004	0.105	-0.055	-0.322
P-Value	**0.080**	**0.081**	0.940	0.167	0.744	0.205
Panel B						
Average Beta	-6.278	-1.112	-0.131	0.842	5.030	13.617
Average Returns	1.125	1.056	0.923	1.005	0.917	-0.208
Carhart Alpha	0.131	0.142	-0.005	0.120	0.013	-0.118
P-Value	0.392	**0.070**	0.926	0.101	0.935	0.641
Panel C						
Average Beta	0.000	-1.213	-0.141	0.917	5.260	5.260
Average Returns	1.000	1.036	0.867	1.069	1.199	0.199
Carhart Alpha	-0.009	0.106	-0.048	0.179	0.332	0.341
P-Value	0.952	0.162	0.394	**0.009**	**0.033**	0.151

Panels A,B and C are showing the results of the analysis based on regressions (2.15) , (2.16) and (2.17). The columns 1 to 5 are the ones presenting the analysis results for five sorted portfolios, number 1 being the lowest and 5 being the highest exposure portfolio. We also have the average return and the 4-Factor alpha for the

portfolio that longs the highest exposure quintile and shorts the lowest exposure quintile of stocks. This would be the last column with label 5-1.The average monthly Jensen's Alpha would be the daily alpha multiplied by 21. If the innovation in the volatility of oil market is a factor which is priced, we would see a decreasing average returns of the portfolio of stocks going from the lowest to the highest exposure to oil volatility. We would also like to see a negative Jensen's Alpha and average return for the high-low portfolio.

Panel (A) of the table shows that the difference between the Carhart alpha of portfolio 5 and Carhart alpha of portfolio 1 is -0.32% but we can see that the Carhart alphas are not monotonically decreasing. Also the average monthly difference between the return of portfolios 5 and 1 is -0.41 %. Again, we can see that the returns are not going down monotonically moving from portfolio 1 towards portfolio 5. The results for portfolios sorted on $\beta_{\Delta VOL}$ after controlling for $\Delta ISOil$ and $\Delta IKOil$ are presented in panels B and C. These two panels show that we see the similar pattern for Carhart alpha and average portfolio returns as the one saw in panel A. We can see that the Carhart alpha in none of the three panels is showing any statistical significance at the 90% confidence level. Overall, the results we got do not show that innovations in oil volatility is a priced factor in cross section of stock returns.

2.3.2 Sorting Based on Exposure to Innovations in Oil Implied Skewness

We do the same analysis that we did in the last section for the innovations in oil skewness by sorting based on $\beta_{\Delta ISOil}$. In addition, regression (2.15) is replaced by the following regression:

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{\Delta ISOil_t}\Delta ISOil + \varepsilon_{i,t} \tag{2.18}$$

The results we got from the analysis in this section are reported in Table 2.2. Panel C of table II shows the results for the case of sorting based on the exposure to skewness risk after controlling for volatility and kurtosis. As we can see, with one exception the downward trend in average returns and Carhart alphas are evident. The average monthly return of the high-low portfolio is -28.4%. The Carhart alpha of the high-low portfolio is -38.6%. The Carhart alpha is on the verge of significance at the 90% confidence level (the p-value is 0.101).
Overall, there is convincing evidence that $\Delta ISOil$ is a priced risk factor with a negative price of risk in the cross-section of stock returns. Comparing the results of Table I and Table II shows that in contrast with the case of volatility, skewness innovations are significantly priced in the cross-section of stock returns.

2.3.3 Sorting Based on Exposure to Innovations in Oil Implied Kurtosis

In this section, we do the same analysis as two last parts. The only difference is that we sort based on $\beta_{\Delta IKOil}$ this time. In addition, regressions (2.15) and (2.16) are replaced by the following two regressions respectively:

TABLE 2.2: Oil Implied Skewness and the Cross-Section of Stock Returns

Factor: $\Delta ISOil$ Quintile Portfolio	1	2	3	4	5	5-1
Panel A						
Average Beta	-0.276	-0.064	-0.007	0.049	0.260	0.536
Average Returns	1.015	0.970	1.090	1.034	0.819	-0.196
Carhart Alpha	0.057	0.035	0.180	0.143	-0.120	-0.176
P-Value	0.698	0.635	**0.001**	**0.063**	0.442	0.455
Panel B						
Average Beta	-0.332	-0.066	-0.006	0.054	0.318	0.651
Average Returns	1.028	0.951	1.113	1.027	0.841	-0.187
Carhart Alpha	0.069	0.022	0.205	0.129	-0.101	-0.170
P-Value	0.638	0.758	**0.000**	**0.088**	0.507	0.461
Panel C						
Average Beta	-0.405	-0.088	-0.007	0.072	0.392	0.797
Average Returns	1.114	0.996	1.029	0.970	0.830	-0.284
Carhart Alpha	0.206	0.094	0.135	0.028	-0.181	-0.386
P-Value	0.182	0.214	**0.021**	0.727	0.235	0.101

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{\Delta IKOil_t}\Delta IKOil + \varepsilon_{i,t} \tag{2.19}$$

$$R_{i,t} - R_{f,t} = \alpha^i + \beta^i_{MKT}(R_{m,t} - R_{f,t}) + \beta^i_{\Delta IVOil}\Delta IVOil + \beta^i_{\Delta IKOil_t}\Delta IKOil + \varepsilon_{i,t} \tag{2.20}$$

The results we got from the analysis in this section is reported in Table 2.3. The difference between monthly average return between lowest and highest exposure portfolios is -0.34 % in Panel C.the average difference between Carhart alphas of the lowest and highest exposure portfolios is -0.45 %. We can also see that the Carhart alpha of portfolio 5-1 is statistically significant at 90% confidence level. Overall, there is convincing evidence that $\Delta IKOil$ is a priced risk factor with a negative price of risk in the cross-section of stock returns.

Figure 5 demonstrates the evolving average monthly returns and Carhart alphas and the t-statistics for the case of sorting based on innovations in implied kurtosis of oil market. The bottom two graphs shows that after controlling for variance and skewness innovations, the t-stat time series shifts downward and there are multiple years for which the t-stats go beyond the confidence bounds, specially after 2004. For the points which do not surpass the confidence bounds, the t-stats remain very close to the confidence bounds. This is inline with all the results we got from the regression analysis which shows kurtosis would be the only significant factor for all the sub-periods of interest.

TABLE 2.3: Oil Implied Kurtosis and the Cross-Section of Stock Returns

Factor: $\Delta IKOil$ Quintile Portfolio	1	2	3	4	5	5-1
Panel A						
Average Beta	-0.084	-0.017	0.000	0.018	0.082	0.166
Average Returns	1.052	1.049	1.045	0.907	0.785	-0.267
Carhart Alpha	0.137	0.150	0.139	-0.022	-0.238	-0.375
P-Value	0.420	**0.048**	**0.024**	0.782	0.135	0.161
Panel B						
Average Beta	-0.094	-0.018	0.002	0.021	0.104	0.198
Average Returns	1.020	1.025	1.040	0.957	0.827	-0.193
Carhart Alpha	0.101	0.134	0.143	0.023	-0.188	-0.288
P-Value	0.543	**0.064**	**0.014**	0.772	0.227	0.271
Panel C						
Average Beta	-0.126	-0.025	-0.000	0.025	0.133	0.259
Average Returns	1.090	1.024	1.030	0.906	0.750	-0.340
Carhart Alpha	0.182	0.135	0.137	-0.051	-0.276	-0.458
P-Value	0.272	**0.058**	**0.013**	0.539	**0.072**	**0.081**

2.4 Financialization Effect

The financialization of commodity market and its effect on the economy has been the subject of a substantial amount of research. Most of the authors believe that the financialization has happened some time between 2004 and 2005. In this section, we follow the literature and split the whole sample period into two sub-periods one of which covering 1996-2004 and the other one covers 2005-2014. We report the results of the analysis for these two sub-periods in tables 2.4 an 2.5.

Panels A,B and C of table 2.4 show the results for innovations in volatility, skewness and kurtosis during the first sub-period. Panel A contains some results which is fairly surprising. Sub-Panel A3 shows that the difference between average monthly returns of the maximum and minimum exposure portfolios is +0.72 %. As we can see, the overall average monthly returns is increasing going from minimum to maximum exposure portfolios, which is counter-intuitive itself. Overall, there is significant evidence that the highest exposure to risk of volatility in oil market results in a higher average returns. This result confirms the result shown in Christofferson and Pan (2015) which shows increasing trend and statistical insignificance of the alphas in this sub-period.Sub-Panel B3 of panel B shows the importance and significance of oil skewness risk for the cross-section of stock returns in the pre-financialization period. The average monthly returns of the high-low portfolio is -0.61% and the Carhart alpha of the portfolio is significant at the 95% confidence level. As we can see the overall results show the strong significance of the innovations of oil skewness market in the cross-section of stock returns during the pre-financialization period. Panel C is presenting the results for the effect of exposure to innovations in kurtosis in the oil market for this sub-period. Sub-Panel C3 of panel C is presenting the results related to innovations in kurtosis in oil market after controlling for volatility and skewness. The average monthly returns associated with the high-low portfolio is -0.56%. Although the Carhart alpha is not showing statistical significance, we can

TABLE 2.4: Oil Risk and the Cross-Section of Stock Returns Before 2004

Factor: $\Delta IVOil$ Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-4.746	-1.086	-0.050	0.976	4.782	9.528
	Average Returns	0.962	0.881	0.771	1.179	0.850	-0.112
	Carhart Alpha	0.324	0.067	-0.173	0.286	0.137	-0.187
	P-Value	0.284	0.688	0.168	0.071	0.692	0.721
Sub-Panel A2	Average Beta	-5.184	-1.166	-0.058	1.038	5.073	10.257
	Average Returns	0.616	0.864	0.793	1.146	1.041	0.425
	Carhart Alpha	-0.004	0.108	-0.189	0.221	0.330	0.334
	P-Value	0.989	0.489	0.150	0.153	0.279	0.499
Sub-Panel A3	Average Beta	-5.628	-1.240	-0.057	1.111	5.506	11.134
	Average Returns	0.554	0.903	0.842	1.151	1.283	0.729
	Carhart Alpha	-0.165	0.088	-0.088	0.224	0.672	0.837
	P-Value	0.582	0.565	0.508	0.122	0.037	0.097
Factor: $\Delta ISOil$ Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-0.298	-0.066	-0.001	0.062	0.292	0.590
	Average Returns	0.863	0.953	1.216	1.085	0.432	-0.431
	Carhart Alpha	0.228	0.046	0.289	0.210	-0.302	-0.530
	P-Value	0.489	0.773	**0.023**	0.244	0.367	0.327
Sub-Panel B2	Average Beta	-0.320	-0.069	-0.001	0.067	0.315	0.635
	Average Returns	1.006	0.921	1.210	1.072	0.315	-0.691
	Carhart Alpha	0.386	0.047	0.275	0.188	-0.441	-0.827
	P-Value	0.221	0.765	**0.037**	0.275	0.188	0.111
Sub-Panel B3	Average Beta	-0.409	-0.091	-0.006	0.076	0.382	0.791
	Average Returns	1.002	0.876	1.095	0.869	0.391	-0.611
	Carhart Alpha	0.513	0.042	0.206	-0.107	-0.515	-1.027
	P-Value	**0.096**	0.796	**0.095**	0.573	0.138	**0.045**
Factor: $\Delta IKOil$ Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-0.107	-0.024	-0.002	0.020	0.100	0.206
	Average Returns	1.005	1.108	1.013	0.797	0.577	-0.428
	Carhart Alpha	0.357	0.232	0.090	-0.070	-0.305	-0.662
	P-Value	0.334	0.115	0.530	0.694	0.397	0.290
Sub-Panel C2	Average Beta	-0.116	-0.026	-0.002	0.021	0.134	0.249
	Average Returns	0.926	1.032	1.129	0.754	0.596	-0.331
	Carhart Alpha	0.274	0.170	0.219	-0.130	-0.275	-0.549
	P-Value	0.450	0.246	0.109	0.439	0.423	0.356
Sub-Panel C3	Average Beta	-0.141	-0.032	-0.003	0.025	0.131	0.273
	Average Returns	0.956	0.982	0.965	0.758	0.397	-0.560
	Carhart Alpha	0.405	0.133	0.090	-0.222	-0.508	-0.913
	P-Value	0.245	0.357	0.461	0.238	0.161	0.137

see that with one exception, there is an strictly decreasing trend in Carhart alphas. Overall, we can see that higher exposure toward kurtosis innovations decreases the average returns of the exposed stocks which is in-line with prior expectations. The results show that the risk of oil kurtosis is priced in the cross-section of stock returns with a negative price of risk.

TABLE 2.5: Oil Risk and the Cross-Section of Stock Returns After 2004

Factor: $\Delta IVOil$ Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-2.585	-0.906	-0.373	0.144	1.771	4.356
	Average Returns	1.215	0.950	0.827	0.656	0.351	-0.864
	Carhart Alpha	0.338	0.166	0.102	-0.035	-0.394	-0.733
	P-Value	0.152	0.171	0.133	0.741	**0.093**	**0.054**
Sub-Panel A2	Average Beta	-2.698	-0.916	-0.358	0.182	1.912	4.609
	Average Returns	1.185	0.949	0.789	0.742	0.450	-0.735
	Carhart Alpha	0.308	0.164	0.068	0.052	-0.297	-0.605
	P-Value	0.218	0.178	0.340	0.609	0.218	0.144
Sub-Panel A3	Average Beta	-3.044	-0.995	-0.359	0.256	2.210	5.254
	Average Returns	1.008	0.895	0.626	0.853	0.908	-0.100
	Carhart Alpha	0.132	0.116	-0.100	0.153	0.170	0.037
	P-Value	0.563	0.315	0.189	**0.096**	0.447	0.915
Factor: $\Delta ISOil$ Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-0.248	-0.072	-0.016	0.039	0.213	0.461
	Average Returns	0.897	0.742	0.868	0.807	0.622	-0.274
	Carhart Alpha	0.059	-0.020	0.150	0.093	-0.176	-0.235
	P-Value	0.771	0.856	**0.045**	0.354	0.463	0.510
Sub-Panel B2	Average Beta	-0.263	-0.073	-0.015	0.043	0.234	0.497
	Average Returns	0.801	0.850	0.851	0.808	0.798	-0.003
	Carhart Alpha	-0.026	0.093	0.138	0.084	-0.009	0.017
	P-Value	0.899	0.405	**0.056**	0.436	0.970	0.961
Sub-Panel B3	Average Beta	-0.364	-0.095	-0.012	0.070	0.338	0.702
	Average Returns	0.962	0.922	0.788	0.824	0.664	-0.298
	Carhart Alpha	0.147	0.171	0.066	0.088	-0.143	-0.290
	P-Value	0.550	0.172	0.449	0.416	0.503	0.429
Factor: $\Delta IKOil$ Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-0.058	-0.012	0.002	0.016	0.063	0.121
	Average Returns	0.887	0.927	0.827	0.733	0.441	-0.445
	Carhart Alpha	0.104	0.204	0.107	-0.029	-0.430	-0.535
	P-Value	0.699	**0.084**	0.132	0.781	**0.057**	0.174
Sub-Panel C2	Average Beta	-0.065	-0.012	0.005	0.023	0.078	0.143
	Average Returns	0.996	0.859	0.787	0.826	0.568	-0.427
	Carhart Alpha	0.225	0.144	0.077	0.063	-0.300	-0.525
	P-Value	0.389	0.220	0.258	0.584	0.210	0.213
Sub-Panel C3	Average Beta	-0.098	-0.021	0.002	0.025	0.103	0.200
	Average Returns	1.018	0.913	0.884	0.726	0.596	-0.423
	Carhart Alpha	0.238	0.190	0.165	-0.034	-0.262	-0.500
	P-Value	0.370	**0.092**	**0.033**	0.755	0.233	0.207

Table 2.5 is presenting the results for the same analysis for sub-period 2005-2014. Panel A again shows the results for innovations in volatility in oil market for this sub-period. Sub-Panels A1 and A2 of Panel A is showing a monotonically decreasing trend in average monthly returns, going from low to high exposure . Sub-Panel A1 shows that the average monthly returns for the high-low portfolio is -0.86% . The

Carhart alpha is significant at 90% confidence level. Moving from Sub-Panel A1 to Sub-Panel A2, we find out that after controlling for the skewness, the magnitude and significance of the Carhart alpha of high-low portfolio is less evident but the downward trend can still be seen. This can be a sign of volatility's effect vanishing after controlling for other features of the distribution of futures returns like skewness. Going from Sub-Panel A2 to A3, we can see that by controlling for kurtosis, the statistical significance of Carhart alphas goes away and the monotonic trends are not seen anymore. This means that after controlling for kurtosis of the distribution, the information available in volatility is not a significant player for the cross-section of stock returns anymore. Looking at different sub-panels of Panel B we can figure out that the innovations in skewness does not show any significance in the cross-section of stock returns during the post-financialization sub-period. We are not able to discover any monotonic trend in Carhart alphas and also not able to find any statistical significance for Carhart Alphas in the case of skewness. Panel C is presenting the results based on innovations in kurtosis in oil market. Looking at Sub-Panel C3 which shows the results when we control for volatility and skewness, we can see that moving from lowest to highest exposure portfolio, there is an strictly decreasing trend in average monthly returns and Carhart alphas of the portfolios sorted based on innovations in implied kurtosis of the oil market. The average monthly returns and Carhart alpha for high-low portfolio are -0.42% and -0.50% respectively. Although the Carhart alpha is not statistically significant, the presence of the downward trend in returns is a clear indications of the importance of innovations in implied kurtosis for the cross-section of stock returns.
The final conclusion about the two formerly mentioned sub-periods is that the only factor which shows a persistent and expectation-consistent effect in both sub-periods is Kurtosis. It is evident that kurtosis is the only factor which the higher exposure towards it, translates into lower average return for the exposed stock returns in both Pre-Finacialization and Post-Financialization periods. In contrast with the absence of any effect from the side of volatility and skewness in post-financialization period , skewness seems to be a significant player in pre-financialization sub-period. However the effect of skewness vanishes by going from the pre-financialization period to post-financialization period. The effect of volatility in post-financialization period also vanishes after controlling for skewness and kurtosis.

2.5 Term Structure Effect

The BKM model-free methodology which we have adopted to estimate the risk-neutral moments and innovations in oil market makes us able to estimate the moments and innovations for different horizons. Intuitively, the implied volatility, skewness and kurtosis which are calculated from N-month maturity options, reflects the risk expectation of the investors during the following N-month period. It would be interesting to see what is the difference between the implications of different option maturities. The reason we report the main results from 60-day maturity is that the results for this maturity are the most convincing results we get from all the analyses we have done, in terms of significance and adaptability of expectations and results.

Tables 2.6 and 2.7 show the results for 30-day and 90-day maturities respectively. Panel A in table 2.6 is showing the results for innovations in volatility for 30-day maturity. Sub-Panels A1 and A2 are showing an increasing trends for average monthly

returns of the portfolios, which is counter-intuitive. Sub-Panel A3 is also showing the increasing trends in average monthly returns. The Carhart alpha of the high-low portfolio is significant at 95% confidence level. The average monthly returns of the high-low portfolio is 0.63%.

Panel B is presenting the results of the analysis using innovations in implied skewness of oil market. In none of the sub-panels we can see any monotonic trend in average monthly returns or any statistical significance for the Carhart alphas of the high-low portfolios. Panel C of this table is presenting the results for innovations in implied kurtosis of oil market. Sub-Panel C3 is showing statistical significance for the Carhart alpha of the high-low exposure portfolio at the 90% confidence level. It also shows that we can get average monthly returns equal to -0.41% for the high-low exposure portfolio. Overall, the results we got from 30-day maturity analysis confirms the results we got from 60-day analysis for Kurtosis. The difference is that for 30-day maturity analysis, we see an increasing trend for volatility innovations which is in contrast with our expectations. Also, skewness is not showing any significance in this maturity.

Table 2.7 is presenting the results for the analysis based on the 90-day maturity innovations. Different sub-panels of this panel do not show any significance for Carhart alphas or trend in average monthly returns in the case of volatility. The Carhart alpha of the high-low portfolios are positive and none of them are showing any statistical significance in the framework of the Carhart 4-factor model. This again confirms the fact that after controlling for third and fourth moments, the second moment in oil market does not have any implication for the cross-section of stock returns. Panel B is showing the results for skewness innovations. The results shown in the two sub-panels B2 and B3 show that once we control for volatility or for both volatility and kurtosis, we can see that Carhart alphas associated with the high-low portfolio is statistically significant at the 95% confidence level. The average monthly return of the high-low portfolio after controlling for volatility and after controlling for volatility and kurtosis are -0.57% and -0.63% respectively. Panel C is presenting the results for the analysis based on innovations in implied kurtosis of oil market for 90-day maturity. All the three sub-panels of this panel are showing a clear downward decreasing average monthly returns going from lowest to highest exposure portfolio.

Overall, we can see that the only moment which is showing stable trends and meaningful presence among all these three maturities in oil market is kurtosis. We can also see that the more we go from 30-days to 90-day maturity, the more important and evident is the role of skewness . The volatility is the moment with very similar pattern within different maturities. Once we control for the presence of innovations in skewness and innovations in kurtosis, volatility is not a significant player anymore. This can show the importance of the analysis for different maturities.

TABLE 2.6: Oil Risk (30-day Maturity) and the Cross-Section of Stock Returns

Factor: $\Delta IVOil$ Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-2.168	-0.533	-0.119	0.290	1.936	4.104
	Average Returns	0.621	0.719	0.834	0.895	1.061	0.439
	Carhart Alpha	-0.203	-0.053	0.088	0.213	0.356	0.559
	P-Value	0.283	0.573	0.224	**0.012**	**0.080**	**0.090**
Sub-Panel A2	Average Beta	-2.320	-0.555	-0.111	0.331	2.132	4.453
	Average Returns	0.518	0.730	0.862	0.882	1.026	0.508
	Carhart Alpha	-0.305	-0.039	0.123	0.188	0.334	0.639
	P-Value	0.113	0.670	**0.068**	**0.028**	**0.083**	**0.043**
Sub-Panel A3	Average Beta	-2.558	-0.590	-0.094	0.400	2.449	5.007
	Average Returns	0.436	0.748	0.764	0.977	1.071	0.635
	Carhart Alpha	-0.375	-0.020	0.025	0.280	0.361	0.736
	Carhart P-Value	**0.039**	0.827	0.683	**0.002**	**0.072**	**0.019**

Factor: $\Delta ISOil$ Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-0.205	-0.053	-0.008	0.037	0.219	0.424
	Average Returns	0.888	0.940	0.879	0.799	0.594	-0.293
	Carhart Alpha	0.095	0.196	0.158	0.087	-0.177	-0.272
	Carhart P-Value	0.668	**0.048**	**0.013**	0.420	0.337	0.429
Sub-Panel B2	Average Beta	-0.224	-0.056	-0.008	0.040	0.207	0.430
	Average Returns	0.857	0.921	0.866	0.842	0.537	-0.320
	Carhart Alpha	0.050	0.170	0.154	0.132	-0.246	-0.295
	Carhart P-Value	0.823	**0.079**	**0.022**	0.211	0.193	0.397
Sub-Panel B3	Average Beta	-0.292	-0.073	-0.009	0.054	0.278	0.570
	Average Returns	0.844	0.830	0.920	0.842	0.547	-0.297
	Carhart Alpha	0.060	0.079	0.206	0.116	-0.229	-0.290
	P-Value	0.793	0.442	**0.002**	0.277	0.223	0.425

Factor: $\Delta IKOil$ Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-0.057	-0.013	-0.000	0.013	0.058	0.115
	Average Returns	0.725	0.944	0.847	0.730	0.627	-0.097
	Carhart Alpha	-0.037	0.233	0.127	-0.014	-0.168	-0.131
	P-Value	0.836	**0.007**	0.106	0.879	0.338	0.631
Sub-Panel C2	Average Beta	-0.065	-0.013	0.001	0.015	0.067	0.132
	Average Returns	0.803	0.951	0.794	0.797	0.573	-0.230
	Carhart Alpha	0.093	0.250	0.076	0.038	-0.263	-0.356
	Carhart P-Value	0.612	**0.004**	0.289	0.693	0.164	0.228
Sub-Panel C3	Average Beta	-0.085	-0.019	-0.001	0.017	0.083	0.168
	Average Returns	0.910	0.931	0.798	0.725	0.499	-0.411
	Carhart Alpha	0.190	0.224	0.068	-0.029	-0.336	-0.527
	P-Value	0.302	**0.007**	0.333	0.773	**0.048**	**0.062**

TABLE 2.7: Oil Risk (90-day Maturity) and the Cross-Section of Stock Returns

Factor: $\Delta IVOil$ Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-3.953	-0.920	-0.043	0.826	3.967	7.921
	Average Returns	0.991	0.991	0.812	1.016	0.893	-0.098
	Carhart Alpha	0.279	0.175	-0.081	0.143	0.126	-0.153
	P-Value	0.212	0.150	0.364	0.194	0.601	0.677
Sub-Panel A2	Average Beta	-4.272	-0.978	-0.042	0.885	4.215	8.488
	Average Returns	0.823	0.983	0.764	1.022	1.005	0.181
	Carhart Alpha	0.113	0.190	-0.131	0.119	0.239	0.125
	P-Value	0.598	0.100	0.154	0.248	0.300	0.730
Sub-Panel A3	Average Beta	0.000	-1.062	-0.047	0.958	4.654	4.654
	Average Returns	0.704	1.004	0.802	1.060	1.148	0.444
	Carhart Alpha	-0.052	0.168	-0.084	0.179	0.461	0.512
	P-Value	0.809	0.129	0.354	**0.072**	**0.044**	0.144

Factor: $\Delta ISOil$ Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-0.277	-0.062	-0.001	0.060	0.299	0.576
	Average Returns	1.065	0.931	1.116	1.031	0.629	-0.435
	Carhart Alpha	0.343	0.078	0.229	0.158	-0.098	-0.441
	P-Value	0.152	0.534	**0.019**	0.213	0.681	0.239
Sub-Panel B2	Average Beta	-0.296	-0.065	0.000	0.064	0.295	0.591
	Average Returns	1.154	0.910	1.122	1.023	0.576	-0.578
	Carhart Alpha	0.446	0.056	0.235	0.151	-0.187	-0.633
	P-Value	**0.057**	0.628	**0.011**	0.222	0.432	**0.087**
Sub-Panel B3	Average Beta	-0.394	-0.088	-0.004	0.078	0.375	0.769
	Average Returns	1.109	0.890	1.074	0.939	0.470	-0.639
	Carhart Alpha	0.484	0.057	0.196	0.017	-0.389	-0.873
	P-Value	**0.037**	0.624	**0.029**	0.897	0.108	**0.016**

Factor: $\Delta IKOil$ Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-0.093	-0.021	-0.001	0.019	0.090	0.183
	Average Returns	1.036	1.108	0.954	0.799	0.748	-0.288
	Carhart Alpha	0.362	0.263	0.065	-0.082	-0.136	-0.498
	P-Value	0.152	**0.008**	0.507	0.498	0.591	0.243
Sub-Panel C2	Average Beta	-0.106	-0.023	-0.000	0.022	0.103	0.209
	Average Returns	1.011	1.062	1.001	0.826	0.708	-0.303
	Carhart Alpha	0.338	0.230	0.115	-0.056	-0.175	-0.513
	P-Value	0.177	**0.018**	0.205	0.640	0.482	0.220
Sub-Panel C3	Average Beta	-0.131	-0.030	-0.002	0.026	0.128	0.260
	Average Returns	0.960	0.947	0.943	0.840	0.642	-0.318
	Carhart Alpha	0.354	0.124	0.078	-0.101	-0.258	-0.612
	P-Value	0.139	0.231	0.380	0.424	0.311	0.140

2.6 Orthogonalizing by Market Moments

We have done many efforts to see if there is any role for the innovations of implied moments in oil market for cross-section of stock returns. However, there might always be a suspicion that these effects can be the ones originating from market moments and not the oil moments themselves. To investigate this, we would use the same analyses that we have done in the past with the oil moments orthogonalized by market moments. We would do the following three regressions in the first step:

$$\Delta IVOil_t = a_0 + a_1 \Delta IVM + e_t^{IVOil} \tag{2.21}$$

$$\Delta ISOil_t = a_0 + a_1 \Delta ISM + e_t^{ISOil} \tag{2.22}$$

$$\Delta IKOil_t = a_0 + a_1 \Delta IKM + e_t^{IKOil} \tag{2.23}$$

The residuals we got from these three regressions(e_t^{IVOil},e_t^{IVOil} and e_t^{IVOil}) can be interpreted as the orthogonalized innovations of oil volatility, skewness and kurtosis by innovations in their counterpart moments of the stock market.
The next step would be to use these residuals and replace regressions (2.15),(2.16) and (2.17) by the following three regressions respectively:

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i (R_{m,t} - R_{f,t}) + \beta_{IVOil}^i e_t^{IVOil} + \varepsilon_{i,t} \tag{2.24}$$

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i (R_{m,t} - R_{f,t}) + \beta_{ISOil}^i e_t^{ISOil} + \varepsilon_{i,t} \tag{2.25}$$

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i (R_{m,t} - R_{f,t}) + \beta_{IKOil}^i e_t^{IKOil} + \varepsilon_{i,t} \tag{2.26}$$

The results for the analysis based on orthogonalized moments presented in Table 2.8. Panel A is presenting the results for orthogonalized innovations in implied volatility of oil market. Looking at this table we can see that after orthogonalization, we cannot see any trend in average monthly returns, moving from lowest to highest exposure portfolios. We also see that there is no statistical significance for Carhart alpha of the high-low exposure portfolio for volatility. This can be an indicator that innovations in implied volatility of oil market do not have any contributions after taking their stock market counterpart into account. Panel B is presenting the results for orthogonalized innovations in implied skewness of oil market. Sub-Panels B1 and B2 are showing neither the monotonic trend in average monthly returns nor statistical significance for the Carhart alphas. After controlling for volatility and kurtosis, we can again see the statistical significance of Carhart alpha. In this case (Sub-Panel B3), the average monthly returns of high-low portfolio is -0.43%. We can also see that the Carhart alpha of high-low exposure portfolio is statistically significant at 90% confidence level. Panel C is presenting the results for innovation in kurtosis

after orthogonalization. Sub-Panel C3 shows that after controlling for volatility and skewness, we can see a clear decreasing trend in average monthly returns, moving from lowest exposure toward the highest exposure portfolio. The average monthly returns of high-low portfolio is -0.42% . We can also see that the Carhart alpha associated with the high-low portfolio is not statistically significant at the 90% confidence level. Although the Carhart alpha is not statistically significant within the Carhart 4-factor model, there is enough evidence for the significance of kurtosis risk with a negative price of risk.

Overall, we can see that among the three different moments, skewness and kurtosis innovations are still meaningful in cross section of stock returns after taking the market moments into account while the volatility effect fades after taking its market counterpart into effect.

TABLE 2.8: Orthogonalized Oil Implied Moments and the Cross-Section of Stock Returns

Factor: $\Delta IVOil$ Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-3.341	-0.808	-0.062	0.692	3.268	6.608
	Average Returns	0.940	1.037	0.864	0.965	0.660	-0.280
	Carhart Alpha	0.041	0.195	0.064	0.183	-0.155	-0.195
	P-Value	0.823	0.074	0.405	0.053	0.431	0.535
Sub-Panel A2	Average Beta	-3.696	-0.838	-0.048	0.750	3.552	7.249
	Average Returns	0.867	0.997	0.896	0.933	0.763	-0.104
	Carhart Alpha	-0.031	0.164	0.087	0.148	-0.066	-0.035
	P-Value	0.864	0.125	0.256	0.118	0.723	0.906
Sub-Panel A3	Average Beta	-3.935	-0.873	-0.003	0.881	4.008	7.943
	Average Returns	0.718	0.837	0.886	1.035	1.043	0.325
	Carhart Alpha	-0.189	-0.006	0.076	0.240	0.241	0.430
	P-Value	0.269	0.956	0.290	0.006	0.181	0.132

Factor: $\Delta ISOil$ Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-0.271	-0.065	-0.004	0.057	0.262	0.533
	Average Returns	0.896	0.860	1.063	0.986	0.627	-0.269
	Carhart Alpha	0.039	0.027	0.258	0.194	-0.213	-0.252
	P-Value	0.836	0.774	**0.001**	**0.057**	0.258	0.403
Sub-Panel B2	Average Beta	-0.299	-0.068	-0.003	0.061	0.283	0.582
	Average Returns	0.926	0.858	1.017	1.031	0.628	-0.298
	Carhart Alpha	0.063	0.024	0.209	0.245	-0.210	-0.273
	P-Value	0.738	0.790	**0.005**	**0.017**	0.268	0.367
Sub-Panel B3	Average Beta	-0.397	-0.096	-0.009	0.076	0.367	0.764
	Average Returns	0.964	0.968	0.883	0.961	0.527	-0.436
	Carhart Alpha	0.151	0.161	0.074	0.147	-0.382	-0.534
	P-Value	0.443	**0.096**	0.304	0.173	**0.044**	**0.082**

Factor: $\Delta IKOil$ Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-0.081	-0.018	0.000	0.018	0.084	0.165
	Average Returns	0.992	1.053	0.932	0.811	0.569	-0.422
	Carhart Alpha	0.154	0.263	0.123	-0.019	-0.350	-0.504
	P-Value	0.465	**0.003**	0.114	0.846	**0.078**	0.132
Sub-Panel C2	Average Beta	-0.092	-0.021	0.000	0.021	0.092	0.184
	Average Returns	0.968	1.015	0.930	0.828	0.586	-0.382
	Carhart Alpha	0.131	0.228	0.113	0.007	-0.315	-0.445
	P-Value	0.532	**0.012**	0.126	0.940	0.113	0.180
Sub-Panel C3	Average Beta	-0.125	-0.030	-0.003	0.023	0.115	0.240
	Average Returns	0.985	0.981	0.937	0.757	0.561	-0.424
	Carhart Alpha	0.152	0.183	0.144	-0.093	-0.339	-0.492
	P-Value	0.478	**0.057**	**0.053**	0.386	**0.086**	0.155

2.7 Dramatic Price Run-Up in 2007-2008

Oil is just one of the numerous commodities across different commodity classes (e.g. metal and agricultural) which experienced a huge price increase in 2007-2008 period. The reason for such price increase in commodities has been the topic of numerous academic and policy-making debates through the recent years. One of the suggested theories for explaining this phenomena is the price distortion cause by financialization. There has also been a theory based on which the financialization has caused a difference in information-discovery in commodity markets.(Among all, Kilian and Murphy (2013), Pindyck (2013), Singleton (2012) and Sockin and Xiong (2012)).
The huge amount of mentioned literature makes this interesting to take a look at the performance of our measures after the price boom of 2007-2008. Performing Wald and Likelihood-Ratio tests, we can detect a single point of structural break during October of 2008 for the three implied moments in oil market. To be precise, the day on which the break has been detected is 14 oct 2008. Tables 2.9 and 2.10 are presenting the results of the analysis for the two sub-periods 1996 to 14-oct-2008 and 14-oct -2008 to 2014.

Table 2.9 is showing the results for the first sub-period. looking at the first panel A we find out that there is no significance for volatility in this sub-period. This is because not only we cannot see any statistical significance, but also we cannot even a trend in average monthly returns moving from lo exposure toward the high exposure portfolio. Panel B is showing the results for innovations in skewness for the sub-period. Sub-Panel B3 shows that skewness is showing both statistical significance and monotonic trend at the same time when we control for volatility and kurtosis. The average monthly returns for the high-low exposure portfolio is -0.54% and the Carhart alpha is statistically significant at the 95% confidence level. Panel C is presenting the results for sorting based on the innovations of implied kurtosis in oil market. The results shown in the three sub-panels of panel C shows that overall, the downward trend in average monthly returns can be seen going from lowest to highest exposure portfolio. The average monthly return of the high-low exposure portfolio is -0.57% and the Carhart alpha is equal statistically significant at 90% confidence level. There are strong indications that skewness and kurtosis are both priced in the cross-section of stock returns in the period before energy crisis of 2008.

Table 2.10 is presenting the results for the second sub-period (14-oct-2008 to 2014). Looking at Panels A, B and C we find out that the only factor which is sill showing its implications after the energy crisis is kurtosis. sub-panel C3 is showing the results for sorting based on kurtosis when we control for volatility and skewness. Looking at the average monthly returns, we can see that the more is the exposure of the portfolio to risk of kurtosis in the oil market in this sub-period, the lower is the average monthly returns associated with the portfolio. Although there is no statistical significance in Carhart alphas in this sub-panel, the decreasing trend in average monthly returns is evident. Overall, we can see that kurtosis is the only moment which its innovations are still having some implications for cross-section of stock returns, even after the energy crisis of 2007-2008.

TABLE 2.9: Oil Implied Moments and the Cross-Section of Stock Returns Before 2008

Factor: $\Delta IVOil$							
Panel A	Quintile Portfolio	1	2	3	4	5	5-1
	Average Beta	-3.851	-0.899	-0.044	0.804	3.864	7.715
Sub-Panel A1	Average Returns	0.859	0.783	0.668	0.860	0.576	-0.283
	Carhart Alpha	0.355	0.162	-0.058	0.139	-0.073	-0.428
	P-Value	0.109	0.157	0.511	0.202	0.764	0.250
	Average Beta	-4.172	-0.953	-0.040	0.864	4.109	8.281
Sub-Panel A2	Average Returns	0.669	0.759	0.674	0.868	0.737	0.068
	Carhart Alpha	0.178	0.173	-0.087	0.123	0.092	-0.086
	P-Value	0.412	0.112	0.327	0.244	0.683	0.814
	Average Beta	-4.609	-1.046	-0.048	0.938	4.506	9.116
Sub-Panel A3	Average Returns	0.495	0.827	0.642	0.897	0.983	0.488
	Carhart Alpha	-0.063	0.196	-0.079	0.164	0.412	0.475
	P-Value	0.773	**0.073**	0.387	0.100	**0.085**	0.191
Factor: $\Delta ISOil$							
Panel A	Quintile Portfolio	1	2	3	4	5	5-1
	Average Beta	-0.282	-0.063	-0.000	0.062	0.280	0.562
Sub-Panel B1	Average Returns	0.794	0.755	0.977	0.839	0.384	-0.409
	Carhart Alpha	0.253	0.062	0.272	0.149	-0.229	-0.482
	P-Value	0.280	0.589	**0.002**	0.218	0.338	0.199
	Average Beta	-0.303	-0.066	0.001	0.067	0.307	0.610
Sub-Panel B2	Average Returns	0.896	0.764	0.971	0.834	0.340	-0.556
	Carhart Alpha	0.348	0.082	0.261	0.143	-0.275	-0.624
	P-Value	0.131	0.460	**0.004**	0.228	0.239	**0.087**
	Average Beta	-0.403	-0.090	-0.002	0.083	0.389	0.792
Sub-Panel B3	Average Returns	0.882	0.790	0.863	0.697	0.335	-0.547
	Carhart Alpha	0.430	0.136	0.185	-0.062	-0.398	-0.828
	P-Value	**0.064**	0.220	**0.034**	0.625	0.101	**0.023**
Factor: $\Delta IKOil$							
Panel A	Quintile Portfolio	1	2	3	4	5	5-1
	Average Beta	-0.094	-0.022	-0.001	0.020	0.091	0.186
Sub-Panel C1	Average Returns	0.870	0.950	0.792	0.613	0.409	-0.460
	Carhart Alpha	0.348	0.248	0.078	-0.068	-0.288	-0.636
	P-Value	0.175	**0.016**	0.441	0.586	0.257	0.137
	Average Beta	-0.106	-0.024	-0.000	0.023	0.120	0.226
Sub-Panel C2	Average Returns	0.876	0.865	0.885	0.612	0.466	-0.410
	Carhart Alpha	0.282	0.174	0.182	-0.069	-0.192	-0.474
	P-Value	0.282	**0.098**	**0.059**	0.595	0.441	0.275
	Average Beta	-0.136	-0.031	-0.002	0.027	0.131	0.267
Sub-Panel C3	Average Returns	0.900	0.764	0.789	0.670	0.322	-0.578
	Carhart Alpha	0.376	0.085	0.093	-0.069	-0.358	-0.735
	P-Value	0.135	0.407	0.287	0.609	0.164	**0.092**

TABLE 2.10: Oil Implied Moments and the Cross-Section of Stock Returns After 2008

Factor: $\Delta IVOil$ Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-2.703	-1.075	-0.560	-0.065	1.455	4.158
	Average Returns	2.038	1.652	1.504	1.327	1.164	-0.874
	Carhart Alpha	-0.013	-0.014	0.108	0.082	-0.127	-0.114
	P-Value	0.964	0.925	0.238	0.546	0.673	0.817
Sub-Panel A2	Average Beta	-2.803	-1.086	-0.549	-0.036	1.596	4.398
	Average Returns	1.901	1.664	1.449	1.424	1.321	-0.580
	Carhart Alpha	-0.134	0.020	0.053	0.163	0.005	0.139
	P-Value	0.639	0.901	0.552	0.197	0.986	0.783
Sub-Panel A3	Average Beta	-3.089	-1.135	-0.542	0.024	1.849	4.937
	Average Returns	1.874	1.490	1.327	1.557	1.808	-0.066
	Carhart Alpha	-0.149	-0.156	-0.059	0.276	0.462	0.611
	P-Value	0.530	0.232	0.524	**0.018**	**0.047**	**0.087**
Factor: $\Delta ISOil$ Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-0.230	-0.078	-0.031	0.016	0.163	0.393
	Average Returns	1.614	1.429	1.478	1.532	1.483	-0.132
	Carhart Alpha	-0.204	-0.114	0.069	0.170	-0.189	0.015
	P-Value	0.293	0.345	0.480	0.146	0.493	0.968
Sub-Panel B2	Average Beta	-0.242	-0.079	-0.030	0.019	0.174	0.416
	Average Returns	1.454	1.524	1.457	1.538	1.703	0.249
	Carhart Alpha	-0.372	0.007	0.054	0.165	0.010	0.382
	P-Value	**0.058**	0.956	0.564	0.165	0.973	0.314
Sub-Panel B3	Average Beta	-0.327	-0.097	-0.028	0.042	0.270	0.596
	Average Returns	1.712	1.646	1.427	1.542	1.539	-0.173
	Carhart Alpha	0.007	0.185	0.029	0.067	-0.177	-0.184
	P-Value	0.980	0.190	0.770	0.632	0.526	0.698
Factor: $\Delta IKOil$ Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-0.040	-0.005	0.005	0.016	0.053	0.093
	Average Returns	1.661	1.541	1.565	1.426	1.332	-0.329
	Carhart Alpha	0.103	0.205	0.137	-0.157	-0.532	-0.635
	P-Value	0.771	0.209	0.120	0.283	**0.064**	0.233
Sub-Panel C2	Average Beta	-0.042	-0.004	0.008	0.021	0.062	0.104
	Average Returns	1.661	1.550	1.430	1.542	1.413	-0.248
	Carhart Alpha	0.122	0.250	0.046	-0.069	-0.542	-0.663
	P-Value	0.708	**0.080**	0.601	0.606	**0.049**	0.176
Sub-Panel C3	Average Beta	-0.071	-0.014	0.003	0.020	0.078	0.149
	Average Returns	1.782	1.720	1.573	1.310	1.477	-0.305
	Carhart Alpha	0.219	0.345	0.176	-0.245	-0.376	-0.594
	P-Value	0.547	**0.026**	**0.053**	**0.069**	0.172	0.270

2.8 Forecasting Market Returns using Oil Moment Innovations

We have already shown that the prices of skewness and kurtosis are priced in some (all) of the sub-periods through the sample. We want to see if the innovations in oil implied moments are significant economic variables for predicting the time-series returns of the stock market. In order to investigate this, we would regress the market excess returns on the oil implied-moment innovations and the lagged market returns. We do our analysis here based on the monthly average returns and monthly innovations in oil implied moments.

TABLE 2.11: Predicting Stock Market Index Returns by Oil Moments

	(1) Indexret_t	(2) Indexret_t
$\text{VolInnov}_{t\text{-}1}$		-0.0711
		(-0.14)
$\text{SkewInnov}_{t\text{-}1}$		0.00824
		(1.55)
$\text{KurtInnov}_{t\text{-}1}$	-0.00407	-0.00384
	(-1.94)	**(-1.84)**
$\text{Indexret}_{t\text{-}1}$	0.0911	0.0953
	(1.23)	(1.44)
Constant	0.000351	0.000347
	(2.10)	(2.08)
Observations	220	220
Adjusted R^2	0.011	0.010

t statistics in parentheses

Table 2.11shows the result for the univariate and multivariate regressions in order to investigate this fact. Column 1 is showing the results for regressing market returns on innovations in implied kurtosis of oil market and lagged market returns. The coefficient associated with the implied kurtosis innovations is negative and statistically significant at the 90% confidence level. We also get Adjusted R-Squares of 1.1% for this regression analysis. Column 2 presents the results for the same analysis when we also control for lagged innovations in implied variance and skewness in the oil market. As we can see, adding variance and skewness innovations in variance and skewness , does not change any fundamental results. The coefficient for the lagged kurtosis innovations is still negative and significant at the 90% confidence level. The only change is that the R-Squared is reduced to 1%, which shows that adding the other two moments does not add any prediction power to our statistical model. Overall, the results of this regression verifies one more time that the innovations in oil implied kurtosis are a significant determinant of stock market returns.

TABLE 2.12: Oil Risk and the Cross-Section of Stock Returns After Omitting Oil and Gas Sector

Factor: $\Delta IVOil$ Panel A	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel A1	Average Beta	-9.482	-2.701	-0.571	1.517	8.286	17.768
	Average Returns	1.053	0.974	0.841	0.816	0.551	-0.502
	Carhart Alpha	0.175	0.204	0.084	0.078	-0.212	-0.597
	P-Value	0.350	**0.021**	0.266	0.416	0.225	**0.043**
Sub-Panel A2	Average Beta	-10.906	-2.795	-0.546	1.643	8.768	18.749
	Average Returns	0.904	0.916	0.866	0.831	0.703	-0.201
	Carhart Alpha	0.051	0.155	0.098	0.078	-0.066	-0.328
	P-Value	0.775	**0.086**	0.222	0.395	0.712	0.267
Sub-Panel A3	Average Beta	0.000	-3.012	-0.553	1.834	9.637	9.637
	Average Returns	0.822	0.896	0.788	0.921	0.884	0.062
	Carhart Alpha	-0.040	0.112	0.032	0.175	0.127	-0.044
	P-Value	0.808	0.207	0.698	**0.040**	0.466	0.872
Factor: $\Delta ISOil$ Panel B	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel B1	Average Beta	-0.233	-0.062	-0.008	0.046	0.215	0.448
	Average Returns	0.808	0.890	0.937	0.939	0.589	-0.219
	Carhart Alpha	-0.016	0.098	0.179	0.196	-0.189	-0.384
	P-Value	0.926	0.266	**0.022**	**0.035**	0.303	0.180
Sub-Panel B2	Average Beta	-0.245	-0.063	-0.006	0.050	0.229	0.474
	Average Returns	0.878	0.834	0.992	0.914	0.603	-0.274
	Carhart Alpha	**0.054**	**0.050**	0.235	0.165	-0.198	-0.463
	P-Value	0.740	0.555	0.003	0.068	0.258	0.091
Sub-Panel B3	Average Beta	-0.321	-0.080	-0.005	0.069	0.308	0.629
	Average Returns	0.856	0.874	0.823	0.960	0.590	-0.266
	Carhart Alpha	0.098	0.116	0.069	0.173	-0.271	-0.580
	P-Value	0.570	0.194	0.391	**0.061**	0.116	**0.038**
Factor: $\Delta IKOil$ Panel C	Quintile Portfolio	1	2	3	4	5	5-1
Sub-Panel C1	Average Beta	-0.067	-0.015	0.001	0.016	0.068	0.135
	Average Returns	0.933	0.946	0.878	0.804	0.540	-0.393
	Carhart Alpha	0.146	0.187	0.126	0.022	-0.326	-0.471
	P-Value	0.469	**0.032**	0.110	0.819	**0.060**	0.132
Sub-Panel C2	Average Beta	-0.074	-0.016	0.002	0.020	-0.980	-0.906
	Average Returns	0.934	0.914	0.927	0.733	0.684	-0.250
	Carhart Alpha	0.147	0.168	0.180	-0.054	-0.180	-0.537
	P-Value	0.449	**0.047**	**0.023**	0.570	0.279	**0.070**
Sub-Panel C3	Average Beta	-0.097	-0.022	0.001	0.024	0.098	0.196
	Average Returns	0.960	0.879	0.813	0.755	0.608	-0.352
	Carhart Alpha	0.211	0.137	0.067	-0.055	-0.279	-0.701
	P-Value	0.269	0.111	0.342	0.576	0.110	**0.021**

2.9 The effect of the Firms in the Oil and Gas Sector

There are a couple of reasons which make it worthwhile to take a look at the effect of oil and gas sector on the average returns of the hedge portfolio. The first complaint could be that the average returns that we got in our analysis is coming from the side of an specific sector, as the oil and gas industry is much more affected by the uncertainty measures which forms the expectation about the oil market. So we need to investigate to find if the effect that is found will sustain after taking the oil and gas sector out of our data. The other reason for investigating the effect of the oil and gas sector is that oil and gas sector and the other sectors react differently to the shocks in oil market, meaning that upside oil shocks has a positive effect on oil and gas sector while it is a negative phenomena for the rest of sectors. This is the case for the case of downside shocks as well. This can make the results weaker when we include oil and gas sector in the data. Table 2.12 presents the results for the case we omit Oil, Gas and Coal Extraction firms from the data, based on the Fama-French 10 industry sic codes. Looking at Panels B and C we can see that although the absolute value of the average returns of the hedge portfolio has a small reduction in this case in comparison to the case of having all the sectors in the data, the statistical significance level of the Carhart alphas in this case is much more evident. The Carhart alphas are significant at the 95% confidence level. The results we got verifies that the average return of the hedge portfolio is not dramatically affected by oil and gas sector and omitting the sector not only doesn't reduce the statistical significance of the results but also it strengthens it.

2.10 Conclusion

Changes in dynamics of the prices of commodities and its effect on the economy has been the core of huge academic literature during the recent years. Among all the commodities, oil is the most important one because of the effects and implications it has for different sections of the economy. In this paper we focus on the implications of moment risks in oil market for the cross-section of stock returns. First , when we sort based on the innovations in three moments of oil, we can see that in contrast with volatility, innovations in risk-neutral skewness and kurtosis are both priced in cross-section of stock returns. We examined the significance of the effects using Carhart 4-Factor model. Although skewness does not pass the significance test, there is strong implications of the risk to be prices in the cross-section of stock returns. We can see that the stocks with higher exposure to the risk of skewness and kurtosis in oil market, earn lower return. The average monthly return for the high-low exposure portfolios of stock to risk of skewness and kurtosis are -0.28% and -0.34% respectively.
Second, we investigate the financialization story by splitting the data in two sub-periods, one of which covers 1996-2004 and the other one 2005-2014. Among the three moments, the only one that shows a monotonic-decreasing trend in returns and statistical significance for both sub-periods is kurtosis.
The next thing we investigate in this paper is the term structure effects. for this purpose we repeat the analysis for 30-days and 90-days maturities. Again, the only moment for which this sorting yield decreasing trend in returns and significant Carhart alpha is kurtosis. The other interesting point about the term-structure effect is that

going from 30-day to 90-day maturity, sorting based on skewness and kurtosis yields stronger results in terms of average return and Carhart alpha magnitude and also in terms of statistical significance. This shows that term-structure effects and different maturities worth to be investigated.
The next thing to study would be to see if the results we are getting are not spurious, meaning that if the main drivers of these results are uncontrolled market moments. To address this problem, we orthogonalize the risk-neutral moments of oil market by their stock market counterparts by using the residuals of the regression of oil market moments on their stock market counterpart. Sorting the stocks based on the new measure shows us two things. The decreasing trend in average return for skewness and kurtosis is much cleaner and more evident. We can also see that the average returns of the high-low exposure increases in comparison with the case of sorting based on the oil non-orthogonalized moments.
The last part of the paper is a discussion about the change in the effect of commodity (specifically oil) market on the cross-section of stock returns. We find a structural break on 14-oct-2008 in the time series of implied moments. The results for 1996 to 14-oct-2008 shows the decreasing pattern and significant alpha in case of skewness . For the second sub-period (after price run-up), the only moment with decreasing trend in average returns (and Carhart alphas) is kurtosis. None of the other moments have either statistical significance or the expected trend in average returns. overall, it is evident that the implications of oil moments for cross section of stocks are impacted by 2007-2008 energy crisis, but even after the crisis, kurtosis has meaningful implications for the cross section of stock returns.

Chapter 3

Determinants of Variance and Skew Risk Premium

3.1 Introduction

The premiums that investors require to face different kinds of risk have been the core of finance for a long time. Most of the work which has been done is about analyzing the risk associated with the asset price variation. However, the price risk is not the only risk investor is exposed to by holding a specific asset. The history of financial econometrics has documented big time variation in variance and skewness of commodity futures returns. These variations introduce additional sources of risk from holding commodity derivatives, referred to as Variance and Skewness risk. Investors generally dislike these variations and they want to get a premium in order to expose themselves to these risks. These premiums are known as Variance Risk Premia (henceforth VRP) and Skewness Risk Premia(henceforth SRP).In general, it is important to know the size and the determinants of uncertainties associated with variance and skewness in order to manage risk and allocate assets effectively, hedge accurately and price the derivatives. It would also be so important for the investors to know if these premia are able to predict the returns of option portfolios and futures. Our focus in this paper is on analyzing all these questions using the data in oil market.

There are a couple of 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.Secondly, we need to have a market which is highly liquid because the tools we are using in order to characterize the risk premia are the options on the asset (here, oil futures). Among all the commodities, crude oil financial derivatives are the most liquid ones in the market.

The results of our paper indicates that using two classes of variables, Economic and Commodity-Specific, we are able to describe a considerable part of variation in the time-series of VRP and SRP. In fact, the results show that the whole variation described by our models are attributable to Economic variables, while the Commodity-Specifics do not show any significance in full specifications. At last, we would also investigate the prediction power of VRP and SRP for return of Delta Neutral and Delta-Vega Neutral portfolio of options and also of the oil futures. The results show that VRP and SRP are significant predictors of return on Delta Neutral and Delta-Vega Neutral option portfolios respectively. The variables are also jointly significant predictors of returns on oil futures.

3.2 Literature Review

Although there is a vast literature on the role of VRP across equity and bond market, there are just a few papers which have tried to show the importance of VRP in Commodity market. In a very recent try, Kang and Pan (2015) has documented a significant effect of Variance Risk Premium in enhancing the ability of model to predict the expected returns of oil futures, even after they control for the classic determinants, from Oil-specific to general macroeconomic variables. They showed the goodness of fit of the model considerably increases as we add VRP as a regressor. They also show that this holds for longer than one-month maturity, which has been the benchmark in commodity VRP literature before this paper. In another attempt to show the importance of oil volatility, Christoffersen and Pan (2014) shows that the Oil Volatility have the power to unveil the effect of the real economy on cross section of stock market. They essentially find that the level of exposure of any stock to oil volatility risk would be one of the most important determinants of the level of expected average returns of the stock. In fact, the higher the exposure, the lower would be the return. Trolle and Schwartz (2008), is the very first attempt of quantifying VRP in commodities, particularly energy commodities (oil and gas). They find that average VRP are negative for both commodities, but are more significant for oil. Prokopczuk and Simen (2014) is the first paper which has tried to quantify VRP across wide array of commodities, using a large panel data and using BKM methodology to replicate the Variance Swap. They found significant VRP in 18 out of 21 commodities. They also investigated the commonalities within and across different classes of commodities. They have also documented an increase in commonalities after 2004, which is the financialization period of commodity market. In addition, they tried to show the relationship between commodity VRP and the Price Risk Premia in commodity, bond and equity markets. Surprisingly, they find very weak effect and explanatory power of commodity VRP in describing the variation across all three classes of assets. Prokopczuk and Simen (2014), investigates the role of adjusting for volatility when we want to see forecasting power of the implied volatility. They found risk adjustment of implied volatility to be an important factor in enhancing its forecasting power. Wang et al.

The literature on SRP is much thinner than the one on VRP. It is not a surprise then that the literature on SRP in commodity market is scant.Ruf (2012) uses the liquidity risk which has been defined as the probability of force selling of speculative position-which is the result of a sudden liquidity shock -as one of the main determinants of option implied skewness and SRP. The paper has used speculative net long positions as a proxy for the liquidation risk variable to show that both implied skewness and SRP are correlated with the net long position variable. The paper also shows that correlation would be stronger in cases that funding conditions are deteriorated. The paper also shows that the proposed trading strategies which are designed in order to calculate SRP have the ability to produce a high monthly yield. Ruf (2012) tries to show that limits to arbitrage affects the relative price of OTM call to OTM put options (which is being defined as option implied skewness). The paper decomposes the skewness price into two components which are the realized skewness and SRP. For doing that, the paper utilizes a panel of commodity options and futures data. The results show that under circumstances that arbitragers hold a larger net long position in options or futures is concentrated among fewer number of investors, the SRP will be increased but the realized skewness remains unchanged. The results show the considerable impact of limits to arbitrage on option returns as

well as the option prices. Rafaela et al (2012) uses the same methodology as our paper to estimate VRP and SRP for Equity, Brent and Carbon emission markets. The fundamental purpose of this paper is to utilize the trading strategy of Kozhan et al (2013) in order to investigate the presence of variance and skewness risk premia in these markets. They find significant variance and skewness risk premia in equity market. The Brent market shows a significant VRP and insignificant SRP while the emission market does not show any significant risk premia, neither in the case of variance nor for the skewness. Christofferson and Pan (2015) uses the logic that the State Price Density is the ratio of Risk-Neutral and Physical densities and propose the idea that the U shaped SPD is being driven by the variation inside these two. Considering the fact that the Risk-Neutral Skew is more volatile than the physical skew, the paper uses the Risk-Neutral Skew as a proxy for the slope of the SPD. They apply their logic to crude oil derivatives. The main question investigated in this research is that if the Risk-Neutral Skew is related to the investors' beliefs. They show that the change in the level of speculation has an effect on Risk-Neutral Skew. one of the other factors which is negatively related to Implied Skew is the ratio of OTM put to OTM call options. They also find that OTM call (put) volume has positive (negative) effect on the Skewness of Risk-Neutral distributions.

3.3 Methodology

3.3.1 Estimating Variance Risk Premia

The methodology used in this paper to quantify the VRP is from Trolle and Schwartz (2008). The main idea here is to use the Variance swaps. At maturity, the return for Variance swap is equal to the Variance swap rate minus the realized Variance over the life of the swap:

$$(V(t,T) - K(t,T))L$$

Where $V(t,T)$ is the realized variance of the underlying asset over the life of the swap (time t to T), $K(t,T)$ is the fixed variance swap rate and L is the notional of the swap. Since we know that net market value of the Variance swap is zero at maturity, based on No-Arbitrage we can get the fixed swap rate from taking the risk neutral expectation of realized Variance over the life of the swap.

$$K(t,T) = E_t^Q[V(t,T)] \tag{3.1}$$

The equation 3.1 tells us that the fixed variance swap rate would be equal to the conditional expectation of the realized variance over the life of the swap, under the Risk-Neutral measure.

Based on Trolle and Schwartz (2008),We can get $K(t,T)$ using:

$$K(t,T) = \frac{2}{P(t,T)(T-t)} \left(\int_0^{F(t,T_1)} \frac{p(t,T,T_1,X)}{X^2} dX + \int_{F(t,T_1)}^{\infty} \frac{c(t,T,T_1,X)}{X^2} dX \right) \tag{3.2}$$

In equation 3.2 , $F(t,T_1)$ is the time-t price of the futures contract which will mature at time T_1. $P(t,T)$ is the time-t price of the zero coupon bond maturing at time T,and $c(t,T,T_1,X)$ and $p(t,T,T_1,X)$ are the price of European call and put options

at time t respectively. Finally X is the strike price of the options. For computation of the realized variance we have:

$$V(t,T) = \frac{1}{N\Delta t}\sum_{i=1}^{N} R(t_i)^2 \tag{3.3}$$

Here, N is the number of days to expiration date of the swap, $\Delta t = t_i - t_{i-1} = 1/252$ and

$$R(t_i) = \log(\frac{F(t_i,T_1)}{F(t_{i-1},T_1)}) \tag{3.4}$$

At the end, we calculate VRP as:

$$VRP = V(t,T) - K(t,T) \tag{3.5}$$

We start by choosing the first nearby futures contract which the options defined on it have at least ten days to maturity. The options we are using are the OTM options which their price is higher than 0.05 USD and open interest higher than 100. For the interest rate we use three month LIBOR coming from Federal Reserves Economic Data-FRED.

The next challenge we face is that the options on futures are American options while the synthesized variance swap uses the European option prices. We use Bjerksund and Stensland (2002) approach to do the American-to-European options conversion and get the implied volatilities.For an option with strike X, having the Log-Normality assumption of Black (1976), moneyness would be calculated as:

$$d = \frac{\log(X/F(t,T_1))}{\sigma\sqrt{(T-t)}} \tag{3.6}$$

In equation 3.6, t is the date at which we are evaluating the options, T is the expiration date of the option, T_1 is the delivery date of the corresponding futures contract and σ is the Black (1976) implied volatility of the closest option to at the money (ATM). For truncation points of the integrals, we truncate at the strikes corresponding to d=-10 and d=10: $X_{\min} = F(t,T_1)e^{-10\sigma\sqrt{(T-t)}}$ and $X_{\max} = F(t,T_1)e^{10\sigma\sqrt{(T-t)}}$ respectively.

The problem here is that we do not have a continuum of implied volatilities. To tackle this problem, we use linear interpolation to get a continuum of implied volatilities. The next stage would be to go from continuum of implied volatilities to continuum of prices. This again, would be done using Black (1976). For the strikes lower than $X_{\min}$ and higher than $X_{\max}$, we use flat extrapolation ,meaning that we put the implied volatility of these points as equal to the implied volatility of the *min* and *max* strikes.

Figure 3.1 shows the time series of risk-neutral(red line) and physical(blue) variance, calculated based on the steps described above.

3.3.2 Estimating Skew Risk Premia

The expression that we introduced in order to calculate the model free implied variance is the one which has been used in Demeterfi, Derman, Kamal, and Zou (1999).Britten-Jones Neuberger (2002) use a slightly different formulation. Carr and Madan (1998) is one of the other papers which uses this formulation. the model has

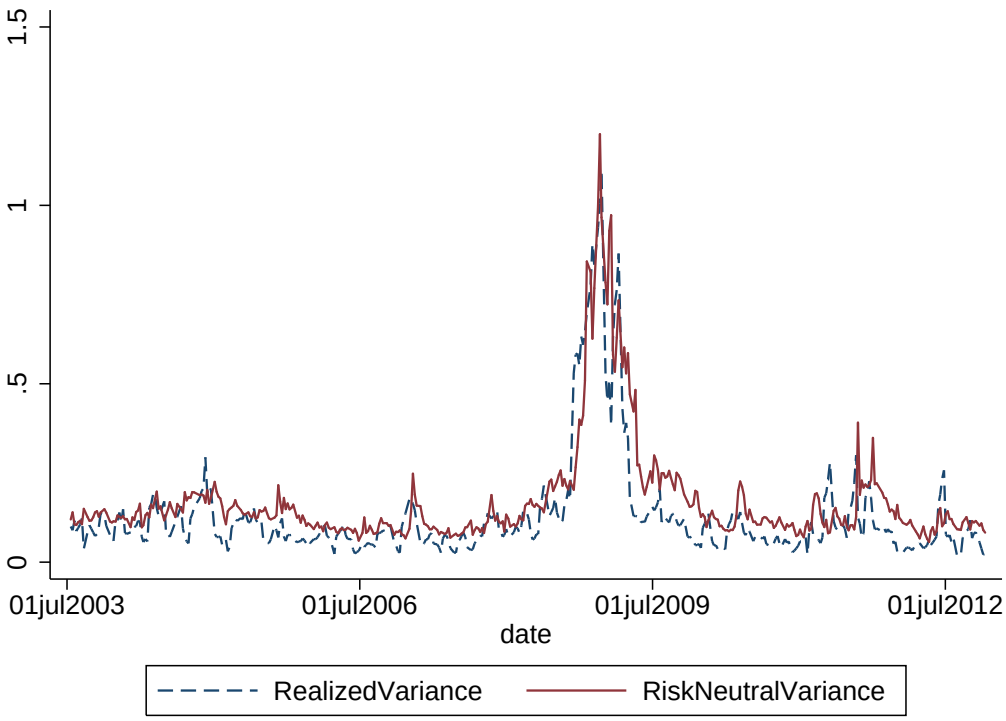

FIGURE 3.1: This figures displays time series of components of Variance Risk Premia .The Figure displays the dynaimcs of the Relized Variance and Model-Free Implied Variance. The difference between these two time series is the time series for Variance Risk Premia. The data ranges from 2003 to 2014.

been extended in Jiang Tian (2005) to incorporate jumps. They also show that the formula is an imperfect formula to calculate the implied variance in the presence of discrete sampling. Kozhan et al. (2013) has introduced a model-free and jump robust alternative measure. They define the implied variance for the log contract, $v^l_{t,T}$ and the implied variance for the enthropy contract $v^e_{t,T}$ as:

$$v^l_{t,T} = 2E^Q[\frac{F_T}{F_t} - 1 - \log\frac{F_T}{F_t}] \tag{3.7}$$

$$v^e_{t,T} = 2E^Q[-\frac{F_T}{F_t} + 1 + \frac{F_T}{F_t}\log\frac{F_T}{F_t}] \tag{3.8}$$

Then, for the log contract $L_{t,T}$, which its payoff has been defined as $\log F_T$, and the enthropy contract $E_{t,T}$ which its payoff is defined as $F_T \log F_T$ we would have:

$$L_{t,T} = E^Q[\log F_T] = \log F_t - \frac{v^l_{t,T}}{2} \tag{3.9}$$

$$E_{t,T} = E^Q[F_T \log F_T] = F_t \log F_t + F_t\frac{v^e_{t,T}}{2} \tag{3.10}$$

We continue by approach and notation of Rafaela et al (2010). By applying Ito calculus we get:

$$dL_{t,T} = \frac{dF_t}{F_t} - \frac{1}{2}(\frac{dF_t}{F_t})^2 - \frac{dv^l_{t,T}}{2} \tag{3.11}$$

$$dE_{t,T} = (1 + \log F_t + \frac{v^e_{t,T}}{2})dF_t + \frac{1}{2}\frac{(dF_t)^2}{F_t} + \frac{1}{2}F_t dv^e_{t,T} + \frac{1}{2}dF_t dv^e_{t,T} \tag{3.12}$$

By using the approach of Carr and madan (2001) we would get the following equations:

$$L_{t,T} = \log F_t - \int_0^{F_t} P(K)\frac{dX}{X^2} - \int_{F_t}^{\infty} C(K)\frac{dX}{X^2} \tag{3.13}$$

$$E_{t,T} = F_t \log F_t + \int_0^{F_t} P(X)\frac{dX}{X^2} + \int_{F_t}^{\infty} C(X)\frac{dX}{X^2} \tag{3.14}$$

As a result, for implied variance of the log and enthropy contract we would have:

$$v^l_{t,T} = (\int_0^{F_t} P(X)\frac{dX}{X^2} + \int_{F_t}^{\infty} C(K)\frac{dX}{X^2}) \tag{3.15}$$

$$v^e_{t,T} = (\int_0^{F_t} P(X)\frac{dX}{XF_t} + \int_{F_t}^{\infty} C(X)\frac{dX}{XF_t}) \tag{3.16}$$

Bakshi et al.(2003) shows that the definition for the implied skewness which is derived from option prices is equal to skew coefficient of the implied risk neutral distribution of the log returns. The problem with this is that there is no ex-post counterpart and no trading strategy. Kozhan et al (2013) has tackled this problem by proposing a trading strategy and as a result, building up a skew swap. The floating leg for skew swap is computed as:

$$rs_{t,T} = \sum_{i=1}^{T} [(\delta v^E_{i,T}(e^{r_{i,i+1}} - 1) + 6(2 - 2e^{r_{i,i+1}} + r_{i,i+1} + r_{i,i+1}e^{r_{i,i+1}})] \tag{3.17}$$

Finally the realized skew would be :

$$rskew_{t,T} = \frac{rs_{t,T}}{\left(v^L_{t,T}\right)^{\frac{3}{2}}} \tag{3.18}$$

We would use trapezoidal integral once again to compute the implied variance of log and enthropy contracts from equations 3.15 and 3.16 and after that, we would

calculate the fixed leg of the skew swap as:

$$Skew_{t,T} \equiv 3\frac{v^E_{t,T} - v^L_{t,T}}{(v^L_{t,T})^{\frac{3}{2}}} \tag{3.19}$$

The SRP would be the difference between the fixed leg and the floating leg of the skew swap:

$$SRP = rskew_{t,T} - Skew_{t,T} \tag{3.20}$$

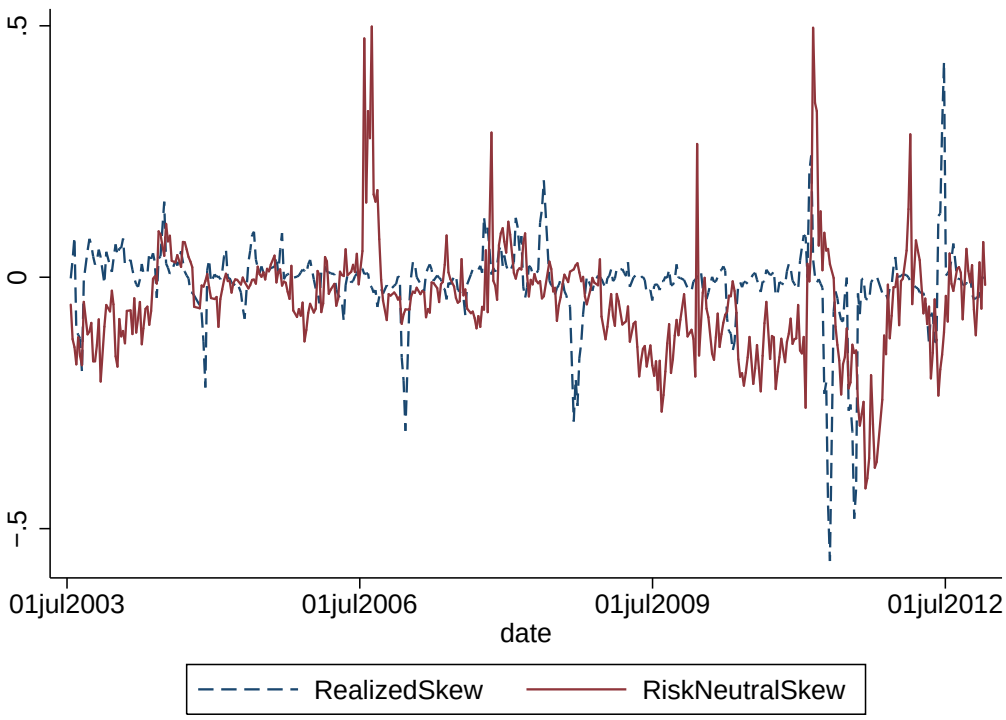

FIGURE 3.2: This figures displays time series of components of Skew Risk Premia.The Figure displays the dynaimcs of the Relized Skew and Model-Free Implied Skew. The difference between these two time series is the time series for Skew Risk Premia. The data ranges from 2003 to 2014.

Figure 3.2 presents time series of risk-neutral (red) and physical (blue) skewness, calculated based on the process described above. Figures 3.3 and 3.4 presents the time series of variance and skewness risk premia.

3.3.3 Forming Delta and Delta-Vega Hedged Option Portfolios

In order to investigate the ability of VRP and SRP to predict option portfolio returns, we need to form two different types of option portfolios. The first type of option portfolio which theoretically should be exposed to VRP is the Delta-Hedge option portfolio. In fact, we are constructing a Delta-Hedged option portfolio in a way

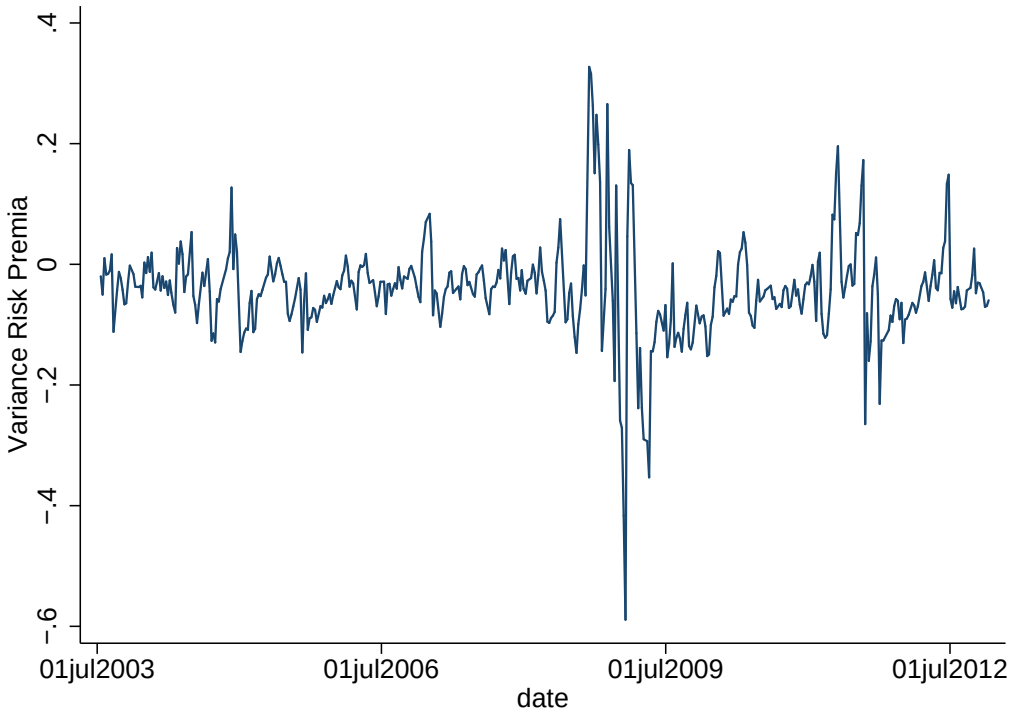

FIGURE 3.3: This figure shows the time series of Variance Risk Premium. The data ranges from 2003 to 2014.

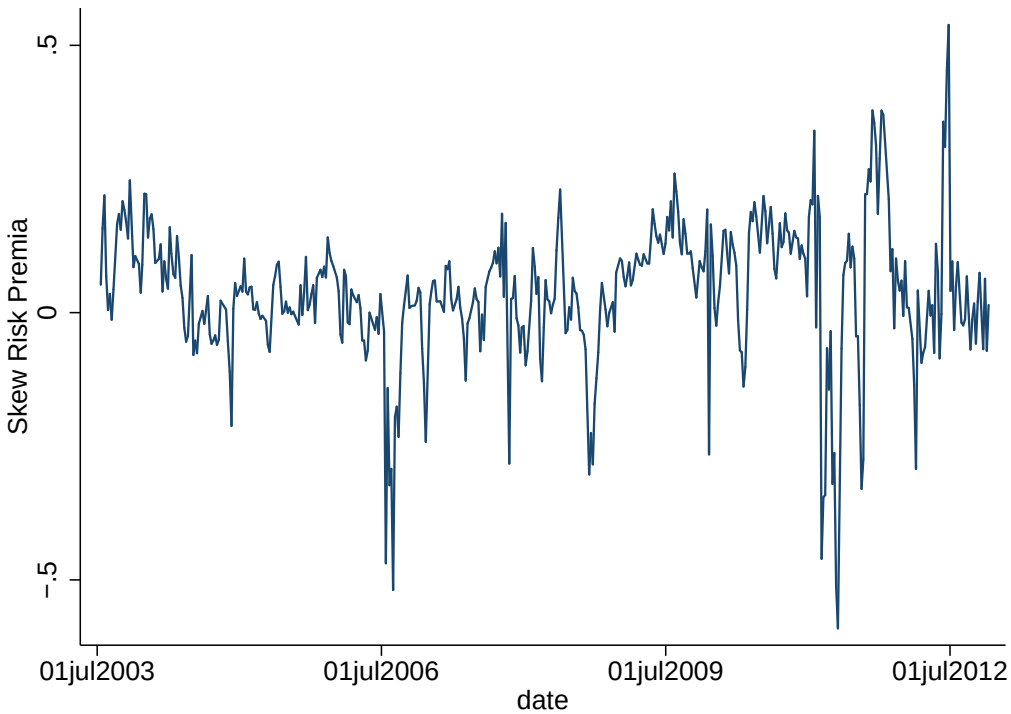

FIGURE 3.4: This figure shows the time series of Skewness Risk Premium. The data ranges from 2003 to 2014.

that its return is not sensitive towards the change in the mean (Delta-Neutral),but it would be prone to Volatility risk. In the same fashion, we construct a portfolio of options which is not sensitive to change in mean and variance but would be prone to change in Skewness (Delta-Vega Neutral). Using the same method as Bali and Murray (2013),we define the Delta Neutral portfolio of options on oil futures with a position of $Pos^{DH}_{C,OTM}$=1 contract of the OTM call option and a position of $Pos^{DH}_{P,OTM} = -(\frac{\Delta_{C,OTM}}{\Delta_{P,OTM}})$ of the OTM put option where $\Delta_{C,OTM}$ and $\Delta_{P,OTM}$ are Delta of the OTM call and OTM put options respectively.We also form the Delta-Vega Neutral portfolio with a position of $Pos^{DVH}_{C,OTM} = 1$ contract of the OTM call, a position of $Pos^{DVH}_{P,OTM} = -(\frac{v_{C,OTM}}{v_{P,OTM}})$ contracts in OTM put and a position of $Pos^{DVH}_{S} = -(Pos^{DVH}_{C,OTM}\Delta_{C,OTM} + Pos^{DVH}_{P,OTM}\Delta_{P,OTM})$ underlying oil futures where $v_{C,OTM}$and $v_{P,OTM}$ are Vega of OTM call and OTM put options respectively.

3.4 Data

There are three major classes of variables which we will consider for our study. The three are Commodity-Specific factors,Macroeconomic factors and Fundamental factors. In the following three sections we talk about these three different classes of data in details.

3.4.1 Futures and Options Data

We get the futures and options data on oil from the NYMEX(New York Mercantile Exchange). The data we use is daily settlement prices from 2003 to 2014.For the interest rate we are using the three month LIBOR rate which has been downloaded from Federal Reserve of St.Louis Economic Data (FRED).

3.4.2 The Fundamental Variables in Oil Market

Supply and Demand Variables

The most important fundamental variables which are the subject of discussion in a big part of oil literature are supply and demand variables. For the supply side, we would use the data available on Energy Information Administration website in monthly frequency. Although we have access to the aggregate oil supply of the world, we would use the OPEC countries data which have been responsible with most of the supply disruption episodes through the history. The data is in million barrels. For the demand side, the best variables in hand is total OECD countries monthly demand. For the demand, we do not have access to the aggregate consumption of all the countries in the world. The last variable within this category is the inventory. The data we are using in this paper for inventory is the aggregate inventory of all of the OECD countries.

Geopolitical Risk

Geopolitical risk is one of the most important factors in the analyses of the experts to predict the future movements in oil prices. To capture this effect, we use the Geopolitical Risk Index by Caldara and Iacoviello. This is the text-search index which is

coming from archives of 11 national and international newspapers.The index is provided in monthly basis and is comprised of the number of articles related to geopolitical matters in these newspapers during the month. The index has been normalized to average a value of 100 in 2000-2009 decade.

3.4.3 Commodity-Specific Factors

The first class that we talk about are Commodity-Specific factors. the importance of this class of variables has been emphasized in multiple studies about Future returns , VRP and SRP in the literature.(e.g. Bessembinder (1992), Bessembinder et al (1992), Gorton, Hayashi and Rowenhorst (2013) and Roon, Nijman and Veld (2000)).

Hedging Pressure in Options and Futures

The data on position of traders for options and futures is coming from U.S. Commodity Futures Trading Commision (CFTC) in the form of reports called Commitment of Traders. In these reports, the traders have been divided into three different groups: Commercials, Non-Commercials and Non-Reporting. For the purpose of calculating the hedging pressure variable for futures and options, we would like to work with the data related to commercial traders.The most widespread measure which has been used in studies very commonly is Hedging Pressure (HP). The variable is defined as the net short exposure via futures and options contracts. The hedging pressure variable for futures and options is calculated as :

$$HPF_{i,t} = \frac{Commercial.Short.Futures - \ Commercial.Long.Futures}{Commercial.Short.Futures + \ Commercial.Long.Futures} \tag{3.21}$$

$$HPO_{i,t} = \frac{Commercial.Short.Options - \ Commercial.Long.Options}{Commercial.Short.Options + \ Commercial.Long.Options} \tag{3.22}$$

There is a chance that the balance between short and long hedgers has some implications for VRP. The role of hedging pressure in explaining risk premiums goes back to Hedging Pressure Hypothesis of Keynes (1930) which simply says that when there is a positive hedging pressure (most of the people is shorting), then the people who are taking the risk of having the asset should be compensated with a risk premium. There are many papers in the literature which has tested and extended the theory. This itself would mean that the higher is the hedging pressure, the lower should be the VRP and SRP. Then we would expect the hedging pressure to have a negative sign in the determinants regression in both cases.Hirshleifer (1989) and Hirshleifer(1990) are among the most important group of these papers.

Working-T Speculative Index

The speculative index is an index proposed by Working (1960) and is usually being used in the literature as a measure of excess speculation. The intuition is that the long and short hedgers do not trade at the same level. The difference is being covered by speculators. When the level of speculation is equal to the hedging needs, the T index would be equal to one. The excess speculation is the number which is being

added to one as a result of Non-Commercial (speculative) to Commercial (Hedging) positions. The T Speculative index for Futures and Options contracts is being calculated using:

$$TF_t = \begin{cases} 1 + \frac{Non.Com.Short.Fut}{Com.Long.Fut + Com.Short.Fut} & if \quad Com.Short.Fut \geq Com.Long.Fut \\ 1 + \frac{Non.Com.Long.Futures}{Com.Long.Fut + Com.Short.Fut} & if \quad Com.Long.Fut > Com.Short.Fut \end{cases} \tag{3.23}$$

$$TO_t = \begin{cases} 1 + \frac{Non.Com.Short.Opt}{Com.Long.Opt + Com.Short.Opt} & if \quad Com.Short.Opt \geq Com.Long.Opt \\ 1 + \frac{Non.Com.Long.Fut}{Com.Long.Opt + Com.Short.Opt} & if \quad Com.Long.Opt > Com.Short.Opt \end{cases} \tag{3.24}$$

Harris et al (2011) shows a relationship between the speculation level and the volatility. The results of the paper shows that the higher is the level of speculative activities, the lower would be the realized volatility. The paper is silent about the effect of speculation on implied volatility, so we would not be able to have a firm guess about the probable sign of the coefficient for this variable as we do not know which measure(Physical or Risk Neutral) has a greater response to change in speculation level. In another interesting paper, Hamilton and Wu (2011) shows that the nature of the risk premia has been changed in recent years. In fact the recent years, which are the so called Financialization period of commoditty market, have been showing increase in speculative activity while the premiums investors demanded has been decreased. This can be interpreted as a sign for the negative relationship between speculative activities and risk premia.

Basis

The way we define basis for oil futures with time to maturity T-t is the following:

$$Basis_{t,T} = \left(\frac{F_{t,T}}{S_t}\right)^{\frac{1}{T-t}} - 1 \tag{3.25}$$

As we can see from the formula, basis is the fraction of futures price to the spot price of commodity .Intuitively, Basis is the net convenience yield. The basis can be a positive or negative number. With our formulation, a positive basis is called Under while a negative basis will be called Over. To justify the presence of Basis in our empirical model we should go back to theory of storage which tells us there is a relationship between volatility and level of inventory. Basis has been widely used as a proxy for inventory in the literature. This is due to the problems researchers have always had to collect inventory data. As we mentioned, the theory of storage talks about the relationship between Physical variance and Basis but it is silent about implied volatility. We do not have any expectations for the sign of basis as the response level of variances under two measures to change in basis is not known. The literature reports some positive relationship between basis and VRP. This itself does not invalidate the theory of storage but only implies that implied volatility shows higher response to change in basis rather than realized volatility.

3.4.4 Macroeconomic Variables

Based on Bollerslev et al. (2010), VRP can be connected to the macroeconomic factors through its connection with risk aversion concept. Using the bridge between the two concepts, we would investigate if the macroeconomic factors are among the ones which has some ability to describe variation inside time series of Variance and Skewn risk premia. The importance of using macro factors in studies related to commodity futures markets has been emphasized in multiple papers in literature.(e.g. Shang (2011), Heath (2016), Watugala(2014), Bailey and Chan (1993), Batten et al (2010)).

Term Spread

As we stated before, the link between VRP and risk aversion is already described in the literature. In line with Prokopczuk and simen (2009), we put Term Spread as one of the variables in our analysis. We use the difference between 10-Year and 1-Year constant treasury rates as a proxy for Term Spread. A positively-Sloped Yield Curve would be a signal for the investors to be optimistic about the future performance of the economy. As we expect the size of the insurance for the investors would be less in the case of positive economic conditions, we expect the sign of Term Spread to be positive, meaning that the higher the Term Spread, the less is the amount of insurance the investors demand. The data for this variable is downloaded from FRED.

ADS Index

The expectations about macroeconomic uncertainty and real business conditions will be proxied using Arouba Diebold Scotti (henceforth ADS) index. It has six different underlyings (monthly payroll employment, industrial production, manufacturing and trade sales, personal income less transfer payments, quarterly GDP and initial jobless claims). One of the biggest advantages of ADS is that it provides high frequency (daily) data. The data for ADS is downloaded form Federal Reserve Bank of Philadelphia.

Credit Default Spread

One of the other determinants of VRP and SRP is Credit Default Spread (henceforth CDS) of banks. The CDS spread is the rate that is paid by buyer of protection on a notional amount in order to transfer the risk of any credit event to seller of the protection. In fact, CDS is the variable which reflects the perception of the market participants about the situation of market and answers the questions about how healthy the financial institutions are. This measure is the one can predict credit events and disasters several months before their occurrence. Here we are concentrating on CDS of the financial institutions whom their situation can affect the market considerably. Among all, We would take a look at the CDS for Barclays, Bank of America, Credit Agricole, Credit Suisse, Deutsche Bank, Goldman Sachs, Morgan Stanley, UBS and Wells Fargo. At One-Year maturity, we take average of the (non-missing) CDS observations across all the mentioned financial institutions. We download the CDS data

for financial institutions from Markit data set on WRDS.

TED Spread

The last variable in the class of macroeconomic variables which we will include in the model is TED Spread. TED spread is being used as a measure of constraints for financial intermediaries. TED spread is being calculated as the difference between 3-Months Libor and 3-Months T-bill. The bigger TED Spread can be the sign of higher risk on financial intermediaries and uncollateralized debt. Interpreting VRP as a kind of insurance, we would expect to get a negative sign for TED spread in regressions which would mean that investors would demand a higher premium in case the economic situation is riskier.The data on TED Spread has been downloaded from FRED.

3.5 Results

3.5.1 Determinants of Variance Risk Premia

Table 3.1 is presenting the result of the regression of VRP on economic and Commodity-Specific factors using the level of the variables. First column of the table is the results of the regression which just includes the Economic factors as regressors. As we can see, economic factors are describing important part of the variation inside VRP. Among the four variables, Termspread and ADS are insignificant variables. This column also shows that economic variables are able to describe 9.8 percent of variation inside VRP. Column two presents the results of Newey-West regression which shows that all the previously-significant variables are still significant after correction of standard errors. The next class of variables which are considered, are Commodity-Specific variables. Columns three and four report the results of the regression of VRP on Commodity-Specific variables using OLS and Newey-West respectively. The OLS regression shows that TF and TO are the significant variables among the commodity specific factors. The regression also shows that the Commodity-Specific factors are able to describe 2 percent of the variation inside VRP.

In contrast with economic factors, commodity-specific factors show no significance by switching from OLS to Newey-West. Columns five and six show the results for the full specification (Economic vars and Commodity-Specific vars).In this regression, other than ADS, the rest of the Economic variables are significant. column six also shows that none of Commodity-Specific variables are significant after we switch from OLS to Newey-West.[1]

[1]To tackle the problem of Non-Stationarity, we use first differences. Appendix C shows the results for the same determinants regression using difference data. We can clearly see that the problem of having conflicting signs for CDS and Tedspread is resolved here. It can also be seen that both classes of variables are significant in difference level regression and the model is able to describe 16.6 percent of variation in diffVRP.

TABLE 3.1: Determinants of Variance Risk Premium

	Economic		Commodity-Specific		All	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
ADS	0.00967	0.00967			0.00646	0.00646
	(1.68)	(0.78)			(1.01)	(0.43)
CDS	-2.355***	-2.355**			-2.886***	-2.886**
	(-4.69)	(-2.94)			(-4.79)	(-3.12)
Termspread	0.00634	0.00634			0.00870	0.00870*
	(1.84)	(1.39)			(1.91)	(2.09)
Tedspread	5.617***	5.617*			6.336***	6.336*
	(5.93)	(2.26)			(6.38)	(2.35)
HPF			0.235	0.235	0.302	0.302
			(1.25)	(0.61)	(1.67)	(1.36)
HPO			0.379	0.379	0.0774	0.0774
			(1.02)	(0.56)	(0.21)	(0.18)
TF			0.994*	0.994	0.972*	0.972
			(2.37)	(1.28)	(2.05)	(1.48)
TO			1.467**	1.467	1.166*	1.166
			(3.22)	(1.38)	(2.00)	(1.53)
Basis			0.0360	0.0360	0.220	0.220
			(0.21)	(0.15)	(1.23)	(0.68)
_cons	-0.0604***	-0.0604***	-1.094*	-1.094	-1.302*	-1.302
	(-7.24)	(-4.48)	(-2.23)	(-1.11)	(-2.40)	(-1.39)
N	438	438	438	438	438	438
adj. R^2	0.098		0.020		0.126	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.5.2 Determinants of Skew Risk Premia

TABLE 3.2: Determinants of Skewness Risk Premium

	Economic		Commodity-Specific		All	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
ADS	0.0239*	0.0239			0.0376***	0.0376*
	(2.59)	(1.66)			(3.92)	(2.30)
CDS	4.768***	4.768*			6.387***	6.387**
	(5.91)	(2.48)			(7.05)	(3.18)
Termspread	0.0115*	0.0115			0.0223**	0.0223
	(2.07)	(0.81)			(3.25)	(1.81)
Tedspread	-3.823*	-3.823			-6.053***	-6.053*
	(-2.51)	(-1.76)			(-4.05)	(-2.50)
HPF			0.194	0.194	-0.201	-0.201
			(0.66)	(0.40)	(-0.74)	(-0.48)
HPO			0.833	0.833	1.452**	1.452
			(1.42)	(0.83)	(2.61)	(1.57)
TF			-0.675	-0.675	0.639	0.639
			(-1.02)	(-0.56)	(0.90)	(0.57)
TO			-2.216**	-2.216	0.297	0.297
			(-3.09)	(-1.43)	(0.34)	(0.23)
Basis			-0.101	-0.101	0.292	0.292
			(-0.37)	(-0.28)	(1.08)	(0.65)
_cons	0.0101	0.0101	0.723	0.723	-0.984	-0.984
	(0.75)	(0.45)	(0.94)	(0.49)	(-1.20)	(-0.72)
N	438	438	438	438	438	438
adj. R^2	0.126		0.090		0.256	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.2 is presenting the result of the regression of Skew Risk Premia on economic and Commodity-Specific factors using the level of the variables. First column of the table is the results of the regression which just includes the Economic factors as regressors. As we can see, economic factors are describing important part of the variation inside SRP. The only significant variable after switching from OLS to Newey-West (column two), is CDS. Column one also shows that economic variables are able to describe 12.6 percent of variation inside SRP. The next class of variables which are considered are Commodity-Specific variables. Column three and column four report the results of the regression of SRP on Commodity-Specific variables using OLS and Newey-West respectively. The OLS regression shows that TO is the only significant variable among the commodity specific factors. Column four shows that

under Newey-West correction none of these variables are significant. The regression also shows that the Commodity-Specific factors are able to describe 9 percent of the variation inside SRP. Columns 5 and 6 show the results for the full specification (Economic vars and Commodity-Specific vars).In the Newey-West regression (column 6), other than Termspread, the rest of the Economic variables are significant, while the Commodity-Specific factors do not show any significance. We can see that the full model is able to capture 25.6 percent of the variation in SRP.[1]

3.5.3 The Role of the Fundamentals of Oil Market

There is a vast literature on the importance of fundamentals of oil market for oil prices and the economy. In this section we aim to see if the fundamentals of oil market are capable of describing the variation in our variables of interest. Using a monthly time series from 1986 to 2014 we have done some analysis to see the importance of these fundamentals. The fundamentals we want to use in these analyses are in four different categories. The four categories are oil supply, oil demand, oil inventory level and geopolitical tension. We use the aggregate oil demand of the OECD countries as the proxy for demand side of the oil market.

For inventory, we would use the inventory level of OECD countries. In order to make sure that the regressors are stationary, we change the OECD inventory level to "month to month" growth in OECD inventory level. To measure the impact and role of geopolitical tensions we would use the monthly geopolitical risk index which is intorduced by Caldara and Iacoviello. The last group of variables that we are interested in are the supply side variables.

[1]To tackle the problem of Non-Stationarity, we use first differences. Appendix D shows the results for the same regression as levels, using difference data. We can clearly see that the problem of having conflicting signs for CDS and Tedspread is resolved here. It can also be seen that the only significant variables in difference level are diffBasis and difffHPF. There is also no sign of significance for Macroeconomic variables. The model is able to describe 5.4 percent of variation in diffSRP.

TABLE 3.3: Fundamental Determinants of Variance Risk Premium

	(1) OLS	(2) Newey-West
Nigeria's Production	-0.132*	-0.132**
	(-2.36)	(-2.64)
Venezuela's Production	-0.0129	-0.0129
	(-0.42)	(-0.60)
Iran's Production	0.0405	0.0405
	(1.17)	(1.12)
Saudi's Production Growth	0.533*	0.533***
	(2.15)	(3.33)
Qatar's Production Growth	-0.338	-0.338
	(-1.64)	(-1.74)
Total OECD Demand	-0.00807	-0.00807
	(-1.41)	(-0.90)
OECD Inventory Growth	-0.956	-0.956
	(-0.84)	(-0.63)
Geopolitical Risk	0.000278	0.000278
	(1.66)	(0.77)
Constant	0.584***	0.584
	(3.53)	(1.95)
Observations	315	315
Adjusted R^2	0.069	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Supply disruption has been the reason for multiple oil price jumps through the history. Among the producers of oil the ones with the most vulnerable countries which are prone to be involved in the midst of geopolitical tensions are the OPEC countries which are mostly a collection of oil producer countries in the middle east and "Persian Gulf" region. The results using the aggregated OPEC supply does not show any significance, so we break down the OPEC oil supply into the supply level of the individual countries. We focus on Iran, Saudi Arabia, Qatar , Venezuela and Nigeria. Among these, we are not able to reject the null hypothesis of unit root for Saudi and Qatar while Iran, Nigeria and Venezuela seem to show a stationary series over time. To tackle this problem and keep all the regressors stationary we use Saudi's and Qatar's supply growth instead of supply levels.

Table 3.3 is showing the results for the regression of Variance Risk Premium on fundamental variables of oil market. The first column shows that the oil supply of Nigeria and supply growth for Saudi Arabia are the two significant determinants

of Variance Risk Premium. The model is able to describe 6.9 percent of variation in Variance Risk Premium. The second column in showing the same regression with the Newey-West correction for standard errors using 27 lags. The results show that the significance of the two variables is still in place moving from OLS to Newey-West analysis.

TABLE 3.4: Fundamental Determinants of Skewness Risk Premium

	(1) OLS	(2) Newey-West
Nigeria's Production	0.0784*	0.0784*
	(2.37)	(2.44)
Venezuela's Production	-0.0466*	-0.0466*
	(-2.58)	(-2.12)
Iran's Production	-0.0490*	-0.0490
	(-2.41)	(-1.54)
Saudi's Production Growth	-0.261	-0.261*
	(-1.78)	(-2.05)
Qatar's Production Growth	-0.122	-0.122
	(-1.00)	(-1.00)
Total OECD Demand	-0.00342	-0.00342
	(-1.01)	(-0.62)
OECD Inventory Growth	-0.860	-0.860
	(-1.28)	(-1.35)
Geopolitical Risk	-0.000270**	-0.000270***
	(-2.73)	(-3.98)
Constant	0.350***	0.350
	(3.59)	(1.97)
Observations	315	315
Adjusted R^2	0.094	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.4 is showing the same analysis as the previous table with the difference that we are looking for determinants of Skew Risk Premium this time. The results show that Nigeria's supply, Iran's Supply and Venezuela's Supply along with the Geopolitical Risk are the significant determinants of Skew Risk Premium. The adjusted R-Squared of the regression is 9.4 percent. Using the Newey-West with 27 lags, the results shown in column two are showing the significance of Nigeria's Production, Venezuela's Production, Saudi's Production Growth and Geopolitical Risk while the Iran's Production is not keeping its significance anymore.

TABLE 3.5: Fundamental Determinants of Risk-Neutral Skewness

	(1) OLS	(2) Newey-West
Nigeria's Production	-0.0959**	-0.0959**
	(-3.31)	(-3.11)
Venezuela's Production	0.0459**	0.0459
	(2.90)	(1.94)
Iran's Production	0.0523**	0.0523
	(2.93)	(1.58)
Saudi's Production Growth	0.114	0.114
	(0.89)	(0.97)
Qatar's Production Growth	0.0424	0.0424
	(0.40)	(0.52)
Total OECD Demand	0.00396	0.00396
	(1.33)	(0.67)
OECD Inventory Growth	1.067	1.067
	(1.81)	(1.59)
Geopolitical Risk	0.000287**	0.000287***
	(3.31)	(3.39)
Constant	-0.349***	-0.349
	(-4.08)	(-1.90)
Observations	315	315
Adjusted R^2	0.123	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5 is presenting the results of the same analysis as the ones for tables 3.3 and 3.4 with the difference of having the Risk-Neutral Skew as dependent variable this time. Column one is showing the results based on OLS. The significant variables are Nigeria's Production, Venezuela's Production and Iran's Production levels. The only other significant variable in this regression is Geopolitical Risk index. The model is able to capture 12.3 percent of variation in the time-series of the Risk-Neutral Skew. The table also shows that among these four variables, Nigeria's Production level and Geopolitical Riska re the two variables which are still significant after switching from OLS to Newey-West using 27 lags.

3.5.4 Forecasting the Cumulative Return of Futures and Option Portfolios

Forecasting the Cumulative Return of Oil Futures

Table 3.6 is presenting the result of the regression of the cumulative future returns on Variance and Skew Risk Premia. Kang and Pan (2014) has developed an extended Mean-Variance model to investigate the ability of VRP to forecast the returns on the futures contracts. Their theoretical model predicts a negative sign of the regression and their empirical results also shows validity of their theoretical model. Obviously, change in the variance of the implied and physical return distributions cannot be predicted without a theoretical foundation as the increase or decrease in the variance of the distribution of the returns would have impact on realization of both positive and negative returns. In contrast, the effect of Skew Risk Premia on the futures return can have a intuitive description. As we can see in Table I both Physical and Risk-Neutral Skewness variables are negative on average (the mean is negative). A higher value for SRP can be an indicator of the Risk-Neutral distribution of the futures returns will be less left-skewed. This itself can be translated into less negative Futures return and we expect the coefficient of SRP to be positive. The results of the regressions in table IV verifies the intuitive prediction. The results also shows that VRP has higher potential to explain the variation in cumulative return. Individual regressions (column one to four) shows that VRP and SRP are describing 15.9 and 8.3 percent of variation inside the expected cumulative return respectively. The full model is able to describe 18.7 percent of the variation inside the futures returns.

Forecasting Cumulative Return of Delta Hedged Option Portfolio

The delta hedged Portfolio of options is formed to absorb the changes in the variance of the left half, right half or the overall variance of the difference between Physical and Risk-Neutral return densities. As we found out in the previous section, higher VRP is a signal towards the higher probability of realization of negative returns. Looking at the structure of delta hedged portfolio, we can see that realization of lower returns- which itself can be a sign for lower underlying (futures) prices- is supposed to increase the value of this portfolio. The reason is that this would increase the value of OTM put options. Because delta of OTM call and OTM put have different signs, portfolio value would be increasing in the price of OTM put option. This move will not change the value of OTM call options and as a result does not change the value of portfolio. The results in table 3.7 is validating the intuitive description by showing a positive coefficient for VRP. Columns one and two shows

TABLE 3.6: Forecasting the Cumulative Return of Oil Futures

	VRP		SRP		VRP-SRP	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
VRP	-0.471***	-0.471***			-0.402***	-0.402***
	(-5.01)	(-8.29)			(-4.15)	(-5.79)
SRP			0.173***	0.173**	0.112*	0.112*
			(3.54)	(2.77)	(2.32)	(2.01)
_cons	-0.00972	-0.00972	-0.00655	-0.00655	-0.0160*	-0.0160
	(-1.26)	(-1.13)	(-0.80)	(-0.79)	(-1.99)	(-1.97)
N	129	129	129	129	129	129
adj. R^2	0.159		0.083		0.187	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 3.7: Forecasting the Cumulative Return of Delta Hedged Portfolio of Options on Oil Futures

	VRP		SRP		VRP-SRP	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
VRP	0.274***	0.274***			0.276***	0.276***
	(5.07)	(3.92)			(4.86)	(3.51)
SRP			-0.0379	-0.0379	0.00387	0.00387
			(-1.29)	(-1.35)	(0.14)	(0.13)
_cons	0.00336	0.00336	-0.00335	-0.00335	0.00314	0.00314
	(0.76)	(0.55)	(-0.68)	(-0.54)	(0.67)	(0.55)
N	129	129	129	129	129	129
adj. R^2	0.162		0.005		0.155	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

that VRP is a significant predictor for return of Delta Hedged portfolio under both OLS and Newey-West approaches. Columns three and four also shows that SRP does not have any predictive powers. Based on Columns five and six the full regression is able to describe 15.5 percent of the variation inside the return of Delta Hedged portfolio of the options. The table also shows that the SRP does not show any significance in full specification.

Forecasting Cumulative Return of Delta-Vega Hedged Option Portfolio

In this section we would use the same technique for forming the portfolio and justifying the results of the regressions as Bali and Murray (2013). The delta-vega hedged portfolio is formed to be insensitive to changes in the mean and variance and to be able to absorb the effects of changes in Skewness. The portfolio has been formed to capture the effect of change in skewness in right side or left side of the distribution of futures returns. Longing the skew asset is the same as longing skewness. If the skew of the right tail of the distribution increases and the left tail remains unchanged, then the value of the OTM call option and skewness asset goes up. If the skewness of the left tail increases and right tail remains unchanged, the value of the OTM put options go up and the value of the portfolio to go down. The short position of OTM put option will be translated to decrease in the overall portfolio value. What we see in the data is that risk-neutral and physical skewness are both negative on average. The mean of SRP is positive because most of the time RNS is more negative than the Physical Skewness. Increase in SRP would mean that the absolute value of RNS is growing with respect to the physical skewness. This would mean that the Implied distribution of option returns would be more negatively skewed. As we described, such a move will decrease the overall value of the delta-vega hedged option portfolio. The result in table 3.8 is verifying the mentioned logic by a negative coefficient for the regression of returns of the delta-vega hedged option portfolio on SRP. Columns one and two show that there is no significance for VRP in the univariate prediction regression. Columns three and four displays the results for univariate regression using SRP as predictor and it is clear that SRP is significant (with negative estimated coefficient) regressor and the univariate model is absorbing 5.6 percent of variation in the returns. columns five and six show that the relationship between the returns and SRP is robust to adding VP to the model. No change is seen in the full specification in comparison to univariate model, other than rise in Adjusted R-Squared to 7.2 percent.[1]

[1] Looking at figures 3.2 and 3.4, we can detect some very big jumps in Time Series of physical Skewness. In order to make sure that the results are not driven by outliers, we would omit the observations that are marked as outliers by Hadi (1992) approach. Appendices E,F,G,H,XI,J and K repeats all regressions after omitting the outliers. Appendix E shows no difference in the results for determinants of VRP. The R-Squared of the model is more than before. Appendix G shows that after omitting the outliers, all economic factors are significant in the case of SRP. In this case, the R-Squared of the regression is less after omitting outliers. Appendix I shows that after omitting the outliers, the SRP is still a significant predictor of futures return. Appendices J and K show that VRP and SRP are still significant predictors of return of Delta and Delta-Vega hedged portfolio options as before. The SRP shows very tiny increase in predictability power while R-Squared of VRP regression stays exactly the same.

TABLE 3.8: Predicting the Return of Delta-Vega Hedge Portfolio of Options Using VRP and SRP

	VRP		SRP		VRP-SRP	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
VRP	-5.552	-5.552			-12.78	-12.78
	(-0.79)	(-1.35)			(-1.80)	(-1.62)
SRP			-9.930**	-9.930**	-11.86**	-11.86*
			(-2.92)	(-2.89)	(-3.36)	(-2.59)
_cons	-3.737***	-3.737***	-2.773***	-2.773***	-3.073***	-3.073***
	(-6.49)	(-4.87)	(-4.87)	(-9.46)	(-5.22)	(-6.66)
N	129	129	129	129	129	129
adj. R^2	-0.003		0.056		0.072	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.6 Conclusion

Using model free approach, we have estimated Variance and Skew Risk Premia in oil market. We used three classes of variables as Fundamental, Macroeconomic and Commodity-Specific to investigate the determinants of Variance and Skew Risk Premia. The results show that we are much more successful in the case of explaining in the variation of SRP than the variation in VRP. The two classes of variables which are important in terms of explaining power of the variation inside VRP and SRP are the Fundamental and Macroeconomic factors. In contrast with the Economic variables, the Commodity-Specific variables are not staying significant when we try Newey-West correction. The full specifications shows that our designed model is more than two times more successful in the case of SRP in comparison with the VRP case in terms of explaining the variation. We have also Investigated the importance of Volatility and Skew risk Premia in predicting the cumulative return on oil futures. The sign of VRP is the same as the one predicted by previous studies (positive). To the best of our knowledge we are the first paper which is looking at the role of SRP for this prediction. The sign for SRP is in conflict with the VRP's sign. It is also clear that VRP has a higher ability in predicting the cumulative return of futures. The last finding of our paper is that the cumulative return of delta hedged and delta-vega hedged portfolios can be predicted by VRP and SRP respectively. Again, the contribution of VRP in predicting the returns in the first case (delta hedged portfolio return) is higher than the one for SRP in the second case (delta-vega hedged return).

Appendices

Appendix A

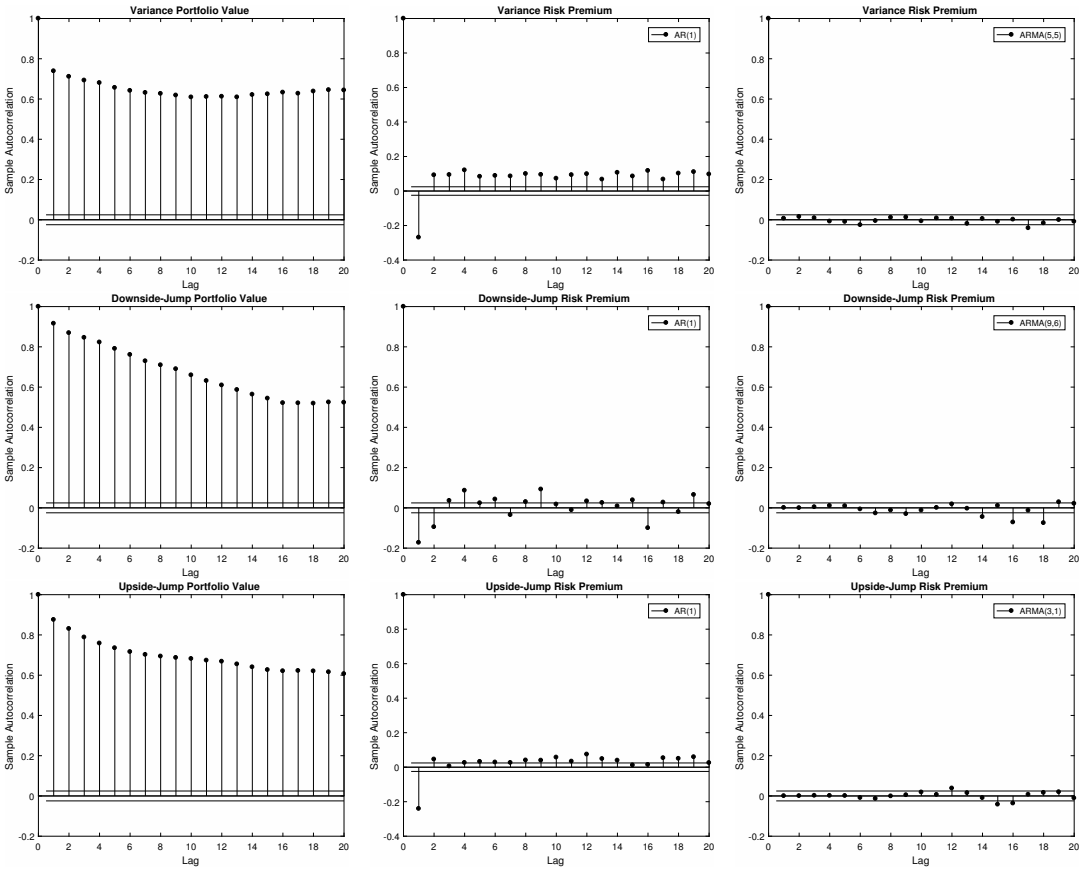

FIGURE A.1: This figure shows the sample autocorrelation functions for different processes. The vertical axis is sample autocorrelation in all the graphs and the horizontal axis shows the number of lags. The top row, middle row and bottom row are showing autocorrelations for volatility,skewness and kurtosis respectively. The graphs show Implied Volatility, Innovations in implied Volatility based on AR(1), Innovations in implied Volatility based on ARMA(2,3), Implied Skewness, Innovations of Implied Skewness based on AR(1) model,Innovations of Implied Skewness based on ARMA(1,1) model, Implied Kurtosis , Innovations of Implied Kurtosis based on AR(1) model and Innovations of Implied Kurtosis based on ARMA(2,3) model in oil market.

Appendix B

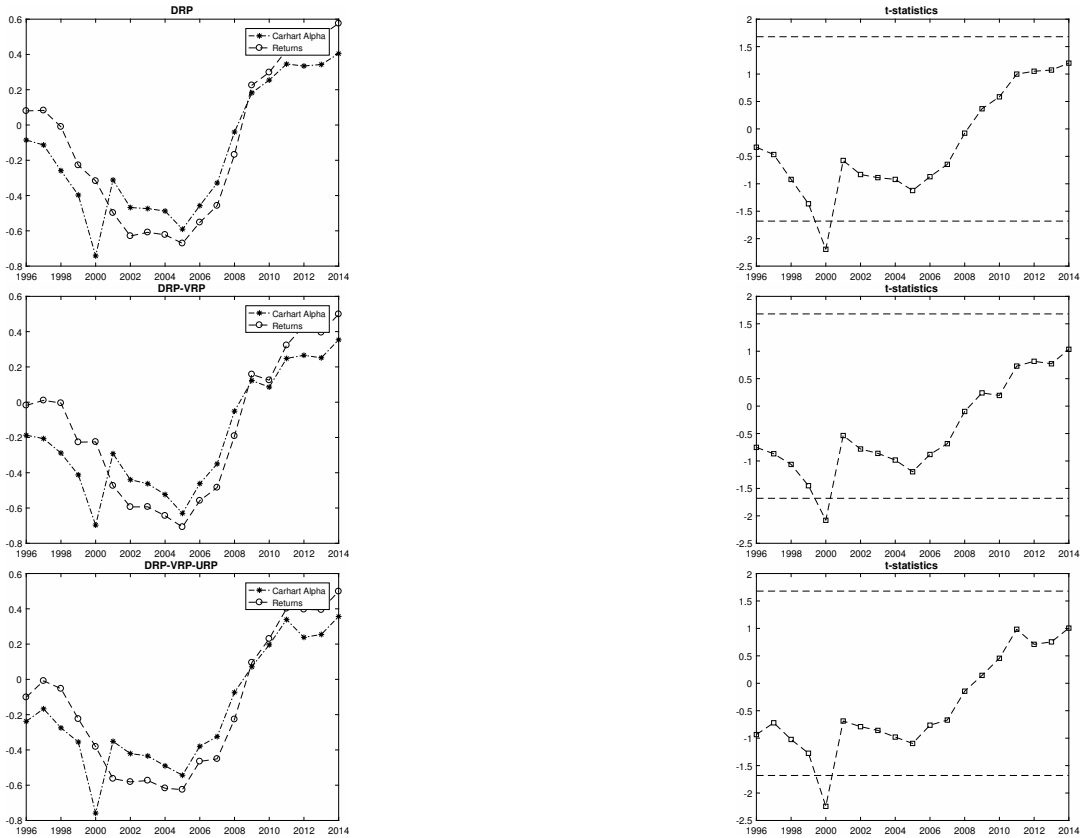

FIGURE B.1: This Figure presents the evolution of average monthly returns and Carhart Alpha of the hedge portfolio through the sample period in the case of sorting based on the exposure to innovations in implied skewness. The left column shows the average monthly returns and Carhart Alpha of the hedge portfolio in case we form the portfolio based on skewness innovations, based on skewness innovations after controlling for volatility innovations and based on skewness innovations after controlling for volatility and kurtosis innovations respectively, moving from top to bottom. The second column shows the corresponding t-statistics for Carhart 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 Carhart alphas are computed based on a 10-year rolling window.

Appendix C

TABLE C.1: . Determinants of Variance Risk Premium Using Differences

	Economic		Commodity-Specific		All	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
diffADS	-0.0120	-0.0120			-0.0160	-0.0160
	(-0.44)	(-0.24)			(-0.62)	(-0.32)
diffCDS	-4.885***	-4.885*			-4.523***	-4.523*
	(-3.66)	(-2.49)			(-3.61)	(-2.15)
diffTermspread	0.0624*	0.0624**			0.0729**	0.0729**
	(2.50)	(2.79)			(3.08)	(2.81)
diffTedspread	-0.0345	-0.0345			-0.0383	-0.0383*
	(-1.55)	(-1.94)			(-1.83)	(-2.22)
diffHPF			0.175	0.175	0.0896	0.0896
			(0.44)	(0.53)	(0.23)	(0.32)
diffHPO			-0.412	-0.412	-0.408	-0.408
			(-0.48)	(-0.54)	(-0.49)	(-0.53)
diffTF			1.728*	1.728*	1.836*	1.836*
			(2.08)	(2.01)	(2.26)	(2.41)
diffTO			1.916	1.916*	1.851	1.851*
			(1.81)	(2.04)	(1.77)	(2.12)
diffBasis			1.098***	1.098**	1.109***	1.109**
			(7.32)	(3.15)	(7.60)	(3.07)
_cons	0.000154	0.000154	-0.000346	-0.000346	-0.0000228	-0.0000228
	(0.05)	(0.12)	(-0.11)	(-0.31)	(-0.01)	(-0.02)
N	436	436	436	436	436	436
adj. R^2	0.049		0.115		0.166	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix D

TABLE D.1: . Determinants of Skew Risk Premium Using Differences

	Economic		Commodity-Specific		All	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
diffADS	0.0484	0.0484			0.0279	0.0279
	(1.17)	(1.36)			(0.69)	(0.78)
diffCDS	2.864	2.864			2.426	2.426
	(1.43)	(1.60)			(1.24)	(1.47)
diffTermspread	-0.0189	-0.0189			0.00261	0.00261
	(-0.50)	(-0.51)			(0.07)	(0.07)
diffTedspread	0.00900	0.00900			0.00723	0.00723
	(0.27)	(0.32)			(0.22)	(0.27)
diffHPF			-1.285*	-1.285*	-1.262*	-1.262*
			(-2.14)	(-2.14)	(-2.10)	(-2.16)
diffHPO			0.376	0.376	0.310	0.310
			(0.29)	(0.28)	(0.24)	(0.23)
diffTF			0.550	0.550	0.430	0.430
			(0.44)	(0.33)	(0.34)	(0.25)
diffTO			0.225	0.225	-0.0135	-0.0135
			(0.14)	(0.13)	(-0.01)	(-0.01)
diffBasis			0.375	0.375*	0.387	0.387*
			(1.66)	(2.15)	(1.70)	(2.23)
_cons	-0.000856	-0.000856	-0.000484	-0.000484	-0.000550	-0.000550
	(-0.17)	(-0.53)	(-0.10)	(-0.30)	(-0.11)	(-0.35)
N	436	436	436	436	436	436
adj. R^2	0.001		0.057		0.054	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix E

TABLE E.1: . Determinants of Variance Risk Premium Using Outlier-Free Levels

	Economic		Commodity-Specific		All	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
ADS	0.0105	0.0105			0.00779	0.00779
	(1.86)	(0.86)			(1.24)	(0.52)
CDS	-2.306***	-2.306**			-2.713***	-2.713**
	(-4.67)	(-3.19)			(-4.54)	(-3.09)
Termspread	0.00543	0.00543			0.00871	0.00871*
	(1.59)	(1.32)			(1.94)	(2.09)
Tedspread	5.764***	5.764*			6.388***	6.388*
	(6.22)	(2.35)			(6.55)	(2.40)
HPF			0.226	0.226	0.290	0.290
			(1.23)	(0.59)	(1.63)	(1.33)
HPO			0.449	0.449	0.152	0.152
			(1.22)	(0.66)	(0.42)	(0.36)
TF			1.027*	1.027	0.973*	0.973
			(2.47)	(1.33)	(2.09)	(1.51)
TO			1.520***	1.520	1.214*	1.214
			(3.37)	(1.43)	(2.11)	(1.62)
Basis			0.0561	0.0561	0.253	0.253
			(0.33)	(0.23)	(1.43)	(0.77)
_cons	-0.0609***	-0.0609***	-1.149*	-1.149	-1.335*	-1.335
	(-7.41)	(-4.62)	(-2.37)	(-1.17)	(-2.50)	(-1.43)
N	432	432	432	432	432	432
adj. R^2	0.107		0.022		0.129	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix F

TABLE F.1: . Determinants of Variance Risk Premium Using Outlier-Free Differences

	Economic		Commodity-Specific		All	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
diffADS	-0.00964	-0.00964			-0.0135	-0.0135
	(-0.35)	(-0.19)			(-0.52)	(-0.27)
diffCDS	-4.864***	-4.864*			-4.495***	-4.495*
	(-3.63)	(-2.49)			(-3.58)	(-2.14)
diffTermspread	0.0629*	0.0629**			0.0735**	0.0735**
	(2.51)	(2.78)			(3.09)	(2.80)
diffTedspread	-0.0351	-0.0351			-0.0391	-0.0391*
	(-1.57)	(-1.95)			(-1.86)	(-2.23)
diffHPF			0.194	0.194	0.109	0.109
			(0.49)	(0.57)	(0.28)	(0.38)
diffHPO			-0.415	-0.415	-0.401	-0.401
			(-0.48)	(-0.54)	(-0.48)	(-0.52)
diffTF			1.713*	1.713*	1.821*	1.821*
			(2.05)	(1.98)	(2.23)	(2.38)
diffTO			1.907	1.907*	1.843	1.843*
			(1.79)	(2.03)	(1.76)	(2.11)
diffBasis			1.091***	1.091**	1.105***	1.105**
			(7.25)	(3.09)	(7.54)	(3.03)
_cons	0.000145	0.000145	-0.000415	-0.000415	-0.000140	-0.000140
	(0.04)	(0.11)	(-0.13)	(-0.36)	(-0.04)	(-0.10)
N	430	430	430	430	430	430
adj. R^2	0.049		0.115		0.166	

t statistics in parentheses

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

Appendix G

TABLE G.1: . Determinants of Skew Risk Premium Using Outlier-Free Levels

	Economic		Commodity-Specific		All	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
ADS	0.0183*	0.0183			0.0326***	0.0326*
	(2.28)	(1.44)			(3.84)	(2.12)
CDS	3.978***	3.978*			5.260***	5.260**
	(5.63)	(2.37)			(6.51)	(3.00)
Termspread	0.0140**	0.0140			0.0222***	0.0222*
	(2.88)	(1.32)			(3.66)	(1.99)
Tedspread	-4.230**	-4.230*			-5.733***	-5.733*
	(-3.19)	(-2.07)			(-4.35)	(-2.50)
HPF			0.220	0.220	-0.165	-0.165
			(0.84)	(0.47)	(-0.68)	(-0.43)
HPO			0.652	0.652	1.154*	1.154
			(1.25)	(0.72)	(2.34)	(1.46)
TF			-0.846	-0.846	0.484	0.484
			(-1.44)	(-0.84)	(0.77)	(0.48)
TO			-2.201***	-2.201	0.131	0.131
			(-3.44)	(-1.65)	(0.17)	(0.12)
Basis			0.0238	0.0238	0.381	0.381
			(0.10)	(0.08)	(1.60)	(0.99)
_cons	0.0170	0.0170	0.792	0.792	-0.903	-0.903
	(1.45)	(1.03)	(1.15)	(0.63)	(-1.25)	(-0.74)
N	432	432	432	432	432	432
adj. R^2	0.148		0.085		0.259	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix H

TABLE H.1: . Determinants of Skew Risk Premium Using Outlier-Free Differences

	Economic		Commodity-Specific		All	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
diffADS	0.0503	0.0503			0.0329	0.0329
	(1.31)	(1.39)			(0.87)	(0.89)
diffCDS	3.000	3.000			2.600	2.600
	(1.61)	(1.68)			(1.43)	(1.59)
diffTermspread	-0.0289	-0.0289			-0.0103	-0.0103
	(-0.83)	(-0.68)			(-0.30)	(-0.25)
diffTedspread	0.0138	0.0138			0.0121	0.0121
	(0.44)	(0.45)			(0.40)	(0.41)
diffHPF			-1.272*	-1.272*	-1.240*	-1.240*
			(-2.26)	(-2.12)	(-2.20)	(-2.11)
diffHPO			0.0762	0.0762	0.00626	0.00626
			(0.06)	(0.06)	(0.01)	(0.00)
diffTF			0.182	0.182	0.0503	0.0503
			(0.16)	(0.11)	(0.04)	(0.03)
diffTO			-0.174	-0.174	-0.382	-0.382
			(-0.12)	(-0.10)	(-0.25)	(-0.21)
diffBasis			0.312	0.312**	0.318	0.318**
			(1.47)	(2.81)	(1.50)	(2.96)
_cons	0.00269	0.00269	0.00296	0.00296	0.00284	0.00284
	(0.57)	(1.06)	(0.64)	(1.11)	(0.61)	(1.10)
N	430	430	430	430	430	430
adj. R^2	0.005		0.050		0.049	

t statistics in parentheses

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

Appendix I

TABLE I.1: . Forecasting the Cumulative Return of Oil Futures Using Outlier-Free Data

	VRP		SRP		VRP-SRP	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
VRP	-0.471***	-0.471***			-0.408***	-0.408***
	(-5.03)	(-8.37)			(-4.17)	(-5.77)
SRP			0.173**	0.173*	0.103*	0.103
			(3.33)	(2.48)	(2.00)	(1.78)
_cons	-0.00898	-0.00898	-0.00653	-0.00653	-0.0152	-0.0152
	(-1.16)	(-1.03)	(-0.77)	(-0.74)	(-1.85)	(-1.85)
N	128	128	128	128	128	128
adj. R^2	0.161		0.074		0.180	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix J

TABLE J.1: . Forecasting the Cumulative Return of Delta Hedged Portfolio of Options on Oil Futures Using Outlier-Free Data

	VRP		SRP		VRP-SRP	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
VRP	0.274***	0.274***			0.276***	0.276***
	(5.05)	(3.92)			(4.80)	(3.45)
SRP			-0.0436	-0.0436	0.00353	0.00353
			(-1.40)	(-1.39)	(0.12)	(0.11)
_cons	0.00339	0.00339	-0.00268	-0.00268	0.00318	0.00318
	(0.76)	(0.55)	(-0.53)	(-0.41)	(0.66)	(0.55)
N	128	128	128	128	128	128
adj. R^2	0.162		0.008		0.155	

t statistics in parentheses

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

Appendix K

TABLE K.1: . Forecasting the Cumulative Return on Delta-Vega Hedged Portfolio of Options on Oil Futures Using Outlier-Free Data

	VRP		SRP		VRP-SRP	
	(1) OLS	(2) Newey-West	(3) OLS	(4) Newey-West	(5) OLS	(6) Newey-West
VRP	-5.537	-5.537			-13.50	-13.50
	(-0.79)	(-1.35)			(-1.89)	(-1.66)
SRP			-10.68**	-10.68**	-12.99***	-12.99**
			(-2.96)	(-3.05)	(-3.44)	(-2.76)
_cons	-3.752***	-3.752***	-2.685***	-2.685***	-2.971***	-2.971***
	(-6.47)	(-4.87)	(-4.57)	(-8.82)	(-4.94)	(-6.55)
N	128	128	128	128	128	128
adj. R^2	-0.003		0.058		0.077	

t statistics in parentheses

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

Bibliography

Alquist, Ron, Lutz Kilian, and Robert J Vigfusson (2013). "Forecasting the price of oil". In: *Handbook of economic forecasting*. Vol. 2. Elsevier, pp. 427–507.

Andersen, Torben G, Tim Bollerslev, and Francis X Diebold (2007). "Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility". In: *The review of economics and statistics* 89.4, pp. 701–720.

Ang, Andrew et al. (2006). "The cross-section of volatility and expected returns". In: *The Journal of Finance* 61.1, pp. 259–299.

Bailey, Warren and Kalok C Chan (1993). "Macroeconomic influences and the variability of the commodity futures basis". In: *The Journal of Finance* 48.2, pp. 555–573.

Baker, Steven D and Bryan R Routledge (2011). "The price of oil risk". In:

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan (2003). "Stock return characteristics, skew laws, and the differential pricing of individual equity options". In: *Review of Financial Studies* 16.1, pp. 101–143.

Bali, Turan G and Scott Murray (2013). "Does risk-neutral skewness predict the cross-section of equity option portfolio returns?" In: *Journal of Financial and Quantitative Analysis* 48.4, pp. 1145–1171.

Bams, Dennis et al. (2017). "Does oil and gold price uncertainty matter for the stock market?" In: *Journal of Empirical Finance* 44, pp. 270–285.

Barsky, Robert B and Lutz Kilian (2001). "Do we really know that oil caused the great stagflation? A monetary alternative". In: *NBER Macroeconomics annual* 16, pp. 137–183.

Batten, Jonathan A, Cetin Ciner, and Brian M Lucey (2010). "The macroeconomic determinants of volatility in precious metals markets". In: *Resources Policy* 35.2, pp. 65–71.

Bjerksund, Petter and Gunnar Stensland (2002). "Closed form valuation of American options". In:

Black, Fischer (1976). "The pricing of commodity contracts". In: *Journal of financial economics* 3.1, pp. 167–179.

Bollerslev, Tim and Viktor Todorov (2011). "Tails, fears, and risk premia". In: *The Journal of Finance* 66.6, pp. 2165–2211.

Britten-Jones, Mark and Anthony Neuberger (2000). "Option prices, implied price processes, and stochastic volatility". In: *The Journal of Finance* 55.2, pp. 839–866.

Carhart, Mark M (1997). "On persistence in mutual fund performance". In: *The Journal of finance* 52.1, pp. 57–82.

Carr, Peter and Dilip Madan (1999). "Option valuation using the fast Fourier transform". In: *Journal of computational finance* 2.4, pp. 61–73.

Chang, Bo Young, Peter Christoffersen, and Kris Jacobs (2013). "Market skewness risk and the cross section of stock returns". In: *Journal of Financial Economics* 107.1, pp. 46–68.

Christoffersen, Peter and Xuhui Nick Pan (2017). "Oil volatility risk and expected stock returns". In: *Journal of Banking & Finance*.

Cremers, Martijn, Michael Halling, and David Weinbaum (2015). "Aggregate jump and volatility risk in the cross-section of stock returns". In: *The Journal of Finance* 70.2, pp. 577–614.

Davis, Steven J and John Haltiwanger (2001). "Sectoral job creation and destruction responses to oil price changes". In: *Journal of monetary economics* 48.3, pp. 465–512.

Dickey, David A and Wayne A Fuller (1979). "Distribution of the estimators for autoregressive time series with a unit root". In: *Journal of the American statistical association* 74.366a, pp. 427–431.

Ebrahimi, Nima and Craig Pirrong (2018). "The Risk of Skewness and Kurtosis in Oil Market and the Cross-Section of Stock Returns". In:

Ellwanger, Reinhard and others (2017). *On the Tail Risk Premium in the Oil Market*. Bank of Canada.

Engemann, Kristie M, Kevin L Kliesen, and Michael T Owyang (2011). "Do oil shocks drive business cycles? Some US and international evidence". In: *Macroeconomic Dynamics* 15.S3, pp. 498–517.

Fama, Eugene F and Kenneth R French (1993). "Common risk factors in the returns on stocks and bonds". In: *Journal of financial economics* 33.1, pp. 3–56.

Gao, Lin et al. (2016). *Oil volatility risk*. Tech. rep. Working Paper.

Hadi, Ali S (1992). "Identifying multiple outliers in multivariate data". In: *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 761–771.

Hamilton, James D and Jing Cynthia Wu (2014). "Risk premia in crude oil futures prices". In: *Journal of International Money and Finance* 42, pp. 9–37.

— (2015). "Effects of Index-Fund Investing On Commodity Futures Prices". In: *International Economic Review* 56.1, pp. 187–205.

Hamilton, James D (2011). "Nonlinearities and the macroeconomic effects of oil prices". In: *Macroeconomic dynamics* 15.S3, pp. 364–378.

Hamilton, James D (1996). "This is what happened to the oil price-macroeconomy relationship". In: *Journal of Monetary Economics* 38.2, pp. 215–220.

Hamilton, James D (2003). "What is an oil shock?" In: *Journal of econometrics* 113.2, pp. 363–398.

Hamilton, James D (1983). "Oil and the macroeconomy since World War II". In: *Journal of political economy* 91.2, pp. 228–248.

Herrera, Ana María, Latika Gupta Lagalo, and Tatsuma Wada (2011). "Oil price shocks and industrial production: Is the relationship linear?" In: *Macroeconomic Dynamics* 15.S3, pp. 472–497.

Hirshleifer, David (1988). "Risk, futures pricing, and the organization of production in commodity markets". In: *The Journal of Political Economy*, pp. 1206–1220.

Hirshleifer, David (1990). "Hedging pressure and futures price movements in a general equilibrium model". In: *Econometrica: Journal of the Econometric Society*, pp. 411–428.

Irwin, Scott H and Dwight R Sanders (2012). "Financialization and structural change in commodity futures markets". In: *Journal of agricultural and applied economics* 44.3, pp. 371–396.

Jiang, George J and Yisong S Tian (2005). "The model-free implied volatility and its information content". In: *Review of Financial Studies* 18.4, pp. 1305–1342.

Kang, Sang Baum and Xuhui Nick Pan (2015). "Commodity variance risk premia and expected futures returns: evidence from the crude oil market". In: *Available at SSRN 2296932*.

Kilian, Lutz and Cheolbeom Park (2009). "The impact of oil price shocks on the US stock market". In: *International Economic Review* 50.4, pp. 1267–1287.

Kilian, Lutz and Robert J Vigfusson (2017). "The role of oil price shocks in causing US recessions". In: *Journal of Money, Credit and Banking* 49.8, pp. 1747–1776.

Kilian, Lutz and Robert J Vigfusson (2013). "Do oil prices help forecast us real gdp? the role of nonlinearities and asymmetries". In: *Journal of Business & Economic Statistics* 31.1, pp. 78–93.

Kilian, Lutz 5 (2009). "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market". In: *American Economic Review* 99.3, pp. 1053–69.

Kilian, Lutz (2014). "Oil price shocks: Causes and consequences". In:

Krugman, Paul (2008). "Commodity prices (wonkish)". In: *New York Times, March 19th*.

Li, Bingxin (2015). "Speculation, Risk Aversion, and Risk Premiums in the Crude Oil Market". In: *Available at SSRN 2585658*.

Mork, Knut Anton (1989). "Oil and the macroeconomy when prices go up and down: an extension of Hamilton's results". In: *Journal of political Economy* 97.3, pp. 740–744.

Newey, Whitney K and Kenneth D West (1986). *A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix*.

Pan, Xuhui Nick (2011). "Investor beliefs and state price densities in the crude oil market". In: *SSRN eLibrary*.

Prokopczuk, Marcel and Chardin Wese Simen (2014). "The importance of the volatility risk premium for volatility forecasting". In: *Journal of Banking & Finance* 40, pp. 303–320.

Prokopczuk, Marcel and Chardin Wese Simen (2014). "Variance risk premia in commodity markets". In: *Variance Risk Premia in Commodity Markets (April 7, 2014)*.

Shang, Hua Helen (2011). *Macroeconomic Factors and the Cross (Section of Commodity Returns*. Tech. rep. Working Paper. Concordia University.

Trolle, Anders B and Eduardo S Schwartz (2008). "Variance risk premia in energy commodities". In: *Available at SSRN 1160195*.

— (2009). "A general stochastic volatility model for the pricing of interest rate derivatives". In: *Review of Financial Studies* 22.5, pp. 2007–2057.

Trolle, Anders B and Eduardo S Schwartz (2010). "Variance Risk Premia in Energy Commodities". In: *The Journal of Derivatives* 17.3, pp. 15–32.

Watugala, Sumudu W (2015). "Economic uncertainty and commodity futures volatility". In: *Office of Financial Research Working Paper* 15-14.

Wu, Feng et al. (2015). "Risk-adjusted implied volatility and its performance in forecasting realized volatility in corn futures prices". In: *Journal of Empirical Finance* 34, pp. 260–274.