

A FEAR INDEX TO PREDICT OIL FUTURES RETURNS

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ABSTRACT

This paper evaluates the predictability of WTI light sweet crude oil futures by using the variance risk premium, i.e. the difference between model-free measures of implied and realized volatilities. Additional regressors known for their ability to explain crude oil futures prices are also considered, capturing macroeconomic, financial and oil-specific influences. The results indicate that the explanatory power of the (negative) variance risk premium on oil excess returns is particularly strong (up to 25% for the adjusted R^2 across our regressions). It complements other financial (e.g. default spread) and oil-specific (e.g. US oil stocks) factors highlighted in previous literature.

KEYWORDS

Oil Futures, Variance Risk Premium, Forecasting

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1. INTRODUCTION

This paper investigates *variance* risk-premia in WTI crude oil futures, by using a model-free approach. Indeed, the financial economics literature has proposed recently a new measure of volatility, defined as the difference between model-free implied volatility (from option prices) and model-free realized volatility (from high-frequency intraday data), coined as ‘Variance Risk-Premia’ (VRP, see among others Jiang and Tian (2005), Carr and Wu (2009), Bollerslev et al. (2009)). A growing literature that analyzes variance risk premia has emerged (see Chen et al. (2011) for an updated discussion).

The variance risk premium in oil markets has been analyzed so far in Doran and Ronn (2008) and Trolle and Schwartz (2010). Doran and Ronn (2008) use a purely parametric approach which is at odds with our empirical analysis. In contrast, our estimate of VRP is completely model-free. On the one hand, the implied volatility is proxied by the CBOE Crude Oil Volatility Index (OVX). The OVX measures the market’s expectation of 30-day volatility of crude oil prices by applying the VIX methodology to the United States Oil Fund, LP (Ticker - USO) options spanning a wide range of strike prices. This CBOE index for oil futures based on the VIX methodology has been studied recently by Aboura and Chevallier (2013). On the other hand, the realized volatility is estimated nonparametrically based on the properties of quadratic variations (see the seminal contribution by Andersen et al. (2003)). Our measure of realized volatility is the standard 5-minute estimator which is a robust candidate for the estimation of conditional volatility with many potential applications, such as volatility forecasting.

Trolle and Schwartz (2010) have investigated variance risk-premia in energy commodities, i.e. crude oil and natural gas. They find that the average risk-premia are significantly negative for both markets. Energy variance risk-premia are found to be time-varying, but systematic factors (returns on equity and commodity market portfolios) or commodity-specific factors (inventories) explain little of their level and variation.

The main interests behind modelling variance risk-premia in WTI crude oil futures are twofold: (i) assess the informational contents of the difference between implied (risk-neutral) and realized (historical) volatility series for oil futures, and (ii) gauge whether oil returns are predictable using this difference. Predicting oil prices has many practical implications for both financial and non-financial institutions, as well as for international institutions such as IMF and the World Bank whose economic forecasts include oil price forecasts as an input (see Baumeister and Kilian (2012)). These findings will also be of interest for investors, who are interested in dealing with the uncertainty in return variance to effectively manage risk, allocate assets, price accurately derivatives, and in understanding the behavior of oil assets in general.

We compare the oil price forecastability of the VRP with alternative predictors that have been used in the existing literature (see Kaufmann (2011) and Coleman (2012) among others). Due to data limitations, our analysis investigates the in-sample properties of the predictive regression of the monthly excess returns for the WTI futures. In particular, the back-calculation of the OVX cannot be extended in a too far past, as the liquidity of options was quite low at this period. We deal with monthly data for oil returns because returns at a higher frequency are too noisy. This is common practice (see Baumeister and Kilian (2012) among others).

Commodity futures returns are notoriously difficult to explain. Fackler and King (1990) is an early study of the forecast of returns and volatility using option-implied information. Their results are confirmed in Silva and Kahl (1993). Melick and Thomas (1997) use option-implied densities from American options on WTI crude oil to predict future oil prices, and find some predictability. Hog and Tsiaras (2011) use option-implied densities to predict the density of returns for the crude oil market. Another, but related, strand of the literature aims at forecasting the volatility of oil

futures (Kroner et al. (1995)). Martens and Zein (2004) make use of intraday data in oil futures markets to compute realized volatility in order to predict future volatility. This paper constitutes one example of the use of intraday, which is not common practice to date in oil markets.

Kroner et al. (1995) also use option-implied information along with historical-based volatility estimates. The authors show the superiority of forecast combinations. A possible explanation behind this result may be found in Ielpo and Sévi (2012) who show that realized volatility dominates implied-volatility for short-horizon forecasts, while the contrary is true for longer horizons.

Alquist et al. (2012) provide an exhaustive review of studies dedicated to the forecast of oil prices. Many contributions use information from the oil market only, as in Alquist and Kilian (2010) or Knetsch (2007), among others. Alquist and Kilian (2010) analyze the forecastability of oil futures prices using quoted prices of futures contracts of various maturities. They conclude that the random walk is not beaten by any forecast using only futures prices as predictors. This leads to the conclusion that additional predictors may be useful for predicting future oil prices. Knetsch (2007) computes the convenience yield in the oil market to predict oil prices. From his analysis, it appears that the convenience yield has some predictive power for future oil prices. Moreover, there is a tight link between oil markets and the macroeconomy. While many papers have investigated how macroeconomic variables are able to predict oil prices (see Alquist et al. (2012) for a review of the existing literature), recent studies have shown how oil variables such as oil prices (see Driesprong et al. (2008)), position in oil futures markets (see Hong and Yogo (2012)) or convenience yield in commodity markets (see Gospodinov and Ng (2013)) are also able to predict financial variables such as stock, bond or foreign exchange returns.

Conrad et al. (2012) show that some macroeconomic determinants play a role in modeling the correlation between oil and stock prices. We do not investigate the determinants of this relation in the present paper. However, these factors can also help to predict oil price as the latent correlation between oil and the macroeconomy naturally shares some commonalities with the oil market. So far, the best results are provided using statistical factor analysis which gathers a large number of macroeconomic and financial variables as in Le Pen and Sévi (2011, 2013). Zagaglia (2010) also uses this methodology to explain and forecast oil prices with some relative success.

To give a sketch of our results, the VRP appears as a serious candidate to predict oil futures across our regressions (up to 25% of the adjusted R-squared). This quantity contains incremental information about the future of oil prices, and therefore stands out as an intuitive measure of investors' threats (i.e. unpriced volatility) in oil markets. As such, the VRP may be viewed as a 'fear index'. We check that the explanatory power of the VRP in our in-sample predictive regressions cannot be confounded with the information that is present in other predictors by mean of multivariate regressions. An econometric model incorporating the VRP as a predictor of the oil price might be able to beat the random walk, which remains a strong benchmark in oil markets (see Alquist and Kilian (2010) and Baumeister and Kilian (2012) for a discussion). Finally, note that we do not perform an out-of-sample forecasting exercise due the relative short data sample (10 years) that we have in hand, rather due to the illiquidity of options data before 2001.

The rest of the paper is as follows. Section 2 details the methodology to compute the variance risk premium, and why this concept can be viewed as a fear index. Section 3 presents the exogenous regressors, and then provide the empirical results from the regression analysis. Section 4 concludes.

2. A FEAR INDEX FOR CRUDE OIL PRICES

In this Section, we first present the different kinds of data used for the oil futures market. Then, we detail how to compute the realized volatility, and finally the variance risk premium.

2.1 Oil Transaction Data

The data includes daily closing prices for a roll-over of nearby futures contracts written on the WTI Light Sweet Crude Oil from the New York Mercantile Exchange (NYMEX), which is now part of the CME Group. The nearby futures contract is selected, since it attracts the greatest amount of trading activity. Futures returns series are calculated as the first difference of the log of closing prices. The sample used for oil is from 11:2001 to 12:2010, which is equal to 2,248 trading days (or 109 months).

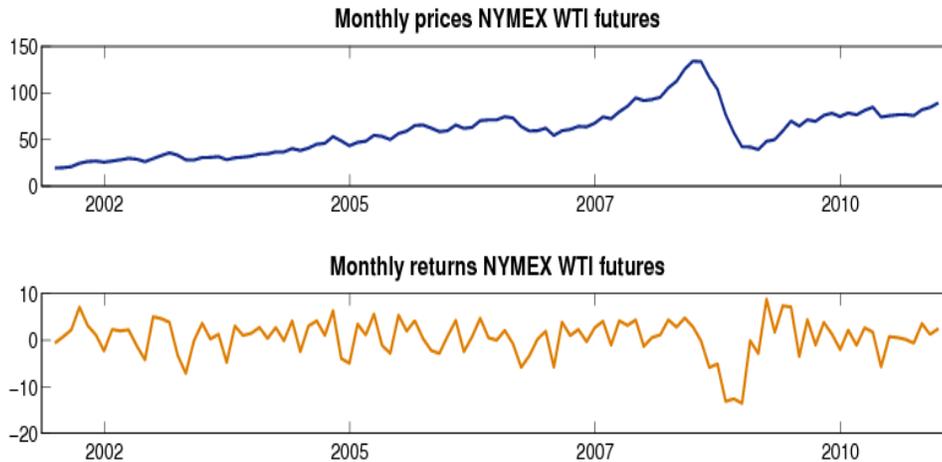


Figure 1: Monthly prices and returns over the period 2001:11-2010:12 for the front-month WTI futures contract traded in CME-NYMEX.

Figure 1 displays the Monthly prices of NYMEX WTI futures in the top panel, along with monthly returns in the bottom panel. In both panels, we remark the high oil price variability during the summer 2008, which was characterized by a boom and a bust in the prices of many commodities, against the background of speculative activity (see Chevallier (2013) for a discussion).

As a proxy for the Implied Volatility (IV) of the WTI price, we use the CBOE Crude Oil Volatility Index ('Oil VIX', Ticker - OVX). The OVX measures the market's expectation of 30-day volatility of crude oil prices by applying the VIX methodology to the United States Oil Fund, LP (Ticker - USO) options spanning a wide range of strike prices. The main advantage of the OVX index is that it provides us with a model-free estimation of the implied volatility (in the spirit of the VIX), which constitutes a much better approximation of the implied volatility than the one based on inversion of the standard Black-Scholes formula with close at-the-money options. The properties of the OVX index for the WTI crude oil futures contract have been previously studied by Aboura and Chevallier (2013). The authors conclude that the OVX is appropriate in empirical studies to capture the properties of the implied volatility of options written on oil contracts. Note that we have hand--back--calculated the OVX for the period before May 10, 2007, as it officially exists since July 14, 2008 (the 2007-2008 period is back--calculated by the CBOE itself).

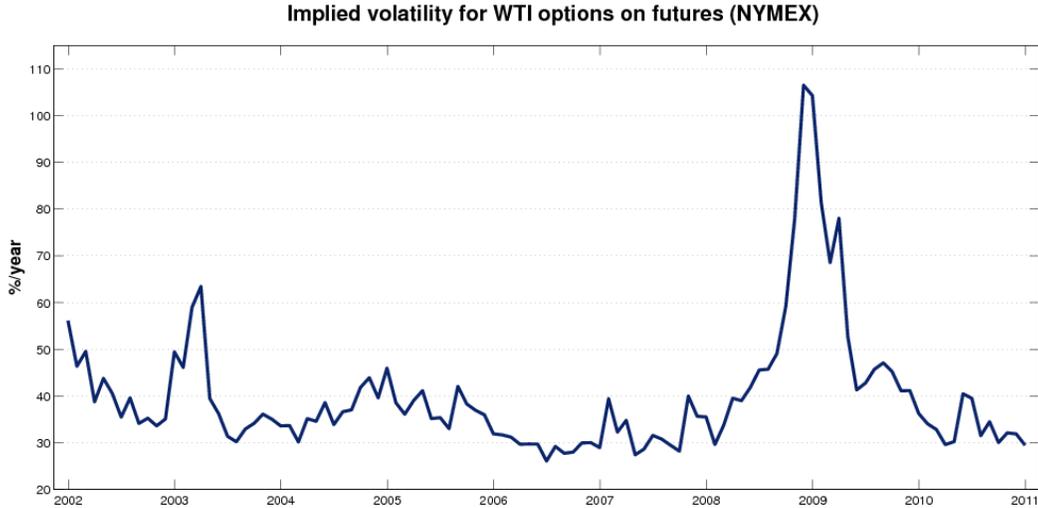


Figure 2: Implied volatility following the OVX methodology in the CBOE.

Figure 2 shows the implied volatility following the OVX methodology in the CBOE for WTI options. It is represented in annualized percentage terms, for comparability purposes with other measures of volatility used in this paper. We also notice from this graph the bump in volatility, which may be attributable to the drop in commodity prices in 2008 and the development of the financial crisis in 2009.

2.2 Estimates of Volatility Using High-frequency Data

Next, our investigation of the variance risk premium relies on estimates of the conditional volatility that are computed using high-frequency data. A vast literature has developed on this topic following the seminal contribution by Andersen and Bollerslev (1998) (an excellent survey is in Andersen et al. (2006)). The idea is to use in-fill asymptotics argument to develop an estimate of the conditional volatility that uses intraday returns.

High-frequency data for the NYMEX Light Sweet Crude Oil Futures contract comes from TickData. The average number of daily trades is equal to 25,000. As detailed in Zivot and Wang (2005), we apply a first filter to remove:

1. transactions outside the official trading period,
2. transactions with a variation of more than 5% in absolute value compared to the previous transaction,
3. transactions not reported in chronological order.

Then, we apply a second filter to eliminate days with insufficient trading activity. Namely, we remove days with less than fifty four 5-minute returns, days with more than eight zero-return, and days with less than 1,000 transactions.

A number of estimators have been suggested so far. In this paper, the ‘naive’ estimator of realized volatility is used. It is defined as:

$$RV_{t,M} = \sum_{j=1}^M r_{t,j}^2 \quad (1)$$

where $r_{t,j}$ are intraday returns for day t and M is the number of returns for the day, which depends on the sampling frequency $1/M$.

As robustness checks, we have experimented various other estimators, such as the ‘two-scale’ estimator of realized volatility by Zhang et al. (2005). These additional tests, available upon request, did not change qualitatively the results.

Estimating realized volatility faces the so-called problem of microstructure noise (MN). This phenomenon emerges from market microstructure problems, whose main examples are the existence of a bid-ask spread, non-synchronous trading, etc. When sampling data at a very high frequency, the MN could therefore strongly bias the estimates. Chevallier and Sévi (2012) provide evidence about the liquidity of the WTI futures market, and show that the 5-minute sampling intervals is a good choice for computing realized variance estimators. That is why we use the standard 5-minute sampling interval in this paper. In addition, Liu et al. (2012) show that the 5-minute sampling frequency is very accurate for forecasting purposes, which makes it a robust tool for an econometric analysis.

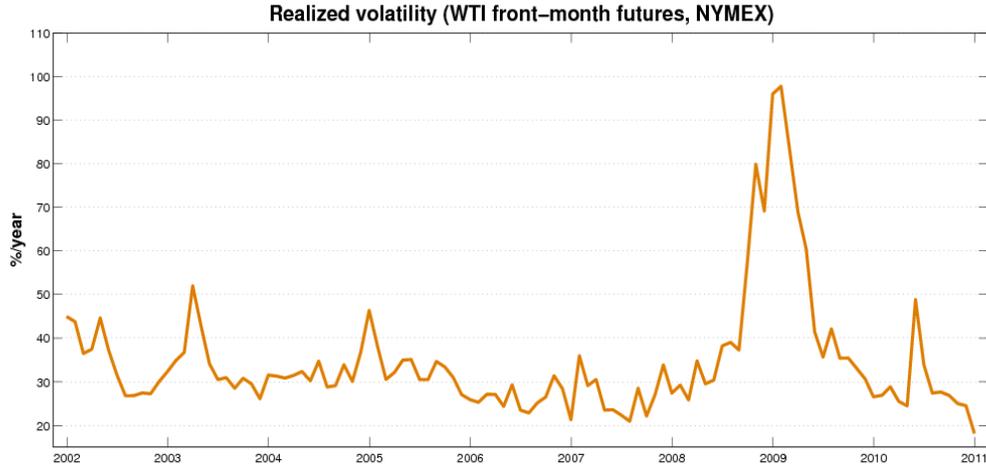


Figure 3: Realized volatility calculated as the squared root of the realized variance.

A plot of the realized volatility is provided in the Figure 3, also in annualized percentage terms. We observe that *RVOIL* is characterized by a very high volatility during the winter 2008-2009.

2.3 Variance Risk Premium Computation

Following Bollerslev et al. (2009), variance risk-premia (noted VRP_t) can be defined as the difference between the ex ante risk-neutral expectation of the future return variation and the ex post realized return variation:

$$VRP_t = IV_t - RV_t \quad (2)$$

Thus, it is computed as the difference between the model-free implied volatility (IV_t) and the model-free realized volatility (RV_t) for a given WTI futures contract. Note that Carr and Wu (2009) define variance risk premia in a slightly different fashion as the difference between the realized

variance and the variance swap rate using the Black-Scholes formula. Given the benefits of the model-free implied volatility explained above, we choose to stick to the approach developed by Bollerslev et al. (2009).

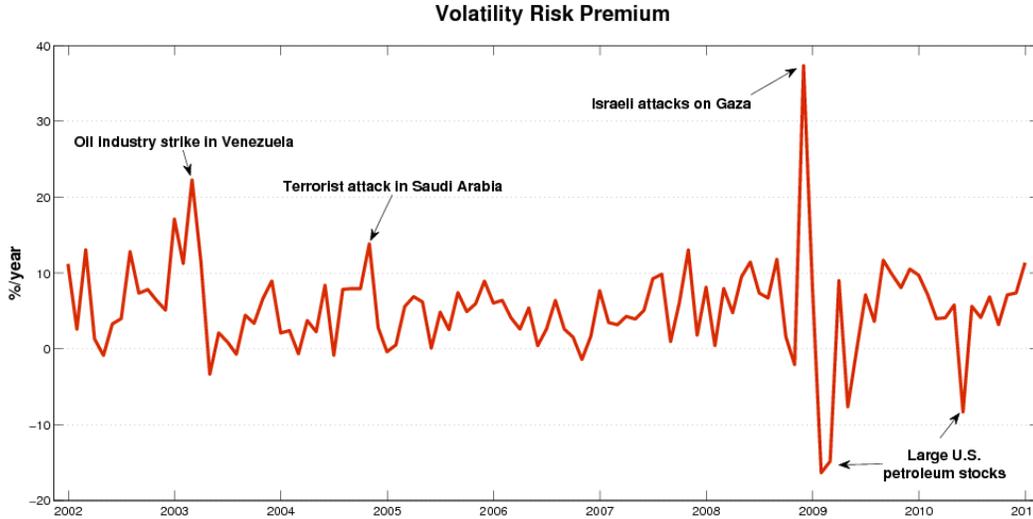


Figure 4: Variance risk premium – difference between implied and realized volatility – along with important events for the oil market during the period.

The variance risk premium is plotted in the Figure 4 in annualized percentage terms. Interestingly, it appears that spikes in the variance risk premium can be associated with major events in oil markets such as the oil industry strike in Venezuela (2003), terrorist attacks in Saudi Arabia (2004) or Israeli attacks on Gaza (2008), while large negative values of the VRP are representative of large U.S. petroleum stocks. This confirms that the variance risk premium materializes oil investor threats, and can be viewed as a ‘fear’ index.

In the next section, we carry out the empirical analysis to examine the forecasting power of the variance risk premium for oil futures returns.

3. EMPIRICAL ANALYSIS

This section investigates the real additional explanatory power – if any – of the variance risk premium beyond standard exogenous variables used in recent contributions to explain oil futures returns. Following Diebold (2012), we use the predictive regression framework to avoid disregarding data in a pseudo out-of-sample exercise. Using the full sample leads to achieve maximum asymptotic power, and Wald tests in this context are superior to model comparison in an out-of-sample experiment that leads to a certain loss of power.

Let us present first the exogenous variables, and second run our OLS regressions.

3.1 Additional Exogenous Regressors

We consider a number a variables that have been able (or should be able) to predict crude oil futures returns:

- $\Delta Stocks$ is the Monthly U.S. oil stocks from the US Energy Information Administration (EIA). It represents a well-known proxy of the physical fundamentals of the crude oil market

(Chevallier (2013)). A linear interpolation has been performed to obtain the data in monthly frequency.

- *Han Index* is a trading activity proxy by Han (2008) using data from the US Commodity Futures Trading Commission (CFTC) Commitment of Traders (CoT) report.¹ This investor sentiment index is calculated as the number of long non-commercial contracts minus the number of short non-commercial contracts, scaled by the total open interest in WTI futures or:

$$\text{Han Index} = \frac{\text{number of long speculative positions} - \text{number of short speculative positions}}{\text{total open interest}}$$

As such, this is a directional index of speculative activity in the futures market.

- *De Roons* is an index to measure hedging pressure in futures markets by de Roon et al. (2000). From CFTC CoT data, the hedging pressure proxy is calculated as the difference between the number of short hedge positions and the number of long hedge positions, divided by the total number of hedge positions, or:

$$\text{DeRoons} = \frac{\text{number of short hedge positions} - \text{number of long hedge positions}}{\text{total number of hedge positions}}$$

The idea behind this measure is to focus on the positions of traders who are hedgers, i.e. who have a cash business for the commodity. This estimate of hedging pressure is quite different to the Han Index for which the denominator is the total open interest and not the total number of speculative positions. As a consequence, we believe that these measures may be complementary in our regression analysis while matching existing literature dealing with futures market trading activity.

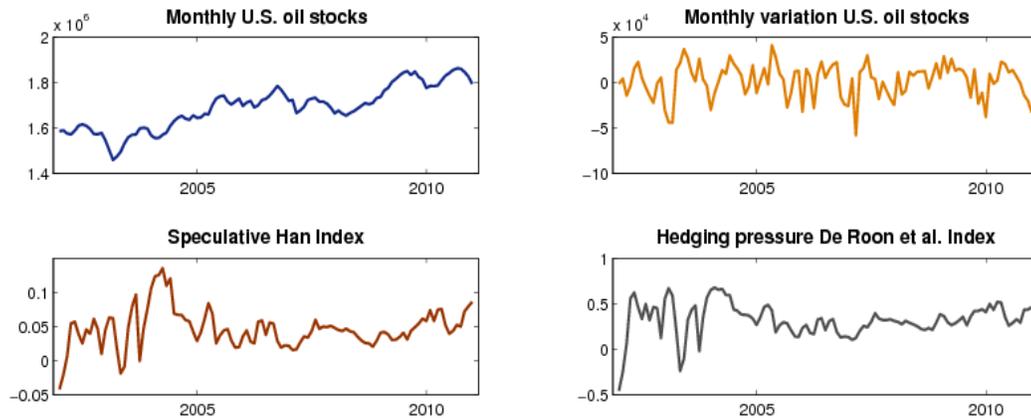


Figure 5: Monthly U.S. oil stocks and oil stocks in first difference (top panels), speculative (Han) index (bottom left panel) and hedging pressure (de Roons et al. (2000)) index (bottom right panel) for the period 2001:11-2010:12.

¹ Following requirements of the CFTC, large traders holding positions above a specified level have to report their positions on a daily basis. Then, the CFTC aggregates the reported data, and releases the breakdown of each Tuesday's open interest in its CoT. The CoT report includes total long and short positions for both 'commercial' traders and 'noncommercial' traders as well as more detailed variables that we do not use here. In other words, 'commercial' traders have to prove an interest for the physical market and are thus considered as hedgers, while 'noncommercial' traders have no relation with the cash business and are simply large speculators.

This first group of exogenous variables is pictured in Figure 5. Monthly US oil stocks have been taken in log-first difference to ensure stationarity.

Along with these data, we also use the Real Activity Index developed in Kilian (2009), which is based on dry cargo single voyage ocean freight rates. This index is explicitly designed to capture shifts in the demand for industrial commodities in global business markets following a long tradition of economists who observed the correlation between economic activity and rates for ocean freight.

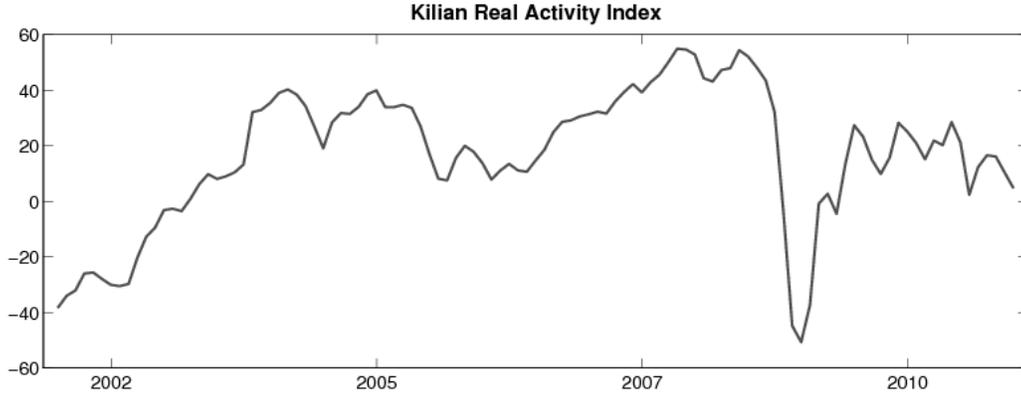


Figure 6: Monthly real activity index from Kilian (2009) over the period 2011:12-2010:12. The activity index is available from the Kilian’s webpage at the University of Michigan.

Kilian’s (2009) Real Activity Index (*Kilian Index*) is shown in Figure 6.

Since the WTI light sweet crude oil futures is based for delivery in Cushing, Oklahoma, we consider another index representative of global business conditions in the USA: the Aruoba - Diebold - Scotti (ADS) Business Conditions Index (Aruoba et al. (2009)). This index is designed to track real business conditions at high frequency. Its underlying (seasonally adjusted) economic indicators (weekly initial jobless claims; monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales; and quarterly real GDP) blend high- and low -frequency information and stock and flow data. It is publicly available from the Philadelphia Fed.

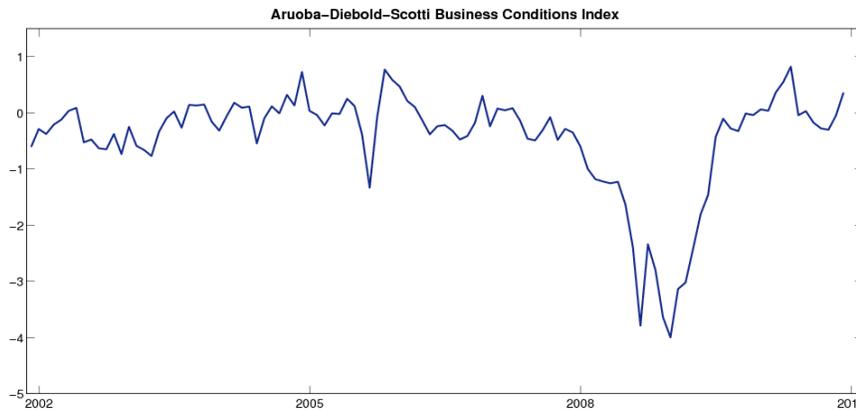


Figure 7: Monthly Aruoba-Diebold-Scotti Business Conditions Index (2009) over the period 2001:12-2010:12. The activity index is available from the Philidelphia Fed.

The ADS index is given in the Figure 7.

Finally, in the spirit of the Fama-French literature, Bali and Peng (2006) and Bali and Engle (2010) have used the following variables to model the hedging component in the ICAPM relationship, which should have predictive power for future returns as they convey some information about the general economic situation:

- ΔFED is the federal funds rate,
- ΔDEF is the default spread calculated as the difference between the yields on BAA- and AAA-rated corporate bonds,
- $\Delta TERM$ is the term spread calculated as the difference between the yields on the 10-Year Treasury bond and the three-month Treasury bill.

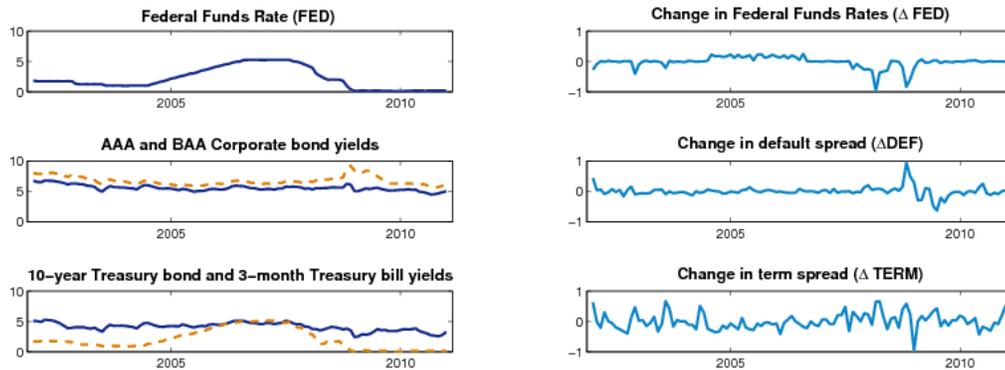


Figure 8: FED, DEF and TERM variables in level (left panels) and first difference (right panels) for the period 2001:11-2010:12.

This last group of exogenous regressors is visible from the Figure 8, both in raw and stationary log first-differenced forms.

Table 1 contains the descriptive statistics for all variables used in the paper, along with a cross-correlation matrix. The descriptive statistics confirm that the time series under consideration are not normally distributed, with negative skewness and excess kurtosis. The cross-correlation matrix allows us to verify that the variables are not too highly correlated, which would cause potential multicollinearity problems in the subsequent regression analysis.

Before proceeding to our econometric analysis, we can summarize the various data frequencies that we have at hand in this paper, and how we have dealt with this issue. Basically, we need to run our OLS regressions on monthly data, because most of the exogenous regressors are available on a monthly basis (at best). Therefore, the volatility time series have all been converted to a monthly frequency. First, the OVX index for implied volatility is available on a daily basis. The monthly implied volatility is taken as the value of the implied volatility on the last day of a given month. Second, intraday data allows to recover daily realized volatility estimates (sampled every 5 minutes). The monthly realized volatility is constructed as the sum of the daily realized volatilities over a given month. Third, the VRP is computed on a monthly basis simply as the difference between IV and RV series in monthly frequency. These data treatments are in line with previous literature. The interested reader can refer to Bollerslev et al. (2009).

Table 1: Descriptive statistics and cross-correlation matrix

<i>Descriptive Statistics</i>	Excess return	OVX	RV	VRP	Δ (stocks)	Kilian Index	Han Index	De RoonS	Δ FED	Δ DEF	Δ TERM
Mean	0.4425	39.8692	34.5634	5.3059	1893.0459	17.2082	0.0464	0.3214	-0.0175	0.0022	0.0038
Std. Dev.	3.9367	13.7096	13.8728	6.2219	18774.7266	24.1449	0.0284	0.1835	0.1873	0.1633	0.2702
Skewness	-1.1200	2.8172	2.7646	0.6715	-0.6812	-0.8296	0.4250	-1.0138	-2.3447	1.3108	0.2891
Exc. kurt.	2.3587	9.6065	8.5907	7.7285	0.2801	0.2629	1.9961	3.3592	8.6215	12.5002	1.0836
Minimum	-13.5577	26.1078	18.1231	-16.3431	-57807.0000	-50.6335	-0.0421	-0.4567	-0.9600	-0.6300	-0.9500
Maximum	8.7750	106.4854	97.7289	37.3450	40942.0000	54.9558	0.1352	0.6765	0.2500	0.9400	0.6700
AR(1)	0.3045	0.8656	0.8625	0.1466	0.3389	0.9345	0.7329	0.6710	0.6750	0.4916	0.2426
<i>Correlation matrix</i>											
<i>Correlation matrix</i>	Excess return	OVX	RV	VRP	Δ (stocks)	Kilian Index	Han Index	De RoonS	Δ FED	Δ DEF	Δ TERM
Excess return	1.0000	-0.3814	-0.4226	0.1018	-0.2152	0.1862	0.3368	0.3343	0.2689	-0.4862	0.0872
OVX		1.0000	0.8983	0.2005	0.1079	-0.4777	-0.2314	-0.0757	-0.3351	0.3169	-0.0359
RV			1.0000	-0.2503	0.2233	-0.4395	-0.2389	-0.1154	-0.2621	0.2386	-0.0228
VRP				1.0000	-0.2602	-0.0726	0.0229	0.0905	-0.1540	0.1662	-0.0282
Δ (stocks)					1.0000	-0.0268	-0.0871	-0.1496	0.0742	0.0523	-0.1111
Kilian Index						1.0000	0.2809	0.1155	0.0473	-0.1379	0.1071
Han Index							1.0000	0.8907	0.1439	-0.2078	0.0002
De RoonS								1.0000	0.1147	-0.2435	-0.0594
Δ FED									1.0000	-0.4380	-0.4678
Δ DEF										1.0000	0.0537
Δ TERM											1.0000

3.2 Univariate OLS Regressions

In what follows, we assess the in-sample properties of the predictive regression of the monthly excess returns for the WTI futures. More precisely, the excess return variable is calculated as the log-difference between the end-of-month oil prices.² Besides, note that any endogeneity concern is alleviated by the fact that we use lagged variables on the right-hand side of the equation, in line with Bollerslev et al. (2009).

In Table 2, we present results from univariate linear regressions that are estimated by Ordinary Least Squares(OLS). The first important result is that while both the OVX (model-free implied volatility) and the realized volatility have no predictive power for oil futures returns, the variance risk premium – defined as the difference between these two quantities – has a strong predictive power for oil excess returns (at the 1% level). More precisely, the estimated parameter is negative, indicating that higher VRP is correlated with future negative returns (decrease in price). The adjusted R-squared is roughly equal to 5% for this regression.

Second, we uncover the statistically significant impact of the variable ΔDEF (for the default spread) on oil excess returns at the 5% level. This equation achieves a fairly good explanatory power, with the adjusted R-squared equal to 12%. Among other significant results, we observe the low predictive power of excess return lagged one period for oil excess returns (at 10%). There is also a relationship between higher stocks (variable $\Delta(stocks)$) and negative returns, and this relation is significant at the 10% threshold. This is very intuitive as higher stocks generally indicate future decrease in prices. Other exogenous variables were not successful in explaining oil excess returns at any statistically significant level.

In the next step, we run multivariate regressions on the monthly excess return for the WTI front-month futures contract traded on the NYMEX. We plug in the significant variables from the previous set of regressions.

² For instance, excess return month MM = $\log(\text{price end of month MM}) - \log(\text{price end of month MM}(-1))$.

Table 2 : Univariate regressions

Constant	0.3242 (0.7442)	0.4910 (0.5331)	2.3008 (1.3605)	1.2788*** (2.4993)	0.5191 (1.0744)	0.2931 (0.4187)	0.4160 (0.3886)	0.4560 (0.5120)	0.5157 (1.2045)	0.4703 (1.1797)	0.4521 (0.8913)	0.1000 (0.2805)
Excess return(-1)	0.3047* (1.7552)											
OVX		-0.0190 (-0.0699)										
RV			-0.0532 (-0.9164)									
VRP				-0.1572*** (-2.6408)								
Δ (stocks)					-0.001* (-1.750)							
Kilian Index						0.0092 (0.5168)						
Han Index							0.8124 (0.0583)					
DeRoos Index								-0.0081 (-0.005)				
Δ FED									3.5419 (0.6861)			
Δ DEF										-8.68** (-2.07)		
Δ TERM											-1.1461 (-0.567)	
ADS												0.3321 (0.7700)
Adj. R^2	0.0841	-0.0093	0.0256	0.0523	0.0100	-0.0061	-0.0093	-0.0094	0.0192	0.1216	-0.0034	0.0200

Note: The endogenous variable is the monthly excess return for the WTI front-month futures contract traded on the NYMEX. The period is 2001:12-2010:12. The exogenous variables are defined in the Descriptive Statistics. The number of observations for each regression is 109. *t*-statistics are provided in parentheses below coefficient estimates. ***, **, * denote statistical significance at respectively the 1%, 5%, and 10% levels.

3.3 Multivariate OLS Regressions

Results from multivariate regressions are meant to compare the explanatory power of the VRP when additional predictors are used. They can be seen as a first sensitivity test of our main result, by accounting for various potential drivers of oil excess returns at the same time. We have run mainly two sets of multivariate regressions, with the constant term and/or with the excess return variable lagged one period.

Results are provided in Table 3. Overall, multivariate regressions confirm the strong explanatory power of VRP in our in-sample forecasting analysis. Indeed, the VRP is always strongly significant and negative in explaining oil excess returns, even when controlling for other potential significant explanatory variables such as $\Delta(stocks)$, ΔDEF , and excess returns (-1).

Finally, we notice that the adjusted R-squared of the multivariate regressions are comprised between 8% and 19%. This result is certainly interesting for the literature on oil price forecasts, where the random walk is still seen as a plausible model candidate. For our best specification, the adjusted R-squared turns out to be quite high, compared to other studies in this strand of literature (see Alquist et al. (2012) for a review).

To our best knowledge, the empirical finding that the difference between the model-free implied and realized volatilities is able to explain a significant proportion of WTI crude oil excess returns is new, and complements that afforded by oil-specific and financial predictor variables.

Table 3 : Multivariate regressions

Constant	1.1495*** (2.5635)	1.4489*** (2.7668)	1.3516*** (2.6418)	1.2462*** (2.7151)	1.5567*** (2.9120)	1.1130*** (2.3732)
Excess return(-1)	0.2238*** (2.4996)	0.3032** (2.1680)	0.1954** (2.2209)			
VRP	-0.1487*** (-2.9357)	-0.2002*** (-4.3851)	-0.1712*** (-3.0945)	-0.1778*** (-4.0512)	-0.1909*** (-3.5914)	-0.1227** (-2.3516)
Δ (stocks)		-3.2739e-05* (-1.8794)	-3.2598e-05* (-1.9357)		-4.5523e-05** (-2.4959)	
Δ DEF	-5.1246 (-1.5670)		-5.1101 (-1.5415)			-7.9179* (-1.9448)
Adj. R^2	0.1797	0.1683	0.1937	0.1545	0.0870	0.1503

Note: The endogenous variable is the monthly excess return for the WTI front-month futures contract traded on the NYMEX. The period is 2001:12-2010:12. The exogenous variables are defined in the Descriptive Statistics. The number of observations for each regression is 109. *t*-statistics are provided in parentheses below coefficient estimates. ***, **, * denote statistical significance at respectively the 1%, 5%, and 10% levels.

3.4 Robustness checks

Besides multivariate regressions, we consider another kind of robustness check with the sub-sample decomposition. More precisely, we re-estimate our best econometric models during the sub-period 2006:06-2010-12. The idea behind this specification is to test whether the forecastability of the oil price based on the VRP is robust to the 2008 financial crisis.

Estimation results are given by Table 4. We remark that the central result of our paper holds, i.e. the VRP is consistently negative and statistically significant across regressions, even when accounting for the influence of the 2008 financial crisis. The resulting adjusted R-squared are even higher than in the previous set of regressions (up to 25%). As a consequence, we can conclude that our results are robust during the financial crisis period.

In light of our analysis, the VRP can be considered as a serious candidate as an oil price predictor in the econometric toolbox of practitioners and industry participants.

Table 4: Multivariate regressions during the sub-period 2006-2012

Constant	0.8145 (1.1736)	1.0015 (1.3443)	0.8944 (1.2553)	0.9284 (1.2901)	1.0740 (1.1773)	0.7390 (0.9591)
Excess return(-1)	0.2898*** (2.5987)	0.4131*** (2.6584)	0.2706*** (2.4894)			
VRP	-0.1494*** (-2.3319)	-0.1817*** (-3.0206)	-0.1550*** (-2.3244)	-0.1759*** (-3.0434)	-0.1924*** (-2.8751)	-0.1322** (-2.0461)
Δ (stocks)		-2.2985e-05 (-0.9031)	-2.6656e-05 (-1.0692)		-3.7060e-05 (-1.3128)	
Δ DEF	-4.8700 (-1.4771)		-5.0763 (-1.5376)			-8.6356** (-2.0917)
Adj. R^2	0.2558	0.2298	0.2517	0.2370	0.0717	0.2149

Note: The endogenous variable is the monthly excess return for the WTI front-month futures contract traded on the NYMEX. The period is 2006:06-2010-12. The exogenous variables are defined in the Descriptive Statistics. The number of observations for each regression is 109. t -statistics are provided in parentheses below coefficient estimates. ***, **, * denote statistical significance at respectively the 1%, 5%, and 10% levels.

4. CONCLUSION

This paper establishes by means of multivariate regressions the predictive power of variance risk-premia for WTI light sweet crude oil excess returns. Variance risk-premia are computed as the difference between model-free implied and realized volatility measures (Bollerslev et al. (2009)). To date, the variance risk premium has been used in a number of studies to predict various quantities of interest.³

Along with a model-free measure of implied volatility, the realized volatility is used to compute the variance risk premium which is an indication of the risk premium for investors that exists to bear the variability of the variance in the oil market. As such, the variance risk premium is a premium dedicated to deal with the volatility-of-volatility risk, which is different from the standard volatility of returns that is a well-known concept in financial economics. The variance risk premium has proved its relevancy and importance in various contexts. In particular, it helps to predict stock returns but also participate in solving a number of existing puzzles in financial economics (see Bali and Zhou (2012)).

Besides, we consider various predictors for crude oil futures relating to macroeconomic, financial or oil-specific variables. The statistical influence of the VRP is consistently verified across all regressions. Other influences on crude oil futures excess returns stem from US oil stocks and the default spread. Using results from univariate regressions, we have estimated a number of multivariate regressions to increase the explanatory power of our in-sample forecasting analysis. By using sub-sample decomposition, we also show that our results are robust the 2008 financial crisis.

The bottom line of our analysis is that variance risk premia can be understood as a volatility which has not been priced accurately in the crude oil returns – either due to option mispricings or to large movements in the historical volatility – and they should be understood as a volatility series as well. This new volatility series can be readily replicated by fund managers, investors and market practitioners, and added to the econometric toolbox for forecasting crude oil prices. These results can be extended by assessing the predictive power of oil VRP for stock and bond returns.

³ Christoffersen et al. (2012) provides an excellent survey of the empirical literature whose aim is to predict quantities using option-implied information. Among others are Bollerslev et al. (2009), Zhou (2009).

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