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Does Speculation Impact What Factors Determine Oil Futures Prices?

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Abstract

Recent studies provide contradictory evidence about the impact of speculation on commodity prices. Rather than directly evaluating this relationship we instead use a novel approach to assess if speculation can inform our choice of factor inclusion in modelling oil futures.

Keywords: Oil futures; speculation; fundamentals; statistical factors

JEL Classifications: G10; G13; G15

Highlights:

- Consider observable and unobservable factors separately for oil futures prices
- Assess each class of factors in subsamples split by speculative activity
- Uncover significant outperformance utilising a composite prediction framework

1 Introduction

Recent sharp price declines in crude oil markets have increased the focus on what factors determine the observed market dynamics. Movements in commodity prices are often attributed to speculation, with Morana (2013) and Juvenal and Petrella (2015) concluding that speculative shocks are a relevant determinant of oil price changes. However, evidence from Büyüksahin and Harris (2011), and Alquist and Gervais (2013) contradict this, finding that the correlation between a speculation index and daily price changes is near zero. We approach the question of speculative impact from a different perspective;

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asking instead how speculation impacts the modelling accuracy of two distinct classes of factors proposed in oil futures literature. The two approaches we refer to are those comprised of observable fundamental macroeconomic, and unobservable latent principal component, factors.

Kilian and Murphy (2014) note that anyone buying crude oil not for current consumption, but for future use is a speculator from an economic point of view. In practice, we consider market participants who take positions to profit from an expected change in the price of oil as speculators. Due to the increased financialization of commodity futures markets, it has been proposed that speculation is now a major component of prices. However, not all speculation is the same. Some speculators provide liquidity and assist in price discovery, meaning that a certain level of speculation is required for a market to function correctly, whilst the activities of other speculators are said to destabilise the market and distort prices (Fattouh et al. 2013).

In this article, we refrain from defining a single value as a cutoff point for high or excessive levels of speculative activity, instead utilising a range of values corresponding to proxies for elevated levels of speculation. Our study contributes by finding that for elevated levels of speculative activity differences between the model accuracy of fundamental and latent factor approaches are uncovered; differences that are not present over the full sample period. The empirical analysis indicates that latent factors pick up additional price dynamics not captured by macroeconomic fundamentals, a main contribution of our study. Through the proposal of a novel composite prediction framework we demonstrate that utilising speculative positions to inform factor selection leads to statistically significantly increased accuracy in modelling oil futures price changes.

2 Empirical approach

We follow previous literature (Büyüksahin and Harris 2011, Alquist and Gervais 2013, and Büyüksahin and Robe 2014) by adopting the Working (1960) T index as a proxy for speculative activity. It is defined as follows:

$$T = 1 + \frac{SS}{HL + HS} \quad if\ HS \geq HL$$

$$T = 1 + \frac{SL}{HL + HS} \quad if\ HS < HL$$

where SS (SL) is the open interest of speculators (non-commercials firms) holding net short (long) positions and HS (HL) is the open interest of hedgers (commercial firms) who hold a net short (long) position. The ratio is predicated on the concept that speculators are necessary only insofar as they constitute a counterparty for hedgers. As highlighted by Büyüksahin and Harris (2011), what might be considered speculation in the market could simply be commercials not hedging or commercials taking a stance on future oil price movements. As there is no one Working's T index value that indicates *excessive* speculation we incrementally use values in the 50-90 percentile range as a measure of increasing levels of speculative activity.

In order to consistently compare the performance of the distinct classes of factors we specify structurally similar integrated models for both the unobservable principal component factors, and the observable macroeconomic factors. Firstly, motivated by Chantziara and Skiadopoulos (2008), we consider the following statistical model for oil futures returns:

$$\triangle CL_t^{\tau} = \beta_0 + \beta_1 PC1_{t-1} + \beta_2 PC2_{t-1} + \beta_3 PC3_{t-1} + \varepsilon_t,$$

where $PC1$, $PC2$, and $PC3$ denote the first, second, and third principal components of the WTI futures curve, and $\triangle CL$ denotes the log return of the continuous WTI crude oil (CL) contract of maturity τ at time t. We refer to this model henceforth, as *PC*.

Secondly, we consider a similarly constructed linear model, this time comprised of oil futures macroeconomic factors from Andreasson et al. (2016):

$$\triangle CL_t^{\tau} = \beta_0 + \beta_1 \triangle SP500_{t-1} + \beta_2 \triangle VIX_{t-1} + \beta_3 \triangle USD_{t-1} + \beta_4 \triangle EcPol_{t-1} + \varepsilon_t,$$

where $\triangle SP500$ denotes the log return of the S&P500 index, $\triangle VIX$ denotes the log change in the VIX volatility index, $\triangle USD$ denotes the log return of the trade weighted US dollar index, and $\triangle EcPol$ denotes the log change in the economic policy uncertainty index for the United States of America. We refer to this model henceforth, as *Macro*.[1] Finally, we produce a composite prediction informed by underlying speculative activity. This approach is motivated by Bates and Granger (1969) who were pioneers in arguing that given the availability of more than one prediction of the same variable, it is rarely (if ever) optimal to identify the best of the competing predictions and use it in isolation.

In line with Chantziara and Skiadopoulos (2008) we use daily WTI crude oil CL1-CL9 prices obtained from the CME Group. The time period for our sample is January 2007 to March 2016. The macroeconomic factors dataset comprises daily VIX quotes obtained from CBOE, S&P500 index values obtained from Yahoo! Finance, and Trade Weighted

[1] The aim of this article is to compare two distinct classes of factors, not to prescribe a specific fundamental factor model for modelling crude oil futures. In comparison with literature outlining macroeconomic factors that model the dynamics of crude oil spot markets there is a relative paucity of literature proposing relevant fundamental determinants of oil futures prices. In further testing we specify an alternative model by including oil inventory (a factor popular in modelling oil spot prices) as an additional macroeconomic factor to those outlined in Anderson et al. (2016). However, regression results show that the inclusion of inventory is not significant.

Table 1: Performance Measures

	PC RMSE	PC MAE	Macro RMSE	Macro MAE	RW RMSE	RW MAE
CL1	0.0253	0.0174	0.0253	0.0175	0.0371	0.0255
CL2	0.0234	0.0165	0.0234	0.0166	0.0343	0.0242
CL3	0.0224	0.0159	0.0224	0.0159	0.0328	0.0232
CL4	0.0217	0.0154	0.0216	0.0154	0.0318	0.0226
CL5	0.0210	0.0149	0.0209	0.0149	0.0307	0.0219
CL6	0.0204	0.0145	0.0204	0.0145	0.0298	0.0213
CL7	0.0200	0.0141	0.0199	0.0142	0.0292	0.0208
CL8	0.0196	0.0138	0.0195	0.0139	0.0286	0.0204
CL9	0.0191	0.0135	0.0191	0.0135	0.0280	0.0199

The predictive accuracy of the PC, Macro, and Random Walk (RW) models for each maturity WTI contract over the January 2007 to March 2016 period are given. The results of a t-test of statistically significantly better performance measures between PC and Macro factors, are indicated with asterisks (*) in the Macro and PC columns. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

US Dollar Index and US Economic Policy Uncertainty Index, both obtained from FRED. The Commitment of Traders Futures Only report obtained from the CFTC, is adopted to calculate Working's T index values. Root mean squared error (RMSE) and mean absolute error (MAE) loss functions are employed to assess the predictive accuracy of each class of factors.[2] As in all empirical studies considering multiple hypothesis tests about a single dataset, there is a risk of falsely inferring significance, known as data snooping bias. We explicitly address this issue through the use of a formal multiple comparisons framework, namely the false discovery rate as proposed by Benjamini and Hochberg (1995), to check our results for robustness and uncover instances of *truly* significant outperformance.

3 Findings and analysis

After fitting both models to the data we measure the predictive accuracy of each class of factors. We can see from the RMSE and MAE measures in Table 1 that the performance of the PC and Macro factors are almost identical across the term structure of the WTI futures curve over the full sample period. As expected, a formal t-test of both performance measures for each of the maturity contracts fails to yield any significant outperformance. Random Walk performance metrics are also provided for benchmark purposes, indicating that the accuracy of both models are better than would be expected by chance alone.

We now examine if underlying speculative activity has any impact on the factors determining WTI futures returns. We do this by referring to observations with Working's T values of greater than or equal to 50, 60, 70 , 80, and 90 percentile full sample index levels respectively, as "*most speculative*" with all other observations being categorised

[2]The squared error and absolute error for each observation are used to conduct the t-tests.

Table 2: Performance Measures for Speculation Subsamples

Percentile	Working's T	$PC\ \overline{RMSE}$	$PC\ \overline{MAE}$	$Macro\ \overline{RMSE}$	$Macro\ \overline{MAE}$
Least speculative subsample					
50%	<1.1153	0.0151	0.0108	0.0151	0.0109
60%	<1.1243	0.0161	0.0116	0.0162	0.0117
70%	<1.1346	0.0174	0.0124	0.0174	0.0124
80%	<1.1472	0.0191	0.0135	0.0189	0.0135
90%	<1.1639	0.0203	0.0143	0.0202	0.0143
Most speculative subsample					
50%	≥1.1153	0.0263	0.0195	0.0262	0.0195
60%	≥1.1243	0.0275	0.0204	0.0274	0.0204
70%	≥1.1346	0.0286	0.0216	0.0286	0.0216
80%	≥1.1472	0.0290	0.0217	0.0292	0.0220
90%	≥1.1639	0.0296	0.0225	0.0302	0.0230

$\overline{RMSE}$ and $\overline{MAE}$ denote the RMSE and MAE performance measures averaged over contracts of CL1-CL9 maturity. They are given for the PC and Macro factors using subsample periods based on increasing percentile Working's T index (1960) values as given in the Working's T column. Observations with Working's T values greater than or equal to 50-90 percentile levels respectively are categorised as "most speculative" with other periods being referred to as "least speculative".

as "*least speculative*". For example, if we use the 90% percentile calculated Working's T index as the cutoff point, we refer to observations with Working's T values greater than or equal to 1.1639 as "*most speculative*" (228 days) and all other periods as "*least speculative*" (2057 days). Table 2 splits the analysis into these subsample periods based on speculative activity. Firstly, analysing the 50-90 percentile least speculative Working's T subsample we again observe very little difference in terms of predictive accuracy between the adoption of Macro and PC factors. The strongest indication of a divergence in performance is for the least speculative 80% of the sample where we observe an RMSE value of 0.0191 versus 0.0189 for Macro and PC respectively, providing an initial suggestion that Macro factors outperform in less speculative periods. The results for the subsample periods with elevated levels of speculative activity are more clear-cut however. Using the most speculative 10-20% of the sample, we see that PC factors outperform Macro factors with MAE metrics of 0.0217 vs. 0.0220, and 0.0225 vs. 0.0230, for 80 and 90 percentile Working's T values, respectively. This demonstrates that in the sample's most speculative periods it is advantageous to adopt PC factors whereas other more benign periods are more accurately modelled using Macro factors.

To both highlight and formally test this dynamic we construct a simple combined model (*Combo* model, henceforth) utilising the prediction from the PC factor model for the subsample of observations with calculated Working's T values of greater than or equal to the 90 percentile figure and the prediction from the Macro factor model in all other

Table 3: Combo Model Performance Measures

	Combo RMSE	Combo MAE	Macro RMSE	Macro MAE	PC RMSE	PC MAE
CL1	0.0252	0.0175	0.0253**	0.0175**	0.0253	0.0174
CL2	0.0233	0.0165	0.0234*	0.0166**	0.0234	0.0165
CL3	0.0223	0.0159	0.0224*	0.0159**	0.0224	0.0159
CL4	0.0216	0.0154	0.0216*	0.0154**	0.0217*	0.0154
CL5	0.0208	0.0149	0.0209*	0.0149**	0.0210*	0.0149
CL6	0.0203	0.0145	0.0204*	0.0145**	0.0204*	0.0145
CL7	0.0198	0.0141	0.0199*	0.0142**	0.0200*	0.0141
CL8	0.0194	0.0138	0.0195**	0.0139***	0.0196*	0.0138
CL9	0.0190	0.0135	0.0191*	0.0135**	0.0191	0.0135
Overall	0.0213	0.0151	0.0214***	0.0152***	0.0214***	0.0151

The predictive accuracy of the PC, Macro, and Combo models over the January 2007 to March 2016 period for each maturity WTI contract are given. "Overall" denotes the performance metric value averaged over all of the CL1-CL9 maturities. The results of a t-test of statistically significantly outperformance for the Combo model over the Macro and PC models respectively, are indicated with asterisks (*) in the Macro and PC columns. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

cases.[3] The full sample results for the combo model are given in Table 3. Comparing the calculated performance measures across the term structure we can see that the adoption of the Combo model results in almost systematic improvements relative to the standalone PC and Macro models. We evaluate this improvement in RMSE and MAE metrics formally through the application of a t-test. We find that supplementing the Macro factors with PC factors in the most speculative periods results in a significantly more accurate model than using Macro factors alone. The tests also show that the Combo model significantly outperforms the PC factor model, however, this outperformance is loss function specific. To address the multiple comparisons problem, p-value adjustments are undertaken in line with Benjamini and Hochberg (1995) (full results available upon request). After explicitly controlling for possible false discoveries 16 of the 25 instances of statistical significant identified in Table 3 are said to be *truly* significant, adding an additional layer of statistical rigour in support of our findings.

[3] Formally, the *Combo* model is defined as:

$$\triangle CL_t^{\tau} = \theta_t^{Macro} \hat{Macro}_t^{\tau} + \theta_t^{PC} \hat{PC}_t^{\tau} + \varepsilon_t,$$

$$\theta_t^{Macro} \begin{cases} 1 & if \quad WT_t < WT_{\%tile} \\ 0 & if \quad WT_t \geq WT_{\%tile} \end{cases},$$

$$\theta_t^{PC} \begin{cases} 1 & if \quad WT_t \geq WT_{\%tile} \\ 0 & if \quad WT_t < WT_{\%tile} \end{cases},$$

where WT_t is the calculated Working's T index value for day t, and $WT_{\%tile}$ is the 90 percentile Working's T cutoff value.

4 Conclusion

As opposed to directly analysing the relationship between speculative activity and oil futures pricing dynamics we take a different approach; examining the impact speculative activity has on the predictive accuracy of two distinct classes of factors in determining the returns on oil futures contracts. The similarity in the performance measures observed for both classes of factors over the full period suggests that principal components capture broadly similar variance to that characterised by the Macro fundamental factors. When we split the analysis into subsamples by levels of speculation we find that in the sample's most speculative periods it is advantageous to adopt predictions based on the PC factors and in other periods to use Macro factor predictions. We demonstrate this further through the empirical evaluation of a simple combined model that utilises both PC and Macro factors, leading us to hypothesise that the latent factors approach can be interpreted as incorporating a proxy for the pricing impact elevated levels of speculation have on the market. Future research might focus on other asset classes and/or seek to economically exploit the dynamic presented here by assessing the profitability of an out-of-sample trading strategy.

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