The Illusion of Oil Return Predictability: The Choice of Data Matters!

Thomas Conlon, Ph.D.
Michael Smurfit Graduate Business School, University College Dublin, Ireland

John Cotter, Ph.D.
Michael Smurfit Graduate School of Business, University College Dublin, Ireland

Emmanuel Eyiah-Donkor, Ph.D.
Michael Smurfit Graduate School of Business, University College Dublin, Ireland

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This article re-examines the previously documented evidence of crude oil return predictability from several popular economic predictors and technical indicators and their combinations. It shows that monthly average oil returns are forecastable, in line with evidence documented in previous studies. On the contrary, no evidence of predictability is found for end-of-month oil returns. The authors conclude that the evidence of oil return predictability documented in previous studies may be misleading, as it stems from the use of within-month averages of daily oil prices in calculating monthly returns whereas end-of-month returns are more relevant for risk management and investment decision making as reflecting actual change in asset value.

Introduction

This article comprehensively re-examines the ability of popular economic predictors and technical indicators predictor variables to forecast crude oil returns both in-sample and out-of-sample, with particular emphasis on the latter. The article considers two forms of crude oil price data to calculate returns used in predictive regression models: within month averages of daily oil prices (monthly average returns) and end-of-month prices (end-of-month returns). The former price series is used in most studies on crude oil forecasting (*e.g.*, Baumeister *et al*., 2018) while the latter is commonly used in stock, bond, currency, and other commodity return forecasting studies (*e.g.*, Lin *et al*., 2018). The purpose of the article is to compare the inferences on crude oil predictability from a study that relies on average monthly returns vis-à-vis the same study (as regards models and predictors) that relies on end-of-month returns instead.

The authors find that monthly average oil returns are forecastable, in line with evidence documented in previous studies. On the contrary, they find no convincing evidence for the predictability of end-of-month oil returns. They conclude that the evidence of oil return predictability documented previously is largely misleading, and attribute this to the common use of within-month averages of daily oil prices in calculating returns. They show that studies that rely on monthly average returns introduce an upward bias in the first-order autocorrelation and variances of returns. Consequently, predictive regression analyses based on average monthly returns are likely to document spurious oil return forecastability.

Although the inferential biases and econometric issues associated with the use of monthly average returns have been well documented in the literature for a long time (*e.g.*, Working, 1960), it is surprising that the

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This digest article was contributed by Ana-Maria Fuertes, Ph.D., Professor in Finance and Econometrics at Bayes Business School, City, University of London (U.K.) and Associate Editor of the GCARD.

vast majority of the literature examining the predictability of crude oil returns continues to use averaged price data to calculate returns. What argument supports this choice is not exactly clear. It may, perhaps, simply stem from some kind of "herd behaviour" in the choice of monthly average prices.

Relevance of the Research Question

The findings in this paper are relevant for crude oil market participants that rely on past research as a guide for risk management and investment decision making. For example, a research paper on a trading strategy that seeks to exploit a market inefficiency might indicate profitability when using monthly average returns. In practise, however, average returns are not achievable and a similar strategy using end-of-month returns may be unprofitable. This article therefore provides a cautionary tale on how the calculation of monthly returns from daily data can influence the evidence of crude oil return forecastability.

Data, Models, and Performance Evaluation

Daily closing and monthly averages of the daily closing prices of WTI crude oil spot are obtained from the website of the U.S. Energy Information Administration (EIA) from January 1987 to December 2016. From the daily prices, we build end-of-month price series. Inflation-adjusted (real) log returns are calculated.

We consider a set of very popular predictor variables. They include, among others, oil-specific variables such as crude oil production, crude oil product spreads; variables that capture broad economic activity such as industrial production, inflation; the bilateral exchange rate between the U.S. Dollar and currencies of commodity exporting countries such as Australia, and South Africa; and commonly used technical indicators such as moving average and momentum rules.

Following the oil return forecasting literature, the paper begins with the following out-of-sample (OOS) predictive regression approach for real crude oil returns. The models are estimated using an initial in-sample period January 1987 to December 1996, and the estimated coefficients are used to forecast crude oil returns OOS for January 1999. Repeating this process recursively (expanding windows) until the end of the sample period enables a sequence of OOS month-ahead forecasts.

The paper also considers forecast combination methods, motivated by the well documented evidence that individual models suffer from parameter estimation risk and model uncertainty resulting from structural breaks in the data. The combination forecasts are linear combinations that include mean, median, trimmed mean, weighted mean, and discounted mean squared forecast error combinations.

The random walk with drift model (RW) that is associated with the no-predictability hypothesis is the benchmark. Thus, the accuracy of the forecast from a given model versus the historical average (or RW forecast) is assessed via the R_{OOS}^2 metric proposed by Campbell and Thompson (2008). Statistical significance of relative forecast accuracy is assessed through the Clark and West (2007) MSFE test.

Results

Some empirical findings of the article are highlighted in Table 1 on the next page. From Panel A, 10 out of the 28 individual economic variables, namely, the futures return, price pressure (PP), spot crack spread (SCS), gasoline spot (GSS), heating oil spot spread (HSS), the exchange rate of Australia, Canada, and South Africa against the U.S. dollar (AUS, CAN, SA), change in the T-bill rate (CTBL), and the Baltic dry index (BDI) contain useful information for predicting future *monthly average* crude oil spot returns. The R_{OOS}^2 values for these are positive and range from 1.71% for the Baltic dry index (BDI) predictor to 5.73% for the Futures return predictor. These values are statistically significant indicating superior performance than the benchmark RW forecast.

As regards the forecastability of *monthly average* returns, the results in Panel B of Table 1 indicate that all the combination forecasts of crude oil returns add notable improvements in OOS predictive performance over the RW benchmark as borne out by large R_{OOS}^2 values that are statistically significant.

By contrast, only two predictors, the crude oil basis and CTBL, provide OOS forecast improvements versus the RW benchmark for *end-of-month* returns. All other individual forecasts are unable to improve upon the RW forecast. Not even the combination forecasts, which are designed to guard against model uncertainty and parameter instability of individual predictive models, are able to improve upon the RW.

Conclusions

This paper re-examines the evidence of crude oil return predictability reported in previous studies. The empirical results show *monthly average* returns are forecastable out-of-sample, consistent with previous studies. On the contrary, we find no convincing evidence of *end-of-month* oil return forecastability.

The authors argue that the evidence for *monthly average* crude oil return predictability is an artefact from the distorted statistical properties of crude oil spot returns that result from the averaging of crude oil prices. These distortions lead to inferential biases, namely, spurious predictability of crude oil returns.

Table 1
Out-of-Sample Forecasting Results Based on Economic Variables, January 1990 to December 2017

	Monthly average returns			End-of-month returns		
Predictor	MSFE	R^2_{OS} (%)	MSFE-adjusted	MSFE	R^2_{OS} (%)	MSFE-adjusted
RWWD						
Panel A: Individual predictive model forecasts						
Futures return	52.92	29.92	5.73***	91.27	0.26	1.07
Basis	76.01	-0.67	-0.27	90.57	1.02	1.57*
HP	76.79	-1.70	1.22	91.83	-0.35	-0.35
PP	73.47	2.69	2.84***	91.62	-0.13	0.45
OI	75.61	-0.14	-0.28	91.89	-0.41	-1.65
SCS	53.82	28.72	5.67***	91.50	0.01	0.94
GSS	53.80	28.75	5.67***	91.50	0.00	0.94
HSS	53.89	28.63	5.67***	91.50	0.01	0.95
GOI	75.78	-0.36	-0.89	92.14	-0.69	-0.51
GOP	75.67	-0.21	0.14	92.56	-1.15	0.17
AUS	72.03	4.61	2.60***	93.06	-1.69	-0.65
CAN	71.23	5.67	3.20***	92.49	-1.07	-0.87
NZ	75.30	0.27	1.11	93.87	-2.58	-1.56
SA	74.25	1.67	2.29**	92.32	-0.89	-0.53
S&P 500 return	76.96	-1.92	-0.44	92.30	-0.86	-0.22
TBL	76.39	-1.17	-1.34	92.44	-1.02	-1.51
CTBL	74.21	1.72	1.52*	89.69	1.98	1.88**
YS	76.81	-1.72	-0.48	92.93	-1.55	-0.82
DFY	78.40	-3.83	-0.07	93.85	-2.57	-0.31
TMS1Y	76.13	-0.82	-0.75	92.17	-0.73	-1.02
TMS2Y	75.94	-0.58	-1.29	92.06	-0.61	-1.36
TMS5Y	76.74	-1.63	-0.32	92.85	-1.47	-0.60
VIX	75.38	0.17	0.57	92.02	-0.57	0.37
REA	76.60	-1.45	-0.42	92.90	-1.52	-0.89
BDI	73.78	2.29	1.71**	92.91	-1.53	0.10
INFL	76.61	-1.46	-0.29	92.59	-1.19	-1.10
CAPUTIL	76.21	-0.92	0.53	92.42	-0.99	-1.03
INDPRO	76.07	-0.74	-0.81	92.07	-0.61	-1.46
Average	72.39	4.14	1.17	92.19	-0.75	-0.28
Panel B: Combination forecasts						
Mean	68.72	8.99	4.79***	91.47	0.04	0.27
Median	74.55	1.27	2.55***	91.56	-0.06	-0.18
Trimmed mean	69.25	8.29	4.78***	91.44	0.08	0.35
Weighted mean	66.71	11.66	5.06***	91.47	0.04	0.28
DMSFE	66.78	11.56	4.51***	91.49	0.01	0.23
PC	57.83	23.41	5.01***	92.46	-1.04	0.71
Average	67.31	10.86	4.45***	91.65	-0.16	0.28

Notes: MSFE is the mean squared forecast error. The R^2_{OS} statistic measures the proportional reduction in MSFE for the competing forecasts given in the first column relative to the RWWD forecast. Statistical significance for the R^2_{OS} statistic is based on the *p*-value for the MSFE-adjusted statistic of Clark and West (2007). This statistic tests the null hypothesis that the RWWD forecast MSFE is less than or equal to the MSFE of the competing forecast against the one-sided (upper tailed) alternative hypothesis that the RWWD forecast MSFE is greater than the MSFE of the competing forecast. The variable Average is the average of the MSFE, R^2_{OS}, and MSFE-adjusted statistics across the predictors. Results are reported for monthly average returns and end-of-month returns. The out-of-sample forecast evaluation period is 1997:01-2016:12. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Endnote

The *GCARD*'s previous articles on crude oil, including on forecasting, are available here.

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Author Biographies

THOMAS CONLON, Ph.D.
Michael Smurfit Graduate Business School, University College Dublin (UCD), Ireland

Dr. Thomas Conlon is an Associate Professor of Banking and Finance in the UCD School of Business. Previously, he worked within asset management and as a consultant in the area of financial services. He obtained his Ph.D. and M.Sc. from Dublin City University and undergraduate degree from Trinity College Dublin. His main research interests are in asset pricing, risk management and fintech. His recent research has been published in journals such as the *Journal of Banking & Finance*, *Journal of Financial Econometrics*, *European Journal of Operational Research*, the *Journal of Empirical Finance* and the *Journal of Financial Stability*. He is an Associate Editor for the *European Journal of Finance* and *International Review of Financial Analysis*. Dr. Conlon has held visiting positions at the Saïd Business School, University of Oxford and Simon Fraser University (Canada). He is a funded investigator with the Financial Mathematics and Computation Cluster and has received funding from Science Foundation Ireland (SFI) as a principal investigator in the area of fintech. He was also the recipient of a prestigious New Horizons Research Grant from the Irish Research Council and a Dobbin Scholarship.

JOHN COTTER, Ph.D.
Michael Smurfit Graduate School of Business, University College Dublin, Ireland

Dr. John Cotter is Professor in Finance and the Chair in Quantitative Finance at University College Dublin. He is a Research Fellow at the UCLA Ziman Research Center for Real Estate. Dr. Cotter has previously had visiting positions at UCLA, London School of Economics, University of British Columbia (Canada) and ESSEC Business School (France). His research, teaching and consultancy interests are in the areas of volatility modeling and measuring, risk management and investment analysis with applications in equity, currency, derivative, fixed income and real estate markets. He has taught extensively on undergraduate, graduate and executive programs. Dr. Cotter has been awarded a UCD Faculty of Commerce Outstanding Educator Teaching Award. He is the founding Director of the Centre for Financial Markets at University College Dublin. In addition, he is the Director of the Financial Mathematics Computation Research Cluster (FMC2), a multi-university cross-discipline research body in Finance. He is an Associate Editor of the *Journal of Banking and Finance*, the *Journal of International Financial Markets*, *Institutions & Money*, and the *European Journal of Finance*. Dr. Cotter has published many professional papers, including in the *Review of Financial Studies*, the *Journal of Banking* *and Finance*, and the *Journal of International Money and Finance*. He has received many research grants including being a Principal Investigator in the Financial Mathematics Computation Research Cluster (FMC2) funded by Science Foundation Ireland. He was awarded an Outstanding Research Contribution Award at the UCD School of Business, University College Dublin. Dr. Cotter is a member of the Group of Economic Advisers for the European Securities Markets Authority (ESMA), the supra-national supervisor of European financial markets. He has consulted for many organizations both in and outside Ireland and has also served as an expert witness in several financial cases.

EMMANUEL EYIAH-DONKOR, Ph.D.
Michael Smurfit Graduate School of Business, University College Dublin, Ireland

Dr. Emmanuel Eyiah-Donkor is an Assistant Professor of Banking and Finance at the College of Business, University College Dublin (UCD). Previously, he was Assistant Professor of Finance at Rennes School of Business in France. He holds a Ph.D. in Finance from UCD, an M.Sc. in Financial Mathematics from Uppsala University (Sweden), and a B.Sc. in Mathematics from the Kwame Nkrumah University of Science and Technology (Ghana). Dr. Eyiah-Donkor's research interests include asset return predictability, dynamic portfolio choice, empirical asset pricing, financial econometrics and, more recently, financial data science. His research has been published in international peer-reviewed journals including the *Journal of Banking and Finance*, *Journal of Commodity Markets*, and the *International Review of Financial Analysis*. He has taught courses in Financial Theory, Quantitative Finance, Corporate Finance, Financial Modeling, Portfolio Choice, and Risk Management at the undergraduate and graduate levels at Rennes School of Business and UCD. At UCD, he currently teaches Portfolio and Risk Management and Programming for Financial Data Science at the graduate level.