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RESEARCH DIGEST ARTICLES

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

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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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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^2_{OOS} 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^2_{OOS} 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^2_{OOS} 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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A Bayesian Perspective on Commodity Style-Integration

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Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4112383

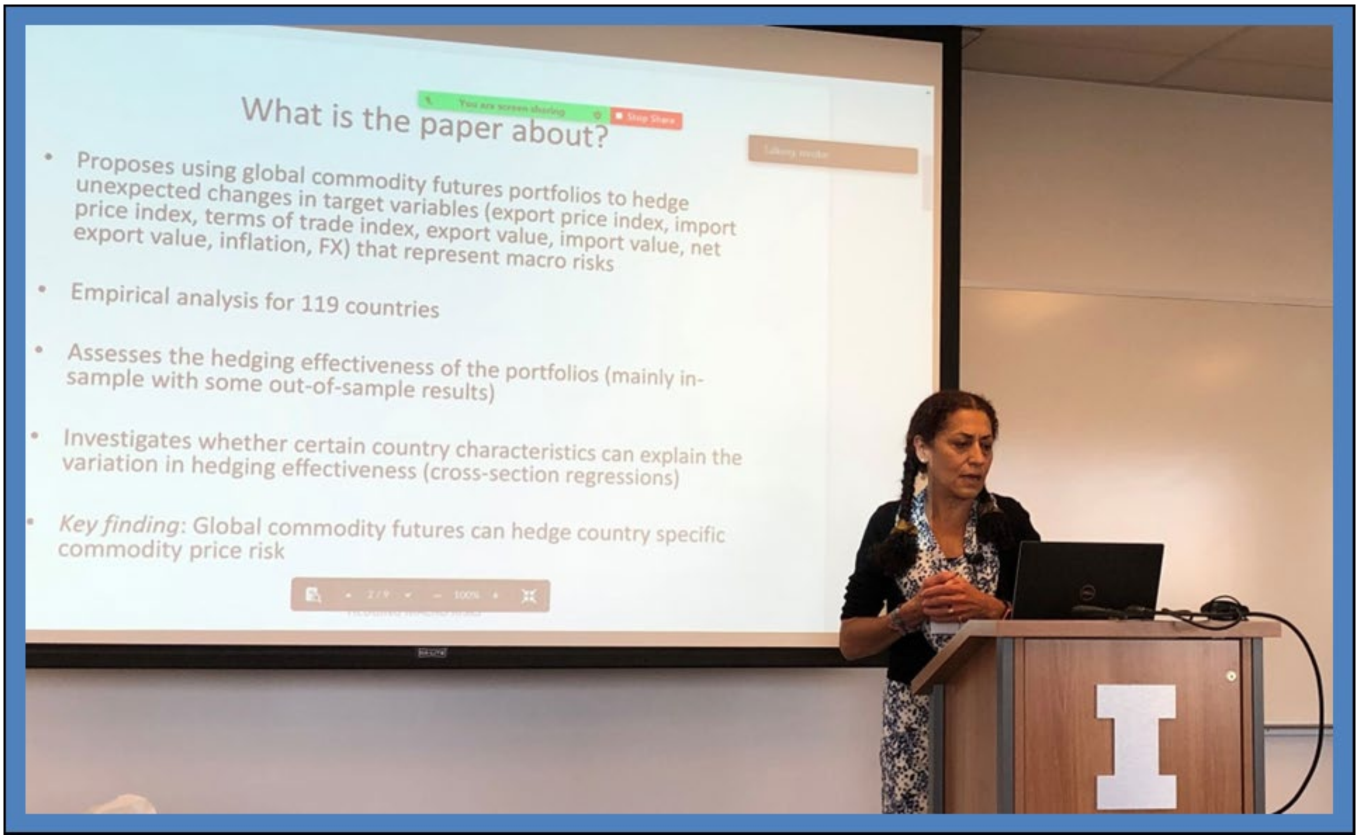
Commodity style-integration is appealing because by forming a unique long-short portfolio with simultaneous exposure to mildly correlated factors, a larger risk premium can be captured over time than with any of the underlying standalone styles. A practical decision that a commodity style-integration investor faces at each rebalancing time is the relative weight of the predictive- or sorting-signal that underlies each standalone style. The authors of this paper develop a new Bayesian optimized integration (BOI) method that accounts for estimation risk in the style-weighting decision. Focusing on the problem of a commodity investor that seeks exposure to the carry, hedging pressure, momentum, skewness, and basis-momentum factors, they demonstrate that the BOI portfolio outperforms not only a battery of parametric style-integrations motivated by the portfolio optimization literature, but also the highly effective equal-weight integrated portfolio. The findings survive the consideration of transaction costs, alternative commodity scoring schemes, and long estimation windows.

Introduction

Individual factors can undergo time-variation or be arbitraged away; namely, styles that have captured a sizeable premium over a period of time may weaken or completely fade away due to "factor crowding" (see *e.g.*, Bhattacharya *et al*., 2017). One way to mitigate this problem is by constructing a long-short portfolio or style-integrated portfolio according to a combination of predictive signals which is also known as the multi-factor approach. Style-integration is in essence the old adage of *don't put all your eggs in the same basket* applied to factor exposure or style investing. The key idea is to harness the diversification of predictive signals towards capturing a larger and more resilient risk premia over time. A key decision that a style-integration investor faces is the relative weight to give to the styles at each portfolio rebalancing time. With a history of returns on each of the styles, the investor can estimate the style-weights that are defined as "optimal" according to some criteria. However, these optimized style-integrations (OIs) suffer from parameter uncertainty, which is the main reason why the naive equal-weight style integration (EWI) has stood out as very effective. In a structured contest among the EWI method and a battery of sophisticated style-integrations, Fernandez-Perez *et al*. (2019) show that the former is not outperformed by the latter. The authors of this paper thus believe it is worthwhile to pursue the research question of whether embedding the style-integration problem within a Bayesian framework that accounts for estimation risk can be fruitful for investors.

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.

The authors develop a Bayesian optimized style-integration (BOI) method that expands the parametric mean-variance optimized integration by allowing investors to incorporate their prior beliefs or knowledge about the merit of the different standalone styles. The priors on the style-weights distribution can then be conveniently mapped into priors on the distribution of excess returns for the candidate commodity futures contracts. In an empirical exercise, the authors compare the reward-to-risk and crash risk profiles of the BOI method with those of the challenging EWI benchmark and of several sophisticated parametric optimized integrations (OI).



Professor Ana-Maria Fuertes of Bayes Business School, City, University of London, U.K., lecturing during the Commodities & Energy Markets Association (CEMA) conference at the University of Illinois' Illini Center in Chicago. This conference took place on June 21st and 22nd, 2022.

Why the Paper's Research Question is Important

Research over the last few years has established that a number of factors can explain return performance in commodity futures but the corresponding style premia are not constant over time. Rewarding factors over specific periods can temporarily weaken. Improving the return profile through mixing styles is, in fact, currently the critical issue for many commodity investors. This paper seeks to assist investors by developing a BOI strategy that seeks efficiently (that is, with a low noise-to-signal ratio) to construct a unique long-short portfolio with exposure to multiple commodity risk. The BOI approach is flexible enough to facilitate integration of any number of styles using an investor-chosen criteria for the optimal estimation of the style-exposures. The research question is also relevant for academics because it allows the authors to advance the Bayesian statistics literature towards commodity style-integration.

Style-Integration Methodology

The investor's decision at portfolio formation time *t* about the relative wealth to allocate to each commodity futures and the nature of the position, long versus short, can be represented by the $N \times 1$ commodity allocation vector $\boldsymbol{\phi}_t$ obtained as

$$\boldsymbol{\phi}_t \equiv \boldsymbol{\Theta}_t \times \boldsymbol{\omega}_t = \begin{pmatrix} \theta_{1,1,t} & \cdots & \theta_{1,K,t} \\ \vdots & \ddots & \vdots \\ \theta_{N,1,t} & \cdots & \theta_{N,K,t} \end{pmatrix} \begin{pmatrix} \omega_{1,t} \\ \vdots \\ \omega_{K,t} \end{pmatrix} = \begin{pmatrix} \phi_{1,t} \\ \vdots \\ \phi_{N,t} \end{pmatrix} \quad (1)$$

where $\boldsymbol{\Theta}_t$ is the $N \times K$ *score* matrix (*N* is the number of assets and *K* the number of standalone styles) and $\boldsymbol{\omega}_t$ is the $K \times 1$ signal- (or style-) weighting vector. The sign of the *i*th commodity allocation weight $\phi_{i,t}$ dictates the type of position (long or short). The element $\theta_{i,k,t}$ is the score assigned to the *i*th commodity futures contract according to the *k*th sorting signal (or style) at portfolio rebalancing time *t*. Alternative scoring schemes are plausible such as defining $\theta_{i,k,t}$ as the signals (appropriately standardized) or standardized rankings or binary long-versus-short signals {+1, -1}.

A key element in the integration is the style-weights vector $\boldsymbol{\omega_t} = (\omega_{1,t}, \ldots, \omega_{K,t})$ where the weight $\omega_{k,t}$ reflects the relative importance given to the *k*th individual investment style (or factor) in the integrated portfolio. The naïve EWI strategy assigns equal importance to the *K* styles, *i.e.*, $\boldsymbol{\omega_t} = \left(\frac{1}{K}, \ldots, \frac{1}{K}\right)'$, at each rebalancing time and thus it is parameter-free. Besides the EWI, various OIs have been deployed in the literature.

In an OI strategy the style-weight decision hinges on solving an optimization problem; namely, at each portfolio rebalancing time *t* the investor ought to find the weights that minimize or maximize a property of the style-integrated portfolio return distribution. For instance, quadratic utility or mean-variance maximization (MV), MV maximization with shrinkage (MVshrinkage), variance minimization (MinVar), diversification-ratio maximization (MaxDiv), power utility maximization (PowerU), PowerU with disappointment aversion (PowerDU) or on style-volatility timing (StyleVol); see, *e.g.,* Ledoit and Wolf (2003), Choueifaty and Coignard (2008), Brandt *et al*. (2009), Kirby and Ostdiek (2012) and Fernandez-Perez *et al*. (2019). A common denominator to these OIs is that albeit they can potentially discriminate better among the *K* styles because they allow for time-varying, heterogeneous exposures to the different styles, such an advantage can be largely contaminated by parameter estimation uncertainty.

The key idea behind the BOI method proposed by the authors is to mitigate uncertainty about the parameters describing the distribution of commodity returns by forming priors that are subsequently updated. Investors do not need to directly form a prior on $\boldsymbol{\mu}_t$, the $N \times 1$ commodity mean excess returns. They can instead harness their beliefs (or information) on the past relative performance of the styles to form a prior on $\boldsymbol{\omega}_t$ which can be mapped onto a prior for $\boldsymbol{\mu}_t$. Given the success of the equal-weight rule in portfolio allocation (DeMiguel *et al*., 2009) and in style-integration (Fernandez-Perez *et al*., 2019), the authors adopt $1/K$ as the informative prior for the mean of the distribution of $\boldsymbol{\omega}_t$ which is assumed Gaussian. A history of commodity excess returns over a window of L months is used to update the priors in order to obtain the posterior density of $\boldsymbol{\mu}_t$ using the Gibbs sampling approach that belongs to the family of Markov Chain Monte Carlo (MCMC) methods. With the posterior density of $\boldsymbol{\mu}_t$ at hand, the MV optimization problem is solved at each portfolio rebalancing time *t* to obtain the BOI style-weights $\boldsymbol{\omega}_t$.

Results

The authors carry out an empirical analysis of style-integration methods in the context of data for a cross-section of 28 commodity futures contracts from January 1992 to December 2021. Without loss of generality, the focus is on five fairly well-known commodity investment styles that exploit as predictive- or sorting-signals, respectively, the basis, hedgers' net short positions, momentum, skewness, and basis-momentum.

The naïve EWI strategy outperforms each of the standalone styles in terms of risk-reward (Sharpe ratio, Omega ratio, and Sortino ratio) and crash risk (semi-deviation, 99% Value-at-Risk, and maximum drawdown). This finding confirms the diversification benefits of style-integration. Another important confirmation result is that the naïve EWI portfolio is not challenged by any of the sophisticated OI portfolios.

The key novel evidence in this paper is that the BOI approach is able to significantly improve upon the challenging EWI benchmark. With a Sharpe ratio of 1.060, maximum drawdown of -0.174, and 99% of VaR of -0.051, the BOI portfolio is a more attractive proposition than any of the alternative OI portfolios, and also the challenging EWI portfolio as regards both reward-to-risk and crash risk profiles; see Table 1 on the next page.

Table 1
Performance of Commodity Style-Integrated Portfolios

		Optimized Style-Integrations (OI)							
	EWI	MV	MVshrinkage	MinVar	StyleVol	MaxDiv	PowerU	PowerDA	BOI
Panel A: *Static portfolio evaluation*									
Mean	0.080	0.054	0.051	0.075	0.082	0.083	0.052	0.052	0.092
StDev	0.101	0.094	0.094	0.084	0.102	0.096	0.093	0.094	0.087
Semi-deviation	0.272	0.258	0.258	0.209	0.275	0.248	0.258	0.262	0.212
Max Drawdown	-0.243	-0.297	-0.287	-0.158	-0.255	-0.219	-0.296	-0.296	-0.174
99% VaR	-0.061	-0.058	-0.058	-0.050	-0.062	-0.057	-0.058	-0.059	-0.051
Sharpe Ratio (SR)	0.815	0.606	0.577	0.904	0.823	0.886	0.588	0.587	1.060
Sortino ratio	1.393	1.012	0.960	1.677	1.400	1.566	0.976	0.970	1.987
Omega ratio	1.900	1.599	1.563	2.041	1.918	2.023	1.576	1.574	2.309
ΔSR (gain versus EWI)		-0.209	-0.239	0.089	0.008	0.071	-0.227	-0.229	0.245
Ledoit-Wolf test p-value		0.883	0.931	0.222	0.383	0.128	0.902	0.901	0.005
Opdyke test p-value		0.199	0.128	0.888	0.915	0.774	0.173	0.101	0.042
Panel B: *Dynamic Sharpe ratio (style ranking)*									
Jan 1992 - Dec 1997	1.108(7)	1.296(3)	1.107(8)	1.293(4)	1.103(9)	1.265(6)	1.278(5)	1.300(2)	1.373(1)
Jan 1998 - Dec 2003	0.999(4)	1.000(3)	0.860(8)	0.671(9)	1.002(2)	0.902(7)	0.923(6)	0.931(5)	1.005(1)
Jan 2004 - Dec 2009	1.115(2)	0.378(9)	0.464(6)	1.058(5)	1.113(3)	1.076(4)	0.411(7)	0.398(8)	1.314(1)
Jan 2010 - Dec 2015	0.979(4)	0.513(9)	0.604(6)	1.042(3)	0.977(5)	1.055(2)	0.547(8)	0.558(7)	1.180(1)
Jan 2016 - Dec 2021	0.193(5)	0.116(6)	0.089(7)	0.496(2)	0.194(4)	0.381(3)	0.081(8)	0.072(9)	0.583(1)

Notes: The table reports summary statistics for the excess returns of the equal-weight style integrated (EWI) portfolio and optimized style-integrated (OI) portfolios with the style-weight vector estimated at each portfolio rebalancing time by quadratic utility maximization (mean variance; MV), mean-variance with shrinkage maximization (MVshrinkage), variance minimization (MinVar), style-volatility timing (StyleVol), diversification-ratio maximization (MaxDiv), power utility maximization (PowerU), maximization of power utility with disappointment aversion (PowerDA), and Bayesian optimized integration (BOI). The length of the rolling estimation window is 60 months. The style-integrations are based on standardized signals as commodity scores. The reported mean and standard deviation are annualized. The hypotheses of the Ledoit and Wolf (2008) and Opdyke (2007) tests are $H_0: SR_i - SR_{EWI} \leq 0$ vs $H_A: SR_i - SR_{EWI} > 0$ where *i* is an OI strategy.

Panel A reports statistics over the full sample period January 1992 to December 2021. Panel B reports Sharpe ratios over 6-year non-overlapping subperiods and corresponding style-integrated portfolio ranking in parentheses.

Adding statistical significance to these results, the Ledoit and Wolf (2008) and Opdyke (2007) tests suggest at the 5% significance level or better that the Sharpe ratio of the BOI portfolio is notably larger than that of the naive EWI portfolio. These key findings are obtained both with fixed-length rolling windows of $L = 60$ months to determine the style-weights, and also with long estimation such fixed $L = 120$ months (rolling) or expanding windows starting from 60 months. Likewise, the superiority of the BOI portfolio survives the consideration of transaction costs and the use of alternative scoring schemes.

Conclusions

A large number of factor models have been suggested to explain returns in commodity markets. Forming a unique long-short portfolio with simultaneous exposure to mildly correlated risk factors is an intuitive "style diversification" idea but it requires a choice of style-weights at each portfolio rebalancing time. To date, the different sophisticated style-integrations attempted have not been as effective as the naïve equal-weights style integration. The reason is that, by contrast with parametric methods, the EWI is not contaminated by estimation risk. This paper develops a novel Bayesian optimized style-integration that alleviates estimation risk. Focusing on well-known commodity styles – basis, hedging pressure, momentum, skewness, and basis momentum – the authors provide evidence to suggest that the BOI portfolio significantly outperforms a battery of sophisticated OIs and the challenging EWI. The main take away of this research is that embedding extant OI methods into a Bayesian framework to account for estimation risk allows investors to harness multiple commodity factor exposures more efficiently towards capturing a larger and more resilient risk premium over time.

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A Trend Factor in Commodity Futures Markets: Any Economic Gains from Using Information over Investment Horizons?

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This paper identifies a trend factor that exploits the short-, intermediate-, and long-run moving averages of settlement prices in commodity futures markets. The trend factor generates statistically and economically large returns during the post-financialization period 2004-2020. It outperforms the well-known momentum factor by more than nine times the Sharpe ratio and has less downside risk. The trend factor is not encompassed by extant factors and is priced cross-sectionally. An analysis of macroeconomic and other market-wide drivers suggests that this trend factor is stronger in periods of low funding liquidity as measured by the TED spread. Overall, the results indicate that there are significant economic gains from exploiting the information content of long histories of commodity futures prices.

Introduction

Trend-following strategies have been widely used by commodity trading advisors (CTAs) and have received extensive attention from academics. Momentum, which utilizes intermediate-term trend signals (usually 6 months or 12 months), is one of the most extensively studied trend-following strategies in the literature (*e.g.*, Erb and Harvey, 2006; Miffre and Rallis, 2007; Moskowitz *et al*., 2012; Huang *et al*., 2020). Researchers also find evidence that the momentum factor is a priced factor and generates a significant risk premium cross-sectionally (e.g., Bakshi *et al*., 2019; Sakkas and Tessaromatis, 2020).

However, the momentum factor ignores short-term and long-term price signals, which also help predict commodity futures returns. For example, Han *et al.* (2016) find that 5-day moving average signals can outperform the buy-and-hold benchmark. A combination of short- and long-term trend signals can also be profitable. For instance, Narayan *et al.* (2015) find that multiple trading strategies based on the difference between the short- and long-term moving averages perform well. Bianchi *et al.* (2016) find that a double-sort strategy based on momentum and long-term reversal generates significant returns.

This paper studies the cross-sectional predictive ability of a composite trend signal that incorporates short-, intermediate-, and long-term trend signals in commodity futures markets. The authors evaluate the performance of the trend factor by comparing it with the traditional momentum factor (constructed from past 12-month cumulative returns) that also exploits cross-sectional predictability. We also use time-series and cross-sectional tests to examine the predictive power of the trend factor. Last but not least, we examine how macroeconomic and other market-wide variables affect the profitability of the trend factor.

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.

The sample period for the analysis is January 2004–December 2020 intentionally because since 2004, speculators (financial institutions and individual investors with no physical exposure to the underlying commodities that trade commodity futures to capture a risk premia) have increased their participation in commodity futures markets. This phenomenon is referred to as the "financialization" of commodity futures (*e.g.*, Tang and Xiong, 2012; Basak and Pavlova, 2016). Algorithmic trading has also gained prevalence.[1] Researchers find that during the post-financialization period, commodity futures markets have been more liquid and have experienced increasing speculative trading (e.g., Gong *et al*., 2021). The highly liquid commodity futures markets during the post-financialization period make the proposed long-short trading strategy more feasible. A further motivation for focusing on the most recent decade is that many factors in the stock market have attenuated in recent years because of increased turnover and liquidity (referred to as "factor crowding"); for instance, the average return of long-short momentum portfolios becomes insignificant after 2001 (Chordia *et al*., 2014).

The paper confirms that the well-known momentum factor has also disappeared in commodity futures markets during the sample period, but the trend factor remains strong. The results suggest that the trend factor performs better when there is lower funding liquidity (as suggested by a wider TED spread) and thus, factor arbitrage is more costly. Kang *et al*. (2021) find that an increase in arbitrage costs (measured both by the TED spread and the repo rate) makes factors less crowded and increases factor returns. Correspondingly, a larger TED spread hinders commodity futures trading strategies based on the trend factor and increases the corresponding return. Our results thus indicate that commodity futures can be attractive alternative assets when funding liquidity in the credit market is low.

Relevance of the Research Question

The research question is important as it relates to ongoing debates about using commodity futures as investment assets, common risk factors in commodity futures markets, and factor crowding. The new trend factor identified by the authors that outperforms the well-studied momentum factor and is not subsumed by extant factors in commodity futures markets ought to be of interest to commodity futures market participants, speculators predominantly but also selective hedgers, and more generally for empirical asset pricing. This is the first study to apply the Han *et al.* (2016) method to commodity futures markets, which jointly considers the short-, intermediate-, and long-term trend signals. The paper contributes to the literature on the source of predictability of trend-based trading strategies by identifying a link between funding liquidity and the profitability of the trend factor.

Data and Methodology

The empirical analysis is based on settlement prices, aggregated open interests, and commercial traders' long and short positions of 35 commodity futures from Bloomberg that cover four main sectors: agriculture (grains and softs), energy, livestock, and metal. There are 8 grains futures (soybean oil, corn, Kansas wheat, oats, rough rice, soybean, soybean meal, wheat), 8 softs futures (cocoa, cotton, ethanol, milk, orange juice, coffee, lumber, sugar), 3 livestock futures (feeder cattle, live cattle, lean hogs), 6 energy futures (WTI crude oil, heating oil, natural gas, gasoline, Brent crude oil, gas oil), and 10 metal futures (aluminum, copper, gold, lead, nickel, palladium, platinum, tin, silver, zinc) in the sample.

The methodology closely follows Han *et al.* (2016). The authors first calculate moving averages (MA) of past settlement prices from 3 days to as many as 600 days (roughly three trading years) for each commodity futures contract. They then run sequential cross-sectional regressions for monthly returns on the different normalized moving averages over a past 5 years. The expected returns for each commodity futures are then obtained as the expected coefficient of the short-, medium- or long- MA signals (where the expectation is proxied by the 60-month window average of the sequential cross-sectional regression coefficient estimates) multiplied by the corresponding commodity-specific normalized moving averages. The trend factor is then constructed by taking long positions in the commodity futures with the highest expected returns and shorting those with the lowest expected returns to exploit cross-sectional predictability.[2] The commodity futures are equally weighted in the long and short portfolios.

The authors conduct time-series and cross-sectional tests to assess whether multifactor models can explain the performance of the trend factor. These include multi-factor models based on portfolio sorts, GRS tests, Fama-MacBeth regressions and panel regressions. To explain the source of predictability of the trend factor, the authors regress the trend factor contemporaneously on the monthly growth rate in industrial production, default spread, term spread, CBOE Volatility Index, liquidity (the TED spread), various stock market factors, and the Baker and Wurgler (2006) investor sentiment proxy.

Main Results

The annualized mean return of the trend factor from January 2004 to December 2020 is 17.19% which is both economically and statistically significant at the 1% level. By contrast, the annualized mean of the well-known momentum factor is 1.9% and is statistically insignificant. Time-series pricing tests reveal that the return of the trend factor cannot be explained by the benchmark multifactor models as borne out by significant risk-adjusted returns (or alphas) of the trend factor. For example, the annual alpha with respect to the Sakkas and Tessaromatis (2020) six-factor model is 15.96% (1.33%×12=15.96%). The GRS tests provide additional support in a joint-regression setting, with F statistics rejecting the null hypothesis that the alphas of the trend portfolios are jointly equal to zero. Additionally, two-pass cross-sectional regressions suggest that the trend factor is priced cross-sectionally. Overall, the results show that the trend signal contains predictability for the cross-section of commodity futures returns.

Multivariate regressions of the trend factor on macroeconomic and other market-wide variables suggests that the TED spread is a significant driver at the 5% level with a positive coefficient. This indicates that when the TED spread is large, there is lower funding liquidity in the credit market which increases arbitrage costs, the trading of the trend factor decreases and the profitability of the trend factor becomes greater. This is in line with the argument in Kang *et al*. (2021) that an increase in arbitrage costs (measured by the TED spread and the repo rate) makes factors less crowded and increases factor returns.

Conclusions

In this paper, the authors put forward a trend signal constructed from the short-, intermediate-, and long-run moving averages of settlement prices in commodity futures markets. A long-short portfolio analysis reveals that the trend strategy proposed outperforms the well-known momentum strategy by generating statistically and economically larger excess returns and exhibiting less downside risk. Time-series and cross-sectional pricing tests suggests that the trend factor is not subsumed by other extant factors such as the slope of the term structure (or basis), hedging pressure, basis-momentum, and value. Overall, the results indicate that long histories of futures prices contain important predictive information for the cross-section of commodity futures returns.

Endnotes

1 See Haynes and Roberts (2019).

2 A time-series trading strategy involves taking positions based on the security's own past returns. In contrast, the positions in a cross-sectional trading strategy are based on the relative performance of securities. See Goyal and Jegadeesh (2018) for a detailed examination of the difference between time-series and cross-sectional tests of predictability. Miffre (2016) also has an excellent summary of the trend literature categorized by the time-series and cross-sectional tests.

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The Hedging Pressure Hypothesis and the Risk Premium in the Soybean Reverse Crush Spread

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This article develops a theory of multiproduct hedging which serves to formalize Keynes's hedging pressure hypothesis that the need to attract speculative capital to match hedgers' trades creates a difference between the futures and expected maturity price. The authors test the theory empirically in the context of the soybean complex which has speculators and hedgers in soybeans, soybean meal and soybean oil. The focus is on the crush spread because it is unlikely that hedgers will want to make simultaneous trades on the opposite side of soybean crushers in all three markets. The findings reveal that there is a significantly positive return to speculators for providing this liquidity.

Introduction

Keynes (1930) postulated that hedgers in futures markets ought to compensate speculators for bearing the risk of price movements. This compensation, also referred as risk premium, if it exists, suggests that the futures contract price deviates from the expected maturity price. There is little consensus in the literature regarding the existence of hedging pressure, in part because it is impossible to know the expected maturity price.

Soybean processors buy soybeans, crush them, and sell the resulting soybean meal and oil. The soybean "crush" thus represents the price difference between the appropriately weighted value of the soybean meal and oil futures, and the purchase of soybean futures, in other words it is a forward-looking measure of their expected margin. They can hedge this margin by buying soybean futures and selling oil and meal futures. Soybean processors commonly use this soybean crush spread as a hedge. Speculators can take "reverse crush" positions, long oil and meal and short soybeans, in order to take advantage of a potential risk premium paid by the crusher. There is no prior research examining whether the soybean crush spreads exhibit properties consistent with the hedging pressure hypothesis. This would happen if the speculators, who routinely take the reverse crush make consistent positive profits, i.e., earn a risk premium. The purpose of this paper is to determine if these profits exist.

Why the Paper's Research Agenda is Important

The price risk insurance role of futures markets remains a controversial debate. The authors contend that the crush spread is an ideal "laboratory" to test the hedging pressure hypothesis for five distinct reasons.

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.

First, the spread itself is small relative to the underlying soybean price. A one- or two-cent risk premium might be detectable in the spread even if undetectable in the flat price of soybeans. Second, when crushers place their hedges in the relevant futures they buy soybeans, pushing their input prices up, and sell oil and meal, thereby putting downward pressure on their output prices. In both cases, their activity works to reduce the crush spread (increase the reverse crush) as measured in the futures markets. Third, crushers have information about the equilibrium size of the spread, which may come from measuring the historic spread for each month or by measuring the average fixed costs that the spread is covering. The appropriate size of the spread is not relevant to those who hedge or speculate in only one of the markets. Therefore, crushers can respond quickly to market conditions that provide them with a favorable spread. Conditions that are favorable to one crusher might lead other crushers to place similar spreads. Fourth, commodities such as corn and soybeans have natural longs and shorts. With natural hedgers on both sides of the market, it is hard to separate hedging pressure from other market forces. Any other market participant is very unlikely to *simultaneously* take the opposite side of the soybean crush for hedging purposes. On days when crushers place large hedges, having natural hedgers in all three underlying futures markets to offset the crush hedge is unlikely. Instead, speculative capital may be needed to provide liquidity in one or more markets; and incentives to attract speculative capital are what may allow us to detect the risk premium.

Theoretical Framework

Each of the three underlying futures markets studied does have natural hedgers on the opposite side of the crusher, which motivates the authors to develop a general theory of how producer-hedgers, processor-hedgers, and speculators in all three markets interact. The authors setup a model under just two types of players – a soybean producer (farmer) and a speculator. They initially leave out the commodity processor because this may take the opposite side from the producer. The speculator serves to clear the futures market by taking the opposite of the producer's desired short position. Net they set up a model in a more realistic scenario with producers, processors and speculators.

The theoretical framework suggests that without the offsetting positions from producer-hedgers, crushers will pay a risk premium to hedge the crush spread. Since there is no natural hedger for the reverse crush, they authors hypothesize that passively taking the reverse crush will yield significant positive returns.

Empirical Analysis

They authors test the aforementioned hypothesis by calculating sample moments of the returns of the soybean reverse crush spread. The main data are futures prices for soybean, soybean meal and soybean oil from *Barchart*. The key control variable is the carryover, which measures the available crop on December 1st from the United States Department of Agriculture to account for both the ending stocks from the previous marketing year as well as the new crop.

To execute a soybean crush hedge, the crusher sells 9 contracts of soybean oil, 11 contracts of soybean meal, and buys 10 contracts of soybeans. This "9-11-10" spread closely replicates the proportions governed by the soybean crushing technology (less 10,000 lbs out of 550,000 lbs of soybean oil, which is left unhedged). Thus, we calculate the reverse crush spread (*rcs*) in month $j < J$ maturing in month J as:

$$rcs_{\mathrm{j},J} \equiv \log(2.2 * meal_{j,J} + 10.8 * oil_{j,J}) - \log(soybean_{j,J}) \text{ with } J = 1,3,5,7,9,11 \qquad (1)$$

The excess return of the soybean futures reverse crush spread is obtained as $\Delta rcs_{\mathrm{j},J} \equiv rcs_{J-1,J} - rcs_{\mathrm{j},J}$ with the reverse crush trade closed one month prior to the maturity month to avoid liquidity and calendar date problems in months when contracts expire.

Table 1 provides details on the average return of the reverse crush spread by contract maturity from 1962 to 2019. There is evidence of a risk premium—the November soybean futures crush spread price with more than three months to maturity overestimated the realized crush margin by approximately 1.5%. The crush spread per bushel of soybeans purchased is typically 20% of the price of one bushel, which, for $10 per bushel soybeans, corresponds to $2 per bushel used. A 1.5% reverse crush margin means that the crusher is paying about $0.03 per bushel crushed and appropriately hedged.

Table 1
Reverse Crush Spread Return by Contract Maturity and by Month to Maturity, 1962–2019

	Holding Period (month)									
Maturity Month	1	2	3	4	5	6	7	8	9	10
Jan	0.004	0.008	0.014	0.015	0.017	0.018	0.018	0.021	0.023	0.021
Mar	0.000	0.000	0.003	0.005	0.010	0.010	0.011	0.013	0.013	0.016
May	0.001	-0.001	0	0.001	0.002	0.004	0.007	0.007	0.007	0.010
July	0.000	0.002	0.004	0.001	0.001	0.003	0.003	0.005	0.009	0.005
Sep	0.005	0.008	0.005	0.007	0.010	0.010	0.011	0.012	0.009	0.005
Nov	0.008	0.010	0.013	0.014	0.013	0.015	0.018	0.018	0.017	0.012

Note: The reverse crush spread is closed one month prior to the maturity month, thus we construct the January reverse crush spread using January contracts closed in December of the preceding year. The November reverse crush spread consists of the November soybean contract and December contracts of soybean meal and oil. The November reverse crush is closed in October.

The sample averages for different maturity and duration combinations are overwhelmingly positive. If the futures forecasts are truly unbiased with equal probability of over- and under-predicting the realized spot prices in a given month, then the Bernoulli probability of observing 59 positive forecast errors out of 60 is very small at $\frac{1.73}{10^{18}}$.

Table 2 summarizes the reverse crush spread by contract maturity of the returns with less than 12 months to maturity. The skew is positive for contracts maturing in January, March, May and November. Chen's (1995) upper-tailed test for the mean of positively skewed distributions indicates these sample averages are significant at the 1% level.

Table 2
Summary Statistics of Reverse Crush Spread Return

	Maturity Month					
	Jan	Mar	May	Jul	Sep	Nov
Mean	0.0157***	0.0080***	0.0038***	0.0033	0.0083	0.0137***
(p-value)	<0.0001	<0.0001	0.0003	\	\	<0.0001
Median	0.0102	0.0019	-0.0001	0.0019	0.0084	0.0099
Std. Dev	0.0354	0.0363	0.0279	0.0272	0.0244	0.0254
Min	-0.0692	-0.0551	-0.0738	-0.1197	-0.0608	-0.0493
Max	0.1443	0.1991	0.1489	0.0838	0.0795	0.0876
Skewness	0.8774***	2.5297***	1.6973***	0.0510	0.1626	0.4894***
(p-value)	<0.0001	<0.0001	<0.0001	0.6221	0.1210	<0.0001
Excess Kurtosis	4.1284***	12.7040***	9.3400***	4.2315***	3.2514	3.0825
(p-value)	0.0002	<0.0001	<0.0001	0.0001	0.2159	0.5939

Note: The table reports statistics for the reverse crush spread of different maturities with less than 12 months to maturity. The sample period is 1962 to 2019. p-values are reported for the mean, skewness, and excess kurtosis are reported. Asterisks denote significance levels as follows: *10%; ** 5%; and ***1% significance.

Conclusions

In this paper, the authors start by arguing that the crush spread represents an ideal laboratory to test Keynes's hedging pressure hypothesis. They develop a general equilibrium model that includes speculators, producer hedgers, commodity processor-hedgers, and hedgers who take the opposite side of the processor in the output market. Testing hypothesis that arise from the model, they provide evidence of hedging pressure in the soybean reverse crush spread. The size of the spread is modest – about $0.03 per bushel hedged – relative to whole soybean prices. This modestly sized risk premium, coupled with a lack of information on what the true expected maturity price is in other futures markets, may explain why support for Keynes's hedging pressure hypothesis has proven so elusive. The results suggest that in markets where net hedging is long, the futures prices will be biased upwards. The opposite is true in markets where net hedging is short. The implications for traders in the soybean pits is that there is likely a small negative bias in new crop soybean futures and a small positive bias in meal and oil futures.

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