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"FROM THEORY TO PRACTICE: MYTHS AND MYSTERIES ABOUT SPECULATION IN THE OIL MARKET"

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From Theory to Practice: Myths and Mysteries About Speculation in the Oil Market

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The article provides unique quantitative insights about highly secretive and poorly understood speculation in the oil market. To demystify the behavior of speculators, we look at the problem from several different angles. First, we explain how the presence of the large over-the-counter (OTC) oil derivatives market leads to mischaracterization of traditional hedgers and speculators. We then explain what makes oil speculation special and different from speculation across many other commodities. Consequently, we identify the winners and the losers in the oil futures market. To model the behavior of the winners which we associate with fast-moving quantitative hedge funds, we develop a novel framework based on a simple neural-network algorithm. We conclude by analyzing a popular investment strategy of following the winners, or the hedge-funds', flows.

Introduction

Ever since the oil market was born, speculation has been an integral part of it. This fact is undeniable, regardless of our wishes, beliefs, or the limitations of conventional empirical methods used to detect it. So why is speculation so difficult to observe? One challenge is the limited access that academic researchers have to timely and relevant data, coupled with an incomplete understanding of the motivations driving many market participants. Another is the reluctance of professional traders to share insights, given the proprietary nature of their trading strategies. This article aims to bridge that gap.

The conventional framework of modelling speculation in commodity markets relies on futures positioning data provided by regulators in the form of the so-called Commitments of Traders (COT) reports. Various versions of COT reports have been in existence for agricultural commodities since the 1920s. Their primary objective is to differentiate between futures and options positions held by hedgers and speculators, which were labelled as commercial (COM) and non-commercial (NC) traders. The presumption is that the COM traders deal with the physical commodity and represent hedgers. In contrast, the NC traders do not handle physical deliveries, thus they are deemed to be speculators.

While this simple categorization may be adequate for certain commodities, it has proven to be of limited value for analyzing participants in a more complex ecosystem of the oil market where speculation and hedging are more intertwined. For example, sophisticated commercial traders that own or lease physical assets, such as storage, pipelines or oil tankers, are also known to be large speculators, as they aim to leverage an informational edge obtained from their ownership of assets. Vice versa, some non-commercial financial investors, which are typically labelled as speculators, often hold oil futures as a hedge against inflation and geopolitical risks for their broader financial portfolios. Finally, in contrast to many other commodities, oil has a large over-the-counter (OTC) market where oil producers and consumers hedge their price exposures, whereas futures are effectively held on their behalf by dealers classified as commercial traders.

Ilia Bouchouev, Ph.D (front row center in the light blue shirt), lectured at Bayes Business School (U.K.) on June 12, 2024. Dr. Bouchouev's workshop covered "Quantitative Trading in the Oil Market." He is the Managing Partner of Pentathlon Investments LLC (U.S.A.) and an Editorial Board member of the *Commodity Insights Digest*.

In an attempt to provide more transparency, the U.S. Commodity Futures Trading Commission (CFTC) revamped the format of its positioning reports. Starting in 2006, the COM category was split into two new subgroups: producers, merchants, processors, and users (PMPU); and swap dealers (SD). The NC category was also split into managed money (MM) and other (OTH) category. These reports became known as the Disaggregated Commitments of Traders (DCOT) reports. While this decomposition brought clarity for many commodities that lack large OTC markets, DCOT reports have not resolved the problem of participant identification in the oil market. In fact, they may have introduced even more confusion by effectively mislabeling some of the largest traders in the market.

The explicit reference to producers under the PMPU category only reinforced the incorrect association between genuine oil producers and the perception of their hedging activity. Since actual hedging by producers occurs predominantly OTC via bilateral agreements with their banks, any evidence of producer hedges typically appears in the SD category. In contrast, the PMPU label in the oil market has become something of a misnomer, as this category is, in reality, still dominated by highly sophisticated physical oil traders who have acquired physical assets primarily to enhance their speculative activity.

In theory, one can deduce some useful information about producer hedging by analyzing the SD category instead, as swap dealers trade with producers OTC and then offset their risks in the futures market. However, swap dealers manage fairly diverse portfolios. They also hold long futures positions as hedges against OTC agreements with consumer-type clients, such as airlines and utilities. More importantly, they also hold long futures positions against OTC commodity index swaps with pensions funds, insurance companies and other financial investors. Long futures positions held on behalf of investors by dealers tend to offset their short positions held on behalf of producers. This makes the SD category a "catch-all" bucket with rather limited informational value.

The DCOT reports did provide some helpful granularity for positions held by non-commercial traders, often associated with financial speculators. To characterize this non-homogeneous group, it is helpful to split it into three types of speculative activity.

The first group consists of large institutional investors who hold oil derivatives as part of diversified investment portfolios. Their positions are predominantly long, as they seek to hedge against inflation risk. While some investors hold futures directly, others prefer to gain exposure to commodity prices through OTC swaps with banks – similar to how oil producers hedge. As a result, the positions held by these so-called passive investors may appear either in the MM category if they trade futures directly or in the SD category if they transact OTC and futures are reported by dealers. The exact split between these two channels is difficult to estimate due to minimal reporting requirements and the highly confidential nature of bilateral OTC transactions.

The second – and likely the most influential – group of non-commercial speculators in today's oil market comprises quantitative hedge funds, or commodity trading advisors (CTAs). These funds rely heavily on algorithmic trading, executing strategies based on quantitative models with little or no human intervention. Quantitative funds have seen tremendous growth over the past decade with the proliferation of new data sources and the continued digitalization of financial markets. Unlike passive investors, CTAs adjust their oil positions rapidly, often contributing to significant short-term price fluctuations. Arguably, this group has become the largest driver of short-term oil prices, and shedding light on their behavior is one of the primary objectives of this paper.

The third category of speculators consists mostly of discretionary traders, including many retail investors. Fortunately, the DCOT reports – while not particularly helpful in clarifying the roles of commercial traders and hedgers – have proven more useful in understanding speculators. Since the nature of oil speculators reported under the NC category is highly heterogeneous, the added granularity provided by the DCOT reports has offered some valuable new insights which we build upon in the following section.

Who are the Winners and Losers in the Oil Futures Market?

Many academic studies of the behavior of participants in commodity markets revolve around the Keynes-Hicks theory of "normal backwardation."[1] This theory asserts that commodity futures market are naturally in disequilibrium as hedging needs of commodity producers structurally exceeds those of commodity consumers. Thus, futures prices must trade at the discount to expected spot price. This discount then provides incentives to speculators to take the other side of the imbalanced futures market. Speculators are then expected to realize gains over time by buying and holding commodity futures.

Given the very convoluted nature of hedging and speculation in the oil market, it should not come as a surprise that this theory does not hold well in the oil market. To illustrate, we take actual weekly positions held by trader groups and calculate their annualized profit and loss (P&L) and the annualized standard deviation (STDEV) of P&L directly in dollar terms. We then use the ratio of the two to measure risk-adjusted performance, similar to the Sharpe ratio (SR).[2] In contrast to many academic studies that use somewhat ambiguous measures of futures returns and normalized measures of speculative and hedging pressure in the context of broader commodity portfolios, our direct P&L-based approach highlights the magnitude of gains and losses and uses metrics commonly employed by traders in the oil market.

We compute these realized performance metrics for the two legacy categories – NC and COM traders in COT reports – as well as for the four participant categories in the DCOT reports. For benchmarking purposes, we include the results of a static rolling long position of 100,000 contracts (equivalent to 100 million barrels).

We use WTI data from June 2006 to June 2024 and Brent data from January 2011 to June 2024, corresponding to the availability of DCOT reports published by the CFTC and ICE, respectively. To enable a direct comparison of the behavior of traders across both markets over the same period, we also present results for WTI for a shorter sample aligned with the Brent DCOT data availability. We assume all trades are rolled to the next futures maturity at the end of each calendar month. Table 1 illustrates our results.

Table 1
Profitability of Different Groups of Traders

	COM	NC	PMPU	SD	MM	OTH	MM-SLOW	MM-FAST	STATIC LONG
a) WTI (2006-2024)									
Annualized P&L	112,747,800	(148,577,800)	266,499,600	(153,751,800)	341,154,900	(489,732,700)	(178,515,000)	519,669,900	(165,550,800)
STDEV	7,883,983,000	7,312,810,000	3,192,569,000	7,871,738,000	4,760,920,000	3,044,494,000	4,847,470,000	1,103,688,000	2,577,695,000
Sharpe Ratio	0.01	(0.02)	0.08	(0.02)	0.07	**(0.16)**	(0.04)	**0.47**	(0.06)
b) BRT (2011-2024)									
Annualized P&L	(42,994,600)	(42,206,220)	(437,904,500)	394,909,900	881,772,700	(923,978,900)	106,674,900	775,097,800	39,088,280
STDEV	2,972,062,000	2,773,672,000	9,253,212,000	7,117,329,000	5,021,280,000	3,269,173,000	5,387,889,000	1,444,252,000	2,386,923,000
Sharpe Ratio	(0.01)	(0.02)	(0.05)	0.06	0.18	**(0.28)**	0.02	**0.54**	0.02
c) WTI (2011-2024)									
Annualized P&L	487,986,700	(425,292,900)	616,907,000	(128,920,400)	64,177,990	(489,470,900)	(630,074,000)	694,252,000	(264,411,800)
STDEV	8,986,299,000	8,350,252,000	2,617,513,000	8,932,683,000	5,258,862,000	3,482,721,000	5,396,155,000	1,162,292,000	2,430,607,000
Sharpe Ratio	0.05	(0.05)	0.24	(0.01)	0.01	**(0.14)**	(0.12)	**0.60**	(0.11)

Since futures trading is a zero-sum game, does this mean that no participants consistently make or lose money and that there are no structural biases driven by the behavior of specific market participants? This is not necessarily the case. To answer this, we need to dig a little deeper to untangle the complex puzzle of trader behavior. In order to derive more meaningful conclusions about the behavior of various market participants – particularly speculators – one approach is to segment them based on trading frequency.

The idea of classifying traders according to how frequently they trade and how long they hold positions is not new. For example, Kang *et al.* (2020) applied this approach to study the elusive Keynesian risk premium across a diversified portfolio of commodities. They concluded that hedgers and speculators provide liquidity to each other on different time scales: in the short term, speculators consume liquidity and pay a risk premium to hedgers; in the long term, speculators tend to collect the risk premium paid by hedgers. We applied the results of their study specifically to the oil market. While we found some evidence of a short-term liquidity risk premium paid by speculators during the earlier period of oil futures trading, this phenomenon appears to have diminished over time. We also confirmed that the long-term hedging premium in oil is statistically insignificant.

Our approach is instead to decompose the crucial MM (managed money) category into MM-SLOW and MM-FAST. MM-SLOW is defined as the three-month moving average of MM positions, while MM-FAST represents the residual – capturing faster trading positions established relative to the three-month average baseline. The decomposition of the MM category into fast and slow components is essential. It allows us to use MM-SLOW to proxy the behavior of passive investors and MM-FAST to represent more dynamic trading by quantitative hedge funds. Notably, the average of MM-FAST positions is approximately zero, reflecting the typical long-short trading patterns of quantitative hedge funds, which are just as likely to be long as short. This also removes the influence of any price bias in the sample.

One can see that neither COM nor NC traders consistently generate profits. This confirms our earlier observation about the absence of any structural hedging or speculative risk premia in the oil market. Furthermore, even when the data are disaggregated into the four DCOT categories, none of the groups consistently produce attractive profits. Their individual Sharpe ratios are economically insignificant.

However, the further segmentation of MM traders into MM-SLOW and MM-FAST reveals a more compelling insight. The performance of MM-FAST – our proxy for the trading behavior of quantitative hedge funds – is notably profitable. On average, MM-FAST traders generate a relatively high Sharpe ratios between 0.47 and 0.60. This highlights that profitable trading opportunities in the oil market tend to be short-lived and cannot be captured by passive investment strategies seeking structural risk premia. For a more detailed discussion of the behavior of other traders, we refer to the full text of the article.

What is clear from the results in Table 1 is that quantitative funds – represented by MM-FAST – possess unique skills that other participants do not. They are able to apply these skills consistently to generate highly significant risk-adjusted returns in both the WTI and Brent markets, regardless of the price bias in the sample. In the next section, we explore what these elusive skills might be – and whether a more casual oil trader can, in some way, replicate their behavior.

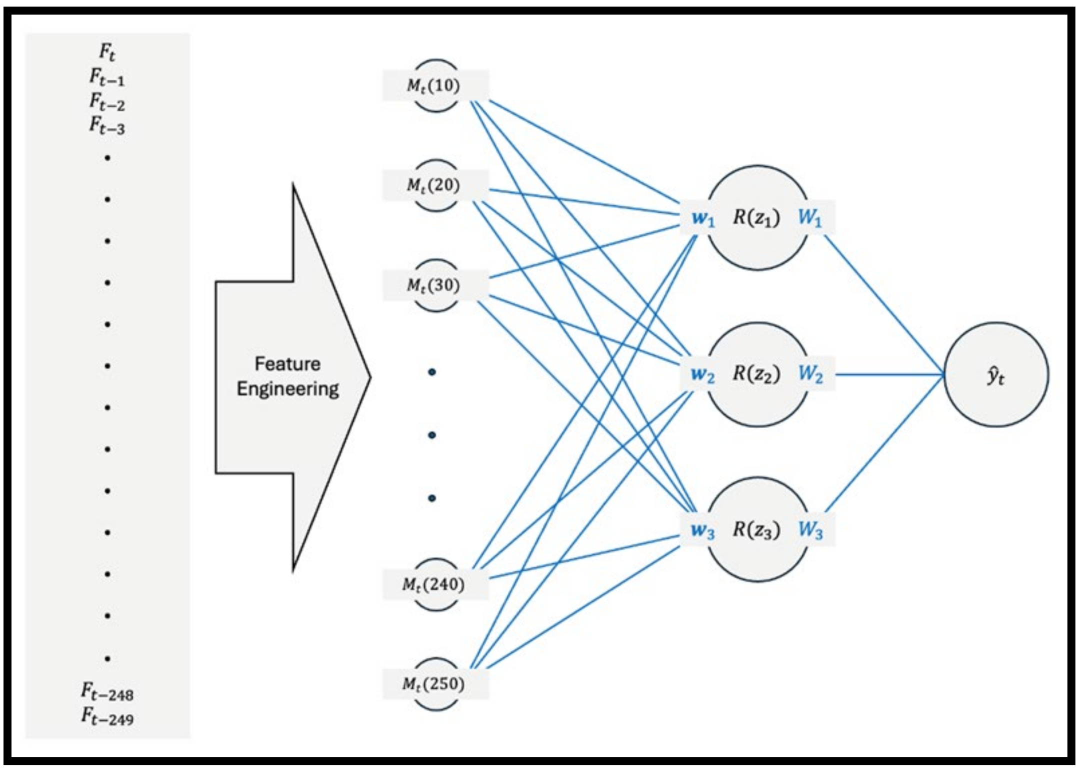
How Can One Replicate the Strategy of the Winners?

In this section, we show how the behavior of quantitative hedge funds can be effectively replicated. It is well known that many quantitative funds favor various momentum strategies, but the exact details of these strategies – especially the dynamic sizing of their positions – remain highly confidential. Obviously, we cannot reconstruct individual hedge funds' trading frameworks, but we demonstrate that valuable insights can be gained about their collective behavior.

This problem is particularly well suited for the application of a mathematical technique known as a neural network. In this framework, historical prices serve as inputs or features, and quantitative funds can be interpreted as neurons, which are activated through a nonlinear function. The process of training the neural network is effectively a form of reverse-engineering the decision-making behavior of hedge funds.

The overarching goal of the neural-network framework is to construct a nonlinear function, $y = f(x)$, that maps the vector of inputs x (known as features) into another vector of observable outputs y (the target). In our case, the features are historical oil prices or some combination of them, and the target is the futures position held by MM-FAST traders at a given time. Since quantitative hedge funds favor momentum-based trading, we use moving averages of prices to construct momentum signals and use those signals as input features – a process known as feature engineering. Figure 1 illustrates our neural network schematically.

Figure 1
The Neural-Network Representation of Momentum Trading

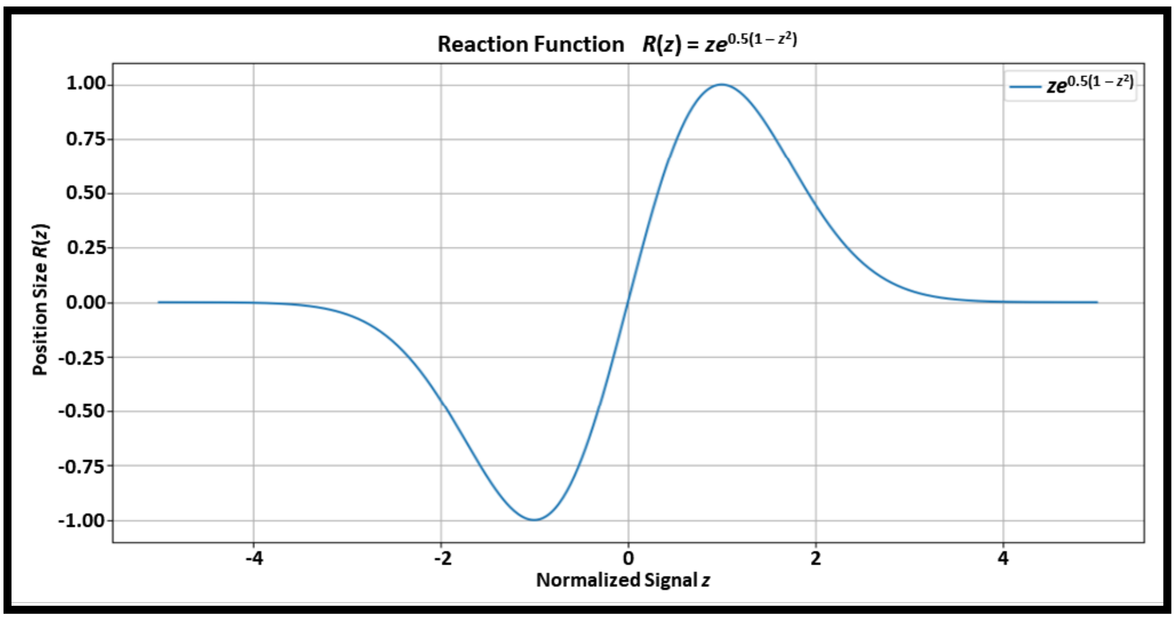


This neural network mimics the behavior of quantitative hedge funds extremely well. In fact, one could even argue that what hedge funds do in practice is a classical definition of a neural network. First, the prices are "re-engineered" into moving averages which are used to construct the momentum signals. Then various linear combinations of basic momentum signals are constructed to form several nodes. The nodes are called neurons, and such construction is designed to mimic the functioning of a human brain. In our diagram, we use three neurons, indexed as $k = 1,2,3$, and the input to each neuron generated by the weighted combination of the basic momentum signals is denoted by z_k. One can think about our network as a representation of an industry aggregate hedge fund trading a portfolio of momentum strategies on three different frequencies.

The incoming weights for each of the three neurons $w_{k,n}$ depend on 25 momentum signals $M_t(n)$ where $n = 10,20, \dots, 250$ refer to the lookback period.[3] In other words, momentum signals could be understood as a vector of 25 features. These linear combinations of features form the so-called hidden layer. In our example, we only use one hidden layer with three neurons. More complicated networks typically contain more neurons and multiple hidden layers. However, with one hidden layer, the neurons can be interpreted as quantitative hedge funds focusing on momentum signals with three different frequencies, the practice commonly adopted in the industry.

The next step in the neural network is to "activate" the neurons by applying some nonlinear function that acts upon certain thresholds. This is analogous to how hedge funds determine the size of their trading positions. In the trading language, such a neuron-activation function is more commonly known as the "reaction" function. Following Bouchouev (2023), we use the reaction function $R(z)$ shown in Figure 2.

Figure 2
An Example of a Reaction Function



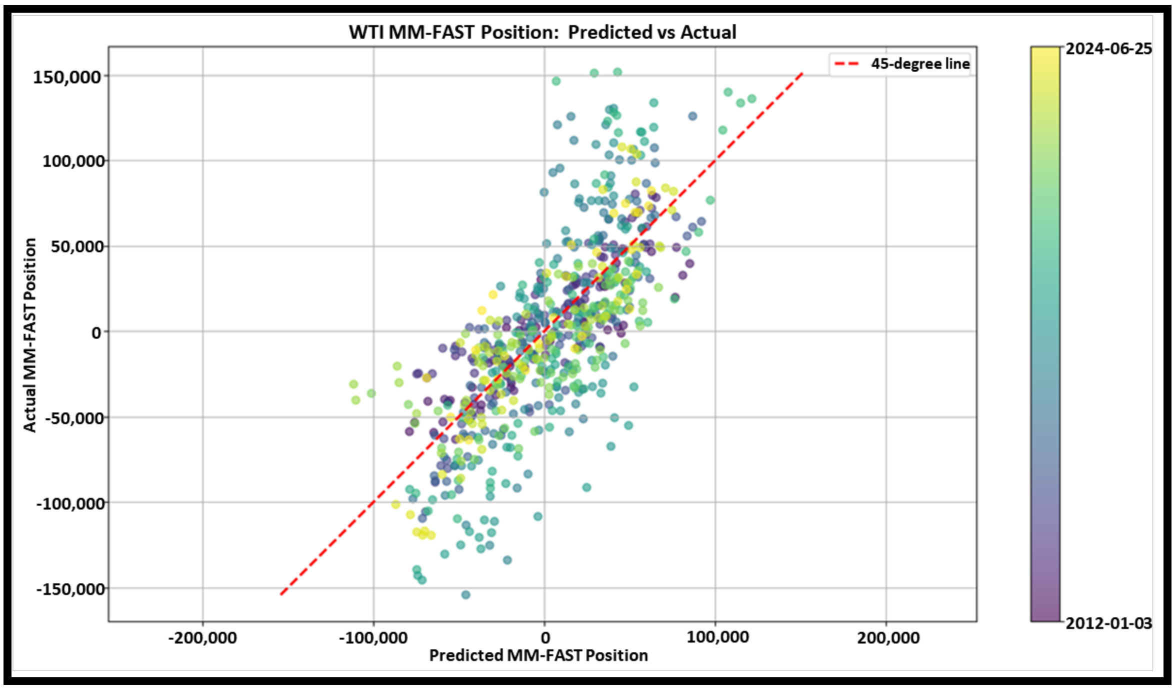
We apply the same reaction function to all three neurons. This function transforms the variable z, which represents a linear combination of momentum signals into the scale of $(-1, +1)$ and determines the size of the position as a percentage of the maximum budget allocation to the strategy.

The linear combination of transformed features produces the target forecast $\hat{y}_t$ for the normalized MM-FAST positions, where we use the hat notation to indicate that this variable is an estimate. The forecast $\hat{y}_t$ is then compared to the target y_t which represents the actual but also normalized futures positions held by MM-FAST. The network is trained by searching for incoming weights $w_{k,n}, k = 1,2,3, n = 10,20, \dots, 250$

and outgoing weights $W_k, k = 1,2,3$, which jointly minimize the difference between the forecast $\hat{y}_t$ and the target y_t. To improve the stability of the process, we apply a regularization technique to the minimizing cost function.

Figure 3 shows the results for the WTI market, which compare MM-FAST positions generated by our neural network to their actual positions.

Figure 3
Predicted Versus Actual MM-FAST Positions in the WTI Market



The model, based on this simple neural-network framework, produces a relatively high R^2 of 0.56, meaning that approximately half of the variance of hedge fund positions can be explained with technical, price-based momentum indicators. The results for Brent are remarkably similar, confirming the robustness of the method. This motivates our interpretation of the model-captured component as systematic, or quantitative, trading, with the residuals representing discretionary trading. In the main text of the paper we use this approach to separate positions held by systematic and discretionary traders and further analyze the time-series dynamics of their model-calculated positions.

Does the Behavior of Speculators Predict Futures Prices?

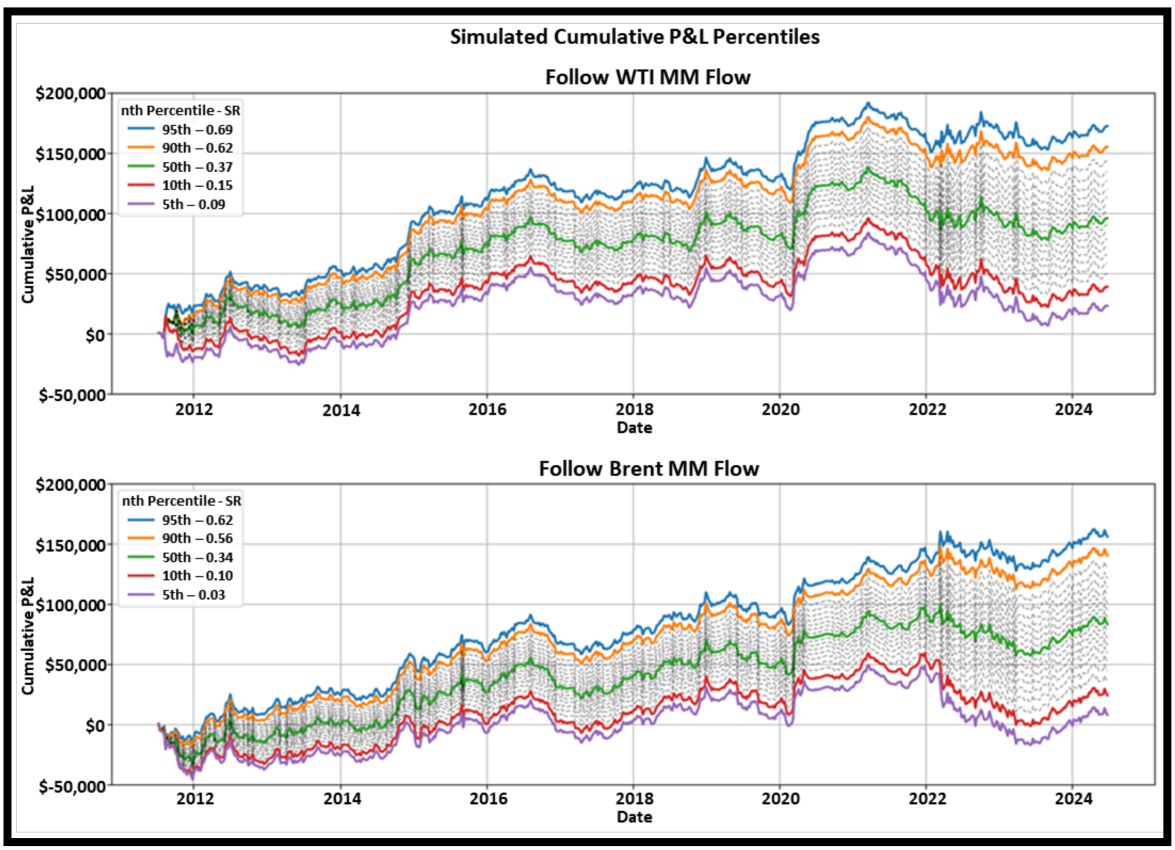
In keeping with the practical approach of this study, the metric we use for price forecasting is the economic performance of a trading strategy that buys and sells futures based solely on past positions held by speculators. Specifically, we analyze a popular investment strategy known as "following the flow" or "following the smart money."[4] This strategy assumes that hedge funds represent the "smart money," and that other investors may benefit by mimicking – as closely as possible – the actual positions held by these informed participants. In other words, investors would buy or sell oil futures as soon as it becomes known that the "smart money" had previously bought or sold contracts.

Having already observed the importance of moving averages of prices in explaining the behavior of "smart money," we now reverse the logic – following standard industry practices – and apply the crossover of moving averages to the actual positions held by MMs to assess whether they can generate price-forecasting signals.

However, the strategies based on moving averages are highly sensitive to the choice of the lookback periods, as detailed in the main text. Instead of trying to find the optimal parameters, we identify the region of acceptable parameters and randomize the set of parameters that define the trading signal in each period. We then run 1,000,000 simulations of this strategy using randomized parameters and group cumulative P&Ls by percentiles with 5% increments.

Figure 4 shows the cumulative performance of such strategies over time for WTI and Brent markets.

Figure 4
Cumulative P&L of "Follow-the-Flow" Strategy for MM Traders



It is evident that while these strategies performed well up until around 2021, their performance has since begun to deteriorate. This decline indicates that the information embedded in hedge fund positions has become more widely recognized by other market participants, reducing the competitive advantage of simply mimicking their behavior. For additional results related to following and counter-following positions held by other market participants, we refer to the full text of the paper.

Conclusion

In this article, we have addressed several important topics related to speculation in the oil market.

First, we identified the main participants in oil futures trading and explained how their identities are often misunderstood or mislabeled in commonly used regulatory reports. This mischaracterization makes it particularly difficult to analyze oil speculation within the framework commonly applied to broader commodity portfolios. The nature of participants in the oil market is notably different – driven in part by the existence of a particularly large OTC market – which makes the oil market somewhat unique. This finding is consistent with previous research showing that the trading patterns of oil hedgers and speculators differ from those observed in many other commodities.

We then analyzed the actual profitability of key market participants and identified the so-called "fast money" group of traders as the primary winners in oil futures trading. This group is predominantly associated with quantitative hedge funds, many of which rely on technical models based on moving average crossovers. Using this concept, we constructed a simple neural-network algorithm. In our model, historical futures prices serve as features, and the hedge funds' position-sizing method – known as the reaction function – acts as the neural activation function in a machine learning framework.

The model explains approximately half of the variance in speculative positions held by hedge funds. The remaining variance is attributed to discretionary speculators and macro traders. We believe that this neural-network framework can be further improved by incorporating additional macroeconomic features, and we view this as a promising direction for future research.

In the final part of the article, we reverse the direction of causality between our two primary variables: oil prices and speculative positions. After explaining speculative positions using past prices, we then examine whether future prices can be predicted based on current and historical positions held by speculators. To study this question, we take a market-based approach and analyze the performance of a popular speculative strategy – simply following the hedge fund flows. While this strategy was profitable in the past, its performance has declined in recent years as the approach became more widely recognized by a broader set of market participants.

In short, speculative oil trading is always evolving – and the winners are those who evolve the fastest.

Endnotes

1 See Keynes (1923), Keynes (1930), and Hicks (1939).

2 In the conventional definition of the Sharpe ratio, one uses returns and subtracts the risk-free interest rate in the numerator. However, since futures positions do not require any initial cash investment besides a fairly small initial margin, one can ignore the contribution of the risk-free interest rate here.

3 The momentum signal $M_t(n)$ is defined as $M_t(n) = F_t - MA_t(n)$ where F_t is futures price and $MA_t(n)$ is n-day moving average. See the main text for more details.

4 See Bouchouev (2023), Chapter 6, for more details.

References

Bouchouev, I., 2023, Virtual Barrels: Quantitative Trading in the Oil Market, Cham, Switzerland: Springer.

Hicks, J. R., 1939, Value and Capital: An Inquiry into Some Fundamental Principles of Economic Theory, Oxford: Oxford University Press.

Kang, W., Rouwenhorst, K. G. and K. Tang, 2020, "A Tale of Two Premiums: The Role of Hedgers and Speculators in Commodity Futures Markets," *The Journal of Finance*, Vol. 75, No. 1, February, pp. 377-417.

Keynes, J. M., 1923, "Some Aspects of Commodity Markets," *The Manchester Guardian Commercial, Reconstruction Supplement*, March 29.

Keynes, J. M., 1930, A Treatise on Money (Vol. II), London: Macmillan.

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