Predictive Abilities of Speculators in Energy Markets

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Abstract

Using nonparametric methodology, I find that speculators are successful in taking profitable positions in energy futures markets, although the magnitude of this effect is lower than that found previously for agricultural markets. A plausible explanation for this difference is that energy markets do not have a natural seasonality around harvest dates, making price forecasting more difficult for the energy commodity investors. Moreover, I find that the energy speculators' returns are due to the existence of the risk premiums rather than to the speculators' forecasting abilities. Analysis of different time periods reveals that futures risk premium is highly time-variant; notably, energy investors' profits have been very limited in the GFC and post-GFC period.

JEL classification: G01; G13.

Keywords: Energy futures; Commodity investors; Predictability of futures prices; Futures risk premium; Commitments of traders; Forecasting skills.

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1. Introduction

Commodity investing, most commonly through the futures markets, is increasingly popular. Büyükşahin, Haigh, and Robe (2008) note that in 1999, there were only about $5 billion of assets tracking the Goldman Sachs Commodity Index (GSCI). However, this amount has rapidly increased and in May 2008 the assets linked to the GSCI or other commodity futures were worth more than $140 billion. Gorton and Rouwenhorst (2005) show that, over the period from 1959–2004, a rebalanced and equally-weighted index of 36 commodities produced a risk premium comparable to the equity risk premium, while achieving lower risks (as measured by standard deviation) and negative correlation with stocks and bonds. Their study suggests that long-only commodity investment has a high diversification potential. In general, long-only fully collateralized commodity investments through tracking a commodity index, such as the GSCI, have performed well. For example, Erb and Harvey (2006) find that between 1969 and 2004 such investments would have produced an annualized compounded return of 12.24%, exceeding the 11.20% return from equity in the same period.

Moreover, commodity investors are not limited to the long-only positions on the futures markets. If they possess any predicting skills, they can maximize their returns by choosing their positions based on their expectations of futures returns. Chang (1985) for the first time showed that speculators (as identified by the commitments of traders reports) have superior forecasting abilities in futures markets and can, consequently, earn positive returns by taking futures positions. The limitation of Chang's work is that the study only covered three agricultural futures markets (corn, wheat and soybeans). Since agricultural commodities follow a clearly defined natural pricing cycle (based on the periods of harvest in North America), predicting future prices and earning abnormal returns for the speculators should be easier on such markets compared to other commodities. As commodities investing and, in particular, investing in energy futures, becomes an increasingly popular vehicle for non-traditional investors, including hedge funds, the question remains whether energy speculators are capable of predicting the direction of future price movements and, therefore, of earning a superior return for their investors.

This study contributes to the literature in the following ways. First, it focuses on testing the forecasting abilities of investors in energy markets. Secondly, it uses a longer period of more recent data to verify whether the speculators are still able to forecast future price movements. Many so-called anomalies in finance, for example, have disappeared after being discovered by academic research, presumably because they were fully exploited by the investors. Thus, the issue of the persistence of speculators' forecasting ability is an important one.

I focus on five most common, liquid energy futures markets with a long history of trading (crude oil, heating oil, propane, natural gas and unleaded gasoline). For the longest-trading contracts, there are over 30 years of data available, which makes the conclusions more reliable. I use the data on commitments of traders, provided by the CFTC, to identify in each one- to two-week period the direction of trading (long or short) of the aggregate large speculators. Conditional on the actual price changes in each period, I apply a non-parametric test to measure the success rate of speculators in taking a correct position in each commodity.

The results indicate that speculators in four out of five energy markets are able to successfully choose the correct side of the market in the futures contracts. In the remaining market (propane), the estimate of the speculative ability is positive, but not statistically significant. For the entire 30-year period, the ability of speculators to take a profitable position is strongly significant, indicating an existence of the positive returns to commodity investors. However, the extent of this effect is lower than that identified by Chang (1985) for the three agricultural futures in his sample. Moreover, contrary to Chang's results, there is no evidence that speculators have an abnormal forecasting ability as most of their profits appear to be driven by the risk premiums provided to speculators by hedgers in exchange for market liquidity and trading opportunities. Further breaking down of the sample by three time periods shows that for most markets, the speculators' returns clearly diminish over time. The best results are achieved in the beginning of the sample, between 1986 and 1997. On the contrary, in the global financial crisis (GFC) and post-GFC period, which in my sample corresponds to 2008 – 2017, there is only one energy commodity market where speculators still appear to be making profits more often than losses. Therefore, the inferior performance of energy market speculators is likely to be caused by two factors: different nature of energy markets compared to agricultural commodities, and time-varying nature of futures risk premium.

The remainder of this paper is organized as follows. In Section 2 I discuss background literature on commodity futures returns and return predictability. In Section 3, I present the empirical methodology used in the paper, while Section 4 details data sources and sample selection. Section 5 presents the empirical results, and Section 6 concludes.

2. Theoretical and empirical background

The theory of normal backwardation was developed by Keynes (1930), and it is commonly used to describe and explain the relationship between spot and futures prices.

Generally, futures traders are divided into hedgers, who use futures to hedge the risks in their underlying spot positions, and speculators, who trade with the sole purpose of making a profit on futures markets. In this setting, futures markets enable commodity producers (hedgers) to transfer business risk to other market participants (speculators) and to lock in future profit in advance. Keynes argued that because producers' hedging pressure significantly exceeds the hedging demand from commodity consumers, hedgers should provide the long position holders of futures contracts with a premium sufficient to motivate speculators to carry the associated risk. In this setting, futures markets act as a kind of insurance market, where hedgers pay a premium to speculators to ensure the future prices of their underlying commodities. The outcome of trading between (mostly short) hedgers and (mostly long) speculators is that the futures price tends to be below the expected future spot price so that speculators can generally earn a profit, or a risk premium. The normal backwardation theory of Keynes has been tested, for example, by Grauer and Litzenberger (1979), who showed that a commodity futures price is a biased estimate of the future spot price of the commodity due to the real risk and the inflation exposure of the contract.

One of the major assumptions in the backwardation theory of Keynes is that hedgers hold net short positions and, consequently, speculators are net long throughout the lives of the futures contracts. This assumption was challenged by Cootner (1960), who found that hedging pressure in agricultural commodities varies across different seasons according to time-to-harvest and inventory situations and is not necessarily net short. On the other hand, Litzenberger and Rabinowitz (1995) observed frequent backwardation in oil futures markets, with futures prices for contracts with longer time to maturity being significantly below spot price.

Chang (1985) made a major contribution to the literature by employing a non-parametric procedure (which is preferable to parametric tests as it does not require restrictive assumptions about the distribution of futures returns) to rigorously test theory of normal backwardation. His finding of the existence of risk premium in futures markets and a confirmation of the Keynes' theory of normal backwardation, therefore, had a significant impact on the follow-up research.

A number of studies used parametric models in order to theoretically and empirically model futures risk premium. For example, Hirshleifer (1990) suggests an equilibrium model that combines modern portfolio theory, the backwardation hypothesis, and market imperfections. In his setting, the sign of the residual risk premium depends on the direction of the net hedging positions. Bessembinder (1992) uses both CAPM and backwardation theory to develop a model of the relationship between systematic risk, hedging pressure and the futures risk premium and find that returns in foreign currency and agricultural futures depend on the net positions of hedgers. Deaves and Krinsky (1995) find mixed evidence on the existence of futures risk premiums for seven commodities they study. In line with Bessembinder (1992), De Roon, Nijman, and Veld (2000) also find that hedging pressure significantly affects futures returns. However, the non-parametric approach and results of Chang (1985), which often underlie assumptions concerning futures risk premium and forecasting abilities of commodities speculators, have not been tested on energy commodities, which currently comprise significant fraction of the total assets of commodity investors.

3. Empirical methodology

I follow the empirical methodology of Chang (1985), which applies the non-parametric procedure developed by Henriksson and Merton (1981) for testing predictive skills of portfolio managers to futures market setting. The underlying motivation for this methodology is that speculators base their trading decisions on their forecasts of the future price changes in the market. That is, if a trader expects the price to increase in the next period, he/she will take a long position in futures, resulting in a positive profit if the forecast turns out to be accurate. If, on the other hand, a trader expects the price to decrease, he/she will take a short position as the value of a short futures position will go up with the underlying futures price decreasing.

Let *F(t)* denote the price of futures contracts at time *t*, and *R(t)* denote the change in futures prices during period *t*; that is, $R(t) = F(t) - F(t - 1)$. The action of the speculator on the market (buy or sell a futures contract) is based on his forecast of *R(t)* being either positive or negative. Let $\gamma(t)$ denote the speculator's forecast dummy at time *t-1*, where $\gamma(t) = 1$ if the forecast for time period *t* is that $R(t) > 0$, and $\gamma(t) = 0$ if the forecast is that $R(t) \leq 0$. The probabilities for $\gamma(t)$ conditional upon the realized price changes on the futures contracts are further defined as

$$P_1^s(t) = prob[\gamma(t) = 0 | R(t) \leq 0] \qquad \text{(la)}$$

$$P_2^s(t) = prob[\gamma(t) = 1 | R(t) > 0] \qquad \text{(lb)}$$

Therefore, $P_1^s(t)$ is the conditional probability of a correct forecast given that $R(t) \leq 0$, and $P_2^s(t)$ is the conditional probability of a correct forecast given that $R(t) > 0$. It is assumed that $P_1^s(t)$ and $P_2^s(t)$ do not depend upon the magnitude of *R(t)*, but only on the direction of a price change. Hence, the conditional probability of a correct forecast depends only on whether or not $R(t) > 0$.

Under this assumption, a necessary and sufficient condition for a speculator's prediction to have no value is that the sum of the conditional probabilities of a correct forecast, $P_1^s(t) + P_2^s(t) = 1$ (Merton, 1981). Consequently, a sufficient condition for a speculator to have a forecasting ability is $P_1^s(t) + P_2^s(t) > 1$.

A non-parametric test of the null hypothesis that the speculators earn no positive profits is accomplished by testing Ho: $P_1^s(t) + P_2^s(t) = 1$.

Let's denote

n_1- number of correct forecasts, given $R(t) \leq 0$,

n - number of times a forecaster predicts that $R(t) \leq 0$,

N_1 - number of observations where $R(t) \leq 0$,

N_2 - number of observations where $R(t) > 0$, and

$N = N_1 + N_2$ - total number of observations.

Henriksson and Merton (1981) show that for large samples, the hypergeometric distribution of the probabilities of correct forecast can be approximated by the normal distribution. The mean and variance parameters for this normal approximation are calculated as

$$E(n_1) = \frac{nN_1}{N} \tag{2}$$

and

$$\sigma^2(n_1) = [nN_1(N - N_1)(N - n)]/[N^2(N - 1)] \tag{3}$$

In line with Chang (1985), this normal approximation is used throughout the paper to test for the predictive abilities of futures markets speculators.

4. Data and sample selection

I focus on the five energy commodities, which had futures contracts traded since the beginning (or close to that) of the data availability for the CFTC Commitments of Traders. These commodities include Crude oil (Light Sweet Crude Oil contract), Heating oil (No. 2 Heating oil, NY Harbor contract), Natural gas, Propane gas and Unleaded gasoline (Unleaded gasoline, NY Harbor contract, replaced by equivalent Gasoline Blendstock (RBOB) contract on 1 July 2006). Crude oil, Gasoline, and Heating oil data starts on 15/01/1986 and is available until the end of the sample (18/04/2017). Natural gas data is only available since 12/04/1990, also until the end of the sample period. Propane data starts on 30/06/1989 and is only available until 02/05/2000.

Information on the long or short net positions of large speculators and large hedgers is identified from the Commitments of Traders in Commodity Futures published by the U.S. Commodity Futures Trading Commission (CFTC). The Commitment of Traders (COT) reports provide information on the size and direction of the positions taken, total for all maturities, by three categories of futures traders: “reportable commercial”, “reportable non-commercial”, and “non-reportable”.

The COT reports contain a breakdown of the open interest in each commodity futures contract. The COT reports classify positions of each trader into reportable and non-reportable depending on whether they are above or below a certain size. Reportable positions are further divided into commercial or non-commercial positions, depending on whether traders

"...engaged in business activities hedged by the use of the futures or option markets". The commercial traders are typically hedgers while non-commercial traders are large speculators. In the following analysis, I focus on whether or not large speculators as a whole earned a risk premium and/or displayed significant forecasting skills. Although small futures traders are commonly assumed to be mostly speculators, their exact motivation to trade is unknown and therefore, their positions are not included in the analysis. The net position of large speculators (hedgers) in each one- or two-week period is determined by the balance of their long and short open interest. If, for example, large speculators' (reportable non-commercial) long position on the reporting date exceeds their short open interest, I record the speculators' net position as a long position for the reporting interval. In doing so, I follow the common assumption that the reported net position of traders for every end of semi-monthly or weekly period is a good proxy for their position for the duration of that period.

The frequency of the CFTC data is semi-monthly from 1986 until September 30, 1992, and weekly after that. This frequency determines the number of observations available for the study, with futures settlement prices measured on the exact CFTC reporting dates.

All futures price data are collected from Datastream for the nearest to maturity contract. Unlike Chang (1985), I do not attempt to split the open positions, reported by CFTC for the entire commodity, into different maturities, and then match them to the futures price changes for each maturity separately. Chang assumes that traders' commitments are equally spread across five maturities for each commodity he studies. However, empirical evidence strongly suggests that trading is most active (and open interest is highest) in the nearest and second-nearest to maturity contracts, and in many markets there is almost no trading in other contract maturities (Veld-Merkoulova and De Roon, 2003). For example, on May 3, 2017, 25.6 percent of the total open interest in NYMEX crude oil futures were in the nearest to maturity contract, while only 3.8 percent were in the fifth-to-maturity contract. For the gasoline futures on the same date, these percentages were 33.4 and 8.1, correspondingly[1]. This evidence indicates that an assumption of uniform distribution of open interest and net trading positions across contract maturities is not supported by data. An alternative approach that I adopt is to treat the total positions in a certain commodity as one observation, according to the way it is reported by CFTC. In this case, when determining whether the speculators or the hedgers made a correct prediction for the price changes, we have to assume that futures prices for all maturities move in the same direction. This is not a particularly unrealistic assumption as futures prices are determined by the cost of carry model and tend to all move in the same direction as the price of underlying commodity. Moreover, the methodology used in this study does not rely on the magnitude of the price changes, but only on their direction. This justifies using the direction of the price changes for the nearest to maturity futures contract as a proxy for the price changes on every contract with the same underlying asset.

Table 1 presents descriptive statistics for the futures data.

[Insert Table 1 here]

The number of observations per commodity varies between 474 (for propane) to 1,442 (for crude oil, gasoline and natural gas). Crude oil futures are most traded by both average daily trading volume and open interest. In line with the expected positive drift in asset prices, most commodities experience slightly more intervals with price increases than periods of price decreases; one exception is natural gas, where this ratio is very close to 50

[1] Source: CME Group website and author's own calculations.

percent. This direction of futures price changes (thereafter referred to as "up-futures" for the time intervals where futures price increased and "down-futures" for the intervals where price decreased) will be important in examining conditional probabilities of correct forecasts by speculators and hedgers in the next section.

5. Results

The first step of the analysis is to study whether speculators in the energy futures markets tend to make correct forecasts of the future price movements. To this end, Table 2 shows three estimates for each commodity: 1) the probability $P_1^s(t)$ that speculators (on aggregate) take a correct short position conditional on futures prices decreasing (that is, in the down-market); 2) the probability $P_2^s(t)$ that speculators (on aggregate) take a correct long position conditional on futures prices increasing (that is, in the up-market); and 3) the sum of these two conditional probabilities.

[Insert Table 2 here]

While the conditional probabilities $P_1^s(t)$ and $P_2^s(t)$ need not be the same, it is the sum of the two that determines whether speculators as a group are able to predict the direction of the price changes to some extent, and therefore take net positions in the markets that earn them a positive return. As Henriksson and Merton (1981) show, the sufficient condition for the speculators to earn profit is that sum of the conditional probabilities is greater than one. As it is highly unlikely that speculators would possess forecasting skills and then use them to purposefully lose money, the null hypothesis of no predictive abilities H_0: $P_1^s(t) + P_2^s(t) = 1$ is tested against the alternative hypothesis H_A: $P_1^s(t) + P_2^s(t) > 1$. In this setting, rejection of null hypothesis means that speculators consistently earn money by taking futures positions, either as a result of their superior forecasting skills or as a reward for risk-taking (risk premium).

Results presented in Table 2 shows that speculators earn positive rewards for the four energy markets out of five. In crude oil, heating oil, gasoline and natural gas markets, large speculators consistently outperformed the rest of the traders, being on the right side of the market more often than not (with significance levels of 1 percent). The propane market is the only exception, where large speculators do not display any statistically significant forecasting power (or earn risk premium). The difference with the other four energy markets is likely driven by both lowest level of the estimated sum of conditional probabilities of being correct (1.052) and the smallest number of observations for propane futures.

The comparison between the conditional probabilities in the up- and down-markets shows that speculators have markedly different success rates across two possible market states. In the extreme, speculators in the heating oil futures take a correct position 88.6% of the time when market goes up, but only 16.7% of the time when market goes down. Overall, their sum of is $P_1^s(t) + P_2^s(t)$ is a strongly significant 1.053, but it is far short from the "perfect forecaster" result of 2. However, unlike the agricultural speculators, the large speculators in energy markets do not take net long positions most of the time. Comparison of is $P_1^s(t)$ and $P_2^s(t)$ for each market suggests that speculators tend to be net long traders in crude oil, heating oil and gasoline, but net short traders in natural gas and propane markets.

A comparison with Chang (1985) reveals that the magnitude of speculators' forecasting abilities is larger for his sample of agricultural futures than for the energy futures

I investigate. Namely, he reports sums of conditional probabilities equal to 1.192 (wheat), 1.167 (corn) and 1.181 (soybeans). For the energy markets, all of the results are lower, ranging from 1.052 (propane) to 1.126 (gasoline). There are two possible (non-mutually-exclusive) explanations for this outcome: difference in the nature of the markets (energy versus agricultural commodities) and different time periods. While there is no overlapping data to directly test for the time period effect, in the analysis that follows I split the sample period into three sub-samples to investigate whether the results change with time, and could this have contributed to the discrepancies between the studies. As for the different nature of the markets, agricultural commodities are characterised by high level of seasonality, driven by the natural harvest cycle. Quite possibly, this seasonality makes price changes in agricultural commodities more predictable and contributes to the finding that speculators have higher success rates in predicting agricultural price changes compared to energy markets.

Table 3 presents the condensed version of the results (sums of conditional probabilities only) for the three sub-periods: 1986 – 1997, 1998 – 2007, and 2008 – 2017.

[Insert Table 3 here]

For the four out of five markets (excluding propane), the trend is clearly in the direction of diminishing forecasting skills of speculators. The highest and most statistically significant results are observed on the first period (1986 – 1997). Level and, to some extent, significance of the forecasting skills declines in the second period (while still above one). However, in the last period (2008 – 2017), which covers global financial crisis (GFC) and post-GFC period, only heating oil market speculators display strongly significant forecasting skills. In crude oil market, the outcome is still above one, but only significant at the 10 percent level. Finally, speculators in the gasoline and natural gas markets display no forecasting skills at all in the last period. As with the overall result, propane market shows the opposite trend, with the lack of accurate forecasts by speculators in the first period, but strongly significant result in the second one.

Overall, the finding that forecasting results in the energy markets were strongest in the first sub-period suggests that the weaker results obtained in this study for the energy markets can be partly explained by the changing nature of the market conditions: either by weaker predictability of the market prices over time, or by decreasing futures risk premium.

So far, I have established that generally speculators earn a positive return in the energy futures markets, which can be explained by either their superior forecasting abilities or by the existence of risk premium. Risk premium here refers to the profits made by the speculators in exchange for accommodating the hedgers' trades and taking the opposite positions to hedgers. As hedgers derive utility by using futures markets to hedge their real asset positions, it is logical to expect that, similar to the insurance market, hedgers should be net losers in futures transactions and speculators should be net winners. The following analysis attempts to determine whether the systematic wins by the energy futures speculators, found in Tables 2 and 3, reflect the futures risk premium. Given that futures trading is a zero-sum game, the existence of risk premium would imply that hedgers should systematically lose out, with $P_1^H(t) + P_2^H(t) < 1$. Table 4 presents the results of this test.

[Insert Table 4 here]

The results in Table 4 fully support the hypothesis of risk premium in energy futures. For all five commodities, sums of conditional probabilities of taking correct positions for hedgers are significantly below one, ranging from 0.893 (crude oil) to 0.954 (propane).

Therefore, my tests confirm that risk premium is present and significant in the energy futures markets as well.

Table 5 conducts similar analysis for three sub-periods discussed above.

[Insert Table 5 here]

The sub-period results confirm the existence of risk premium for all five markets for the first two periods, although the hedgers' losses seem to decrease from period one to period two. However, after 2008 only two out of four markets (crude oil and heating oil) still exhibit evidence for the risk premium at 5 percent significance level. In natural gas and gasoline markets this effect completely disappears, meaning that speculators no longer get a reward for providing an opportunity for hedgers to hedge their asset positions. This suggests that risk premium is highly time-variant, rather that always present or following a specific time trend.

Finally, the last test attempts to separate the effect of the speculators' forecasting skills from the existence of the risk premium. While Tables 2 and 3 present results suggesting that speculators generally earn positive profits in energy futures by consistently taking correct positions, findings in Table 4 and 5 suggest that at least some of these profits are due to the rewards accrued to speculators for taking on the hedgers' risks and providing an opportunity for them to trade and hedge. An attempt to determine whether another part of speculators' profits come from their superior forecast skills is based on comparison of the performance of actual large speculators and that of a hypothetical naïve speculator who does not attempt to predict the prices. The naïve speculators would earn pure risk premium by always taking a position exactly opposite to that of large hedgers. The difference between the sums of conditional probabilities of actual and naïve speculators can be estimated as $P_1^s(t) + P_2^s(t) -$

$[2 - P_1^H(t) - P_2^H(t)]$. This difference is entirely due to the forecasting skills exhibited by the real speculators, and the test of these forecasting skills involves testing the null hypothesis H_0: $P_1^s(t) + P_2^s(t) - [2 - P_1^H(t) - P_2^H(t)] = 0$ (no forecasting skills) against an alternative hypothesis H_A: $P_1^s(t) + P_2^s(t) - [2 - P_1^H(t) - P_2^H(t)] \neq 0$. Table 6 presents results of these tests for the entire sample for the three sub-periods separately.

[Insert Table 6 here]

Unlike the results of Chang (1985) that shows existence of speculators' forecasting skills for one commodity out of three (wheat), results in Table 6 do not support the hypothesis that energy futures speculators systematically exhibit superior forecasting abilities. Most of the results are insignificant; moreover, even the signs of estimates are not consistent across time periods and commodities.

Overall, the results of my study confirm that speculators in energy markets do earn positive profits, but these profits reflect their risk-taking rather than superior price forecasting skills.

6. Summary and conclusions

A prominent study of Chang (1985) influenced a lot of researchers' understanding of the theory of normal backwardation in futures markets and its effects on the profits and losses of hedgers and speculators in futures markets. The importance of investors in energy futures markets has dramatically increased in the last years. However, relying on the original study of Chang to provide support for these investors' activities is becoming increasingly difficult for two reasons: (1) energy futures were not part of Chang's sample, and (2) by now, the data used in this study is outdated, which is particularly significant in this case as original results already showed considerable degree of time-variance. Thus, my study answers a pertinent question: do the results of Chang (1985) stand when tested using recent data for energy markets?

Using the most recent 30 years of data from five energy futures markets (crude oil, natural gas, heating oil, propane and unleaded gasoline), I confirm that most of the results, obtained by Chang for agricultural markets, are still applicable to energy futures. Namely, large speculators as a group tend to take correct positions, leading to potential profits to speculators and losses for hedgers. This confirms the view of Keynes (1930) regarding the role of speculators as "insurance providers" for hedgers, and is in line with normal backwardation theory. At the same time, there is very little evidence that these speculators profits are due to their superior forecasting abilities. Rather, speculators' profits appear to reward their risk taking and providing liquidity and a trading opportunity for hedgers. Finally, the returns to speculators clearly reduced during my sample period, being highest in 1986 – 1997 and lowest in the GFC and post-GFC period.

The economic implication of the results of this study is that there is a sound financial basis for the energy futures investment activities, in the form of futures risk premium. However, investors do not appear to be able to forecast the markets (contrary to the stated goals of many hedge and commodity funds). Moreover, the risk premium varies in time, with the most recent decade showing very little returns to speculators, which may be caused by the downwards pressure of the increased flow of funds on investors' returns.

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Table 1. Descriptive Statistics.

This table presents the summary statistics of the futures contracts used in the study. *Sample period* covers all the available dates where both commitment of traders and pricing data are available. *Average open interest* is the daily mean total open interest (in number of contracts) for the sample period. *Average daily trading volume* is the daily mean total trading volume (in number of contracts) for the sample period. *Average closing price* is the daily mean settlement price (in dollars) for the nearest-to-maturity contract for the sample period. *Percent of price increases* reports the percentage of the periods between consecutive observations, when the settlement price of the nearest-to-maturity contract has increased. *Percent of price decreases* reports the percentage of the periods between consecutive observations, when the settlement price of the nearest-to-maturity contract has decreases.

Contract	Sample period	Number of observations	Exchange	Average open interest	Average daily trading volume	Average closing price	Percent of price increases	Percent of price decreases
Crude oil	15/01/1986 – 18/04/2017	1442	NYMEX	788,700	304,185	43.01	52.01	47.99
Gasoline	15/01/1986 – 18/04/2017	1442	NYMEX	152,423	61,168	1.24	51.32	48.68
Heating oil	15/01/1986 – 18/04/2017	1442	NYMEX	186,882	62,103	1.25	51.11	48.89
Natural gas	12/04/1990 – 18/04/2017	1340	NYMEX	546,877	137,511	3.89	49.93	50.07
Propane	30/06/1989 – 02/05/2000	474	NYMEX	2,283	174	0.33	51.69	48.31

Table 2. Conditional Probabilities of a Correct Market Position of Large Speculators.

This table presents probabilities that large speculators take a correct (long or short) position, conditional on futures prices decreasing (down market) or increasing (up market). Last column presents the sum of conditional probabilities in both up and down markets. Asterisks indicate the significance level of one-tailed test of the predictive power of speculators, where null hypothesis is $P_1^s(t) + P_2^s(t) = 1$, and alternative hypothesis is $P_1^s(t) + P_2^s(t) > 1$. *** denotes significance at 1% level.

Commodity	**N**	**Down Market** $\boldsymbol{P_1^s(t)}$	**Up Market** $\boldsymbol{P_2^s(t)}$	**All Markets** $\boldsymbol{P_1^s(t) + P_2^s(t)}$
Crude oil	1442	0.337	0.753	1.090***
Gasoline	1442	0.407	0.719	1.126***
Heating oil	1442	0.167	0.886	1.053***
Natural gas	1340	0.729	0.368	1.096***
Propane	474	0.672	0.380	1.052

Table 3. Sum of Conditional Probabilities of a Correct Market Position of Large Speculators.

This table presents the sums of conditional probabilities that large speculators take a correct (long or short) position, conditional on futures prices decreasing (down market) or increasing (up market), for the three sub-periods. Numbers of observations are in parentheses. Asterisks indicate the significance level of one-tailed test of the predictive power of speculators, where null hypothesis is $P_1^s(t) + P_2^s(t) = 1$, and alternative hypothesis is $P_1^s(t) + P_2^s(t) > 1$. *** denotes significance at 1% level, ** denotes significance at 5% level, and * denotes significance at 10% level.

Commodity	1986 - 1997	1998 - 2007	2008 – 2017
Crude oil	1.188*** (436)	1.107*** (521)	1.016* (485)
Gasoline	1.123*** (436)	1.050** (521)	1.000 (485)
Heating oil	1.206*** (436)	1.118*** (521)	1.073*** (485)
Natural gas	1.157*** (334)	1.143*** (521)	0.992 (485)
Propane	1.013 (352)	1.165*** (122)	NA

Table 4. Conditional Probabilities of a Correct Market Position of Large Hedgers.

This table presents probabilities that large hedgers take a correct (long or short) position, conditional on futures prices decreasing (down market) or increasing (up market). Last column presents the sum of conditional probabilities in both up and down markets. Asterisks indicate the significance level of one-tailed test of the predictive power of hedgers, where null hypothesis is $P_1^H(t) + P_2^H(t) = 1$, and alternative hypothesis is $P_1^H(t) + P_2^H(t) < 1$. *** denotes significance at 1% level, ** denotes significance at 5% level, and * denotes significance at 10% level.

Commodity	**N**	**Down Market** $\boldsymbol{P_1^s(t)}$	**Up Market** $\boldsymbol{P_2^s(t)}$	**All Markets** $\boldsymbol{P_1^s(t) + P_2^s(t)}$
Crude oil	1442	0.645	0.249	0.893***
Gasoline	1442	0.829	0.115	0.944***
Heating oil	1442	0.783	0.144	0.927***
Natural gas	1340	0.481	0.466	0.948**
Propane	474	0.865	0.090	0.954*

Table 5. Sum of Conditional Probabilities of a Correct Market Position of Large Hedgers.

This table presents the sums of conditional probabilities that large hedgers take a correct (long or short) position, conditional on futures prices decreasing (down market) or increasing (up market), for the three sub-periods. Numbers of observations are in parentheses. Asterisks indicate the significance level of one-tailed test of the predictive power of hedgers, where null hypothesis is $P_1^H(t) + P_2^H(t) = 1$, and alternative hypothesis is $P_1^H(t) + P_2^H(t) < 1$. *** denotes significance at 1% level, ** denotes significance at 5% level, and * denotes significance at 10% level.

Commodity	1986 - 1997	1998 - 2007	2008 – 2017
Crude oil	0.775*** (436)	0.884*** (521)	0.976** (485)
Gasoline	0.872*** (436)	0.944*** (521)	1.000 (485)
Heating oil	0.783*** (436)	0.937*** (521)	0.944** (485)
Natural gas	0.901*** (334)	0.920*** (521)	1.024 (485)
Propane	0.954** (352)	0.958* (122)	NA

Table 6. A Test of Large Speculators' Forecasting Ability.

This table presents the differences between the sum of conditional probabilities of a correct (long or short) position of large speculators and that of the hypothetical naïve speculators, conditional on futures prices decreasing (down market) or increasing (up market), for the three sub-periods and for the entire sample period. Hypothetical naïve speculators are assumed to always take a position opposite to the large hedgers' position. Asterisks indicate the significance level of two-tailed test of the forecasting power of speculators, where null hypothesis is $P_1^s(t) + P_2^s(t) - [2 - P_1^H(t) - P_2^H(t)] = 0$, and alternative hypothesis is $P_1^s(t) + P_2^s(t) - [2 - P_1^H(t) - P_2^H(t)] \neq 0$. *** denotes significance at 1% level, ** denotes significance at 5% level, and * denotes significance at 10% level.

Commodity	**1986 - 1997**	**1998 - 2007**	**2008 – 2017**	**1986 - 2017**
Crude oil	-0.037	-0.009	-0.008	-0.017
Gasoline	-0.005	-0.006	0.000	0.070
Heating oil	-0.011**	0.055	0.017	-0.020*
Natural gas	0.058	0.063	0.016	0.044
Propane	-0.033	0.123*	NA	0.006