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Hedgers, funds, and small speculators in the energy futures markets: an analysis of the CFTC's Commitments of Traders reports

Dwight R. Sanders[a,*], Keith Boris[b], Mark Manfredo[c]

[a] *Department of Agribusiness Economics, Southern Illinois University, Mail Code 4410, Carbondale, IL 62901-4410, USA*
[b] *Louis Dreyfus Corporation, USA*
[c] *Arizona State University, USA*

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Abstract

The Commodity Futures Trading Commission (CFTC)'s Commitments of Traders (COT) data are examined for crude oil, unleaded gasoline, heating oil, and natural gas futures contracts. The collection procedures for the COT data are first examined, followed by Granger causality tests to determine if relationships between trader positions and market prices exist. A positive correlation between returns and positions held by noncommercial traders, and a negative correlation between commercial positions and market returns, are found. Furthermore, positive returns result in an increase in noncommercial net positions in the following week, whereas the net long positions held by commercial hedgers decline following price increases. However, traders' net positions do not lead market returns in general.

JEL classification: G1; N7

Keywords: Commitments of Traders; Energy futures markets; Futures funds; Causality

> In order for prices to continue higher, there must be strong buying support and, according to the latest *Commitments of Traders* report, that may be difficult for at least one segment of the market. According to the CFTC, noncommercials [funds] have increased their net longs... to near record levels. (NGI's Daily Gas Price Index, August 16, 1999)

* Corresponding author. Tel.: +1-618-453-1711; fax: +1-618-453-1708.
E-mail address: dwights@siu.edu (D.R. Sanders).

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> We're long crude oil... I'm making the bet because I can't find a place, in any market, on any chart, where speculator sentiment has been above 90–95% in one direction where betting against their position hasn't been the right thing to do. (Michael Williams, Genesis Trading Group, Barrons, July 20, 1998)

1. Introduction

The Commodity Futures Trading Commission (CFTC) collects data on the composition of open interest for all futures contracts. A subset of this data is released to the public through the CFTC's Commitments of Traders (COT) report. The open interest is divided into *reporting* and *nonreporting* traders, where reporting traders hold positions in excess of CFTC reporting levels. Reporting traders are further categorized as *commercials* or *noncommercials*. Commercials are associated with an underlying cash-related business and they are commonly considered to be hedgers. Noncommercials are not involved in an underlying cash business; thus, they are referred to as speculators. Furthermore, reporting level noncommercial activity is generally considered to be that of managed futures or commodity funds. Overall, the COT data are broadly discussed in terms of hedgers (reporting commercials), funds (reporting noncommercials), and small speculators (non-reporting traders).

As illustrated in the opening quotes, the CFTC's COT report is widely anticipated and closely analyzed by commodity futures traders. In particular, futures traders tend to focus attention on positions held by reporting noncommercials (typically funds). Some analysts suggest that the anticipatory buying of futures contracts in front of the activity of reporting noncommercials can be a profitable strategy. At the same time, other analysts suggest that large fund positions signal market reversals; thus, fund activity can be viewed as a contrary indicator. Still, others argue that following the commercial trade is a profitable strategy (Welling, 1998). Regardless of the supposition, these views are rarely supported by statistical evidence.

The COT data are also used by academics to examine a number of issues including the flow of funds among trader groups (Hieronymus, 1971), the forecasting ability of traders (Hartzmark, 1991; Leuthold et al., 1994; Buchanan et al., 2001), and the existence of risk premia (Chatrath et al., 1997), and is used as a measure of investor sentiment (Wang, 2001, 2002). Yet, the source, reliability, and definitions underlying the data set are rarely scrutinized. Given the widespread use of these data by both academics and industry professionals, it is essential that users have a thorough understanding of how the COT report is compiled and what information it contains.

Given this, the overall objective of this study is to examine the information contained in COT reports, with focus on the COT data specific to the energy futures markets, namely, crude oil, gasoline, heating oil, and natural gas futures. First, the COT data for these futures markets are assessed in terms of collection procedures, trader definitions, and trader categorizations. In doing this, we fully describe the data collection procedures utilized by the CFTC and highlight the strengths and weaknesses of the COT data. It is important that researchers understand these issues, or they risk misinterpreting the results of their studies. Second, the COT data for these markets are evaluated in terms of how they relate to market prices. In particular, we ask the question: "Are trader positions useful for predicting market returns?" This is not meant to be a test of market efficiency or trading profitability; rather, we are investigating the informational content of these data in a broad sense. Similar in spirit to that of Buchanan et al. (2001), we evaluate whether traders' positions relate to futures prices and subsequent price movements. In doing this, we use a Granger causality framework to examine if returns lead trader positions, and if trader positions lead returns. We also determine the impact of extreme trader positions using a market timing framework similar to that of Cumby and Modest (1987).

The CFTC's COT data are widely used by traders and academics alike, but are not always well documented or understood. This research represents the first comprehensive look at the COT data for the energy futures complex (crude oil, unleaded gasoline, heating oil, and natural gas). While Buchanan et al. (2001) provide insight into the information content of the COT data for the natural gas futures market, namely, the ability of trader positions to predict the direction of futures returns, we provide a more comprehensive look at this issue using different techniques over a larger cross-section of energy futures markets. Furthermore, this study pays special attention to the information contained in the COT reports beyond its ability to predict direction of returns. Namely, this research provides vital information with regards to the analysis of the data collection procedures, and interpretation of the trader categories used by the CFTC. Thus, we provide a more complete picture of the COT data's potential applicability, as well as how to interpret empirical results from studies where these data are used. Given the importance and size of the energy futures complex, as well as the role energy futures markets play in price discovery (Fleming and Ostdiek, 1999; Foster, 1996), it is important that researchers as well as traders in the energy complex have an understanding of this unique, publicly available data.

The remainder of the paper is organized as follows. In Section 2, we present various academic studies, which use the COT data, and mention how a misunderstanding of the COT data could potentially lead to interpretative problems. In Section 3, we examine the CFTC large-trader reporting system, and specifically examine the information in the Commitment of Traders report in Section 4. Section 5 outlines the data, methods, and results used in linking the COT data to energy futures market returns, while Section 6 provides a summary of the research and conclusions.

2. Literature review

Information contained in the COT data has been used by academics to examine a number of issues. Namely, researchers have used these data in three closely related veins of research including the level and adequacy of speculation in futures markets, the flow of funds or forecasting ability of traders, and the existence of risk premia or hedging pressure in futures markets.

In examining the adequacy of futures market speculation, Leuthold (1983) (see also Peck, 1981) uses a version of Working's (1960) speculative index, which incorporates the use of COT data in its calculation. Specifically, the speculative index uses COT data to quantify speculative levels (noncommercial positions) relative to hedging needs (commercial positions). Leuthold (1983) finds that there is ample speculation in livestock futures markets to absorb the demands of hedgers. However, Leuthold (1983) does note that it is difficult to fully understand how the results are influenced by hedgers that may fall into the nonreporting classification.

The forecasting ability of traders is typically examined using a finer version of the CFTC's large-trader data set than that released in the COT report. Hartzmark (1991) as well as Leuthold et al. (1994) use detailed end-of-day position data for individual traders to evaluate their forecasting ability. Hartzmark (1991) concludes that large traders' returns are generated randomly, whereas Leuthold et al. (1994) state that select traders in frozen pork bellies can profitably forecast prices. Kahn (1986) uses the COT report to mimic the positions of reporting noncommercial traders. He finds that following their positions (upon release of the COT reports) does not generate statistically significant profits. On the other hand, Wang, in examining the return predictability in agricultural futures based on the positions held by commercial and noncommercial traders, finds that over intervals from 1 to 12 weeks, noncommercial traders' positions forecast price continuations and commercial traders forecast price reversals. However, upon taking into account the risk premium speculators earn for assuming hedgers' nonmarketable risks, Wang concludes that noncommercial speculators do not possess superior forecasting skills. Still, Buchanan et al. (2001), using weekly trader position and return data, suggest that noncommercial speculative positions provide information on the magnitude and direction of price changes in the natural gas futures market.

Many researchers (e.g., Chang, 1985; Bessembinder, 1992; Chatrath et al., 1997) use the COT data to test for hedging pressure or risk premia in futures markets. For instance, De Roon et al. (2000) use the COT data to examine hedging pressure in futures markets. They find strong statistical evidence that hedging pressure impacts futures returns. They define hedging pressure as the difference in commercial short and commercial long positions divided by total commercial positions. In a regression framework, net short hedging by reporting commercials is associated with statistically positive futures returns. In their theoretical model, the authors assume that there is no quantity risk; thus, the regression results reflect a strictly contemporaneous relationship.

While these studies have made important contributions, researchers utilizing COT data often take the trader classifications at face value. That is, they assume that all traders classified as commercials are hedgers, and all noncommercials are speculators. While this may be a standard assumption, a careful inspection of the COT data collection procedures may aid in its interpretation and use. In addition, academic researchers make numerous assumptions about how traders' positions change or do not change over reporting intervals. For instance, Chang assumes that traders' commitments are static over a reporting month—the same as they are at the end of the reporting interval. Often, these assumptions lead to an implicit overlap between price and position data that may bias conclusions concerning trader profitability, price pressure effects, or hedging pressure. In the following sections, we first examine the collection procedures employed by the CFTC in compiling the COT data, and then we explicitly examine the lead–lag nature of the data.

3. The CFTC's large-trader reporting system[1]

The CFTC is charged with regulating futures and options trading to ensure that the markets are free from manipulation. One of the measures used to accomplish this goal is the CFTC's market surveillance program. The market surveillance program is intended to "spot adverse situations in futures markets" (CFTC, No. 5-92). To accomplish this, "a market surveillance program must determine when a trader's position in a futures market becomes so large relative to other factors that it is capable of causing prices to no longer accurately reflect legitimate supply and demand conditions" (CFTC, No. 5-92). The large-trader reporting system collects daily positions [from futures commission merchants (FCMs), clearing members, and foreign brokers] for traders that have positions larger than the reportable level. The reportable level is defined by the CFTC for a given future (a single contract month in a futures market).[2] The reportable level is on a futures-equivalent or delta-adjusted basis.[3] That is, option and spread positions are adjusted to reflect their sensitivity (delta) to the underlying futures price. So, a trader may hold contracts in excess of the reportable level, but if the position is delta-neutral, then it is not a reportable position.

Each futures account is identified with an "owner" and a "trader." The "trader" is an entity that makes trading decisions or has material financial interest. For example, a large corporation may have refining, exploration, and retail divisions. The overall corporation is the account "owner," but each division may be considered a separate "trader." A "trader" may have accounts with a number of FCMs. Positions are aggregated across accounts controlled by the same entity and those in which the entity has a 10% or greater financial interest.[4] Thus, within the context of the COT reports, a "trader" is any entity that directly controls trading (i.e., is an authorized trader) or has at least a 10% financial interest in an account. A trader's position is aggregated across all such accounts.

FCMs file a CFTC Form 102 when an account has a reportable position. Form 102 provides the CFTC with preliminary information concerning financial interests and the commercial nature of the account. The account trader is required to complete a CFTC Form 40 within 10 days of acquiring a reportable position. Form 40 collects detailed information on the controlling interest in the account. Also, in Form 40, the trader is asked to self-identify as a commercial or noncommercial, where a commercial is "engaged in business activities hedged by use of the futures and option markets... this would include production, merchandising, or processing of a cash commodity, asset/liability risk

[1] The following discussion reflects the procedures for reporting large-trader positions as of January 1, 2000. The information was taken from publications on the CFTC website (2000b, 2000c, 2000d, 2000e) as well as personal interviews with the CFTC surveillance staff. It is important to note that reporting procedures and requirements have had numerous changes through time. Please see the footnotes provided in this paper and the CFTC's website (http://www.cftc.gov) for details.

[2] As of January 1, 2000, if a trader holds a reportable position in any future, then all of his positions in all futures are reported. Previously, only those held in that particular future were recorded.

[3] Prior to 1996, traders' futures and options positions were not combined on a delta equivalent basis. There were separate reporting levels for futures and options (CFTC). The respective futures exchanges provide the CFTC with the deltas for adjusting option positions.

[4] Exceptions to this rule exist for commodity pool operators (CPOs) where it can be demonstrated that the commodity trading advisors (CTAs) act independently.

management, security portfolio risk management, etc." (CFTC Form 40). In addition to whether the trader is a commercial or noncommercial, more detailed data are collected about the trader's motives. For instance, noncommercials are asked to identify themselves as commodity trading advisors (CTAs), commodity pool operators (CPOs), or floor brokers. Likewise, commercials are asked to identify the cash markets in which they have underlying risk and the nature of their commercial business (e.g., producer, processor, merchandiser, or end-user). Form 40 is updated every 2 years or upon special calls by the CFTC.

4. The Commitments of Traders reports

The large-trader reporting system collects detailed daily information on the positions of reportable traders. Only a subset of this data is released to the public through the CFTC's COT reports. Although the CFTC large-trader reporting system contains more detailed information, the COT report only discloses positions at the commercial versus noncommercial aggregation level for reporting traders. Specifically, noncommercial open interest is divided into long, short, and spreading, whereas, commercial and nonreporting open interest is simply divided into long or short. The following relation explains how the market's total open interest (TOI) is disaggregated:

$$\underbrace{\overbrace{[\mathrm{NCL}+\mathrm{NCS}+2(\mathrm{NCSP})]}^{\text{Noncommercial}}+\overbrace{[\mathrm{CL}+\mathrm{CS}]}^{\text{Commercial}}}_{\text{Reporting}}+\underbrace{[\mathrm{NRL}+\mathrm{NRS}]}_{\text{Nonreporting}}=2(\mathrm{TOI}) \tag{1}$$

where, NCL, NCS, and NCSP are noncommercial long, short, and spreading positions, respectively. CL (CS) represents commercial long (short) positions, and NRL (NRS) is a long (short) position held by nonreporting traders. Reporting and nonreporting positions must sum to the market's TOI, and the number of long positions must equal the number of short positions.

From the collection and identification process described, it seems that the basic classification of reporting versus nonreporting is relatively clean across traders. It is unlikely that there are large measurement errors with respect to position size. However, this delineation tells us nothing about the motives of nonreporting traders. Nonreporting traders may be hedgers, speculators, or market makers. Furthermore, the disaggregation of reporting traders into commercial versus noncommercial market participants has potential sources of error. In particular, commercial traders may not always be hedgers, and hedgers may not always be hedging. For instance, because of the speculative position limits placed on noncommercials, there is some incentive for traders to classify themselves as commercials. Also, since cash positions for true commercials are unknown, their positions may be speculative in nature. Therefore, true hedging positions are some subsets of the commercial traders' positions. In total, commercial positions are likely to reflect very diverse motives. This conclusion is consistent with the findings of Ederington and Lee (2002) in their examination of commercial traders in the heating oil market.

In contrast, there are no obvious incentives to self-classify as a speculator. So, reporting noncommercials most likely represent a relatively pure subset of total speculative positions. It would seem particularly difficult for a CTA to describe themselves as a commercial; thus, it is indeed likely that reporting noncommercial positions largely reflect those held by managed funds.

In summary, the trade's labels of "funds," "hedgers," and "small speculators" placed on the CFTC trader classifications of reporting noncommercials, reporting commercials, and nonreporting traders, respectively, are somewhat tenuous. First, there is no information about the motives of nonreporting traders. We only know that they do not hold positions in excess of CFTC reporting levels. Second, pure hedge positions are a subset of the reporting commercial classification, and reporting commercial positions likely reflect a diverse set of motives in aggregate (see also Ederington and Lee, 2002). Finally, the "funds" or reporting noncommercials are probably the most precise classification, effectively capturing the positions of a subset of speculators (i.e., managed funds).

5. Relating COT data to market prices—methods and results

In this section, we establish the methodology and present results that are used to determine if energy futures traders' positions relate to energy futures prices. In doing this, we first present two measures of trader positions, then present data and summary statistics on these measures as well as returns data for crude oil, unleaded gasoline, heating oil, and natural gas futures. Granger causality tests are then used to determine if returns lead traders' positions, and, subsequently, if traders' positions lead returns. Finally, tests are conducted to determine if extreme trader positions impact energy futures market prices.

5.1. Position measurement

In relating traders' positions to market returns, we focus on two relative measures of position size. The first is simply the percent of the total open interest held by each CFTC trader classification. This measure is the sum of the long and short positions held by the trader class divided by twice the market's total open interest.[5] For instance, the percent of the total market held by commercial traders is calculated as follows:

$$\text{Reporting commercials}' \ \text{percent of TOI}_t = \frac{\text{CL}_t + \text{CS}_t}{2(\text{TOI}_t)}. \tag{2}$$

The second measure captures the net position of the average trader in a CFTC classification.[6] The percent net long (PNL) position is calculated as the long position

[5] This is seen by multiplying through Eq. (1) by 1/(2TOI). For example, reporting noncommercials' percent of total open interest is calculated as [NCL + NCS + 2(NCSP)]/(2TOI).

[6] All of the results in this paper apply to the average trader in each group. Certainly, there are individual exceptions.

minus the short position divided by their sum. The PNL is calculated for each CFTC trader classification, and for each energy futures contract examined. For instance, the percent net long for the reporting commercials at time t is defined as follows:

$$\text{Commercial PNL}_t = \frac{\text{CL}_t - \text{CS}_t}{\text{CL}_t + \text{CS}_t}. \tag{3}$$

Thus, the PNL for each CFTC classification represents the net position held by the group normalized by its total size. De Roon et al. (2000) calculate the PNL for reporting commercials and refer to it as "hedging pressure."[7] Here, we follow De Roon et al. (2000) and use their PNL as the measure of position size for each trader classification.

5.2. Data and summary statistics

Since October 1992, the COT reports have been issued every other Friday and contain traders' positions on the previous two Tuesdays.[8] Thus, from October 1992 to present, there is a continuous weekly (Tuesday–Tuesday) time series of energy traders' futures positions. The COT data are collected on the four actively traded energy futures markets: crude oil, unleaded gasoline, heating oil, and natural gas.[9] The data are collected weekly from October 6, 1992 through December 28, 1999 for futures only positions.[10] Given this, the COT data reflect traders' positions as of Tuesday's close. A matching set of futures returns $R_t = \ln(p_t/p_{t-1})$ is calculated for nearby futures using Tuesday-to-Tuesday closing prices. We make no assumptions about how or why traders' positions might change over the course of a week, and there is no overlap between the return series (R_t) and one lag of the position series PNL_{t-1}. Both the return series and the PNL series are all stationary (Dickey–Fuller tests).

The first position measure examined is the percent of total open interest held by each CFTC grouping, as shown in Eq. (2). The summary statistics are presented in Table 1. Examining the data, it is clear that reporting commercial traders are the largest position holders in energy futures markets. Commercials comprise a low of 59.3% of the open interest in heating oil to a high of 70.9% in natural gas futures. The next largest group is nonreporting traders, who hold from 18.7% of futures contracts in natural gas up to 30.7% in heating oil. The smallest group is the reporting noncommercials or "funds." As shown in Fig. 1, the relative size of each trader category changes through time. The reason for

[7] Following the naming device presented by De Roon et al. (2000), the percent net long position held by noncommercials $\frac{\text{NCL}_t - \text{NCS}_t}{\text{NCL}_t + \text{NCS}_t + 2(\text{NCSP}_t)}$, would be referred to as "speculative pressure" and that held by nonreporting traders $\frac{\text{NRL}_t - \text{NRS}_t}{\text{NRL}_t + \text{NRS}_t}$ as "small trader pressure." Note that the PNL for each CFTC classification, when weighted by their percent of the total market open interest, will sum to zero.

[8] The COT reports were issued monthly prior to 1991 and bimonthly from January 1991 to November 1992. From 1975 through 1991, the data are available monthly. Prior to 1975, the reports were issued semimonthly.

[9] The CFTC reporting level for these markets are 350, 150, 250, and 175 contracts (futures-equivalent) for crude oil, gasoline, heating oil, and natural gas, respectively.

[10] The "optionized" or futures-equivalent data are available weekly from March of 1995 through December of 1999 (250 observations). Over this interval, the correlation between futures only and the futures-equivalent positions were all greater than 0.90, except in natural gas, which was 0.83. In fact, most of the correlations are greater than 0.95; so, it is unlikely that the combined futures and options data set would produce empirical results markedly different from those presented for futures only.

Table 1
Percent of total open interest held by CFTC reporting categories, October 1992–December 1999 (378 weekly observations)

	Crude oil	Gasoline	Heating oil	Natural gas
Reporting noncommercial	11.6[a] (5.9, 19.6)[b]	12.1 (11.8, 23.6)	10.0 (3.3, 19.7)	10.4 (4.4, 23.3)
Reporting commercial	67.2 (60.0, 78.1)	67.3 (55.2, 77.2)	59.3 (47.0, 72.6)	70.9 (58.8, 84.3)
Nonreporting	21.2 (22.0, 28.8)	20.6 (11.2, 30.6)	30.7 (15.1, 41.8)	18.7 (7.5, 30.8)

[a] The average percent of the total open interest held by the CFTC trader category.

[b] The minimum and maximum sample values are presented in parentheses (minimum, maximum).

these trends could stem from increases in speculative limits during the late 1990s (CFTC) and the general growth in managed futures (see Irwin and Yoshimaru, 1999).

The remainder of the analysis focuses on net market positions, as measured by the PNL in Eq. (3). The summary statistics for PNL are presented in Table 2. Across all the energy markets, reporting commercials hold net short positions, while reporting commercials and nonreporting traders hold net long positions.[11] These data suggest that energy hedgers are traditional short hedgers usually associated with production hedging. Furthermore, in all instances, the PNL is volatile, with each group swinging from net long to net short over the sample period. The exception is nonreporting traders in natural gas who did not have a net short position over this sample interval. The most volatile group is the reporting noncommercials where the PNL can reach extremes less than − 50% (short) and greater than 70% (long). The volatility of the noncommercials' net positions is clearly illustrated in Fig. 2. From these data, it is clear that noncommercials, although not a large percent of the total market, must be active traders who will change from long to short over the course of a week. The volatility of each category's net position indirectly reveals information about the diversity of motives within each group. It would appear that the least diverse set of motives exists for noncommercial traders. In fact, the data suggest that traders in this group largely act in concert, relative to traders in other groups. Thus, it is not surprising that they are thought to influence the market. This proposition is explicitly tested in the following sections.

Before specifically examining the lead–lag relationships between traders' positions (PNL) and market returns (R), it is worthwhile to examine the contemporaneous relationships between PNL_t and R_t. To measure this, simple correlation coefficients are calculated and presented in Table 3. All of the correlation coefficients in Table 3 are statistically different from zero at the 5% level. The results clearly indicate a positive contemporaneous correlation between the PNL for noncommercials and returns and a negative relationship between reporting commercials and returns. That is, reporting noncommercials are net buyers in rising markets, while commercial hedgers are net sellers. This characteristic of the data can support numerous theoretical results from hedging pressure by commercials (De Roon et al., 2000) to positive feedback trading by noncommercials (De Long et al., 1990). Certainly, it is no surprise that the correlations are opposite since the market as a whole must retain a neutral net position. Next, we explicitly consider the lead–lag relationship between net positions and returns.

[11] The position held by nonreporting traders is a residual measure. It must be the opposite of that held by reporting traders, which itself is a weighted average of reporting commercial and noncommercial positions.

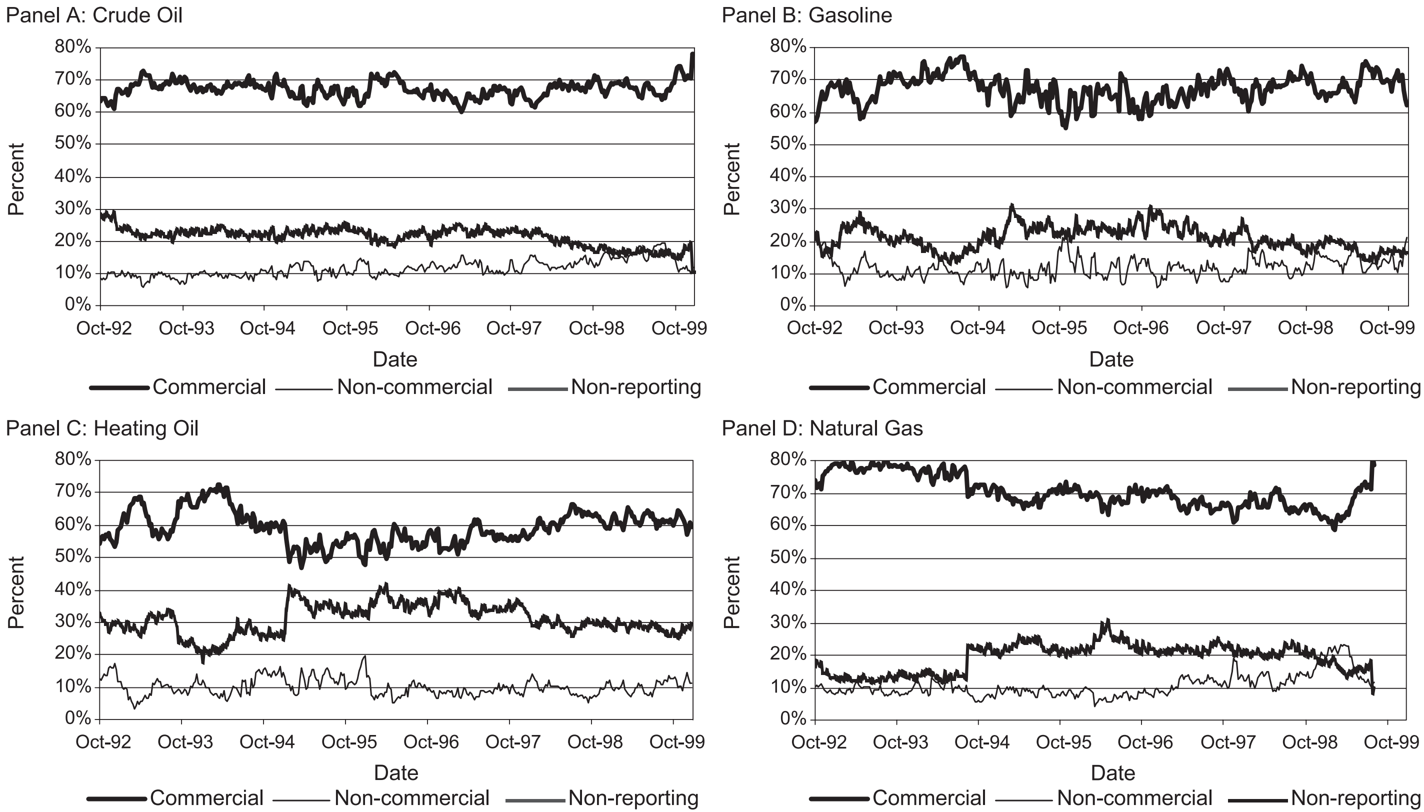

Fig. 1. Traders' positions as a percent of total open interest, October 1992–December 1999.

Table 2
Percent net long held by CFTC reporting categories, October 1992–December 1999 (378 weekly observations)

		Crude oil	Gasoline	Heating oil	Natural gas
Reporting noncommercial	Mean[a]	7.5	22.3	9.0	13.4
	S.D.[b]	25.1	31.1	30.1	37.0
	Range[c]	(− 54.6, 72.6)	(− 58.6, 84.4)	(− 51.9, 81.6)	(− 59.8, 85.1)
Reporting commercial	Mean	− 1.5	− 6.3	− 10.6	− 7.4
	S.D.	6.7	9.2	8.7	6.8
	Range	(− 17.1, 18.2)	(− 37.5, 17.3)	(− 30.2, 7.7)	(− 23.2, 8.0)
Nonreporting	Mean	0.6	5.8	16.7	20.3
	S.D.	7.5	11.8	7.4	6.8
	Range	(− 18.6, 17.9)	(− 20.0, 38.1)	(− 2.3, 35.3)	(3.6, 39.4)

[a] The average percent net long (PNL), calculated as long minus short positions divided by their sum. All of the means are statistically different from zero at the 5% level (two-tailed t test) except for nonreporting traders in crude oil. All the series are stationary at the 5% level (Dickey–Fuller test).

[b] Standard deviation.

[c] The minimum and maximum sample values are presented in parentheses (minimum, maximum).

5.3. Do returns lead traders' positions?

It is of interest to know if traders' positions relate to past price changes. That is, do traders alter their positions based on market movement? Traders who buy following price increases or sell following price declines may be trend followers. Conversely, traders who buy following price declines may be employing a contrarian or value strategy. In either case, it is interesting to understand how positions react (if at all) to past market returns. This relationship is easily tested in the traditional Granger causality framework. Hamilton (1984, p. 302) suggests the direct or bivariate Granger test for examining the lead–lag relationship between two series. The null hypothesis that futures returns do not lead trader positions is tested by estimating Eq. (4) under the null hypothesis that $\theta_j = 0$ for all j:

$$\mathrm{PNL}_t = \phi + \sum_{i=1}^{m} \lambda_i \mathrm{PNL}_{t-i} + \sum_{j=1}^{n} \theta_j R_{t-j} + \omega_t. \tag{4}$$

The lag structure (m,n) in Eq. (4) is determined by estimating the models for all values of $i = 1,2,\ldots,12$ and $j = 1,2,\ldots,12$, and then choosing the model that minimizes Akaike's information criteria (Beveridge and Oickle, 1994). The model is tested for serial correlation with a Lagrange multiplier test and heteroskedasticity with White's test. If there is serial correlation, then additional lags of the independent variable are added until it is eliminated. If the model is heteroskedastic, then we utilize White's heteroskedastic consistent covariance estimator. We also calculate the cumulative impact of lagged values of R and test that the $\Sigma\theta_j = 0$.

The p values from the Wald chi-square tests are presented in Table 4. The results for reporting noncommercials are consistent across markets. The null hypothesis is rejected at conventional levels in all cases, and the impact is uniformly positive. That is, positive futures returns result in reporting noncommercials, increasing their net long position the

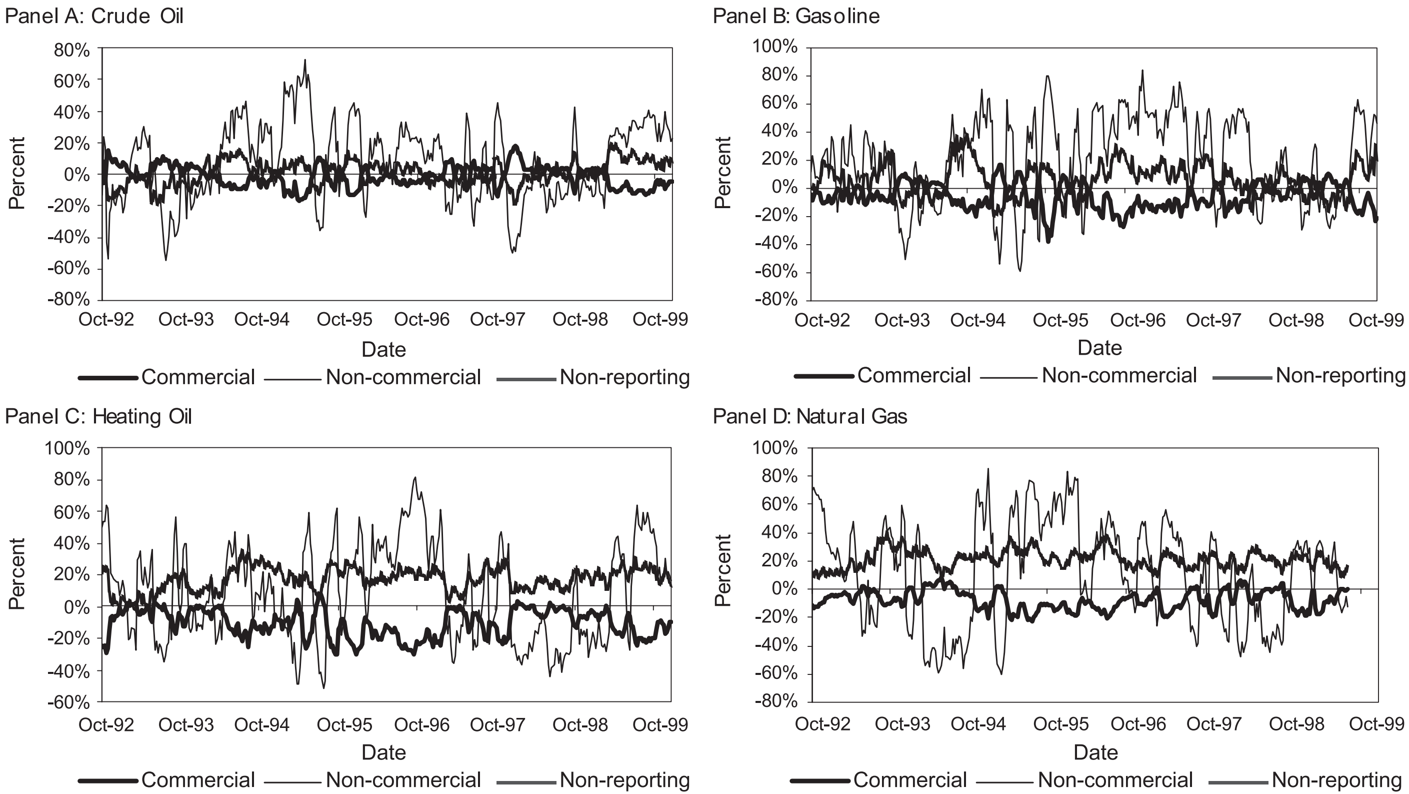

Fig. 2. Traders' percent net long positions, October 1992–December 1999.

Table 3
Contemporaneous correlation coefficients between futures returns and percent net long positions, October 1992–December 1999 (378 weekly observations)

Trader category	Crude oil	Gasoline	Heating oil	Natural gas
Reporting noncommercial	0.287[a]	0.281	0.185	0.231
Reporting commercial	−0.324	−0.315	−0.229	−0.252
Nonreporting	0.329	0.252	0.224	0.149

[a] Simple correlation coefficients calculated over 378 observations. Using a two-tailed t test, any correlation greater than 0.10 in absolute value is statistically significant at the 5% level.

following week. This could be indicative of a class of positive feedback traders or trend followers as described by De Long et al. (1990).

The results for reporting commercials (second row) are also fairly consistent. Returns lead net positions and the impact is uniformly negative: commercials increase long positions as prices fall. This could characterize "value hedgers" or negative feedback traders who sell in rising markets. Alternatively, this could be a manifestation of the data constraint that longs must equal shorts, where commercials take the opposite position of positive feedback noncommercial traders. The empirical results clearly allow for a wide range of theoretical interpretations.

The results are mixed for nonreporting traders in Table 4. Although the p values suggest that the lagged returns are important in determining net positions held by nonreporting traders, the directional impact is mixed. This could stem from the nonreporting category containing an unknown mix of hedgers and speculators.

To increase the power of these tests, Wang suggests estimating Eq. (4) as a system. Following this suggestion, Eq. (4) is estimated as a cross-sectional time series with the data pooled across the four energy markets. That is, for each trader category, the data are pooled across markets and estimated in a seeming unrelated regression framework adjusted for cross-sectional heteroskedasticity (Kmenta, 1986, p. 635). The pooled estimation facilitates presentation and tests for common characteristics in the data (Wang, 2001,2002). The SUR pooling procedure is appropriate given prior evidence of common trends in the data (Serletis, 1994) and a relatively high correlation among weekly returns.[12]

The lag lengths for the pooled models are chosen based upon the maximum lags chosen across the individual markets. For instance, looking at the reporting noncommercial models in Table 4, the maximum m across the four markets is 7 and the maximum n across the four markets is 4, so the pooled model is estimated with $m=7$ and $n=4$. This procedure avoids the possibility of an underspecification bias at the expense of estimating a few additional coefficients.

The pooled estimation results are presented in Table 5. The p value (last row) clearly results in a rejection of the null hypothesis that returns do not lead positions. This is consistent with the individual market results. The individual parameter estimates show that for noncommercials, the impact of returns is positive. Positive returns lead to net buying by noncommercials. Furthermore, the impact is statistically significant out to a 3-week lag. For instance, a 10% price increase leads to a 5.918% increase in commercials PNL

[12] Crude oil, gasoline, and heating oil returns are all correlated at 0.75 or greater. The correlations with natural gas are lower, ranging from 0.20 for crude oil to 0.27 for heating oil.

Table 4
Granger causality test that returns lead percent net long positions, October 1992 – December 1999 (378 weekly observations)

Trader category		Crude oil	Gasoline	Heating oil	Natural gas
Reporting noncommercial	(m,n)[a]	7,1	1,2	1,4	2,3
	p value[b]	0.0036	0.0000	0.0000	0.0018
	Impact[c]	(+)*	(+)*	(+)*	(+)*
Reporting commercial	(m,n)	5,1	1,2	4,1	2,1
	p value	0.0004	0.0000	0.0002	0.0000
	Impact	(−)*	(−)*	(−)*	(−)*
Nonreporting	(m,n)	3,7	7,8	6,2	3,1
	p value	0.0000	0.0000	0.0076	0.0543
	Impact	(+)	(−)	(+)*	(+)

[a] The lag structure (m,n) specified for each OLS regression: $\mathrm{PNL}_t = \phi + \sum_{i=1}^{m} \lambda_i \mathrm{PNL}_{t-i} + \sum_{j=1}^{n} \theta_j R_{t-j} + \omega_t$.

[b] The p value from the Wald chi-squared test of the null, $\theta_j = 0\ \forall_j$. Rejection of the null implies that returns, R, lead traders' positions, PNL.

[c] The cumulative impact of lagged values of R. The (+) or (−) is the sign of $\Sigma\theta_j$, and an asterisk (*) denotes a rejection of the null that $\Sigma\theta_j = 0$ at the 5% level (Wald chi-square test).

positions the following week, a 2.484% increase 2 weeks later, and a 2.418% increase 3 weeks later (all else equal). Conversely, commercial traders tend to sell after rising markets: positive returns lead to net selling on the behalf of commercial hedgers. For instance, a 10% increase in price results in a 0.839% decline in commercials PNL position the following week. The results for nonreporting traders are mixed. At 1- and 2-week lags, there is a positive impact between returns and positions; however, at 3- to 8-week lags, the

Table 5
Pooled estimation results: futures returns lead percent net long positions, October 1995 – December, 1999

Dependent variables	Reporting noncommercials	Reporting commercials	Nonreporting traders
Constant	0.0142**	− 0.0046**	0.0058**
PNL_{t-1}	0.9060**	0.9756**	0.7523**
PNL_{t-2}	− 0.0303	− 0.0319	0.1591**
PNL_{t-3}	− 0.0535	− 0.0678*	− 0.0326
PNL_{t-4}	0.0255	0.0477	0.0554
PNL_{t-5}	0.0355	− 0.0013	0.0733**
PNL_{t-6}	− 0.0596*		− 0.0372
PNL_{t-7}	0.0464*		− 0.0087
R_{t-1}	0.5918**	− 0.0839**	0.0830**
R_{t-2}	0.2484**	− 0.0120	0.0367*
R_{t-3}	0.2418**		− 0.0171
R_{t-4}	− 0.0428		− 0.0375*
R_{t-5}			− 0.0728**
R_{t-6}			− 0.0516**
R_{t-7}			− 0.0375*
R_{t-8}			− 0.0349*
p value[a]	0.0000	0.0000	0.0000

[a] p value from the chi-square test that the coefficient estimates on lagged returns R jointly equal zero.

* Statistically different from zero at the 10% level.

** Statistically different from zero at the 5% level.

relationship is negative. Again, the mixed results for nonreporting traders may stem from the fact that the motives for this trader class are not well defined.

5.4. Do traders' positions lead returns?

Practitioners and academics alike are interested in whether or not traders' positions are useful in predicting subsequent market returns. If they are, practitioners may develop profitable trading strategies, and academics can gain insight into theories concerning risk premiums and hedging pressure. To test if traders positions, as measured by PNL, are useful in forecasting market returns, we again employ Granger causality.

In Eq. (5), the series PNL_t is said to lead futures returns R_t if they are useful in predicting R_t. The null hypothesis that PNL_t does not lead R_t (H_0: $\beta_j = 0\ \forall\ j$) is tested with a Wald chi-square test in the following OLS regression, where the model is specified and estimated with the same procedures presented in Section 5.3:

$$R_t = \alpha + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j \mathrm{PNL}_{t-j} + \varepsilon_t \tag{5}$$

The results (p values) for testing the null that PNL_t does not lead R_t are presented in Table 6. Looking at the first row, it is clear that models with short lag structures are selected, and there is little evidence that reporting noncommercial or "fund" positions contain any predictive information about returns. That is, we cannot reject the null that positions do not lead returns at the 5% level. Furthermore, the directional impact is mixed. One possible interpretation of the results is that funds do not increase long (short) positions prior to rising (falling) futures prices. That is, funds do not exhibit systematic forecasting ability over 1-week intervals.

The impact of reporting commercials' positions is mixed and statistical significance is weak. Again, the optimal lag structure is relatively short with only one or two lags of PNL

Table 6
Granger causality test that percent net long positions lead futures returns, October 1992–December 1999 (378 weekly observations)

Trader category		Crude oil	Gasoline	Heating oil	Natural gas
Reporting noncommercial	(m,n)[a]	1,1	1,1	1,1	3,2
	p value[b]	0.3055	0.4841	0.6975	0.1029
	Impact[c]	(+)	(+)	(−)	(+)
Reporting commercial	(m,n)	1,2	1,1	1,1	3,1
	p value	0.0342	0.3923	0.8838	0.4067
	Impact	(−)	(−)	(+)	(−)
Nonreporting	(m,n)	1,2	1,1	1,1	3,2
	p value	0.0033	0.2857	0.5803	0.2988
	Impact	(+)*	(+)	(+)	(+)

[a] The lag structure (m,n) specified for the OLS regression: $R_t = \alpha + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j \mathrm{PNL}_{t-j} + \varepsilon_t$.

[b] The p value from the Wald chi-square test of the null $\beta_j = 0\ \forall\ j$. Rejection of the null implies that the PNL leads futures returns R.

[c] The cumulative impact of lagged values of PNL. The (+) or (−) is the sign of $\Sigma\beta_j$, and an asterisk (*) denotes a rejection of the null that $\Sigma\beta_j = 0$ at the 5% level (Wald chi-square test).

specified. Only in crude oil can the null hypothesis (that net positions do not lead returns) be rejected at the 5% level. In this case, the directional impact is negative, which is consistent with the findings of Wang for agricultural futures markets. The impact of nonreporting traders is consistently positive, but only statistically significant in crude oil. Because the motives of this trader classification are not known, interpretation of the results is difficult. Collectively, the results in Table 6 do not suggest that there is a systematic tendency for any of the trader groups' positions to predict market returns. What little evidence that does exist is isolated to the crude oil futures market.

Eq. (5) is estimated as a system across the four energy markets using the SUR procedure described in Section 5.3. The results are presented in Table 7. The null hypothesis that percent net long positions do not lead returns cannot be rejected at the 5% level for any of the trader classifications. The null is, however, rejected at the 10% level for noncommercials. In this case, the coefficient estimates suggest price reversals following changes in noncommercials positions. Oddly, this result is opposite to that of Wang, who finds that noncommercial positions predict price continuations in agricultural futures markets.

In summary, the Granger causality tests suggest the following. First, there is no pervasive evidence that traders' PNL positions contain general predictive information about market returns. Second, there is consistent evidence that positive futures returns cause the net long positions held by noncommercial traders to increase. Conversely, commercial traders show a tendency to be net sellers of futures positions the week following an increase in prices. The results for nonreporting traders are mixed. The evidence that speculators are potentially trend followers is consistent with similar work using sentiment indices in energy futures markets (Sanders et al., 2000).

5.5. Impact of extreme trader positions

Practitioners (see opening quotes) suggest that traders' positions may only have a market impact when they reach extreme levels. To test this assertion, we follow Wang and define an extreme position as the upper and lower 20th percentile of the prior 3-year range. So, we define the variable LO = 1 if PNL is in the lower 20th percentile of its range from

Table 7
Pooled estimation results: percent net long positions lead futures returns, October 1992 – December 1999

Dependent variables	Reporting noncommercials	Reporting commercials	Nonreporting traders
Constant	0.0012	0.0014	0.0004
R_{t-1}	− 0.0105	− 0.0151	− 0.0189
R_{t-2}	0.0458*	0.0415	0.0363
R_{t-3}	0.0691**	0.0646**	0.0582**
PNL_{t-1}	− 0.0048	0.0049	0.0132
PNL_{t-2}	− 0.0016	0.0112	− 0.0146
p value[a]	0.0927	0.1588	0.6737

[a] p value from the chi-square test of the null hypothesis that the estimated coefficients on lagged PNL jointly equal zero.

* Statistically different from zero at the 10% level.

** Statistically different from zero at the 5% level.

the prior 3 years, and LO = 0 otherwise. The variable HI = 1 if PNL is in the upper 20th percentile of its 3-year range, and HI = 0 otherwise. The following OLS regression is then used to test the impact of extreme positions on market returns:

$$R_t = \alpha_0 + \alpha_1 \mathrm{LO}_{t-1} + \alpha_2 \mathrm{HI}_{t-1} + \varepsilon_t. \tag{6}$$

The null hypothesis that extreme positions do not impact market returns ($\alpha_1 = \alpha_2 = 0$) is tested with a Wald chi-square test. Eq. (6) is a version of the market timing test proposed by Cumby and Modest. It is essentially a difference in means test, where $\alpha_0 + \alpha_1$ is the mean return conditioned on extremely low net long positions, and $\alpha_0 + \alpha_2$ is the expected return following extremely high net long positions. If the mean return conditioned on extremely short positions ($\alpha_0 + \alpha_1$) or extremely long positions ($\alpha_0 + \alpha_2$) is different from the unconditional mean (α_0), then extreme PNL positions are useful in forecasting market returns. Note that the use of the first 3 years of the data set to define "extreme" positions results in a reduction of observations from 378 to 221 weekly observations.

The estimates of Eq. (6) for individual markets are presented in Table 8. In no case does the *F* test reject the null hypothesis that extreme position levels do not predict returns at the 5% level. There are a few cases where individual coefficients are statistically significant (5% level, two-tailed *t* test). In those instances, the coefficients tend to suggest price continuation, not reversals. For instance, when noncommercial gasoline traders show an extremely small PNL position, the ensuing week's return is a statistically negative 0.59% (0.0068 – 0.0127). Likewise, when nonreporting natural gas traders have a relatively large PNL position, subsequent weekly returns are 2.61% (– 0.0080 + 0.0341). Other than these isolated instances, there is little evidence that extreme position levels are consistent predictors of price movement.

To increase the power of this test and to make a more general statement about the impact of extreme trader positions in the energy markets, a pooled version of Eq. (6) is estimated using the methodology described in the prior sections. The estimated parameters

Table 8
Extreme level regressions, October 1995 – December – 1999 (221 weekly observations)

Trader category	Variable	Crude oil	Gasoline	Heating oil	Natural gas
Reporting noncommercial	Constant	0.0024	0.0068	0.0054	0.0001
	LO = 1	– 0.0016	– 0.0127*	– 0.0118	– 0.0027
	HI = 1	0.0052	– 0.0051	– 0.0033	0.0008
	p value[a]	0.7346	0.1850	0.2646	0.9759
Reporting commercial	Constant	0.0006	0.0041	0.0031	– 0.0075
	LO = 1	0.0070	– 0.0005	0.0034	0.0155
	HI = 1	0.0055	– 0.0060	– 0.0096	0.0116
	p value	0.5946	0.6966	0.3191	0.4023
Nonreporting	Constant	– 0.0022	0.0035	0.0038	– 0.0080
	LO = 1	0.0093	– 0.0037	– 0.0073	0.0132
	HI = 1	0.0148**	– 0.0001	– 0.0041	0.0341**
	p value	0.1147	0.8725	0.6218	0.0900

[a] *p* value from *F* test that all slope coefficients equal zero.
* Statistically different from zero at the 10% level.
** Statistically different from zero at the 5% level.

Table 9
Pooled estimation results: extreme level regressions, October 1995–December 1999

Dependent variables	Reporting noncommercials	Reporting commercials	Nonreporting traders
Constant	0.0032	0.0021	0.0017
LO = 1	− 0.0011	− 0.0010	0.0011
HI = 1	0.0043*	0.0006	0.0008
p value[a]	0.1704	0.8961	0.8779

[a] p value from the chi-square test of the joint that the coefficients on LO and HI are both zero.
* Statistically different from zero at the 10% level.

are presented in Table 9. The results are similar to those found in the individual markets. For all three trader classifications, the null hypothesis of no timing ability is not rejected at conventional levels. Only the estimated coefficient on HI for noncommercials is statistically different from zero (10% level), and it suggests a pattern of price continuation following large PNL positions taken by noncommercials. Again, there is no pervasive evidence that CFTC traders' positions are useful for predicting returns in the energy futures markets.

Interestingly, the above results are in contrast to those documented by Wang for agricultural futures markets. Wang consistently documents return predictability based on traders' positions in agricultural futures markets. In particular, he shows that commercial positions covary negatively with subsequent market returns (price reversals), and large noncommercial positions predict positive returns (price continuation). Wang's methodology differs in three primary ways: (1) different markets are analyzed; (2) different time horizons are used; and (3) the statistical methodology differs.[13] Any three of these could underlie the different results. However, it is clear that the empirical results using COT data in one industry apparently do not imply similar results in other markets. Therefore, it is important that researchers and practitioners be aware of these results and how the COT data may be used in analyzing energy futures markets.

6. Summary and conclusions

The CFTC collects detailed daily information on the positions held by reporting traders. A subset of that information is released to the public in the biweekly COT reports. A futures market's open interest is disaggregated into positions held by reporting and nonreporting traders, and reporting traders are further identified as commercials or noncommercials. These groups are commonly referred to as funds (reporting noncommercials), hedgers (reporting commercials), and small speculators (nonreporting traders).

The collection methodology underlying the COT data leads to the following conclusions. First, the data provide no information about nonreporting traders other than that they do not hold positions in excess of reporting levels. Second, the trading motives in the reporting commercial classification are likely to extend beyond just hedging. That is, pure

[13] The authors attempted to reconcile the differences between the presented results and those of Wang. Alternative intervals or horizons were used (up to 4 weeks), but the results were not markedly different from those presented. Longer lag structures were employed in the all the tests; but, again, the conclusions were similar.

hedging positions are a subset of those represented by CFTC reporting commercials. Finally, reporting noncommercials are the trader category least prone to reporting error. Since there are no incentives to self-classify as a speculator, the reporting noncommercial positions likely reflect a pure subset of true speculative positions.

The empirical analysis focused on traders' positions in crude oil, gasoline, heating oil, and natural gas futures from 1992 through 1999 (378 weekly observations). The empirical analysis shows that the largest positions are held by reporting commercials and the smallest by reporting noncommercials. Noncommercials are a relatively small percent of the total market (between 10% and 12% of the open interest for the tested markets), but they are active traders who may change from extreme net long positions to extreme net short positions over the course of a week.

The contemporaneous relationship between the PNL for each CFTC trader class and market returns (R_t) is analyzed. The results indicate that reporting noncommercials increase their long positions in rising markets, and commercials decrease their long positions in rising markets. The fact that the noncommercials and commercials show inverse changes in their positions is not surprising, since longs and shorts must balance. Importantly, this contemporaneous relationship can support a number of competing theoretical models such as hedging pressure or positive feedback trading.

The lead–lag relationship between net positions and market returns is analyzed in a Granger causality framework. The results clearly indicate that positive futures returns Granger cause increases in the net long positions held by reporting noncommercial traders, whereas commercials are net sellers following price increases. There is no consistent evidence that traders' PNL positions contain any general predictive information about market returns. That is, PNL positions do not generally lead market returns. Furthermore, there is little evidence that extreme PNL positions in energy futures provide information about market returns.

The above findings are important for accurately interpreting prior empirical results and theoretical models. First, any research that assumes positions at the end of a time period that are the same as those held during the time period must be carefully evaluated (see Chang, 1985; Bessembinder, 1992; Catrath et al., 1997; De Roon et al., 2000). The contemporaneous correlation between returns and positions will generate results showing that commercial traders create hedging pressure, which results in a risk premium flowing to noncommercials. Or, it will appear that noncommercials are profitable traders and commercials are not. The lead–lag relationships presented in this research, however, show that neither group's positions are systematically useful in predicting returns. In fact, for both groups, returns lead positions. That is, commercials are net sellers the week following an increase in prices, and noncommercials are net buyers. It is not clear that the COT data provide any information concerning the profitability of trader groups in energy futures markets.

The finding that traders' positions are not useful in predicting returns cast a doubt on their usefulness as an independent indicator of market direction. In this analysis, it is assumed that the COT data are available immediately (on Tuesday). Historically, there is lag between when the data are collected and when they released to the public (Friday of the same week). In the interim, traders' positions can change dramatically, especially those held by noncommercials. Thus, it is even more unlikely that the public release of the data is useful in predicting returns. However, our tests certainly do not rule out the possibility that these data can be used in conjunction with other information to forecast energy prices. Regardless, the CFTC's COT is a unique data set that provides numerous opportunities for additional research in energy futures markets.

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