Determinants of Trading Profits of Individual Futures Traders: Risk Premia, Information, and Luck

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August 2009

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Abstract

Using a unique proprietary data set of trades in the crude oil, gasoline, and heating oil futures markets, we explore determinants of the trading profits/losses of individual traders. Consistent with the risk premium hypothesis, futures prices are significantly related to hedging pressure and hedgers' mean trading profits are significantly negative while the mean trading profits of speculators (hedge funds especially) are significantly positive. Moreover, the profits of individual traders (whether speculators or hedgers) are a strong positive function of the extent to which the trader shorts (longs) when hedgers in the aggregate are long (short). While some individual traders may have an informational advantage, the trading profits of speculators in general and hedge funds in particular are primarily due to employing trading strategies which take advantage of the risk premium, i.e., to longing (shorting) when hedgers are net short (long). Thus our evidence indicates that speculator profits are primarily due to the liquidity and risk absorption services they provide hedgers. Not counting their profits from the bid/ask spread, market maker profits are significantly negative indicating an information asymmetry in which they tend to lose on trades with better informed traders. We also find that (excepting households) profitability is a positive function of the rates at which traders turn over their portfolios and that spread trades tend to be profitable.

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One of the oldest and most basic issues in finance is the extent to which differential trading profits/losses among security traders represent differences in risk taking, differences in information or skill, or luck. This paper seeks to provide evidence on this issue by examining trading profits of individual traders in three energy futures markets: crude oil, gasoline, and heating oil.

According to the traditional risk premium (or normal backwardation) theory of Keynes (1930) and Hicks (1939), expected trading profits should be positive for speculators and negative for hedgers. The assumption is that rational speculators will not enter the market unless expected profits from speculation are positive. Since futures market trading is a zero-sum game before transaction costs, this means that hedgers lose on their futures' positions on average. If most hedgers have long positions in the underlying asset (as Keynes and Hicks assumed) so hedge by shorting in the futures market, futures prices will be pushed below expected future spot prices (backwardation) and speculators can make positive profits on average by going long. If most hedgers are short in the underlying asset and long in the futures market, futures prices will be biased upward (contango) and speculators can make expected profits by shorting futures.

In the past, this theory has primarily been tested by relating ex-post returns on hypothetical futures' positions to aggregate open interest positions of commercial and non-commercial traders as reported in the CFTC's weekly "Commitments of Traders" (COT) report. The presumption is that commercial traders are more likely to be hedgers than non-commercial traders so that the risk premium hypothesis predicts positive average returns on long (short) positions when commercial traders in the aggregate are net short (long). Using this approach, Bessembinder (1992), Bessembinder and Chan (1992), de Roon et al (2000), and Wang (2001) find evidence supporting the risk premium theory. Kolb (1992) does not. Fama and French (1987) find some evidence for a risk premium but conclude it is too weak " to resolve the long-standing controversy about the existence of non-zero expected premiums." (1987, p. 72). The underlying supposition of these tests that commercial traders are more likely than non-commercial to be hedgers has been challenged by Ederington and Lee (2002).

The luck hypothesis and evidence is most forcefully stated by Hartzmark (1987, 1991) in two of the very few papers that present evidence on individual traders. Hartzmark (1987) finds that commercial traders earn small positive futures trading profits on average while non-commercial trading profits are negative - directly the opposite of the risk premium hypothesis prediction. In a follow-up (Hartzmark, 1991), he finds: 1) that the number of traders with consistent forecasting ability (as measured by consistent profits) is no more than one would expect due to chance, and 2) that winners in the first half of his study period are no more likely than first half losers to be winners in the second half. He concludes that "luck that determines trader performance." (1991, p.49).

A growing body of evidence outside of futures markets - stock markets in particular - calls both the risk premium and luck hypotheses into question. First, a number of studies, including Odean (1998, 1999), Barber and Odean (2000), and Barber et al. (2005) argue that much individual investor trading is driven by over-confidence so that individual investors, particularly those that trade frequently, earn below average profits. Applied to futures markets, this would suggest that some speculators may not be deterred by losses to the extent predicted by a model of rational decision making. In other words, while the expected profits from speculation might be negative if rationally calculated, some speculators view them as positive.

Second, a number of stock market studies find that informational and/or skill levels differ between investors leading to differential trading profits - at least before transaction costs. Papers by Carhart (1997), Grinblat and Titman (1989, 1993), Wermers (2000), and Chen et al (2000) among others find that some mutual funds have superior stock picking ability while Ackerman et al. (1999), Ibbotson and Chen (2005), Kosowski et al. (2007), and Jagannathan et al. (2008) find the same for hedge funds. We would expect informational differences to be at least as great in the energy futures markets as in the stock market - particularly since companies are not under the equal disclosure requirements in these markets that they are in stock markets. Large producers may be able to forecast supply and demand from their own production, inventories, and order flow while pipelines and marketers seem particularly well placed to observe flows, orders, and inventories. Consistent with differential information, Leuthold et al. (1994) find in the pork bellies futures market that "a subset of elite traders possesses significant forecasting ability," leading to consistent trading profits.

Third, the distinction between hedgers and speculators is not sharp since many hedging programs apparently include some speculation. Dolde (1993), Bodnar, Hayt and Marston (1998) and Glaum (2002) provide survey evidence suggesting that the practice of selective hedging, i.e., firms incorporating their views about future market movements into their hedging programs, is widespread in the U.S. and Europe. Stulz (1996) suggests that selective hedging would be rational if firms possess the ability to forecast future market movements based on private information they acquire in the course of their business. However, Adam and Fernando (2006) and Brown, Crabb, and Haushalter (2006) find no evidence that firms are able to outperform the market by selective hedging.

In this paper, we test how trader profits in the three large energy futures markets: crude oil, gasoline, and heating oil depend on: 1) whether the trader is most likely a hedger or speculator, 2) possible informational and skill differences, 3) trader trading strategies, and/or 4) luck using a unique proprietary data set of trades by individual large and mid-size traders over 46 months. As part of its market surveillance, The CFTC requires brokers to report daily open interest positions of all traders whose open interest positions exceed thresholds set to capture about 70% - 90% of total open interest. We utilize this disaggregate daily data on individual traders, which is normally only in highly aggregated form, to calculate trader profits. Since both the likelihood that a trader is primarily hedging or speculating and their access to information should differ by industry or line of business, each traders is classified into one of the eleven trader categories as described in Table 1: refiners, independent producers, marketers/distributors/pipelines, large energy consumers, commercial banks, energy traders, hedge funds, individuals, investment banks, floor traders, and unknown (unclassified). We also hypothesize that trading profits will differ with trader size, experience, and trading strategies.

Our findings include the following. One, in contradiction of Hartzmark's luck hypothesis, we document persistent profit differences among individual traders. Two, supporting the risk premium hypothesis, we find a significant relation between the risk premium and net hedging pressure, implying that net longing (shorting) by hedgers pushes futures prices above (below) expected future spot prices creating profit opportunities for speculators. Three, also consistent with the risk premium hypothesis, likely hedgers, as identified by their line of business, tend to have futures trading losses while likely speculators, hedge funds in particular, turn consistent profits. Four, individual trader profits are a positive function of the extent to which they take positions opposite to those of likely hedgers, i.e., longing (shorting) when likely hedgers in the aggregate are net short (long). Five, hedge funds are the most profitable of the eleven trader types we examine and their profits are almost totally due to their exploitation of the risk premium, i.e., longing when likely hedgers in the aggregate are net short and shorting when likely hedgers are net long. Six, not counting their profits from the bid/ask spread, floor traders (the major market makers in these markets) have sizable trading losses indicating that they operate at an informational disadvantage and lose on average from their trades with more informed traders. Seven, ceteris paribus, trading profits tend to be higher for more active traders. However there is no evidence that larger traders have an information advantage. Eight, consistent with the evidence in Büyükşahin et al. (2008), spread traders were able to profit from mispricings during this period. In general, our evidence indicates that speculator profits are largely due to the liquidity and risk absorption services they provide hedgers.

The remainder of the paper is organized as follows. Our unique data set is described in the next section and our profit measures in section II. In III, we develop our hypotheses and independent variables. Results are described in section IV and V concludes the paper.

I. Data

Our data comes from the CFTC's Large Trader Reporting System (LRTS). Haight et al. (2007) provide a good description of this system. The CFTC requires daily reports on the holdings of all traders whose total open interest position exceeds set thresholds, currently 350 contracts for crude oil, 250 for heating oil, and 150 for gasoline. According to the CFTC, these thresholds are set so that the reported positions normally account for 70% to 90% of total open interest (CFTC website, August 2008). The remaining 10% to 30% or so represents positions of smaller traders. From this data set, the CTFC compiles the weekly COT report on the aggregate open interest positions of commercial and non-commercial traders used in past tests of the risk premium hypothesis. While normally available only in this highly aggregated form, the Department of Energy (DOE) provided us with the disaggregated data on the open interest positions of individual reporting traders in the NYMEX's crude oil, heating oil (also known as #2 fuel oil), and gasoline futures markets from June 1993 through March 1997. On average over this period, these reporting traders account for 77.7% of open interest in the crude oil futures market, 81.3% of gasoline open interest, and 68.4% of heating oil open interest.

To classify traders as commercial or non-commercial for the COT reports, the CFTC asks on the reporting form: "Is the reporting trader engaged in business activities hedged by the use of futures and options markets?" If the answer is yes, the trader is classified as "commercial" and if no as "noncommercial." There are a couple of aspects of this classification worth noting. First, the traders self select (though the CFTC staff may overrule them) which may lead to a bias toward the "hedger" category. Second, the question is general, not market specific. The traders answer once for all markets though the CFTC staff assign different classifications for different markets. For instance, an investment bank which answers "yes" because it hedges its stock market exposure with stock index futures but which speculates in other futures markets would normally classified as commercial in all. Ederington and Lee (2002) argue that in the energy futures markets, the "commercial" category includes many likely speculators.

The CFTC also assigns sub-classifications, which are described in Haight et al. (2007) and Büyükşahin et al. (2008) to most traders. For our trader type classifications, we utilize their non-commercial sub-classifications which include: commodity pool operators, commodity trading advisors, managed money, futures commission merchants, floor traders, and floor brokers. According to Haight et al. (2007), the first three sub-classifications are similar and composed primarily of hedge funds so, like Haight et al. (2007), we combine these three into a single hedge fund/managed money category. Because trades by floor brokers and futures commission merchants for their clients are reported for the latter, the trades reported under these two sub-classifications represent (like floor traders) trades for their own account. Since these are the major market makers in futures markets, we combine them into a single market maker/floor trader category. There are a number of non-commercial traders with no subclassification code which proved to be individuals or households. In summary, we assign the CFTC's non-commercial traders to three trader types: hedge funds, market makers/floor traders, and individuals.

The CFTC's sub-classifications of commercial traders, e.g., manufacturer, dealer/merchant, etc.) proved less useful so we developed our own subclassifications which are described in Table 1: refiners, independent producers, marketers/distributors/pipelines (MDPs), large consumers, commercial banks, investment banks and brokers, and energy traders.[1] The latter are hedge funds or hedge-fund-like-traders but are primarily offshore and classified by the CFTC as commercial so we treat them separately. We separate energy producers into those with refining capacity (refiners) and without (independent producers) since the latter are clearly long in the physical crude oil market while the former could be either long or short.[2] A residual group of smaller commercial traders could not be classified.

In addition to the eleven trader types listed in Table 1, we separate the traders into: 1) likely hedgers, 2) likely speculators, 3) market makers, and 4) others (or unknown). A major limitation of our study is that we know only the traders' futures market positions. We can not observe their cash market, forward, or swap positions.[3] Hence, our judgment of the likelihood that a trader is hedging or speculating is based partially on their line-of-business.[4] We regard the first five of the commercial classifications listed in Table 1 as the traders most likely to be hedging. The first four classifications: (1) refiners, (2) energy independents, (3) MDPs, and (4) large consumers all have sizable cash and/or forward energy market positions which they could be hedging and banking regulations restrict commercial banks (the fifth classification) to hedging activities. Conversely, we view hedge funds and individuals from the CFTC's non-commercial category and energy traders from the commercial category as likely speculators since they have no known physical or forward market positions. Investment banks/brokers are the major unknown on the hedging/speculating spectrum since they could either be hedging their OTC swap positions or speculating. Hence, we consider them separately. Market makers/floor traders are also considered separately.

As indicated above, the LRTS data which we utilize is normally available only in highly aggregated form. Like us, Hartzmark (1987, 1991) and Leuthold et al (1994) use dis-aggregated LRTS data to calculate profits of individual traders. However, they only know whether the individual traders are classified as commercial or non-commercial, not their line of business. Haight et al. (2007), Büyükşahin et al. (2008), and Büyükşahin and Harris (2009) utilize the CFTC subclassifications but do not calculate individual trader profits.

Our data set contains 939 traders for which there are 1,059,616 trader/day/contract observations and 486,334 trades. However, many of these 939 traders were only active a few days during our data period or made small trades. To obtain enough observations for each trader to test profit tendencies, to ensure continuous series for most traders,[5] and to make the trader classification task described above more manageable, for inclusion in our final sample we require that the trader hold an open interest position at least 100 days during our period and make at least 50 trades. This results in a final sample of 382 traders. These 382 account for 96.3% of the trader/day/contract observations and 97.9% of total open interest, so we lose very little by restricting the sample to these 382 more active traders. Descriptive statistics are reported in Table 2 for our three markets.[6] Note that the crude oil market is the largest accounting for 64.9% of open interest in terms of contracts and 60.6% in dollar terms, and 50.6%, of our observations. Also, times-to-expiration tend to be longer in the crude oil futures market.

Descriptive statistics for our eleven trader types are in Table 3. As shown there, in terms of both open interest and trades, the energy futures markets are dominated by refiners, investment banks, and MDPs which together account for 68.7% of open interest and 57.7% of trades. On the other hand, there was little trading by major energy consumers such as airlines, trucking companies, and utilities. Combined, the similar hedge fund and energy trader classifications represent roughly eleven percent of both open interest and trades.[7] Making numerous small trades, market makers account for 12.9% of trades but only 4.4% of open interest. These figures undoubtedly understate market maker trading since we only capture positions held overnight. While numerous, the unclassified traders represent a minor portion of trading and even less of the open interest.

The figures in Table 3 indicate some speculation or selective hedging by energy firms. To hedge future sales, refiners should short gasoline and heating oil contracts[8] and independent producers should short crude oil. Yet, long positions account for roughly a third of their open interest in these contracts. The consumer category consists primarily of airlines which one would expect to hedge their fuel needs by longing fuel oil contracts and that (85% of open interest) is primarily the case. Commercial bank open interest is concentrated in crude oil where they are generally short - the expected pattern if hedging loans to energy producers. Individuals (households) are generally long.

II. Profit Measures

We observe changes in end-of-day open interest rather than trades directly. If a trader's open interest in a particular futures contract changes between the close of day t-1 and close of day t it is obvious that a trade occurred on day t. However, we miss any trades reversed the same day.

Our profit measure is the daily holding period profit resulting from marking the traders' positions to market at the end of each day. If there is no trade on day t, the profit/loss on trader i's holding in a given futures contract is $X_{i,c,m,t-1}(P_{c,m,t}-P_{c,m,t-1})$ where $X_{i,c,m,t}$ is trader i's open interest position in contract type c (crude oil, gasoline, or heating oil) maturing in month m at the close on day t and $P_{c,m,t}$ is the closing price of contract c-m (henceforth we will use the term "c-m" to designate a contract of type c expiring in month m) on day t. If i's position in contract c-m is short on day t, $X_{i,c,m,t}<0$. Suppose trader i longs contract c-m on day t so $X_{i,c,m,t}>X_{i,c,m,t-1}$. Since we don't observe actual trade prices, we approximate using closing prices. For the day t purchase price, we use an average of the closing prices on days t and t-1 so the holding period profit/loss on day t is calculated as $X_{i,c,m,t-1}(P_{c,m,t}-P_{c,m-1}) +(X_{i,c,m,t}-X_{i,c,m,t-1})[P_{c,m,t} - .5(P_{c,m,t}+P_{c,m,t-1})]$. If i shorts contract c-m on day t, the profit loss is$X_{i,c,m,t}(P_{c,m,t}-P_{c,m,t-1}) + (X_{i,c,m,t-1}-X_{i,c,m,t})[.5(P_{c,m,t}+P_{c,m,t-1})-P_{c,m,t-1}]$. So whether i longs, shorts or does not trade, her profit/loss on contract c-m on day t may be calculated as:

$$PL_{i,c,m,t} = .5\,(X_{i,c,m,t} + X_{i,c,m,t-1})\,(P_{c,m,t} - P_{c,m,t-1}) \qquad \textbf{(1)}$$

Each day we sum trader i's profits/losses over all contracts obtaining:

$$PL_{i,t} = \sum_{c=1}^{3} \sum_{m=1}^{M} PL_{i,c,m,t} \qquad \textbf{(2)}$$

Note that, except for our use of estimated day t trade prices, this profit/loss measure is identical to the mark-to-market calculation used to credit profits and debit losses to a trader's account and to determine margin calls. Since $PL_{i,t}$ does not incorporate bid/ask spreads or other transaction costs, trading profits after trading costs are slightly overstated for all traders except market makers for whom they are understated.

Since dollar profits and losses vary with the size of a trader's position, we also calculate percentage profits. Since futures involve no up-front investment, returns do not have the same meaning as in other markets. Moreover traders may hold long, short or spread positions. Nonetheless, return-like measures are useful so we calculate trader i's profit on contract c-m on day t as a percentage of her average dollar open interest in that contract, specifically:

$$\%PL_{i,c,m,t} = \frac{PL_{i,c,m,t}}{.5\,[\,|X_{i,c,m,t}|\,P_{c,m,t} + |X_{i,c,m,t-1}|\,P_{c,m,t-1}]} * 100 \qquad \textbf{(3)}$$

Since trader i may hold positions in numerous contracts, her percentage profit on day t is calculated by weighting the percentage profit/loss on each contract c-m by its dollar open interest as a percent of the total dollar open interest across all contracts, i.e.,

$$\%PL_{i,t} = \sum_{c=1}^{3}\sum_{m=1}^{M} \%PL_{i,c,m,t} \frac{.5\,[\,|X_{i,c,m,t}|\,P_{c,m,t} + |X_{i,c,m,t-1}|\,P_{c,m,t-1}]}{\sum_{c=1}^{3}\sum_{m=1}^{M} .5\,[\,|X_{i,c,m,t}|\,P_{c,m,t} + |X_{i,c,m,t-1}|\,P_{c,m,t-1}]} \qquad \textbf{(4)}$$

Note if a trader longs one contract at $100 and shorts it 50 days later at $100 but the price fluctuates up and down in the interim, we calculate 50 separate non-zero daily mark-to-market profit/loss figures instead of one round trip trade with zero net profit.

Finally, trader i's average daily percentage profit/loss over the entire period is calculated by weighting each day's $\%PL_{i,t}$ by the size of her average open interest position on day t:

$$\%PL_{i} = \sum_{t=1}^{T}\sum_{c=1}^{3}\sum_{m=1}^{M} \%PL_{i,c,m,t} \frac{.5\,[\,|X_{i,c,m,t}|\,P_{c,m,t} + |X_{i,c,m,t-1}|\,P_{c,m,t-1}]}{\sum_{t=1}^{T}\sum_{c=1}^{3}\sum_{m=1}^{M} .5\,[\,|X_{i,c,m,t}|\,P_{c,m,t} + |X_{i,c,m,t-1}|\,P_{c,m,t-1}]} \qquad \textbf{(5)}$$

There are several suspicious observations in our data which could not be checked. For instance, there are a few instances in which a position (with the same exact number of contracts throughout) is recorded as short for several days, suddenly switches to long for a day or two, and then back to short. To guard against outliers caused by possible data errors contaminating our results, we winsorize replacing $\%PL_{i,t}$ values in the lower 1% tail of i's daily profit figures with i's 1% value and similarly for values in the upper 1% tail.

III. Issues and Variables

In contrast to Hartzmark's luck hypothesis, we expect differences among traders in either information, skill, trading objectives (i.e., hedging versus speculation), and/or trading strategies to result in consistent profits by some traders and losses by others. There are two underlying theoretical hypotheses on which we seek to present evidence. The first is the standard risk premium hypothesis that expected trading profits must be positive to entice speculators into the market which (since trading is a zero sum game prior to transaction costs) implies that hedgers must be willing to bear negative expected trading profits. Alternatively the supply of speculators might be perfectly elastic so that there is no difference in expected profits between hedgers and speculators. The second underlying hypothesis is that more informed or skilled traders will make profits at the expense of less informed - at least before deducting information costs. Since we cannot observe directly who is hedging, who is speculating, and who is more informed, we relate profitability to trader and trade characteristics as outlined below.

III.1. Trader line-of-business or type

As argued above, we expect a high proportion of hedgers in the first five categories listed in Tables 1: refiners, independent producers, MDPs, large consumers, and commercial banks - the first four because of their cash/forward market positions and commercial banks because of regulations. Conversely, we expect the next three: energy traders, hedge funds, and individuals to be dominated by speculators. Therefore according to the risk premium hypothesis, trading profits should be negative on average for refiners, independent producers, MDPs, large consumers, and commercial banks, and positive for energy traders, hedge funds, and individuals. It is quite possible that information and/or skill levels also differ among trader types leading to profit differences. For instance, we suspect that MDPs might be more informed about physical market conditions and investment banks and hedge funds better informed about trading strategies which could lead to positive trading profits for these classifications on average. So profit differences among trader types could reflect either hedging/speculation or information/skill differences. Determining which will be a major task of the paper below.

Market makers are a separate and interesting case. A basic tenet of market microstructure theory is that market makers set the bid/ask spread to compensate for their losses on trades with more informed investors (Glosten and Milgrom (1985)). In other words, informed traders tend to buy (sell) and maker makers therefore tend to sell (buy) before a price increase (decrease). Since our measure of trading profits is based on closing prices so does not include their bid/ask spread profits, this theory would imply that our trading profit measure should be negative on average for market makers. On the other hand, it is sometimes argued, e.g., Manaster and Mann (1996), Brown and Zhang (1997) and Ready (1999), that due to their presence on the floor where they can observe the order flow, floor traders have an information advantage implying positive average profits. To our knowledge, our data provides the first opportunity to test these two conflicting theories for market makers in futures markets. It bears repeating that we only observe positions that market makers hold overnight, not their more numerous day trades.

III.2. Directional versus Spread Trading Strategies

Speculator trading strategies differ. Some may speculate that the price will rise or fall in the future by taking large long or short positions respectively (which we will term "directional trades"); others may speculate on future price relationships by longing some contracts and simultaneously shorting others ("spread trades). Examples of the latter would be: 1) calendar spreads in which the speculator longs some maturities and shorts other maturities of the same type, and 2) crack spreads in which the speculator longs (shorts) crude oil and shorts (longs) gasoline and/or heating oil.

We have a couple of goals in this area. First, anticipating that directional positions are much riskier than spread positions, we seek to quantify the risk difference.[9] Second, we seek to test for differences in average profits. If, as anticipated, directional trades are much riskier than spread trades, average profits might have to be higher in order to attract directional speculators. On the other hand, it may be that market mispricings lead to arbitrage possibilities which astute spread traders can exploit leading to higher profits on spread trades. Büyükşahin et al. (2008) present evidence that prior to 2002 "near- and long-dated futures prices [in the crude oil futures market] were priced as though traded in separate markets" but since 2004 have become cointegrated implying that during our data period there were price differences that astute calendar spread traders could profitably exploit.

Let $L_{i,c,m,t}$ represent trader i's open interest position in contract c-m on day t if long and $S_{i,c,m,t}$ her position if short. In other words, $L_{i,c,m,t}=X_{i,c,m,t}$ if $X_{i,c,m,t}>0$ and =0 otherwise and $S_{i,c,m,t}=-X_{i,c,m,t}$ if $X_{i,c,m,t}<0$ and =0 otherwise. We measure how much of trader i's <u>futures</u> position is hedged on day t by taking spread positions (SP) as:

$$SP_{i,t} = \frac{2 * \mathrm{Min}[\sum_{c=1}^{3}\sum_{m=1}^{M} L_{i,c,m,t}, \sum_{c=1}^{3}\sum_{m=1}^{M} S_{i,c,m,t}]}{\sum_{c=1}^{3}\sum_{m=1}^{M}(L_{i,c,m,t} + S_{i,c,m,t})} \qquad \textbf{(6)}$$

If trader i holds equal numbers of long and contracts on day t, $SP_{i,t}=1$. If i holds only long or only short positions, $SP_{i,t} = 0$. We calculate a summary measure for each trader i, i.e., SP_i by averaging $SP_{i,t}$ over all days t with non-zero open interest. Note that SP_i measures only the degree to which trader i's *futures* position is hedged. If we observed and included cash and forward market positions, then SP_i would tend to be close to one for hedgers but since cash and forward positions are not observed, a hedger's SP measure will be lower.

Means of SP_i by trader type are reported in Table 4 where the statistic that stands out is the mean of 15.0% for hedge funds. Their SP median is only 5.0%. Clearly the majority of hedge funds during this period were neither trading calendar or crack spreads nor hedging their trades by longing some contracts and simultaneously shorting others. Instead, they generally placed large directional bets by going all long or all short - somewhat more often long according to the figures in Table 3.

In summary, we expect the time series volatility of trader i's trading profits, i.e., the standard deviation of $\%PL_{i,t}$, to be a negative function of SP_i. We also are interested in the relation, if any, between i's mean trading profits, $\%PL_i$, and SP_i where the risk premium and mis-pricing hypotheses imply different coefficient signs.

III.3. Trader Size

Ceteris paribus, we expect large traders to be better informed than smaller traders. There are two reasons. First, spending funds to obtain information is more cost effective for large positions than small. Spending say $100,000 to obtain information is harder to justify for a 100 contract position than for a 10,000 contract position. Second, larger energy firms, such as some of those in the refiner and MDP categories could have superior information because they themselves are a large part of the energy market or observe a large part. Since the traders' identities are unknown to us, we can only measure size in terms of their open market positions so hypothesize that trading profits will tend to be higher for traders with large open market positions on average. As shown in Table 3, by this measure the largest traders are investment banks followed by commercial banks.

III.4. Trader Activity

Along the same lines, we hypothesize that trading profits will be positively correlated with i's trading activity. While this need not always be the case, we expect hedgers to hold their positions longer than speculators on average. If they do, then the risk premium hypothesis would imply that traders who turn their positions over frequently should have higher profits on average. Again we would point out that our trading profit calculations are before deducting trading costs so confirmation of this hypothesis does not necessarily imply higher profits after transaction costs. On the other hand, papers by Odean (1999), Barber and Odean (2000), and Barber et al (2005) find that in the stock market active individual traders tend to make losses. To test the relation between trading activity and profits, we measure each trader i's frequency of trades or position turnover,

$TURN_i$, by dividing i's average daily trading volume by i's average open interest position. The two averages are calculated only over days with non-zero open interest at either the beginning or end of the day.. As reported in Table 4, turnover rates are highest for market makers/floor traders followed by hedge funds and individuals and are lowest for commercial and investment banks and independent producers.

In addition, it is possible that traders who are only in the market a few days and make only a few trades, are less skillful due to the lack of experience implying lower trading profits. To test this, we relate trading profits to the percentage of the 962 days in our sample when the trader maintained a non-zero open interest position expecting a positive coefficient. Note that this test is subject to a possible survivorship bias because traders making losses may tend to drop out.

III.5. Long or Short Relative to Hedgers

As we would interpret the risk premium hypothesis, a trader's expected profits should depend not just on whether she is a hedger or speculator but on her long/short position relative to the bulk of hedgers. Consider for instance the position of an airline wishing to hedge future fuel purchases. Heating oil and jet fuel are roughly the same (kerosene) so an airline's natural hedge is to long heating oil futures which, as documented in Table 3, is what they normally do. However, as also documented in Table 3, in these futures markets, energy consumers are grossly outnumbered by producers. If many refiners and MDPs are shorting heating oil futures while only a few airlines are longing, the former may push futures prices down so that (like speculators) the airlines' expected trading profits are positive. The airline hedger might be willing to accept expected losses on average but does not have to. So according to this interpretation of the risk premium hypothesis, an individual trader's expected profits should be negative when her long/short position matches that of hedgers in general and positive when it differs. Presuming again that traders in our first five trader type classifications are more likely to be hedgers, we hypothesize that an individual trader's trading profits will tend to be negative when the sign of her open interest position (long or short) in a specific market matches the sign (long or short) of the aggregate open interest position of refiners, independents, MDPs, large consumers, and commercial banks and positive when her long/short position differs from theirs. To test this, for each of our 382 traders, we define a hedger concordance (HC) measure of the extent to which the signs of i's various open interest positions match the signs of the aggregate positions of likely hedgers. Specifically,

$$HC_i = \frac{\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T} D_{i,,c,m,t} \,|X_{i,c,m,t}|}{\sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T} |X_{i,c,m,t}|} \quad \textbf{(7)}$$

where $X_{i,c,m,t}$ is trader i's open interest position (long or short) in contract c-m on day t. $D_{i,c,m,t} = 1$ if $X_{i,c,m,t}$ is long when likely hedgers are net long in the aggregate or short when likely hedgers are net short in the aggregate. $D_{i,c,m,t} = 0$ if $X_{i,c,m,t}$ is long when likely hedgers are net short in the aggregate or short when likely hedgers are net long in the aggregate.[10] So HC_i varies between zero and one and we hypothesize that trader i's mean profits, PL_i, will be negatively correlated with HC_i.

Means of HC_i for the different trader groups are reported in Table 4. We think two statistics are of note. First, while the means for all five likely hedger types exceed 50%, none exceeds 60.3% so there are numerous cases in which individual traders in the likely hedger category hold positions in some contracts opposite in sign to the aggregate likely hedger position. In these cases, the traders are either speculating or their hedging needs run counter to the majority of likely hedgers and we would expect them to actually benefit from any risk premium on these positions. Second, the mean HC_i for hedge funds is 22.1% and the median is only 18.6%. These are far lower than any other trader type. Clearly hedge funds generally take positions opposite in sign to the aggregate positions of likely traders.

IV. Results

IV.1. Trading Profits and Luck.

First, we test the contention that futures trading profits are determined solely by luck, as concluded by Hartzmark (1991). For this we estimate an analysis of variance (ANOVA) across our 382 traders to test if the number of traders tending to make consistent profits or losses is more than one would expect due to chance based on the 183,634 daily percentage profit observations, $\%PL_{i,t}$. One issue in an ANOVA estimation is whether to assume variances are the same or different. As explained above, we expect profit variances to differ by trader since profits should be less variable for traders taking spread positions than for those whose open interest positions are mostly long or mostly short. Testing this using the Brown-Forsythe test for homogeneity of variances, with an F stat of 99.98, the homogeneity null is rejected at the .00001 level. Given this result, we employ Welch's AVOVA statistic which presumes differing variances. With an F of 2.15, the null that the profit differences among traders are due to chance is rejected at the .00001 level. Clearly some traders tend to turn consistent profits and others consistent losses on their futures positions.

For further evidence on this issue, for each of our 382 traders, we calculate z-values for the test of the null hypothesis that their mean daily trading profits, i.e., the mean of $\%PL_{i,t}$ across all days t, is zero. By chance approximately 3.82 traders should have mean profits significantly greater than zero at the 1% level. In our sample, twelve traders do. The expected number with profits significantly greater than zero at the 5% level is 19.1 while 35 actually are. There are even more extreme observations at the other end of the spectrum. Twenty-two have negative mean profits significantly different from zero at the 1% level and 58 at the 5% level. To test whether trader profit/loss patterns are persistent, we calculate $\%PL_i$ over both the June 1993 - May 1995 and June 1995 - March 1997 sub-periods restricting the sample to the 224 traders with at least 25 trades and 50 observations in each sub-period. The correlation coefficient of +.140 is significantly different from zero at the .05 level.

IV.2 Trading Profits and Trader Type Classifications

Next we test for average profit differences between our likely hedger (first five categories in Table 1) and likely speculator categories (categories 6-8 in Table 1). Results are presented in Panel A of Table 5 for two different calculations of mean daily profits. In columns 2-5, we present statistics based on the individual trader/day observations, $\%PL_{i,t}$. Then, for each day t, we combine the open interest positions of all likely hedgers into a combined hedger position and calculate the percentage profits on this combined position. We do the same for likely speculators and report those means and standard deviations in columns 6 and 7 respectively. Hence the means in column 3 are unweighted treating each $\%PL_{i,t}$ equally while the means in column 6 are weighted by size of each trader's open interest position that day. For the stats in columns 2-5, there are 97,510 hedger/day observations and 50,561 speculator/day observations; for the stats in columns 6-7, there are 962 day observations for both. Having seen that profit variances differ substantially for different traders, the p-values in column 4 for the tests of whether mean trader/day profits differ from zero are based on standardized profits $\%PL_{i,t}/\sigma_i$ where σ_i is the time series standard deviation of $\%PL_{i,t}$.

For likely hedgers, the average unweighted daily trading profit is -0.0154% (-3.80% annualized). For likely speculators the average daily trading profit is 0.0394% (10.40% annualized). Both are significantly different from zero and each other at the .0001 level. The average combined or weighted daily profit is -.0173% (-4.27% annualized) for likely hedgers and .0312% (8.18% annualized) for likely speculators. Due to the reduced number of observations, significance levels are lower for the combined position. Still the two combined means are both significantly different from zero and each other at the .05 level. In summary, the mean profits of likely hedgers and speculators are consistent with the risk premium hypothesis.

In panel B, the same statistics are presented for the eleven trader type classifications. Consistent with the risk premium hypothesis, unweighted mean profits are negative for all five likely hedger classifications and positive for all three likely speculator classifications, though two of the combined means switch signs. However, within the likely hedger category, mean profits are significantly less than zero[11] (at the 1% level for the unweighted means and 5% for the combined means) only for refiners and commercial banks. Within the likely speculator categories, mean profits are significantly positive only for hedge funds/money managers. Their profits, 15.2% of open interest when annualized, are significantly higher than either of the other speculator categories (individuals and energy traders). We were unsure whether the bulk of the trades by investment banking houses would be hedges or speculations. It is interesting, therefore, that their mean profits are small and insignificantly different from zero suggesting a mix.

Interestingly the group with the second largest mean loss are the market makers. The unweighted daily mean of -.0370% implies an annualized loss of -8.9%. This is consistent with the hypothesis that, before profits from the bid-ask spread, market makers tend to lose money due to trades with more informed investors. Clearly, there is no evidence that market makers are more informed because they can observe the order flow. It seems unlikely that market makers/floor traders would continue in this line of work if these losses were representative of their overall trading profits. We presume the losses we observe are offset by profits from the bid/ask spread and/or intraday trades. Still it is clear that, at least on positions held overnight, market makers/floor traders have no special skills or knowledge and lose on their trades with more informed investors. Alternatively, these losses could represent a tendency, even among these supposedly sophisticated traders, to sell winners quickly, i.e., the same day, but hang on to their losers as observed for individual stock traders by Odean (1998).

In Panel A of Table 6, we report the hedger/speculator distributions of those traders whose mean daily trading profits are significantly greater or less than zero at the .05 level. While the overall sample is approximately evenly split between likely hedgers and speculators, over two-thirds of the traders with significant losses are likely hedgers and almost three-quarters of those with significant trading profits are likely speculators. The null that the distribution between the hedgers and speculators is the same for traders with significantly positive and negative profits is rejected at the .01 level. Clearly traders with significant positive profits are more likely to be speculators and those with significant losses are more likely to be hedgers.

In Panel B of Table 6, we report the distribution across all eleven trader types of the traders with significantly positive or negative profits at the 5% level. The two categories that stand out here are hedge funds and market makers. While hedge funds make up 18.8% of the full sample of 382 traders, they account for 40% of those with significant positive profits and only 3.4% of those with significant negative trading profits. Conversely market makers account for 18.1% of the total sample but 36.2% of those with significant negative profits and only 11.4% those with significant positive profits. Commercial banks are also bunched in the losers group though their numbers are too small to allow strong conclusions.

The profit figures in Table 5 are prior to transaction costs. Net profit figures after deducting estimated round-trip transaction costs of $15 per contract are reported in Table 7 for all except market makers.[12] Mean daily profit figures are reduced by .003 to .005 percentage points. Mean hedge fund profits are significantly greater than zero even after deducting transaction costs.

In summary, we find significant differences in futures trading profits by trader type with likely speculators tending to make profits and likely hedgers tending to make losses. Hedge funds are particularly profitable. Ignoring their profits from bid/ask spreads, market makers/floor traders also tend to make losses on positions held overnight.

IV.3. Risk Premia or Superior Information?

We find that mean trading profits are significantly negative for likely hedgers and significantly positive for likely speculators as predicted by the risk premia hypothesis. However, a possible alternative explanation for the profit difference is that speculators may have superior information or skills so make profits at the expense of hedgers who are less informed or skilled. Furthermore, the finding that hedge funds are more profitable than other speculators may be viewed as consistent with the information hypothesis if one regards hedge funds as particularly likely to be informed or skilled. So next we explore whether the profit evidence is more consistent with the risk premia or information hypotheses.

The first issue we investigate is whether futures prices reflect hedging pressure as the risk premia hypothesis maintains. According to the risk premia hypothesis, if hedgers are long (short) on balance, futures prices will be pushed above (below) expected future spot prices, creating positive expected profits for traders who short (long). Directly testing whether hedging pressure pushes futures prices away from the expect future spot price is complicated by the difficulty in measuring expected future spot prices. However, since futures prices converge to the spot price as maturity approaches, an implication is that ceteris paribus futures prices will tend to fall (rise) over time when hedgers on balance are long (short). To test this, we measure net hedging pressure in contract c-m on day t, $NHP_{c,m,t}$, as the aggregate long positions of likely hedgers minus aggregate likely hedger short positions divided by total open interest in contract c-m on day t. The percentage change in the futures price on day t on contract c-m is measured as $\%\Delta P_{c,m,t} = (P_{c,m,t} - P_{c,m,t-1})/P_{c,m,t-1}$. The hypothesis that hedging pressure pushes prices away from the expected future spot price implies that $\%\Delta P_{c,m,t}$ will be negatively correlated with $NHP_{c,m,t-1}$. To pick up the impact of $NHP_{c,m,t-1}$ on $\%\Delta P_{c,m,t}$ it is important to try to control for other forces causing changes in $P_{c,m,t}$, especially changes in the expected future spot price. Most of these should have similar impacts across the futures' term structure so we approximate them with the percentage change in the price of the nearby futures contract. Let m=n designate the nearby contract of type c so $\%\Delta P_{c,n,t}$ represents the percentage change in the nearby contract. We regress $\%\Delta P_{c,m,t}$, where m>n, on $\%\Delta P_{c,n,t}$ and $NHP_{c,m,t-1}$. To ensure accurate measures of net hedging pressure we restrict the sample to contracts with at least five traders on day t-1.

Results of this regression are reported in Table 8. The coefficient of $NHP_{c,m,t-1}$ is negative and significantly different from zero at the .01 level implying that when hedgers in the aggregate are net long (short), the futures price is pushed above (below) the expected future spot price potentially creating profit opportunities for speculators.

Next we explore whether the profit differences between likely hedgers and likely speculators are in fact due to the latter taking advantage of the potential profit opportunities created by the impact of hedging pressure on futures prices. In section III.5 and equation 7, we defined a "hedger concordance" measure, HC_i, of the extent to which the sign (long or short) of trader i's open interest positions matchs the sign of the aggregate open interest position of likely hedgers. If trader i always longs when likely hedgers are net long and shorts when likely hedgers are net short, HC_i=1. If i always shorts when likely hedgers are net long and longs when likely hedgers are net short, HC_i=0. If traders profit from the impact of net hedging pressure on futures prices by taking positions opposite to those of hedgers, then trader profits should be negatively correlated with HC_i.

In Model 1 in Table 9, we report the results of the regression of trader i's average daily percentage trading profits, $\%PL_i$ on HC_i estimated over the 382 traders i.[13] As reported in Table 9, with a t-value of -7.686, trader profits are a strong negative function of the extent to which the signs of trader i's open interest positions match the net aggregate positions of likely hedgers. The coefficient of HC_1 in Model 1 implies that annualized percentage trading profits are 45.6 percentage points higher for a trader who always longs (shorts) those contracts in which the majority of hedgers are short (long) versus a trader whose long and short positions always match the signs of the aggregate positions of likely hedgers. Of course there are no traders who are always in complete agreement or disagreement with the net aggregate hedger positions. To be more realistic, suppose we compare a trader whose long/short position agrees with the aggregate likely hedger position 75% of the time with one whose position disagrees 75% of the time, i.e., HC_i = .75 versus HC_i=.25. Approximately 25.9% of the traders in our sample are outside these two bounds. According to the coefficient of HC_1 in model 1 of Table 9, annualized annual trading profits tend to be approximately 22.7 percentage points higher for the trader with HC_i=.25. This is a sizable difference which is considerably more than the speculator/hedger profit difference documented in Table 5.

To determine whether the profit differences between likely hedgers and likely speculators documented in Tables 5 and 7 are due to speculators exploiting the risk premium by taking positions opposite to likely hedgers, we add HC_i to a regression with trader type dummy variables. First however, Model 2 in Table 9 presents the results of a regression of $\%PL_i$ on zero-one dummy variables for likely hedgers, speculators, market makers, and investment banks without HC_i. Unclassified traders are the left out group so the coefficients measure the profit difference between that trader type and the unclassified group so are not particularly important in themselves. Of more importance is the difference between the coefficients of the likely hedger and speculator dummies which is negative, significant at the .001 level, and implies that the annualized percentage trading profits of likely speculators are approximately 14.2 percentage points higher than those of likely hedgers.

In Model 3, we add the variable HC_i to this regression. HC_i is again highly significant. Importantly, the likely hedger and speculator coefficients are not significantly different from zero or each other. Indeed the likely hedger coefficient is slightly higher which would imply (if significant) that after controlling for HC_i profits are slightly higher for traders in the likely hedger category. While it is possible that some individual speculators profit because of unique information or skills, the Model 3 results reveal that the higher profits of speculators as a group are due to their exploitation of the risk premia caused by hedging pressure - not systematic information differences. Together the evidence in Tables 8 and 9 indicates that when hedgers in the aggregate are net long (short), futures prices are pushed above (below) expected future spot prices creating profit opportunities for speculators who short (long) the futures and this completely accounts for the mean profit differences between hedgers and speculators.

Next we estimate regressions with dummies for all trader types except the unclassified group with and without the HC_i variable. We are particularly interested in whether hedge fund profits are due to exploitation of the risk premia since, as seen in Table 5, they are the most profitable of the eleven trader types and, as seen in Table 4, they tend to take positions opposite to the aggregate hedger position more often than any other trader type. Estimation results with trader type dummies only are reported in Model 4 in Table 9 and with HC_i included in Model 5. The results in Model 4 largely repeat those in Table 5 indicating that hedge funds are the most profitable trader type. The null than profits don't differ by trader type rejected at the .001 level. However, when HC_i is added to the regression in Model 5, the hedge fund coefficient is no longer significant. Excluding market makers, whose losses (net of the bid-ask spread) are predicted by market micro-structure theory, the null that profitability differs among trader types after controlling for the extent to which trader positions mimic or differ from the net hedger position cannot be rejected at the .10 level. In summary, excluding market makers, differences in profitability by trader type (and hedge fund profits in particular) appear due to differences in the extent to which they take advantage of the risk premia by taking positions opposite to the net hedger position.

A final issue is whether HC_i can account for trading profit differences among different hedgers or among different speculators. As noted above, the figures in Table 3 suggest that some traders within the likely hedger category may be fact speculating or employing a selective hedging strategy. If so, they, like speculators, could conceivably benefit by longing (shorting) when the majority of hedgers are short (long). Also hedging needs differ so some hedgers may hedge by longing (shorting) when the majority are short (long). For instance, if the heating oil market is dominated by refiners who are shorting to lock in a sale price, airlines who are longing to lock in a purchase price should, like speculators, benefit from the hedging pressure. In columns 2 and 3 of Table 10, we regress $\%PL_i$ on HC_i for the hedger subset. Again the coefficient of HC_i is negative and significant indicating that profit differences among likely hedgers are a function of the extent to which the sign (long or short) of their open interest positions matches or differs from the majority. Likewise speculator trading strategies differ so in the last two columns of Table 10, we regress $\%PL_i$ on HC_i for the speculator subset. Again the coefficient of HC_i is negative and significant indicating that speculators who take positions opposite in sign to the net aggregate hedger positions tend to make higher profits than those following other strategies.

In summary, while individual speculators may profit from superior information or skills, the mean profits of speculators in general, and of hedge funds in particular, appear completely due to their strategy or tendency to short when hedgers in the aggregate are long and long when hedgers are short. In other words, they take advantage of the risk premia created by hedging pressure on futures prices. This implies that speculator and hedge fund profits are due to the risk absorption and/or liquidity services they provide hedgers. We further find that the profits of individual hedgers are higher if their long/short positions differ from the majority. Finally those speculators who follow a strategy of longing (shorting) when a majority of hedgers are short (long) make higher profits than those who do not.

IV.4. Differences in trading profit volatility

We observed above that some traders' trading profits vary much more day-to-day than others and hypothesized that this was because some traders tend to employ spread trades with roughly equal long and short positions so that their overall futures positions are roughly delta neutral while others take mostly short or mostly long positions. The latter could either be speculators betting on whether energy prices will rise or fall or hedgers whose overall positions are hedged but whose futures positions are not. To test this, in Table 11, we regress the time-series standard deviation of trader i's daily trading profits (as a percent of her total open interest) on SP_i, our measure of the extent to which i's futures position is hedged by balancing longs and shorts as defined in equation 6. We anticipate a negative coefficient, i.e., lower volatility on spread positions. We also include the log of trader i's average open interest position anticipating that larger traders will tend to hedge their positions. The regression is estimated first without trader type dummy variables and then with. In the latter regression, unclassified traders are the left out category so the coefficients measure the estimated difference between that type's volatility and the unclassifieds.

As expected, the volatility of a trader's profits over time is largely determined by whether she tends to take spread positions. According to SP_i's Model 1 coefficient, the standard deviation of a trader's percentage profits is about 1.03 percentage points higher if they always take either solely long or short positions versus if they always hold equal numbers of long and short energy contracts. Since the average standard deviation is only 1.09%, this is a considerable difference.

IV.5. Other determinants of trading profitability

In addition to trader line of business and how the sign of the trader's open interest positions normally compares with the aggregate position of likely hedgers, we hypothesized above that trader profits would covary with trader size, number of days in the market, portfolio turnover, and whether the trader generally takes spread or directional positions. In Table 12, trader i's mean daily percentage profits/losses from June 1993 through March 1997, $\%PL_i$, are regressed on: 1) HC_i, 2) SP_i, 3) trader i's size as measured by her mean log open interest position, and 4) turnover measured as i's average daily trading volume divided by her average daily open interest, 5) the percentage of days trader i was in the market during this period, and 6) zero-one dummies for the ten trader types. Unclassified traders are the left out type so trader type coefficients measure differences in profitability between that trader type and unclassified traders. Results are shown in Model 1 in Table 12. We discuss results for each of the determinants hypothesized in section III in turn.

IV.5.1. Spread versus directional positions

We anticipated that profitability could differ between traders taking all long or all short positions and traders taking spread positions. As noted above, Büyükşahin et al. (2008) present evidence that prior to 2002 "near- and long-dated futures prices were priced as though traded in separate markets" potentially creating price differences that astute calendar spread traders could profitably exploit. It is possible that crack spread opportunities were also present. On the other hand, profits could be higher on totally long or short positions due to their greater riskiness as documented in Table 11. The results in Table 12 are consistent with the former hypothesis. The coefficient of SP_i in Model 1 is significant at the .05 level and implies that (ceteris paribus) annualized percentage profits are about 10.4 percentage points higher for traders who always balance long and short positions versus traders who are always either totally long or totally short. In Table 4 we observed that hedge funds generally take overwhelming long or overwhelmingly short positions - not spread positions. Since the coefficient of SP_i is positive in the Table 12 regressions, it is clear that the high hedge fund profits are not due to this strategy. Instead hedge fund profits are explained by their low HC_i values.

IV.5.2. Trader size

We hypothesized in section III that larger traders would tend to be more informed so would tend to have higher profits, ceteris paribus. However, the coefficient of the size variable is insignificant and is actually negative. Clearly there is no evidence larger traders have an informational advantage.

IV.5.3. Trading activity

Profits are a positive, but insignificant, function of the percentage of the 962 days that the trader held a non-zero open interest position. However, as expected, mean trader profits vary positively with turnover indicating that traders who turn their positions over more often tend to have higher profits - at least before transaction costs. Since this seemingly contradicts the finding of Odean (1999), Barber and Odean (2000), and Barber et al (2005) that in the stock market more active individual traders tend to make losses, we wondered whether the relationship between turnover and profitability was different for individuals. To test this, we added an interaction variable, IND_TURN_i, equal to $TURN_i$ when i is an individual and zero otherwise. Results are shown in the columns labeled Model 2 in Table 12. Clearly, the turnover-profit relation is different for individual traders since the coefficient of IND_TURN_i is negative and significant. The sum of the two coefficients is an insignificant -.037 indicating little relation between turnover and profits for individuals.

IV.5.4. Hedger concordance

The hedger concordance variable, HC_i, remains highly significant when these other variables are added to the equation. Again we find that, consistent with the risk premia hypothesis, trader profits tend to be considerably higher if the trader generally longs (shorts) when a majority of hedgers are short (long) and that this is the most important determinant of trader profits.

IV.5.5. Trader types

As in Table 10, the results in Table 12 indicate market makers tend to lose money after controlling for other determinants of trading profits but before including their profits from the bid ask spread. This confirms the micro-structure theory that because they are willing to take the other side of trades with more informed investors, market makers tend to make losses before profits from the bid ask-spread are included. The are no significant profit differences between any of the other trader types. In Model 3 in Table 5, we drop all trader type dummies save the market maker dummy; the adjusted R^2 actually improves. In summary, except for market makers who tend to make losses before counting their profits from the bid ask spreads, all other profit differences between trader types are explained by our independent variables - the HC_i variable in particular.

V. Conclusions

We find that about 31% of the variation in mean profits among different traders in the energy futures markets can be explained by differences in their trading objectives (hedging versus speculation) and strategies. We find strong support for the risk premia hypothesis. First, mean speculator profits are significantly higher than mean hedger profits. Second, our evidence indicates that hedging pressure pushes futures prices away expected future spot prices. Third, individual traders (whether hedgers or speculators) who generally short when likely hedgers in the aggregate are net long and long when likely hedgers in the aggregate are net short make considerably higher profits on average than traders who generally long (short) when likely hedgers are long (short).

Classifying futures traders into eleven line of business types we find significant mean profit differences with hedge funds the most profitable and market makers the least - not counting their profits from the bid-ask spread. However, excepting market makers, mean profit differences among the other ten trader types are completely explained by the extent to which they exploit the risk premium by longing (shorting) when hedgers are short (long). Hedge funds in particular tend to exploit the risk premium and to earn higher than normal profits due to this strategy.

We further find that traders who generally hold spread positions tend to have higher profits that those who do not and that, excepting individuals or households, traders with higher turnover rates tend to have higher profits. Not counting their profits from the bid-ask spread, maker makers tend to have significant trading losses on the positions that they hold overnight indicating that they tend to lose on their trades with more informed investors.

While it is quite possible that some traders profit from superior information of skills we find no evidence of systematic information differences in our data - unless one views turnover rates or the tendency to conduct spread trades as correlated with information or skill. In particular, there is no evidence of systematic information or skill differences between hedgers and speculators or among the ten trader types since their profit differences are completely explained by the risk premia, i.e., by whether they tend to long (short) when hedgers in the aggregate are long (short) or the reverse. Also, there is no evidence that larger traders profit at the expense of smaller traders.

In summary, we find that the main determinant of a hedger's mean profits are whether she contributes to the risk premium by longing (shorting) when hedgers in the aggregate are net long (short) or exploits the risk premium by shorting (longing) when hedgers in the aggregate are net long (short). In other words, our evidence indicates that the profits of speculators in general, and hedge funds in particular, are due to the liquidity and/or risk absorption services they provide hedgers by being willing to short (long) when hedgers in the aggregate are net long (short).

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Table 1 - Energy Trader Type Classifications		
The energy futures trader classifications used in this study are described. Traders identified as “commercial” traders in the CFTC’s Large Trader Reporting System (LTRS) files were placed into classifications 1-6 and 9 with the assistance of the Office of Policy at the Department of Energy in a manner that maintained trader autonomy. Classifications 7, 8, 10, and 11 based on the CFTC’s classifications of “non-commercial” traders.		
Classification		**Description and Classification Procedure**
Likely Hedgers		
1	Refiners	Oil and gas firms with refineries.
2	Independent Producers	Oil and gas producers without refinery capacity - commonly referred to as exploration and production companies.
3	Marketers/Distributors/ Pipelines	Pipeline companies and companies primarily involved in marketing and distributing oil and refined products. Some may produce oil as well but their primary business is in transporting, marketing, and/or distributing.
4	Large Consumers	Non-energy companies which are consumers of refinery oil products or natural gas, e.g., airlines, trucking firms.
5	Commercial Banks	Two digit SIC code of “60.”
Likely Speculators		
6	Energy Traders	Energy trading companies (mostly offshore) with no known energy assets. Classified as commercial by CFTC.
7	Hedge Funds/ Commodity Pools	Non-commercials identified in the CFTC’s LTRS files as commodity pool operators, commodity trading advisers, or money managers.
8	Individuals	The residual category of non-commercial traders in the CFTC’s LTRS files.
Other or Uncertain		
9	Investment Banks and Brokers	Two-digit SIC code of “62.”.
10	Floor Traders	Exchange members trading for their own accounts. Includes trades for their own accounts by floor brokers and futures commission merchants.
11	Other	Unidentified traders.

Table 2 - Energy Futures Markets Description				
Descriptive statistics are presented for the crude oil, gasoline, and heating oil futures markets for June 1993 - March 1997 period. Statistics for our full data set of 939 traders are presented in panel A and for our working data set of 382 more active traders in panels B and C. Open interest figures are gross, i.e., longs + shorts.				
	Crude Oil	Gasoline	Heating Oil	All Three Markets
Panel A - Full Data Set - 939 traders				
Avg. Daily Gross Open Interest (contracts)	607,085	125,160	192,619	924,864
Avg. Daily Gross Open Interest ($ billions)	$10,704	$2,868	$4,234	$17,806
Trader/contract/day observations	538,097	211,215	310,304	1,059,616
Panel B - Working data set - 382 traders				
Avg. Daily Open Interest (contracts)	593,723	123,165	189,522	906,410
Avg. Daily Open Interest (in billion $)	$10,456	$2,821	$4,162	$17,439
Trader/contract/day observations	516,172	203,864	300,438	1,020,474
Trades	228,532	118,705	139,097	486,334
Avg Daily Open Int. per trader (contracts)	4,404	1,243	1,748	4,579
Avg Trade Size (contracts)	264	158	151	206
Panel C - Time-to-expiration of open interest positions				
Mean time-to-expiration (months)	14.6	1.6	2.8	5.0
Median time-to-expiration (months)	5.8	1.6	2.3	2.7
Cumulative Percent of contracts expiring in				
1 month or less	14%	32%	22%	18%
2 months or less	27%	62%	45%	41%
3 months or less	35%	78%	60%	54%
6 months or less	50%	97%	88%	73%
12 months or less	62%	99%	99%	88%
24 months or less	72%	100%	100%	96%

Table 3 - Descriptive Statistics

Descriptive statistics are presented for the eleven trader line-of-business categories described in Table 1. The percentage of the 1,020,474 trader/day/contract observations accounted for by each category are reported in column 3 (% obs). The percentage of total open interest accounted for by each is reported in column 5 and the same for each of our three markets in columns 8-10. In the last three columns (11-13), we report the percentage of the open interest positions in each market which are long (the remained being short).

Trader Categories	# Traders	% of total Obs	% of total Trades	% of total Open Int.	Mean Daily Trader O.I. (contracts)	Mean Trade Size in contracts	% of Market Open Int.			% Long (of Open Interest positions)		
							Crude Oil	Gaso-line	Heat. Oil	Crude Oil	Gaso-line	Heat. Oil
Refiners	57	28.1%	28.1%	28.6%	5,842	213	26.0%	36.5%	31.5%	45.2%	31.4%	34.9%
Independent Producers	14	2.4%	1.4%	2.2%	2,690	160	2.6%	0.5%	1.8%	30.1%	68.8%	26.8%
MDPs	22	12.2%	12.1%	12.8%	7,665	210	10.4%	17.9%	17.2%	54.3%	42.5%	48.5%
Energy Consumers	6	0.7%	0.7%	0.7%	2,197	211	0.5%	0.2%	1.9%	76.7%	42.5%	85.5%
Commercial Banks	16	9.3%	9.1%	9.1%	8,950	159	11.6%	3.2%	4.9%	37.4%	85.6%	70.8%
Energy Traders	14	5.8%	4.4%	4.5%	4,574	151	5.1%	3.1%	3.4%	54.2%	47.8%	35.7%
Hedge Funds	72	7.7%	7.7%	6.9%	1,916	289	5.7%	7.9%	10.1%	63.4%	65.4%	54.1%
Individuals	28	2.6%	3.0%	1.8%	1,612	190	2.1%	1.5%	1.0%	66.2%	87.0%	71.3%
Investment Banks	19	17.9%	17.5%	27.3%	21,606	285	29.9%	21.3%	23.1%	55.6%	73.9%	48.2%
Market Makers	69	9.4%	15.0%	4.7%	1,687	132	5.0%	4.3%	4.0%	42.8%	49.5%	58.8%
Unclassified	65	3.9%	3.8%	1.4%	576	114	1.0%	3.6%	1.1%	41.4%	28.0%	42.9%

Table 4 - Trader Characteristics by Trader Type

Means of hypothesized determinants of trader profitability are reported. The percentage of days in the market is measured as the percentage of the 962 days in our sample when the trader's open interest position was not zero. Turnover is measured as mean daily trading volume divided by mean total open interest (long positions plus short positions). The spread measure, SP, is a measure of the extent to which the trader holds spread positions as defined in equation 6 in the text. If the trader always holds equal numbers of long and short contracts, SP=1; if the trader always holds only long or only short positions, SP =0. Hedger confluence, HC, is a measure of the extent to which the sign (long versus short) of a trader's position in particular futures contract on a particular day matches the sign of the aggregate net position of likely hedgers in that contract that day as defined in equation 7 in the text.

	Percentage of days in Market	Turnover (TURN)	Spread Measure (SP)	Hedger Confluence (HC)
Refiners	79.4%	13.3%	43.9%	60.3%
Independent Producers	54.5%	9.0%	38.3%	59.5%
MDPs	69.5%	15.9%	51.1%	57.6%
Large Consumers	54.3%	11.0%	20.5%	51.3%
Commercial Banks	58.4%	7.9%	38.6%	57.4%
Energy Traders	64.8%	13.3%	44.6%	50.3%
Hedge Funds	48.6%	22.4%	15.0%	22.1%
Individuals	39.6%	21.9%	32.7%	40.5%
Investment Banks	60.9%	8.3%	46.9%	49.7%
Market Makers/Floor Traders	42.6%	35.3%	44.4%	40.9%
Unclassified	37.6%	18.8%	33.2%	58.0%

Table 5 - Trader Profits

Statistics are presented for daily trading profits as a percentage of the trader's total open interest before transaction costs. Statistics are presented for likely hedgers (the first five categories in Table 1) and likely speculators (the next three categories) in Panel A and for eleven separate lines-of-business in Panel B. The p-values are for tests of the null that the mean percentage profits are zero.

Panel A - Likely hedgers and speculators

Category	Individual trader/day observations				Combined positions - 962 day obs.		
	Obs.	Mean	p-value	Std. Dev.	Mean	p-value	Std. Dev.
Likely hedger	97510	-0.0154%**	.0001**	1.0548%	-0.0173%	.0212*	0.2330%
Likely speculator	50561	0.0394%**	.0001**	1.2288%	0.0312%	.0329*	0.4540%
Panel B -							
Refiners	42760	-0.0129%**	.0087**	.9808%	-0.0193%	.0476*	0.3026%
Independent Producers	7077	-0.0204%	.1567	1.0859%	-0.0407%	.0640	0.6819%
MDPs	14594	-0.0062%	.5903	0.8461%	0.0035%	.4550	0.1440%
Large Consumers	2999	-0.0095%	.6466	1.3516%	-0.0230%	.5050	1.0684%
Commercial Banks	8838	-0.0397%**	.0001**	.8371%	-0.0252%	.0218*	0.3409%
Energy Traders	8557	0.0113%	.6283	0.9165%	-0.0030%	.6573	0.2132%
Hedge Funds	32011	0.0561%	.0001**	1.3295%	0.0519%	.0415*	0.7901%
Individuals	9993	0.0102%	.2298	1.1548%	0.0119%	.5556	0.6259%
Investment Banks	11037	0.0021%	.7146	.7671%	0.0066%	.3719	0.2306%
Market Makers/Floor Traders	24537	-0.0370%	.0001**	0.9346%	-0.0228%	.0014**	0.2210%
Unclassified	21242	-0.0159%	.1248	1.3176%	-0.0086%	.5697	0.4665%

Table 6 - Distribution of Highly Profitable and Unprofitable Traders

Divisions between likely hedgers and speculators are reported in Panel A for traders whose mean daily trading profits are significantly positive or negative at the .05 level. Divisions by line of business are reported in Panel B. Statistcs for the entire sample of traders are reported for comparison. In panel A the sample is restricted to those identified as likely hedgers or speculators, i.e., excluding maker makers and unknowns.

Category	Sample		
	Profits significantly positive at 5% level	Profits significantly negative at 5% level	Overall
Panel A - Likely hedgers and speculators - sample restricted to likely hedgers or speculators			
Likely hedgers	25.9%	68.0%	50.2%
Likely speculators	74.1%	32.0%	49.8%
Panel B- Eleven line-of-business categories - full sample			
Refiners	11.4%	13.8%	14.9%
Independent Producers	2.9%	2.9%	3.7%
MDPs	5.7%	1.7%	5.8%
Large Consumers	0.0%	0.0%	1.6%
Commercial Banks	0.0%	10.3%	4.2%
Energy Traders	5.7%	1.7%	3.7%
Hedge Funds	40.0%	3.4%	18.8%
Individuals	11.4%	8.6%	7.3%
Investment Banks	2.9%	3.4%	5.0%
Market Makers/Floor Traders	11.4%	36.2%	18.1%
Unclassified	8.6%	17.2%	17.0%

Table 7 - Trader Profits After Transaction Costs

Statistics are presented for daily percentage trading profits after deducting round-trip trading costs of $15 per contract . Statistics are presented for likely hedgers (the first five categories in Table 1) and likely speculators (the next three categories) in Panel A and for ten separate lines-of-business in Panel B. The p-values are for tests of the null that the mean percentage profits are zero.

Panel A - Likely hedgers and speculators

Category	Individual trader/day observations				Combined positions - 962 day obs.		
	Obs.	Mean	p-value	Std. Dev.	Mean	p-value	Std. Dev.
Likely hedger	97510	-.0209%	.0001**	1.055%	-0.0213%	.0047**	0.233%
Likely speculator	50561	.0316	.0001**	1.230%	0.0266%	.0695	0.454%
Panel B -							
Refiners	42760	-.0187%	.0001**	0.981%	-0.0248%	.0073**	0.287%
Independent Producers	7077	-.0249%	.0735	1.086%	-0.0478%	.0218*	0.631%
MDPs	14594	-.0117%	.1161	0.846%	-0.0015%	.7253	0.133%
Large Consumers	2999	-.0145%	.5038	1.351%	-0.0256%	.4309	1.008%
Commercial Banks	8838	-.0425%	.0001**	0.837%	-0.0286%	.0040**	0.307%
Energy Traders	8557	.0064%	.9373	0.917%	-0.0064%	.3131	0.198%
Hedge Funds	32011	.0476%	.0001**	1.322%	0.0490%	.0378*	0.730%
Individuals	9993	.0016%	.9859	1.155%	0.0023%	.9024	0.582%
Investment Banks	11037	-.0001%	.8274	0.767%	0.0027%	.6886	0.212%
Unclassified	21242	-.0224%	.0224*	1.318%	-0.0147%	.2912	0.433%

Table 8 - Hedging Pressure and Futures Prices

The percentage change in the price of futures contract c-m from day t-1 to t,$\%\Delta P_{c,m,t}$, is regressed on the percentage change in the price of the nearby futures contract, $\%\Delta P_{c,n,t}$, and a measure of net hedging pressure the previous day, $NHP_{c,m,t-1}$. $NHP_{c,m,t-1}$ is measured as the aggregate long positions of likely hedgers in contract c-m on day t-1 minus aggregate short positions of likely hedgers in that contract that day divided by total open interest in contract c-m on day t. The sample is restricted to contracts with maturities m exceeding the nearby contract and to days with at least 5 traders with open interest positions in contract c-m. The reported p-values are for rejection of the null that the coefficient is zero.

	Coefficient	p-value
Intercept (x100)	.0050	.2302
$\%\Delta P_{c,n,t}$	.4739	.0001
$NHP_{c,m,t-1}$ (x 100)	-.0546	.0065
adjusted R^2	.595	
Observations	34224	

Table 9 - Trader Profits and Risk Premia Exploitation

Trader i's mean daily profits/losses (as a percent of her mean total open interest position) over the June 1993 - March 1997 period are regressed on: 1) dummies for the trader type, and 2) a measure, HC_i, of the extent to which the sign (long versus short) of trader i's positions match the aggregate position of likely hedgers. $HC_i = \sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T} D_{i,c,m,t}\,|X_{i,c,m,t}| \;/\; \sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T} |X_{i,c,m,t}|$ where $X_{i,c,m,t}$ is trader i's open interest position (long or short) in contract c-m on day t. $D_{i,c,m,t} = 1$ if $X_{i,c,m,t}$ is long when likely hedgers are net long in the aggregate or short when likely hedgers are net short in the aggregate. $D_{i,c,m,t} = 0$ if $X_{i,c,m,t}$ is short when likely hedgers are net long in the aggregate or long when likely hedgers are net short in the aggregate. t-values with the White correction for heteroskedasticity are reported in parentheses. The regression is estimated over 382 traders. * and ** denote coefficients significantly different from zero at the .05 and .01 levels respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	.0799 ** (6.691)	-.0233 (-1.637)	.0952** (4.404)	-.0233 (-1.623)	.0971 (3.881)
Hedger Concordance (HC_i)	-.1853** (-7.686)		-.2043** (-6.830)		-.2077** (-5.622)
Likely hedgers		.0074 (0.481)	.0091 (0.633)		
Likely speculator		.0599** (3.487)	.0030 (0.160)		
Market maker/Floor trader		-.0233 (-1.238)	-.0582** (-3.186)	-.0233 (-1.228)	-.0588** (-3.124)
Investment bank		.0261 (1.286)	.0092 (0.534)	.0261 (1.276)	.0089 (0.511)
Refiner				.0125 (0.773)	.0173 (1.139)
Independent Producer				-.0031 (-0.104)	.0002 (0.007)
MDP				0.0128 (0.799)	.0121 (0.781)
Large Consumer				.0381 (1.580)	.0241 (0.942)
Commercial Banks				-.0207 (-0.986)	-.0219 (-1.092)
Energy Traders				.0390* (1.990)	.0232 (1.223)
Hedge Funds				.0766** (3.931)	.0021 (0.082)
Individuals				.0275 (1.227)	-.0088 (-0.429)
Adjusted R^2	.148	.088	.202	.096	.198

Table 10 - Separate Hedger and Speculator Regressions

Trader i's mean daily profits/losses (as a percent of her mean total open interest position) over the June 1993 - March 1997 period are regressed on a measure, $HC_{i,}$ of the extent to which the sign (long versus short) of trader i's positions match the aggregate position of likely hedgers.

$$HC_i = \sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T} D_{i,,c,m,t}\,|X_{i,c,m,t}| \;/\; \sum_{c=1}^{C}\sum_{m=1}^{M}\sum_{t=1}^{T} |X_{i,c,m,t}|$$

where $X_{i,c,m,t}$ is trader i's open interest position (long or short) in contract c-m on day t. $D_{i,c,m,t} = 1$ if $X_{i,c,m,t}$ is long when likely hedgers are net long in the aggregate or short when likely hedgers are net short in the aggregate. $D_{i,c,m,t} = 0$ otherwise. Equations are estimated separately for the likely hedger and likely speculator sub-samples. t-values with the White correction for heteroskedasticity are reported in parentheses * and ** denote coefficients significantly different from zero at the .05 and .01 levels respectively.

	Likely hedger subsample		Likely speculator subsample	
	Coefficient	t-value	Coefficient	t-value
Intercept	.0907	2.397*	.0784	5.584**
Hedger Concordance (HC_i)	-.1812	-2.686**	-.1287	-3.445**
Adjusted R^2	.095		.0581	
Observations	115		114	

Table 11 - Determinants of Futures Trading Profit Volatility

The standard deviation of trader i's daily percentage profits/losses from June 1993 through March 1997 is regressed on: 1) a measure (defined in equation 7) of the extent to which the trader hedges her futures position by taking spread positions, SP_i, in which she balances long and short positions, 2) trader i's size as measured by the mean log of her total open interest. If i always balances long positions with an equal number of short positions, SP_i=1. If she always takes either all long or all short positions, SP_i=1. Unclassified commercial traders are the left out line-of-business group. The regression is estimated over 382 traders. * and ** denote coefficients significantly different from zero at the .05 and .01 levels respectively.

Variable	Model 1		Model 2	
	Coefficient	t-value	Coefficient	t-value
Intercept	1.9391	37.842**	1.9789	32.377**
Spread Position Measure, SP_i	-1.0293	-32.075**	-1.0104	-29.395**
Log of average open interest	-.0707	-9.363**	-.0740	-7.560**
Refiners			.0277	.796
Independent Producers			.0201	.401
MDPs			-.0245	-.558
Large Consumers			.1610	2.265*
Commercial Banks			-.1156	-2.286*
Energy Traders			-.0208	-.409
Hedge Funds			-.0206	-.706
Individuals			-.0977	-2.587*
Investment Banks			-.0495	-.987
Market Makers/Floor Traders			-.552	-1.871*
Adjusted R^2	.810		.819	

Table 12 - Futures Trading Profitability Regressions

Trader i's mean daily profits/losses, as a percent of her mean total open interest position, are regressed on: 1) a measure, HC_i (defined in equation 7) of the extent to which the sign (long versus short) of trader i's positions match the aggregate position of likely hedgers, 2) a measure, SP_i, (defined in equation 6) of the extent to which i takes spread positions, 3) trader i's size as measured by the mean log of her total open interest, 4) i's turnover, $TURN_i$, measured as average daily trading volume divided by average daily open interest, 5) the percentage of days the trader was in the market, 6) an interaction variable, IND_TURN_i, equal to $TURN_i$ when i is an individual and zero otherwise, and 7) zero-one dummies for the trader type. Unclassified traders are the left out trader type. The regressions are estimated over 382 traders. * and ** denote coefficients significantly different from zero at the .05 and .01 levels respectively. t-values are based on White heteroskedasticity consistent standard errors.

Variable	Model 1		Model 2		Model 3	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Intercept	.1071	2.317*	.1028	2.285*	.0858	2.323*
Hedger concordance (HC_i)	-.1998	-5.928**	-.2015	-5.930**	-.1947	-8.382**
Spread trader measure, SP_i	.0392	2.335*	.0406	2.451*	.0434	2.695**
Log of mean open interest	-.0098	-1.883	-.00987	-1.877	-.0059	-1.280
Turnover, $TURN_i$	.1475	2.762**	.1689	3.245**	.1634	3.274**
Percent of days in market	.0260	1.513	.02605	1.550	.0276	1.771
Refiners	.0238	1.416	.0243	1.438		
Independent Producers	.0166	0.520	.0182	.707		
MDPs	.0131	0.830	.0129	.817		
Large Consumers	.0438	1.631	.0451	1.669		
Commercial Banks	.0042	0.208	.0059	.293		
Energy Traders	.0318	1.879	.0322	1.906		
Hedge Funds	.0061	0.286	.0047	.218		
Individuals	-.0105	-0.048	.0316	1.156		
Investment banks	.0362	1.893	.0375	1.959		
Market Makers/Floor Traders	-.0893	-4.664**	-.0936	-4.896**	-.1032	-7.334**
IND_TURN_i,			-.1979	-2.433*	-.1475	2.252*
Adjusted R^2	.299		.311		.316	

ENDNOTES

1. This line-of-business classification was done in a manner which preserved trader anonymity from the authors. The CFTC data set identifies traders by number only. Separately, The Office of Policy at the U.S. Department of Energy provided us with the names (without numbers attached) of the traders in our data set. Commercial and investment banks/brokers were identified by two-digit SIC codes. With assistance from the Office of Policy, the remaining traders were classified by line-of-business. The Office of Policy then matched the line-of-business codes, but not names, to each trader number and them to us.

2. Ederington and Lee (2002) regard energy independent producers as likely speculators in the heating oil market since they do not have refining capacity so do not produce heating oil. Since they do produce crude oil, we regard them as potential hedgers in that market. To avoid complicating and confusing the results presentation we keep the classifications the same across all three markets.

3. We do have some data on their option positions but the data for puts and calls and different strikes are aggregated so we cannot calculate option trading profits. Fortunately, it is clear from this data that, for almost all traders, option positions are quite small relative to their futures positions.

4. Below we will present some evidence consistent with these classifications.

5. Brokers are only required to report a trader's open interest if it exceeds the set threshold. In practice, once a trading system is initiated for a trader it appears to normally continue when open interest falls below the minimum. Nonetheless, reporting could stop once a trader's open interest falls below the minimum so this requirement increases the likelihood that our observations for a trader are complete.

6. The gross open interest reported in Table 1 = total long positions + total short positions. This differs from the usual open interest figure reported for the market as a whole which is total long positions = total short positions.

7. According to US Senate Staff Report (2006), Haight et al. (2007) and Büyükşahin et al. (2008) hedge fund trading in these markets increased substantially subsequent to our data period - perhaps attracted by the hedge fund profits which we document below.

8. Whether refiners hedge by longing or shorting crude oil future would depend on whether their crude production exceeds their refining capacity or the reverse.

9. Note that because the denominator in equation 4 is total dollar open interest, $\%PL_{i,t}$ will tend to be smaller in absolute terms for traders taking spread positions. Consider the following four positions: A) long 200 March 1995 crude oil contracts, B) long 100 March 1995 crude contracts and short 100 June 1995 crude contracts, C) long 100 crude, short 50 gasoline, and short 50 heating oil - all March 1995, D) long 125 March 1995 and short 75 March 1996 crude contracts. Total open interest is the same for all four so, ignoring price differences, the denominator in equation 4 is the same for all four. However, B and C are clearly spread positions so for them the numerator in equation 4 should be smaller in absolute terms than for trader A. Position D lies somewhere in between. Thus the time series standard deviation of $\%PL_{i,t}$ should differ across different traders i and is one measure of the riskiness of their futures trading strategies,

i.e., the extent to which they hedge by taking spread positions.

10. Likely hedgers are net short in 58.7% of the 46,253 contract/maturity/day observations in our sample and net long in 41.3%.

11. While this statement is for a one-tailed test, the p-values in Table 4 are two-tailed since different signs are expected for different categories and no sign was hypothesized for three.

12. Estimates for transaction costs in energy futures markets revolve around this figure. Haight and Holt (2002) use roundtrip costs of $15 per contract while Girma and Paulson (1998) use $100 for the roundtrip cost of six contracts. This amounts to a little less than one tick in the crude oil market and 2 to 3 ticks in the heating oil and gasoline markets.

13. The t-values are corrected for heteroskedasticity using the White procedure since, as will be shown in the next section, profit volatility varies considerably across different traders.