Identifying Informed Traders in Futures Markets

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ABSTRACT

We use daily positions of futures market participants to identify informed traders. These data cover the period from 2000 to mid-2009 and contain 8,921 unique traders. We identify between 94 and 230 traders as overnight informed and 91 as intraday informed with little overlap between these two groups. Floor brokers/traders are over-represented in the overnight informed group, suggesting that ability to process order flow information creates success at this horizon. The intraday informed group is dominated by managed money traders/hedge funds and swap dealers, with commercial hedgers significantly under-represented in this group. We find that trader characteristics such as experience, average position size, amount of trading activity, and type of positions held offer significant predictive power for who is informed. An analysis of daily trader profits confirms that our methods select highly profitable traders.

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JEL classification: G10, G13

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I. INTRODUCTION

Informed traders are an essential feature of market microstructure models, but there is little research that establishes who is an informed trader.[1] Most researchers detect the presence of informed traders from price responses to order flow. Because permanent price responses signal informed trades, consistent profits gained from positions or trading activity provide an indicator of who is informed. However, data limitations make trader identities unavailable to most previous studies so the characteristics and profits of the informed are generally unknown.[2]

In this paper we identify informed traders, those whose actions show they hold valuable short-term price information. Our methods separate these traders from thousands of other participants whose profits (if any) arose due to luck in the sampling process. From the subset we identify as informed, we use inverse regression techniques to analyze their characteristics and to examine how their net trading and end-of-day positions set them apart from other participants. This approach complements that of Menkhoff and Schmeling (2010), who relate price impacts from trades in the dollar/rouble FX market to trader and market characteristics such as order size, timing, total volume, and origin.[3]

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[1] Research based on insider trading cases can identify informed traders (e.g., Meulbroek (1992), Cornell and Sirri (1992) and Fishe and Robe (2004)), but none of these cases address futures markets. Other researchers have examined whether groups are differentially informed, such as institutional traders (Chakravarty (2001)) or floor brokers (Anand and Subrahmanyam (2008)), but have not isolated which participants in these groups cause their results. An exception is Keim and Madhavan (1995) who analyze motives for trading by 21 institutions in which they have all order flow data.

[2] An extensive literature documents the presence of informed traders. This includes trade indicator models (e.g., Glosten and Harris (1988) and Huang and Stoll (1997)), variance decomposition models (e.g., George, Kaul, and Nimalendran (1991)), vector autoregression models (e.g., Hasbrouck (1988) and Menkhoff and Schmeling (2010)), structural likelihood models (e.g., Easley, Kiefer, O'Hara, and Paperman (1996)), as well as general aggregate models and special cases (e.g., Evans and Lyons (2002) and Ito, Lyons, and Melvin (1998)).

[3] Our results also complement studies that focus on investor characteristics, particularly those that analyze retail brokerage records and mutual fund returns. Odean (1999) and Barber and Odean (2000) find that retail investors tend to lose money trading equities, which suggests that they lack information as a group. Grinblatt, Keloharju and Linnainmaa (2009) find that high-IQ investors in Finland outperform low-IQ investors in stock-picking ability.

We examine data on trader positions from 2000 to mid-2009 for twelve futures markets. We find that traders who hold information about intraday price changes are not the same as those who hold information about the next day's price—the overnight informed. Depending on the test and reference price, we identify from 94 to 230 traders as overnight informed and 91 traders as intraday informed out of 8,921 unique traders. These two types of informed traders are analogous to the *ex ante* and *ex post* notion of informed trading.[4] The ex ante informed are those who *possess* a precise signal about future returns, such as found when insiders trade in advance of a corporate announcement. The ex post informed are those who *process* order flow information into accurate predictions of future returns (e.g., Evans and Lyons (2002, 2008) in foreign exchange markets, Brandt and Kavajecz (2004) for U.S. Treasury securities, and Deuskar and Johnson (2010) for the S&P 500 index). Our results suggest that the overnight informed are efficient processors of information like the ex post informed; these results are also consistent with a noisy rational expectations model of trading (e.g., Grundy and Kim (2002)). The intraday informed are like the ex ante informed as they appear to possess the best signals about very short horizon price changes and trade to capitalize on this knowledge.

We use end-of-day positions and the daily change in these positions to identify informed traders. As such, our methods identify a *subset* of the informed population: those whose information advantage can be extracted from overnight holdings and net daily trading. Informed traders whose information advantage is realized by specific intraday trades, such as measured by

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Nicolosi, Peng and Zhu (2009) find that individual investors learn from past trading to become better investors. Several researchers find that mutual fund managers do not offer a positive alpha (e.g., Wermers (2000) and Fama and French (2009)). However, recent work shows that some managers exhibit significant information processing or forecasting ability (e.g., Chen, Jegadeesh, and Wermers (2000), Kosowski, Timmermann, Wermers, and White (2006) and Barras, Scaillet and Wermers (2010)).

[4] Examples of research on *ex ante* informed trading include Kim and Verrecchia (1991), Easley, Kiefer, O'Hara and Paperman (1996), Fishe and Robe (2004) and Pasquariello and Vega (2007). Examples of research based on *ex post* processing of information include Harris and Raviv (1993), Kandel and Pearson (1995), Kim and Verrecchia (1997), Green (2004) and Love and Payne (2008).

price impact models (e.g., Hasbrouck (1991)) may not be selected by our methods, unless their net daily trading reflects these informed trades. For commodities in which we identify informed traders, we find that the average daily profits per trader are significantly greater for the informed than those of the not informed group. For the overnight informed in crude oil, we find the largest differences in average daily profits: $45,237 for the informed versus losses $3,401 for the uninformed. For intraday informed, the largest difference in average daily profits is found in natural gas: $95,885 for the informed versus losses of $2,693 for the not informed.

Our results also show that floor brokers/traders (FBT) are over-represented and commercial firms—those with an underlying reason to hedge—tend to be under-represented among overnight informed traders. These findings support those of Kurov and Lasser (2004) for exchange locals and Anand and Subrahmanyam (2008) for floor traders and specialists.[5] The overnight informational advantage of FBTs may stem from their access to order flow as they are not likely to have better access to market fundamentals than commercial firms, nor are they likely to conduct superior analysis compared to hedge funds. Consistent with the latter observation, we also find that the intraday informed are dominated by money managers/hedge funds (MMT) and swap dealers, with commercial firms again significantly under-represented. We find essentially no firms that systematically take losing positions, including natural hedgers such as producers, merchants and processors.

Although line-of-business variables predict representation in our informed groups, variables that measure trader characteristics have even stronger predictive power. Using inverse regression methods (e.g., Li (1991)), we estimate that intraday informed traders have 15% more experience, 39% more activity and hold 58% larger positions than the average trader. Informed

[5] Our methods are different from Kurov and Lasser (2004) and Anand and Subrahmanyam (2008) as they examine information shares for traders in a group, not the sequence of positions or trades for specific participants.

traders, particularly overnight informed, are generally more likely to trade on both sides of the market (i.e., both long and short). We also find that simultaneously holding positions in more contract expirations affects representation in the informed group, but this effect differs between the overnight and intraday informed. The overnight informed tend to hold positions in more expirations, again consistent with FBTs processing information from order flows, while the intraday informed hold positions in fewer expirations, consistent with selective trading by MMTs and swap dealers based on precise signals.

We also develop methods based on intraday trading activity to identify which participants demand and supply liquidity and which participants behave as contrarian or momentum traders. Our results show that commercial firms (hedgers) are over-represented in the group of liquidity suppliers and that MMTs are over-represented in the group of liquidity demanders. This result differs from those using earlier aggregate data, which showed that commercial hedgers brought price pressure to futures markets when they adjusted their positions (deRoon, Nijman and Veld (2000)). As our sample period includes a substantial increase in index fund participation, our evidence suggests that the normal role of commercial hedgers has changed from that of demanders to suppliers of liquidity (Harris and Buyuksahin (2009), Tang and Xiong (2009)).

This research builds on a small but insightful body of previous work in commodity futures markets. Early studies of informed trading focused on the forecasting ability of futures traders using data on small traders at a single brokerage firm (Hieronymus (1977) and Teweles, Harlow and Stone (1977)) or placed traders into aggregate groups from monthly or semi-monthly observations (Houthakker (1957), Rockwell (1964) and Chang (1985)). Hartzmark (1987) found that commercial traders as a group earn significant daily profits compared to non-commercial traders. This result suggests that commercial traders are informed, but a later study by Hartzmark

(1991) finds commercial traders with superior forecasting ability only in the pork bellies market, a finding supported by Leuthold, Garcia and Lu (1994). In energy markets, Phillips and Weiner (1994) found some intraday profits for large integrated oil companies in the crude oil market, and Dewally, Ederington and Fernando (2010) found that profitable individual traders in energy futures tend to hold positions opposite those of commercial firms.

These previous studies offer few consistent conclusions on whom, if anyone is informed in futures markets. One reason for the differing results is that past studies use different statistical methods. Importantly, these methods make no allowance for the multiple-testing problem found in these studies.[6] The multiple-testing problem arises because there are thousands of traders in futures markets, which gives rise to thousands of test statistics, a fraction of which are expected to be large because of chance. To control for these chance effects, we implement the false discovery rate (*FDR*) method of Benjamini and Hochberg (1995) and Storey (2002). Using this method produces a median p-value of 0.00018 across all our tests, which suggests that multiple-testing bias would be pronounced if we had applied a classical 5% critical value.

This paper is structured as follows. The next section develops our methodology. We explain how we isolate informed from other traders and how the *FDR* method is applied to our sample. Section III describes the CFTC data and provides summary statistics for the explanatory variables used in our empirical analysis, which is described in Section IV. We use an inverse regression technique to make inferences about the representation of trader characteristics and business lines in the informed population. Our conclusions are offered in Section V. The

[6] The statistical techniques we employ are similar to those used by Bajgrowicz and Scaillet (2010) and Barras, Scaillet and Wermers (2010). Bajgrowicz and Scaillet (2010) examine the performance of 7,846 technical trading rules using daily prices of the Dow Jones Industrial Average (DJIA) index between January 1897 and June 2010. Although valuable trading rules arise in earlier periods, their results establish that no technical trading rules offer persistent profits in the post-1962 period. Barras, Scaillet and Wermers (2010) focus on estimating the population probability of a positive alpha mutual fund, whereas we seek to identify informed and liquidity traders and examine their characteristics. An important difference in methods is that we develop an alternative approach to identifying the probability that a trader is null in the population.

Appendix explains how we implement the *FDR* method for our hypothesis tests.

II. METHODOLOGY

To identify informed traders, we must define profits and use them to measure trading success. Let $\{OI_{0,t}^k, OI_{1,t}^k, OI_{2,t}^k, \ldots, OI_{J_k,t}^k\}$ denote the sequence of positions held by a trader in contract k on day t, where a positive value indicates a long position and a negative value indicates a short position. The day starts with position $OI_{0,t}^k$ and after J_k trades the day ends with position, $OI_{J_k,t}^k$. Our data report the end-of-day open interest in each contract in each market, which means that we observe $OI_{0,t}^k$ and $OI_{J_k,t}^k$, but we do not observe intra-day position changes.

Aggregating over all trades (j=1, 2,…, J) and contracts (k=1, 2,…, K) on day t, we write profit as

$$\pi_t^* = \sum_{k=1}^{K} \sum_{j=0}^{J_k} OI_{j,t}^k \left(P_{j+1,t}^k - P_{j,t}^k\right), \tag{1}$$

where $P_{j,t}^k$ denotes the price of contract k at the time of trade j. The initial day t priceis $P_{0,t}^k$, and the final price, $P_{J_k+1,t}^k$, is the day t closing price. We rewrite equation (1) as

$$\pi_t^* = \sum_{k=1}^{K} OI_{0,t}^k \left(P_{J_k+1,t}^k - P_{0,t}^k\right) + \left(OI_{J_k,t}^k - OI_{0,t}^k\right)\left(P_{J_k+1,t}^k - P_{*,t}^k\right), \tag{2}$$

where

$$P_{*,t}^k = \frac{\sum_{j=1}^{J_k}\left(OI_{j,t}^k - OI_{j-1,t}^k\right)P_{j,t}^k}{\sum_{j=1}^{J_k}\left(OI_{j,t}^k - OI_{j-1,t}^k\right)}$$

represents a *reference* price. It is a size weighted average of the trade prices for a given trader and is defined only if the closing open interest differs from day t-1 to t.

Equation (2) shows daily profits as a function of observables and a single unobserved variable, $P_{*,t}^k$. Because the j subscript is redundant, we consolidate notation and rewrite (2) as

$$\pi_t^* = \sum_{k=1}^{K} OI_{t-1}^k \Delta P_t^k + \Delta OI_t^k \left(P_t^k - P_{*,t}^k\right), \tag{3}$$

where $\Delta P_t^k = P_t^k - P_{t-1}^k$ denotes the change in closing price for the k^{th} expiration and $\Delta OI_t^k = OI_t^k - OI_{t-1}^k$ denotes the change in closing open interest between day t-1 and t.

The first term in equation (3) is the *position profit* and the second term is the *trading profit*.[7] Position profit measures the profit if a trader holds a closing position throughout the next day. Trading profit measures the incremental profit from a net position change. Trading profits are unobserved in our data without the reference price, $P_{*,t}^k$. Any proxy for $P_{*,t}^k$ that is measured before the closing price, P_t^k, confounds actual trading profits with foregone trading profits. For example, if the opening price acts as a proxy for $P_{*,t}^k$, then a momentum trader who responds to intra-day price changes would appear to have positive trading profits even though she traded after the price change rather than before it.

We develop our profit-based approach to measure success in the following subsections, beginning with the position profit method of Hartzmark and Leuthold, et al. and concluding with how we use the *FDR* method to control for the multiple-testing problem.

A. Measuring Success Using Position Profits

Consistent with previous studies, we define two *profit rules* using the binary variable theta (θ) to measure a trader's success:

(i) Position Profits: θ_t^p $= 1$ *iff* $\sum_{k=1}^{K} OI_{t-1}^k \Delta P_t^k > 0$
$= 0$ otherwise.

(ii) Lagged Trading Profits: θ_t^c $=$ undefined *iff* $\sum_{k=1}^{K} \left|\Delta OI_{t-1}^k\right| = 0$
$= 1$ *iff* $\sum_{k=1}^{K} \Delta OI_{t-1}^k \Delta P_t^k > 0$
$= 0$ otherwise.

[7] Equation (3) represents trading profits from net daily position changes. Some traders may have many offsetting trades in a day and no net position change. We do not capture this because we do not observe individual trades.

Success means that θ_t^p or θ_t^c equals one, which implies that the position or net trades are profitable based on the next day's prices. The lagged trading profits rule refines the position profits rule by including only days in which a trader's net position changes. Specifically, it recognizes that $OI_{t-1}^k = OI_{t-2}^k + \Delta OI_{t-1}^k$, which implies that position profits can be decomposed as $\sum_{k=1}^{K} OI_{t-2}^k \Delta P_t^k + \Delta OI_{t-1}^k \Delta P_t^k$. Lagged trading profits therefore measure the incremental effect of net trading decisions on day *t*-1. We use the qualifier "lagged" to distinguish this measure from the within-day trading profits in equation (3). We sum positions and trades over all expirations within a day, so that we capture informed traders with information about the spread between contract prices as well as those with information about price levels.

We use a binary measure of success (θ) rather than profit levels for three reasons. First, the daily profits of traders have heavy tails (excess kurtosis), which distorts the statistical properties of hypothesis tests based on average daily profits. Specifically, heavy-tailed data produce light tailed *t*-statistics causing under-rejection of the null hypothesis (e.g., Cressie 1980). A binary success measure offers better control in the presence on excess kurtosis and therefore better power to detect informed traders. A second reason to use a binary measure is that open interest increased substantially over the sample period, so the size of profits in later periods may not be comparable to earlier periods due to inflation. We do not want our choice of inflation adjustment to affect these tests. Finally, for a given expiration, profits sum to zero across traders, which is a constraint on tests using profit levels. The binary measure is not similarly constrained because it is not dependent on the amount of profits.

In spite of the benefits of a binary measure, we may miss some types of informed traders. Specifically, we may miss those who profit from skewness in returns; that is, traders who make money by taking many small losses but occasionally large gains. In fact, our binary measure would assign such traders a success rate less than 50%. We also may miss traders with fleeting information—those who are informed only infrequently and hold positions for only a few days. Thus, as noted earlier, our results represent a subset of the informed trader population.

B. *Identifying Overnight Informed Traders*

We compute binary success statistics using a close-to-close price window to identify the overnight informed traders. For each trader, we test the null hypothesis that the trader is successful half of the time; that is, we test $H_o\colon E\left(\theta_t^p\right) = 0.5$ for position profits and $H_o\colon E(\theta_t^c) = 0.5$ for lagged trading profits. We call this an *unconditional test* for informed trading. Thus, traders who randomly take positions expect positive profits on only 50% of days. This null is reasonable as the literature on futures price behavior shows little evidence of systematic daily price bias (e.g., Erb and Harvey 2006).

While there may be no systematic price bias, some traders may benefit from trends, such as those described by Moskowitz, Ooi, and Pedersen (2010). To adjust for trends, we also implement a test suggested by Henriksson and Merton (1981), called the *HM test*. This is a conditional test with the null of no informed trading defined by:

$$H_o\colon \Pr(i \in Long \mid \pi_i^L > 0) + \Pr(i \in Short \mid \pi_i^S > 0) = 1, \tag{4}$$

where *i* is a trader index, π_i^L are the profits in cases where trader *i* holds a net long position, and π_i^S are the profits in cases where trader *i* holds a net short position. A trader whose long or short positions are informative will have on average more than 50% of her long positions profitable, more than 50% or her short positions profitable, or both, such that the combined probabilities in equation (4) exceed unity. The logic of the HM test is that traders are not informed if they cannot discriminate sufficiently in both up and down markets. Thus, the HM and unconditional tests have power in different directions: the HM test is most sensitive to dependence between positions and returns, whereas the unconditional test is most sensitive to the success rate.

C. *Characterizing Trader Types for Intraday Analysis*

The analysis above focuses on finding overnight informed traders using end-of-day trades and positions prior to next day's prices. However, informed traders may have incentive to adjust positions during the day particularly if their information is time sensitive. These trades may reveal information to the market, and thereby remove such traders from the set we identify as overnight informed. To find the intraday informed, we must separate them from other trader types using the price and position information in our data.

Table 1 characterizes six trader types: informed, uninformed, large liquidity demanders, large liquidity suppliers, momentum, and contrarian traders.[8] The informed trade correctly in advance of price changes, whereas the uninformed trade incorrectly as judged by subsequent prices. Momentum and contrarian traders are effectively the causal inverse of informed and uninformed traders because they adjust open interest *in response to price changes*, not before them (Conrad and Kaul (1998)). The large liquidity demander and supplier are symbiotic traders. With finite depth at a given price, a large liquidity demander pays a premium to trade (Grossman and Miller (1988)). Correspondingly, large liquidity suppliers receive a premium for facilitating such trades.

The classification in Table 1 shows that the informed, momentum and large liquidity demanders are observationally equivalent for a given change in *daily* prices. That is, each trader type changes open interest in the same direction as the open-to-close price change. In the context of equation (3), these trader types differ by the value of their unobserved reference price $P_{*,t}^{k}$; for informed traders, this reference price occurs before a price change, for momentum traders it occurs after a price change and for large liquidity demanders it occurs contemporaneously with

[8] A noise or random trader represents a seventh trader type. This trader's open interest changes randomly relative to price changes in the day.

price changes. Similarly, the uninformed, large liquidity suppliers and contrarian traders are also observationally equivalent. The problem then is to separate these combined types, so that we can isolate the intraday informed from the liquidity demanders and suppliers.

To start, we define the following success measure to determine whether a trader's open interest changes are consistent with intraday price changes:

(iii) Intraday Trading Profits: θ_t^d $= \text{undefined } iff \sum_{k=1}^{K} \left|\Delta OI_t^k\right| = 0$

$$= 1 \;\; iff \; \sum_{k=1}^{K} \Delta OI_t^k (P_t^k - P_{o,t}^k) > 0$$

$$= 0 \text{ otherwise.}$$

Informed, momentum and large liquidity demanders all exhibit $E(\theta_t^d) > 0.5$, whereas the uninformed, large liquidity suppliers and contrarian traders all exhibit $E(\theta_t^d) < 0.5$. Thus, our identification problem requires two additional pieces of information to partition the six trader types in Table 1. We develop two joint tests to solve this problem.

Consider the group composed of the informed, liquidity demanders and momentum traders. We can partition momentum traders by their expected response to overnight close-to-open price changes, $P_{o,t}^k - P_{t-1}^k$. After the market opens, momentum traders will use this information in their strategy. To the extent that $P_{*,t}^k - P_{o,t}^k$ is small relative to $P_{o,t}^k - P_{t-1}^k$, the close-to-open price change will predict momentum trades. In contrast, informed traders are not affected by the close-to-open price change as their trades are forward looking by definition. Also, liquidity demanders will view such information as noise. Thus, we expect to find a positive correlation between ΔOI_t^k and both $(P_t^k - P_{0,t}^k)$ and $(P_{0,t}^k - P_{t-1}^k)$ for momentum traders. With informed and liquidity traders, however, we expect only a positive correlation between ΔOI_t^k and $(P_t^k - P_{0,t}^k)$.

We therefore define the following momentum-trading rule to measure the propensity for a trader's position to respond to the previous overnight price change:

$$\text{(iv) Momentum Trading:} \quad \theta_t^m \begin{array}{l} = \text{undefined } \textit{iff } \sum_{k=1}^{K} \left|\Delta OI_t^k\right| = 0 \\ = 1 \ \textit{ iff } \ \sum_{k=1}^{K} \Delta OI_t^k (P_{o,t}^k - P_{t-1}^k) > 0 \\ = 0 \text{ otherwise.} \end{array}$$

Momentum traders exhibit the quality that $E(\theta_t^m) > 0.5$, whereas for informed and liquidity demanders we expect $E(\theta_t^m) = 0.5$. Similarly, contrarian traders will have $E(\theta_t^m) < 0.5$ whereas we expect $E(\theta_t^m) = 0.5$ for uninformed and large liquidity suppliers, as illustrated in Table 1.

D. Identifying Intraday Informed Traders

Under the null hypothesis of no relationship between open interest changes and prices, and assuming no correlation between close-to-open and open-to-close price changes, θ_t^m and θ_t^d each equal one with probability 0.5 and are independent. Thus, for a null trader, $E[(1-\theta_t^m)\theta_t^d] = 0.25$. In contrast, we expect informed and liquidity demand traders to do no worse than luck predicts when judged by last night's close-to-open price changes, but to exceed the 50% chance of success when judged by today's open-to-close price changes, i.e., we expect $E[(1-\theta_t^m)\theta_t^d] > 0.25$. However, momentum traders' success rate is expected to exceed 0.5 for both price changes, so reversing the definition for close-to-open success (i.e., not predictive of this change) reduces the probability of the combined events to less than 0.25 for momentum traders.[9] Thus, we formulate the pairs test to identify the intraday informed and liquidity demanders:

Pairs Test $\qquad$ H_0: $E[(1-\theta_t^m)\theta_t^d] = 0.25.$

[9] This claim always holds when the chance a momentum trader's open interest responds directly to close-to-open prices is the same as the chance of responding to open-to-close prices. To the extent that the chance is less for close-to-open prices, this test may contain some leakage of momentum traders into the resulting group.

This is a joint test that a trader trades in the same direction as today's open-to-close price changes but *does not* respond directly to last night's close-to-open price changes. Significant upper-tail (lower-tail) traders in the pairs test will identify the informed and liquidity demanders (uninformed and liquidity suppliers).

The pairs test finds liquidity demanders and informed traders jointly. To separate these two groups, we extend the horizon from the intraday close, P_t^k, to the opening price on the next day, $P_{o,t+1}^k$. Large liquidity demanders are not expected to have positions that predict subsequent price changes. In contrast, informed traders expect their trades and resulting end-of-day open interest positions to yield profits; otherwise, they could have continued to trade on day *t* until the market had fully priced their information. Thus, we test whether those who are intraday successful based on changes in their open interest are also informed about next day's close-to-open price change, $P_{o,t+1}^k - P_t^k$, based on their day *t* net position.[10]

Effectively, we extend the pairs test to include the following day's price change. We call this the *triple test* as it combines all of the results noted above about informed, momentum and large liquidity. The null probability for the triple test is 0.125 with the null hypothesis given by:

Triple Test $\quad H_0$: $E[(1-\theta_t^m)\theta_t^d\theta_{t+1}^p] = 0.125.$

The triple test may select some non-informed traders because the three components of the test allow flexibility in how to reject the null. For example, we may reject the null if a trader's day *t* position changes are negatively correlated with previous overnight close-to-open price changes but positively correlated with intraday price changes and not generally predictive of tomorrow's close-to-open price change. In effect, the triple test is flexible relative to the null.

[10] If informed traders make profitable trades within day *t* and do not close their positions by the end of the day even when they expect no subsequent gains, then their end-of-day *t* positions may not be predictive. The test is still valid; however, as we would expect informed traders not to consistently lose money against next day's price changes versus the likelihood that a liquidity demander faces a price reversal.

To overcome this "flexibility", we impose the original premise established in Table 1 about informed traders. Specifically, the informed are those whose intraday position change is significantly (and positively) correlated with the intraday open-to-close price change. Thus, using the significant results in the upper tail of the triple test, we classify a trader as informed if that trader is also significant in a single hypothesis test comparing her position change to the intraday open-to-close price change.

In sum, we classify traders intraday as follows:

Informed:	$E\left[(1-\theta_t^m)\theta_t^d\theta_{t+1}^p\right] > 0.125$ and $E[\theta_t^d] > 0.5$
Large Liquidity Demander:	$E[(1-\theta_t^m)\theta_t^d] > 0.25$ and $E[\theta_t^d] > 0.5$, but not $E\left[(1-\theta_t^m)\theta_t^d\theta_{t+1}^p\right] > 0.125$
Momentum:	$E[\theta_t^m] > 0.5$
Uninformed:	$E\left[\theta_t^m\left(1-\theta_t^d\right)\left(1-\theta_{t+1}^p\right)\right] < 0.125$ and $E[\theta_t^d] < 0.5$
Large Liquidity Supplier:	$E\left[\theta_t^m\left(1-\theta_t^d\right)\right] < 0.25$ and $E[\theta_t^d] < 0.5$, but not $E\left[\theta_t^m\left(1-\theta_t^d\right)\left(1-\theta_{t+1}^p\right)\right] < 0.125$
Contrarian:	$E[\theta_t^m] < 0.5$

E. Multiple Testing for Predictive Ability

Because we have thousands of traders, the usual significance levels give rise to a multiple testing problem (Miller, 1981). The classical approach to multiple-testing limits the family-wise error rate. This approach sets a high bar for rejection because it controls the probability of making a *single* type I error. In our application, we are not averse to falsely rejecting the null hypothesis for a few traders if doing so enables us to discover numerous informed traders. Thus, we apply the framework developed by Benjamini and Hochberg (1995) to control the false discovery rate. The *FDR* equals the proportion of rejected hypotheses that are in fact true.

To explain this method, suppose there are three types of traders, null traders (no predictive ability), uninformed traders (negative predictive ability) and informed traders (positive predictive ability). We denote the population proportion of null traders by π_0. For each trader (j = 1,2,…,n), we calculate a statistic, z_j. This statistic has an asymptotic standard normal distribution under the null hypothesis and is centered away from zero under the two alternative hypotheses. Suppose that, for each trader, we use a critical value, c, to test the one-sided hypothesis that the trader is informed. Now suppose that we randomly pick the j^{th} trader from among those for whom the null hypothesis is rejected. The *FDR* is the probability that this trader is null, defined by:

$$\begin{aligned} FDR(c) &= \Pr\left(j \in \{\text{null}\} \,\middle|\, z_j > c\right) \\ &= \frac{\Pr\left(z_j > c \,\middle|\, j \in \{\text{null}\}\right)\Pr\left(j \in \{\text{null}\}\right)}{\Pr\left(z_j > c\right)} \\ &= \frac{\Pr\left(z_j > c \,\middle|\, j \in \{\text{null}\}\right)\pi_0}{\Pr\left(z_j > c\right)} \end{aligned} \tag{5}$$

Using *FDR* to control the size of the false discovery group, we choose the minimum c such that $FDR(c) \le 0.05$, and we reject the null hypothesis for each trader with a z-statistic that exceeds c. We thus produce an informed group that is expected to contain no more than 5% null cases.

The *FDR* method has three useful features. First, the method adjusts the critical value depending on the location of the informed traders. If the null and alternative hypotheses are close together, then there is a greater chance of confounding these hypotheses, which leads to a more conservative (greater) critical value. If the null and alternative hypotheses are far apart, then the critical value can be chosen more aggressively.

The second useful feature is that the critical value c is independent of the number of traders because it controls the proportion of null traders for whom the null hypothesis is rejected. In contrast, controlling the family-wise error rate requires the critical value to increase with the number of hypothesis tests.[11] Our primary objective is to separate informed from lucky traders. If a particular trader is successful, we want to find that trader, so we do not want a rule for separating luck from skill that depends on the number of other traders considered.

Finally, the *FDR* method adjusts the critical value depending on the proportion of traders in the population who are null (π_0). As this proportion increases, the chance increases that a particular successful trader is merely lucky. Consequently, the method chooses a larger critical value when the proportion of null traders is greater. The Appendix explains how we implement the *FDR* method using our data.

III. DATA

The data for this study are derived from the Large Trader Reporting System (LTRS) maintained by the CFTC. The LTRS provides end-of-day positions for all traders who exceed mandatory reporting thresholds. According to the CFTC, the aggregate of all traders' positions reported in the LTRS represents 75-95 percent of the total open interest in any given market. We study twelve commodities, with three each from grains (corn, soybeans and wheat), metals (copper, gold and silver), and energy (WTI crude oil, heating oil and natural gas). In addition, we include cotton, soybean oil, and sugar futures contracts. These data cover the period from January 2000 to May 2009 and include 8,921 unique traders.

The LTRS also reports a trader's business line activity, which is self-reported on Form 40 to the CFTC. This information is used by the CFTC to classify some traders as "commercial", which generally implies that they have an operating interest or holding in the underlying

[11] An alternative test is that proposed by Kosowski, Timmermann, Wemers and White (2006) in their assessment of mutual fund performance. They convert the multiple tests into a single test using the sequence of *z*-statistics.

commodity. However, this group also includes swaps dealers.[12] Traders that have not identified an underlying hedging purpose are labeled "non-commercials" and are not eligible for hedging exemptions to CFTC position limits. The non-commercial groups include floor brokers and traders (FBT), hedge funds/managed money (MMT) and non-registered participants (NRP). The hedge funds/managed money group includes commodity pool operators, commodity trading advisors, associated persons and any others who manage money for clients. The non-registered participants are traders with positions large enough to meet the CFTC reporting requirements, but do not have to register under the rules of the Commodity Exchange Act. These non-registered participants are generally smaller financial firms.[13]

Table 2 provides statistics on trader-specific characteristics in Panel (A); the distribution of traders across business lines in Panel (B); and the representativeness of the reported trader data in Panel (C). To generate trader characteristics, we average positions for each trader over time and across traders by commodity as described in the notes to Table 2.

We characterize traders by their experience, which is measured by the number of days they hold an open position. On average traders have 1.4 years of trading experience with substantial variation across commodities. Traders are also fairly large as judged by average position size and active in most commodities. The average participant trades on more than half of the days in which they hold open positions. Participants also typically hold positions in multiple expirations, with traders in the energy commodities holding on average the most contract expirations.

[12] The business lines that make up commercial interests include: dealers or merchants (AD) who are usually wholesalers, manufacturers (AM) who are generally fabricators or refiners, producers (AP), agricultural/natural resources (AO) and other companies that are end users, and commodity swaps/derivative dealers (AS), which aggregates both swap dealers, arbitrageurs and broker dealers. In our results, we combine AD, AM, AP and AO into one commercial group and report results for AS in a separate group.

[13] There are a small number of traders with specialty designations, such as non-U.S. commercial bank, insurance company, corporate treasurer, etc., and these traders and NRPs are combined into an "Other" category.

We characterize the one-sided choices of trades with average net long and net short futures position sizes, both relative to absolute futures position size. To generate these statistics, we divide traders into those who hold more long positions than short positions on average and those who hold a greater number of short than long positions. For all net long (or short) traders, we calculate the proportion of all positions that are long (or short). This proportion equals one for a net long trader who never holds a short position; it is close to zero for a net long trader who holds only slightly more long than short positions. For example, Table 2 shows that across all crude oil traders who are net long on average, the ratio of average long to average total position is about 48%. Across all commodities, this average is about 60% for both net long and net short traders. For comparison, in the entire sample about half of all traders are net long on average, 20% of traders are always long, and 14% are always short.

Panel (B) shows that almost half of traders are non-registered participants or specialized traders, who average nearly 46% in the sample. MMTs are the second most populous group at 23%, with all commercials at about 18% of participants. Panel (C) confirms the claim that the data reported by the CFTC represents between 75 and 95 percent of the total open interest of all traders. This panel also shows the distribution of trader counts by commodity. The grain contracts attract the greatest number of participants, with the energy complex and gold futures containing about 60-70% of these numbers. The other commodities have fewer traders, but each case contains hundreds of traders. In this light, each commodity presents a multiple testing problem as we seek to identify who is informed.

IV. ANALYSIS

A. Identifying Overnight Informed Traders

We implement the *FDR* method to detect forecasting ability using one-sided tests on each tail of the sample distribution. Table 3 reports the overnight informed counts using the profit rules (i) and (ii). These counts provide a lower bound on the actual number of informed traders. Specifically, we may omit some informed traders who were only mildly successful because we could not select them without also selecting other traders who were merely lucky.[14] By setting the FDR to 5%, we stipulate that at least 95% of traders in the informed group are informed.

The lagged trading profits test measures success by whether net trades made on day t-1 provide positive profits when evaluated at day t closing prices. This test identifies almost no informed traders. Out of 8,921 unique traders across commodities, we find a total of five informed traders. Thus, very few traders change their net positions systematically one day in advance of price changes the next day. This result suggests that the net effect of trading reveals information that is assimilated into prices within the trading day.

The position profits rule, which measures end-of-day positions against the next day's price change, detects many more overnight informed traders than the lagged trading profits rule. Silver reveals the largest number of informed in the unconditional test, with 93 selected as informed (12% of traders; 14.3% of OI). In the HM test, copper produces the highest count at 51 informed traders (8.1% of traders; 7.9% of OI). Other commodities also show meaningful counts, particularly corn, soybean oil and soybeans. In total, we identify 246 informed traders (230 unique) in the unconditional tests and 96 traders (94 unique) in the HM tests. The small number

[14] We also implemented two-sided tests and investigated close-to-open prices with very similar results. In addition, we ran tests based on combining lagged trade and position profit rules; that is, use the lagged trade profit rule if there is a trade, otherwise use the position profit rule. These results are consistent with our findings here and are available on request.

of overlaps shows that we find only a few traders who are informed in multiple commodities.

The HM test shows that about half of informed traders appear to benefit from participating during trending episodes. Specifically, the overnight informed counts for copper, corn, silver, and soybean oil are significantly reduced for the HM test. In general, the position profits rule identifies between 1.1% and 2.6% of our sample as overnight informed traders, with the higher percentage skewed by copper, corn, silver, and soybean oil counts.

Table 3 also reports the range of critical values (c) chosen by the *FDR* method. The table contains 48 counts across 12 commodities and 4 tests. We observe 25 zero counts, which implies that the *FDR* exceeds 0.05 for all observed z statistics. Of the remaining 23 entries, four critical values lie between two and three, 16 between three and four, and the remaining three between four and five. In all tests, the commodity with the highest informed count exhibits the smallest selected critical value, underlying the point that the counts in Table 3 signify the number of informed traders we identify rather than the number of informed *per sé*. If the informed traders do not have sufficiently large z statistics, then controlling the FDR requires a larger critical value and produces a smaller count irrespective of the total number of informed. The median critical value across all tests is 3.57, which corresponds to a one-sided p-value of 0.00018 and suggests that multiple-testing bias would be severe if we had applied classical critical values.

We also applied the FDR method to a test of the null hypothesis that average daily position profits equal zero, i.e., a test of H_0: $E\left[\sum_{k=1}^{K} OI_{t-1}^{k} \Delta P_t^k\right] = 0$ rather than $E\left[\theta_t^p\right] = 0.5$. We found only 33 informed traders across the 12 commodities. As kurtosis in the distribution of daily profits is 13.9, this result is consistent with the result that heavy-tailed data produce light tailed t-statistics causing under-rejection of the null hypothesis (e.g., Cressie 1980). Our binary success statistic does not exhibit heavy tails, and so has more power in this environment. We also find almost no significant traders in the left tail of the distribution, which suggests that our data do not contain traders who make money by taking many small losses but offset by occasionally large gains.

To check calendar patterns in our informed counts, we ran several additional tests. First, we applied the FDR method separately to the 2000-04 and 2005-09 sample periods. We found more informed in the latter sample period, but almost all traders who are significant in the split-sample test are also identified as informed in our full sample test. Because of the shorter sample on each trader, the split-sample test misses some informed that the full sample identifies but still produces an 85% overlap in the informed. We also ran tests in which we used only the nearest-to-delivery or highest trading volume contracts and found that the informed tend to favor higher volume (generally nearby) contracts. Overall, these additional results are consistent with our main findings and are available on request.

Overall, the informed counts in Table 3 show that relatively few, but nonetheless a meaningful number of traders consistently hold end-of-day *positions* that reveal superior information. There appears a great deal of information specialization across these twelve commodities as few traders are identified as informed in multiple commodities. Importantly, we find almost no traders whose lagged net *trading* decisions consistently predict subsequent profits.

B. Characteristics of Overnight Informed Traders

We are interested in both identifying informed traders and describing their characteristics; specifically, whether their business activities suggest that they are commercial traders, hedge funds, floor brokers, or swap dealers, and how their trading activity compares to the average trader. Thus, we condition on the informed already found to identify their characteristics. This approach is called an inverse regression (e.g., Li (1991)). The task is essentially the opposite of discriminant analysis, which uses observed characteristics to classify among observations. To accomplish our goal, we run a linear regression of the binary variable indicating membership in the informed group (y) on a matrix of characteristics X, specified as follows:

$$y = X\beta + \varepsilon = [x_j \quad X_{-j}] \begin{bmatrix} \beta_j \\ \beta_{-j} \end{bmatrix} + \varepsilon, \tag{6}$$

where $E(X'\varepsilon) = 0$, x_j denotes a particular variable of interest, and X_{-j} denotes the other variables in X. The coefficient β_j can be written as

$$\begin{aligned} \beta_j &= \frac{E(y_i x_{ji}) - E(y_i \hat{x}_{ji})}{E(x_{ji} - \hat{x}_{ji})^2} \\ &= \frac{E(x_{ji} |\, y_j = 1) \Pr(y_j = 1) - E(\hat{x}_{ji} |\, y_j = 1) \Pr(y_j = 1)}{E(x_{ji} - \hat{x}_{ji})^2} \end{aligned} \tag{7}$$

where $\hat{x}_j = X_{-j}(X'_{-j}X_{-j})^{-1}X'_{-j}x_j$ is the linear projection of x_j onto the column space of X_{-j}. To re-interpret β_j based on characteristics, we re-write this expression to obtain

$$\tilde{\beta}_j \equiv \beta_j \frac{E(x_{ji} - \hat{x}_{ji})^2}{\Pr(y_j = 1)} = E(x_{ji} |\, y_j = 1) - E(\hat{x}_{ji} |\, y_j = 1) \tag{8}$$

Thus, by scaling the regression coefficient appropriately, we obtain a measure of the difference between the expected value of x_j for all the observations in the informed group (i.e., $y_j = 1$) and the expected value of x_j from a prediction based on the other variables in X. In effect, we estimate a forward regression of y on X to derive an inverse regression interpretation.

For example, suppose x_j denotes the log of the average size of positions held by trader i, and X_{-j} contains only a constant. Then $\hat{x}_{ji} = n^{-1}\sum_{i=1}^{n} x_{ji}$ is the sample mean of x_{ji}. It follows that

$$\tilde{\beta}_j = E(x_{ji} |\, y_j = 1) - E(x_{ji}), \tag{9}$$

which is the difference between the average log-position-size of informed traders and the corresponding average *across all traders*. Similarly, if x_{ji} is a dummy variable signifying whether trader i is a managed-money trader (MMT) and X_{-j} contains a set of dummy variables signifying whether trader i is of another type, then $\hat{x}_{ji} = 0$ and the adjusted coefficient becomes

$$\tilde{\beta}_j = Pr(x_{ji} = 1 | y_i = 1). \tag{10}$$

In this case, $\tilde{\beta}_j$ measures the proportion of traders in the informed group who are classified as MMT. If X_{-j} includes a trader characteristic such as log-position-size, then $\tilde{\beta}_j$ would measure the representation of MMT traders x_j in the informed group holding log-position-size constant.

Table 4 shows the inverse regression results for traders selected by the unconditional and HM tests based on the position profits rule. These regressions pool observations across commodities and include commodity fixed effects. We pool across commodities because not every commodity revealed informed trading. However, the sign and significance of the parameters is quite similar in separate regressions for commodities with more than fifteen informed traders. When estimating standard errors, we correct for heteroscedasticity using White's (1980) estimator and cluster by trader. The coefficient estimates in Table 4 are those produced by the projection in equation (8) with the significance of the underlying coefficient shown next to the estimate of $\tilde{\beta}_j$.

We show three models in Table 4 for each test. We show results including business line dummy variables alone, trader characteristic variables alone, and both combined. In terms of R^2, the trader characteristics better predict membership in the informed group than the business line variables. However, the business line variables provide insights into the characteristics of the informed. The relative change in the business line coefficients across these models helps filter out the effects of business type from those due to the characteristics of traders. For identification purposes, we exclude the constant term and show the sample proportion of the business line variables for comparison. Thus, a group is over-represented among the informed if the coefficient on that group's dummy variable exceeds the sample proportion for that group.

To understand how to interpret the coefficients in Table 4, consider how the projected effect for the Commercial group changes from model (1) to model (3). The significant coefficient of 0.06 in model (1) implies that the proportion of overnight informed traders who are commercials is 6%, which is lower than the overall sample representation of 21%. Because commercial traders are generally hedgers, this result suggests that hedgers are underrepresented in the overnight informed group. In model (3), this coefficient is 0.02 and insignificant, which suggests that the proportion of the informed that are commercials is only 2% greater than would be expected based on other trader characteristics. Thus, based on the trader characteristics, we would have expected 4% of the informed to be commercial firms but we instead found 6%.

Comparing the results from the unconditional test to the HM test, we tend to see relatively more FBTs selected as informed by the HM test. Correspondingly, the HM test selects relatively fewer traders from the other business lines. In the HM test, FBTs comprise 40% of the informed, which significantly exceeds the 14% representation that FBTs have in the full HM test sample. This estimate drops to 27% when we add trader characteristic variables.

The over-representation of FBTs, who tend to be market makers, among the informed suggests that the ability to understand and process order flow information determines much of what it means to be overnight informed. These traders are less likely to possess private information about flows of the physical commodity than commercial traders, and they are less likely to trade based on sophisticated technical models than managed money traders. However, their role as liquidity providers places them in a position to track and predict order flow. This result is consistent with Evans and Lyons (2008), who show that most of the effect of macroeconomic news on the deutschmark/dollar exchange rate is transmitted through order flow, as well as the findings of Anand and Subrahmanyam (2008) for intermediaries trading equities on the TSX. Thus, these FBTs appear to behave as the superior information processors described in microstructure models, such as Kim and Verrecchia (1997).

Among the trader characteristics, the net long and net short variables have larger negative coefficients in the HM results than in the unconditional results. Model (6) shows that the average net position of informed traders is 19% less long and 22% less short than the average trader in that commodity. This result shows that traders whose net position is predominately on one side of the market are much less likely to be selected as informed than traders such as FBTs whose net position alternates on both sides of the market. Moreover, the similar magnitude of these coefficients shows that it is being on one side of the market that is under-represented in the informed group, rather than being long or short *per se*. In the unconditional test, however, net long traders are not significantly less likely to be in the informed group. This result shows that the HM test differs from the unconditional test by filtering out those traders who consistently made good forecasts by being predominately net long during a period of increasing prices.

Among business categories, the commercial firms are under-represented as informed traders. The MMTs show a slight over-representation in the unconditional test, but not in the HM test. This result suggests that some MMTs may benefit from taking long positions during a period of rising prices. The swap dealers and index traders (AS) are generally insignificant in these results. The "other" category, which includes non-registered participants, shows no real indication of being under- or over-represented after controlling for trading characteristics.

In the full models, the experience variable stands out as always significant and positive. As it is defined in logs, the coefficient implies that informed traders are between 10% and 25% more experienced than the average trader, *ceteris paribus*. Informed traders in the HM test tend to hold larger size positions and be more active than the average trader, which is consistent with the results of Menkhoff and Schmeling (2010) in a foreign exchange market. The size coefficient increases in the full model estimates, which reveals that informed traders within a particular business line are more likely to be larger than the average trader in that business line.

Although FBTs feature prominently in the informed groups, most FBTs are not informed. In fact, for the HM test sample, the average success rate of FBTs is the lowest of any business-line group; the average success rate is highest for AS firms. If we had aggregated all FBTs into a single category rather than studying individual accounts, then we would have missed the fact that some FBTs have predictive ability. Thus, our results differ from what would be found if we had aggregated firms by business line and conducted our tests in a manner similar to past studies.

C. Identifying Trader Types from Intraday Activity

The lagged trading profits tests in Table 3 selected almost no informed traders, which may indicate that information held by informed traders makes its way into prices during the trading day. Thus, we analyze intraday price changes using the methods introduced in Section II.D. Table 5 reports results using the pair and triple tests to identify the intraday informed and liquidity traders.

Table 5 shows trader counts for various trader types by commodity. We use a test of the null hypothesis $E(\theta_t^m) = 0.5$ to identify momentum and contrarian traders and the triple test to isolate informed and liquidity traders. We find relatively low counts for liquidity suppliers and demanders, with about 1% of all traders in each of these categories. These low counts may reflect the fact that only large traders are likely to move prices when they demand liquidity. The liquidity supplier counts show only three duplicates across commodities, but there is greater cross-commodity overlap in liquidity demanders. There are 115 unique traders in the total count of 152, of which 92 appear in a single commodity and 14 in two commodities. No participant is an identified liquidity demander in more than six commodities.

Consistent with the overnight informed results, the triple test identifies relatively few intraday informed traders. We find a total count of 158 informed traders, which represents 91 unique traders. Of these 65 show up as informed in a single commodity, 12 in two commodities and the remaining 14 in three or more commodities. Of these 158 cases, only 6 also were identified as overnight informed in the HM test and 18 in the unconditional test. Thus, the overnight informed are different than the intraday informed. This result is consistent with the model of Kim and Verrecchia (1997), who describe two types as informed: those possessing private information signals and those who profit by processing information efficiently. We view the intraday informed as possessing private signals and the overnight informed as superior information processors. We find only eight uninformed traders, i.e., those who are significant traders in the left tail of the triple test (not shown in Table 5).

The counts for momentum and contrarian traders are sizable across nearly all commodities. On average across commodities, 8% of futures traders follow momentum strategies and 11% follow contrarian strategies. There is also significant overlap across commodities, so the total number of unique traders is less than the totals of 834 and 1,170 shown in Table 5. Specifically, we find a total of 444 unique momentum traders, which is five percent of all traders. Of these, 298 are identified in a single commodity, 64 in two commodities, 36 in three commodities, and the remaining in four or more commodities. A total of 10 firms are identified as momentum traders in at least 10 of the 12 commodities. We find a total of 912 unique contrarian traders, including 742 who are contrarian in a single commodity, 117 in two commodities, 34 in three commodities and 19 in four or more commodities. We identify no firms as contrarian in more than eight commodities. Momentum and contrarian traders are more concentrated in the metals, although the corn market also exhibits a substantial fraction of identified contrarian traders.

D. Characteristics of Traders Identified from Intraday Activity

Table 6 reports inverse regression results for liquidity, informed, momentum, and contrarian traders identified by the intraday tests. The liquidity demanders and suppliers selected by the triple test show stark differences in composition. Commercial traders comprise 42% of liquidity suppliers and just 2% of liquidity demanders, whereas managed money traders comprise only 7% of liquidity suppliers but 52% of liquidity demanders. The FBTs are over-represented among liquidity suppliers, consistent with their traditional role as market makers, but they are also somewhat over-represented among liquidity demanders. Swaps dealers are also over-represented in both groups, and the Other category is under-represented in both groups, which is consistent with this group acting as noise traders.

The trader characteristics variables show that liquidity demanders hold positions 57% larger in size, but they are no more experienced than the average trader. In contrast, liquidity suppliers hold positions that are insignificantly different in size, and they are 41% more experienced than the average trader. Liquidity demanders hold concurrent positions in about 41% fewer contract expirations and are less likely to be on one side of the market than the average trader. Both groups tend to be more active traders than average. The full models in (3) and (6) show that trader characteristics explain much of the difference in representation of the various business lines in the liquidity trader groups. In particular, the representation of managed money in the liquidity demander group drops from 0.52 to 0.37 when we control for trader characteristics. Similarly, the representation of commercial firms among liquidity suppliers is close to its representation in the sample (25%) once we control for experience, trading activity and a tendency to be on the short side of the market.

These results suggest that there are essentially no commercial firms who pay a liquidity premium to hedge. Rather, a subset these firms, especially dealers and merchants, tend to *supply* liquidity services; they trade in the opposite direction to concurrent price changes, but do not possess information to predict the following day's price change. It appears instead as if selected large managed money traders and hedge funds may pay for immediacy and are met by liquidity from experienced commercial firms and FBTs. This result is the opposite of that obtained by deRoon, Nijman and Veld (2000) who found that, in aggregate, commercial hedgers tend to apply price pressure when they adjust their positions.

Our approach identifies liquidity demanders and the informed as traders who change open interest in the same direction as prices during the day but do not follow overnight price changes. The difference between these two groups is that the intraday informed tend to hold overnight positions that better predict the next day's opening price. Table 6 shows that these informed tend to be even larger, more active, and in fewer expirations than the liquidity demanders. In addition, MMTs and swaps dealers are substantially over-represented and commercial firms are under-represented in the informed group. The FBTs comprise 13% of the informed, which is the same as their representation in the whole sample and much less than their representation in the overnight informed. This result suggests that FBTs do not provide information during the trading day, but rather MMTs and swap dealers bring information to the markets.

When comparing momentum to contrarian traders, the largest difference is the representation of MMT and commercial traders. Managed money traders are strongly over-represented among the momentum group; they comprise 56% of momentum traders and just 13% of contrarians.

Conversely, commercial firms show over-representation among contrarians; they comprise 46% of these traders and only 8% of momentum traders. Each of these two business lines constitutes about a quarter of all traders.

The trading characteristic effects show that momentum traders hold positions in about 34% fewer contract expirations than the average trader. Contrarian traders hold 8% more contract expirations than average. Thus, momentum traders are more concentrated on the term structure than the average trader. In contrast, contrarians tend to hold a more diverse set of contracts, as indicated by their presence in a greater number of expirations. These results paint a picture of a subset MMTs following momentum strategies and being matched with hedgers. Both contrarians and momentum traders tend to be about 20% more experienced than the average trader.

In sum, our intraday analysis shows that commercial traders are under-represented among liquidity demanders and over-represented among liquidity suppliers. The MMTs are strongly over-represented in the liquidity demander and with swap dealers are over-represented among informed traders. The FBTs are over-represented among liquidity suppliers. Liquidity demanders and the informed tend to be large, active traders who trade in few contract expirations at a time.

E. Profits of Informed Traders

For robustness, we examine whether we identify traders who are indeed profitable as judged against other traders in the sample not selected as informed. To do this, we approximate the daily profits for each type of trader: the informed and the collection of those who are not right-tail informed. We compute these daily profits using equation (3) with the reference price equal to the midpoint between the open and closing price. For the intraday informed, we evaluate only trading profit (i.e., the second term in equation (3)) as that sample conditions on those traders who have a position change. We use as our measure the average daily profit per trader.

Table 7 reports the results of our tests comparing profits in panels (A) and (B). We apply two tests to the daily profit per trader data: the Wilcoxon rank-sum non-parametric test because the data may not be normal and the t-test for the difference between means in the event that our statistics are approximately normal. The table shows results for the informed counts of both position tests in Table 3 and for the intraday informed in Table 5. The one-tail p-value for the Wilcoxon rank-sum is shown along with the mean rank-sums for both informed and not informed participants by commodity. The t-test is reported below the Wilcoxon results. The one-tail p-value for the t-test is computed assuming unequal variances.

Panel (A) reports the overnight informed results. For the informed found in the unconditional tests, the Wilcoxon mean ranks and p-values show significant differences in all commodities. This also generally holds for the corresponding t-tests that the average daily profits per traders, except for natural gas and wheat. For the HM tests, the Wilcoxon results are similarly strong, except for gold and wheat. The t-tests also show that natural gas, soybean, and soybean oil are not significant. The t-tests fail here because there is significant variation in these data partly due to the small count of informed in these commodities and because they may also be affected by excess kurtosis in the daily profit data.

Panel (B) shows the profit results for intraday informed traders versus the non-informed. Here the non-informed include all the other trader types: momentum, contrarian, liquidity demanders and suppliers. With the exception of heating oil—only three informed traders—the Wilcoxon tests show that the informed earn significantly higher daily profits per trader than the non-informed. The t-tests also support this conclusion, but for soybeans and heating oil the results are not significant. In general, these results indicate that the FDR method has identified traders who have an exceptional information advantage compared to other traders.

V. CONCLUSIONS

In this article, we characterize individual traders in futures markets by the positions they hold and their trading performance. We find that few if any traders systematically trade one day in a way that increases profits the following day. However, we identify between 1.1% and 2.5% of the traders who hold positions at the end of a day that systematically predict the next day's price change. A high proportion of such traders are floor brokers, although it is their trading behavior, particularly their experience, presence on both sides of the market, and their larger than average size that characterizes them more than their business classification as floor brokers, *per sé*. Neither commercial firms, nor hedge funds/managed money show a propensity for holding positions that are profitable the following day.

We also find numerous traders who move either with (or against) prices during the day; their positions change systematically in the same (or opposite) direction as prices. From these traders, we identify two groups whose actions suggest that they tend to either supply or demand liquidity. This screen allows us to isolate the group who may be intraday informed. We find that commercial firms tend to provide liquidity to the hedge funds/managed money traders who demand it. We also find that hedge funds/managed money and swap dealers are over-represented among the intraday informed, with commercial hedgers significantly under-represented.

In addition, we find that the intraday informed have only a small overlap with the overnight informed group. The characteristics of these two informed groups suggest that information that leads to superior forecasting abilities varies across such traders. Possibly, end-of-day informed traders may gain their skills from the ability to process and forecast order flows and intraday informed traders from possessing signals that require trade actions, such as those from macro-type information or commodity specific announcements. An analysis of daily trader profits confirms that our methods have selected highly profitable traders.

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APPENDIX: IMPLEMENTING THE FALSE DISCOVERY RATE (FDR) METHOD

Implementing the *FDR* procedure requires that we estimate the three terms in Bayes theorem as shown in equation (5) in the text. Given *c*, the first term, $\Pr\left(z_j > c \mid j \in \{\text{null}\}\right)$, is the *p*-value for z_j, which can be retrieved from the standard normal distribution. The second term $\Pr\left(z_j > c\right)$ can be estimated from the proportion of null hypotheses that are rejected at critical value *c*.

Formulating an estimator for the third term, π_0, the proportion of null traders in the population requires assumptions about the distribution of z_j for the informed and uninformed traders. In their seminal paper, Benjamini and Hochberg (1995) avoid such assumptions by setting $\pi_0=1$, which reduces the *FDR* to

$$FDR_{BH}\left(c\right) = \frac{\Pr\left(z_j > c \mid j \in \{\text{null}\}\right)}{\Pr\left(z_j > c\right)} \qquad \text{(A1)}$$

Because π_0 cannot exceed one, equation (A1) provides an upper bound on the true *FDR*. Benjamini and Hochberg prove that this approach generates a conservative test, for which the proportion of falsely rejected hypotheses is less than FDR_{BH}.

Alternatively, Storey (2002, 2004) provides a method of estimating π_0 based on the view that *z*-statistics close to zero are generated by null traders. In terms of *p*-values, he assumes that null traders generate all *z*-statistics for two-sided *p*-values greater than some level, λ. We write Storey's assumption as

$$\Pr\left(j \in \{\text{null}\} \,\Big|\, 2\left(1-\Phi(|z_j|)\right) > \lambda\right) = 1, \qquad \text{(A2)}$$

where Φ denotes the standard normal CDF and $2\left(1-\Phi(|z_j|)\right)$ is the two-sided *p*-value. Rewriting the condition $2\left(1-\Phi(|z_j|)\right) > \lambda$ as $|z_j| < \Phi^{-1}\left(1-0.5\lambda\right)$ and applying this assumption yields

$$
\begin{aligned}
\pi_0 &= \Pr\left(j \in \{\text{null}\}\right) \\
&= \frac{\Pr\left(j \in \{\text{null}\} \,\middle|\, |z_j| < \Phi^{-1}\left(1-0.5\lambda\right)\right)\Pr\left(|z_j| < \Phi^{-1}\left(1-0.5\lambda\right)\right)}{\Pr\left(|z_j| < \Phi^{-1}\left(1-0.5\lambda\right) \,\middle|\, j \in \{\text{null}\}\right)} \\
&= \frac{\Pr\left(|z_j| < \Phi^{-1}\left(1-0.5\lambda\right)\right)}{1-\lambda}
\end{aligned}
\tag{A3}
$$

where the denominator in the last line follows from the definition of λ. Thus, for a given λ we can estimate π_0 as

$$
\hat{\pi}_0 = \frac{1}{(1-\lambda)n}\sum_{i=1}^{n} 1\left(|z_i| < \Phi^{-1}\left(1-0.5\lambda\right)\right)
\tag{A4}
$$

where 1(•) denotes the unit indicator function. Combining Storey's approach with estimates for the first two terms gives the follow estimator for equation (5):

$$
\widehat{FDR}(c) = \frac{\left(1-\Phi(c)\right)\hat{\pi}_0}{n^{-1}\sum_{i=1}^{n} 1\left(z_i > c\right)} = \frac{\left(1-\Phi(c)\right)\sum_{i=1}^{n} 1\left(|z_i| < \Phi^{-1}\left(1-0.5\lambda\right)\right)}{(1-\lambda)\sum_{i=1}^{n} 1\left(z_i > c\right)}
\tag{A5}
$$

We implement the *FDR* test by choosing the minimum *c* such that $\widehat{FDR}(c) \leq 0.05$, and judge trader *j* to have predictive ability if $z_j > c$. Our test is conservative because we choose a 5-percent critical level to determine "c".

The important question presented by Storey's approach is how to choose λ. Storey (2002) uses a bootstrapping method, which is also implemented by Barras, Scaillet and Wermers (2010). For our analysis, we develop a chi-square goodness-of-fit test to select an optimal λ. This method is simple to implement and also provides information on how much the alternative hypothesis vitiates the null population.

To illustrate Storey's and our approach, consider how Dalmasso, Broet and Moreau (2005) construct the general problem of identifying π_0 as a mixture of distributions. In any set of multiple tests, the observed *p*-values will be distributed under the null with probability π_0 and under the alternative(s) with probability (1- π_0). Thus, the expected p-value across tests is defined by the following mixture using the mixing parameter, π_0:

$$E[P] = \pi_0 E_0 [P] + (1 - \pi_0) E_1 [P] \qquad \text{(A6)}$$

where E_0 and E_1 are expectations taken over the null and alternative distributions, respectively. Under the null, p-values are uniformly distributed with the n^{th} moment from the origin equal to $1/(n+1)$. Dividing (A1) by $E_0[P^n]$ produces an obvious estimator that is expected to bound π_0:

$$\pi_0 \leq (n+1) \sum_{i=1}^{M} p_i^n \Big/ M \qquad \text{(A7)}$$

where M is the number of tests and p_i is the observed p-value of each test. Dalmasso, Broet and Moreau (2005) develop a class of estimators based on generalizing (A6) to the expectation over a transformation of P. The transformation they develop has the feature that the bias for π_0 is decreasing in n. In contrast, the bias of the moments estimator in (A7) is increasing in n, so the best choice is $n = 1$, or two times the sample mean of the p-values.

Storey (2002) uses the result that the null distribution is uniform to develop his bootstrapping approach for bounding π_0. This method relies on finding a good cutoff point (λ) in the distribution of ordered p-values (lowest to highest) beyond which the p-values are likely from the null and exhibit uniformity. For a given cutoff, the estimate of π_0 is defined as:

$$\pi_0^*(\lambda) = \frac{\#\{p_i > \lambda\}}{M} \frac{1}{(1-\lambda)} \qquad \text{(A8)}$$

where the first term represents the fraction of p-values exceeding the cutoff and the second term rescales this fraction to the entire distribution of p-values.

Storey's (2002, 2003) method computes $FDR(\lambda,\alpha)$ for the sample p-values over a discrete range (R) of possible λ, given a known rejection rate (α). The procedure then bootstraps the sample distribution of p-values to compute $b = 1,2,3\ldots,B$ samples of size M. In the b^{th} sample, let

$FDR_b(\lambda,\alpha)$ define the false discovery rate statistic, then over all B samples the mean square error (MSE) is computed as:

$$MSE(\lambda) = \frac{1}{B}\sum_{b=1}^{B}\left[FDR_b(\lambda,\alpha) - \min_{\lambda' \in R}\{FDR(\lambda',\alpha)\}\right]^2 \qquad \text{(A9)}$$

The value of λ that minimizes (A9) is selected as the optimal cutoff and used in (A8) to estimate an upper bound on π_0.

We offer an alternative procedure for estimating the optimal cutoff that avoids the bootstrapping method. To implement this approach, divide the ordered p-values into $i = 1,2,3\ldots,r$ discrete groups according to the discrete range of possible λ. Beginning with the last two groups, which contain the highest of the ordered p-values, compute the chi-squared goodness-of-fit test statistic for the null that these groups are drawn from a uniform distribution. The last two groups are r and r-1. Let $\chi^2(\lambda(r\text{-}i), k)$ denote this test statistic, where k (= i) defines the degrees of freedom and $\lambda(r\text{-}i)$ represents the cutoff value implied by the $(r - i)^{\text{th}}$ group. Select the cutoff value from the results across all groups:

$$\lambda_{best} = \arg\max_{i=1\ldots(r-1)}\left\{prob\left[\chi^2\left(\lambda(r-i),k\right)\right]\right\} \qquad \text{(A10)}$$

The solution to (A10) produces a cutoff value implied by the set of p-values that are *least likely* to reject the null hypothesis of a uniform distribution. This solution is substituted into (A8) to estimate the bound on π_0. The intuition for this test is same as Storey (2002) offered for equation (A8), which is that the greatest effect from an alternative hypothesis is likely to be found in the lowest p-values. Thus, for some group of high p-values, we expect that the uniform distribution is a good fit. The chi-squared statistic offers a functional measure to define that fit, although other measures may also perform well (e.g., the Anderson-Darling statistic). In applying this test to our empirical analyses, we use 10 bins to define the number of groups, although 20 bins gave similar results.

Table 1
Six Trader Types

A trader is characterized by whether her net daily change in open interest is of the same sign as the price change and whether it occurs before, during or after the price change. We separate these types using the following daily profit measures defined in the text: intraday trading profits (θ_t^d), momentum profits (θ_t^m), and next-day position profits (θ_{t+1}^p). The omitted group type is a trader that acts completely at random (i.e., a noise trader) and exhibits OI changes that are uncorrelated with daily price changes.

	Net daily OI change is positively correlated with daily price change	**Net daily OI change is negatively correlated with daily price change**
OI moves before prices	Informed	Uninformed
OI moves with prices	Large Liquidity Demander	Large Liquidity Supplier
OI moves after prices	Momentum	Contrarian

Table 2
Sample Characteristics

This table provides summary information for our sample data, which includes all futures positions held at the end-of-day by traders in who reported to the CFTC. The sample includes all contracts traded between January 2000 and May 2009. Trader-specific characteristics are shown in Panel (A) with an explanation of how each characteristic is measured. Panel (B) shows the distribution of traders across business lines. Panel (C) shows how represesntative the CFTC sample is compared to all positions in the market and the total number of unique reporting traders by commodity. Excluding the overlap between commodities, the sample include 8,921 unique traders.

Characteristic	Crude oil	Copper	Corn	Cotton	Gold	Heating oil	Natural gas	Silver	Soybean oil	Soybeans	Sugar	Wheat
Panel (A): Trader-Specific Characteristics												
Experience: Average number of position days; that is, OI>0	359	346	449	156	338	457	437	361	429	343	160	357
Active: Days with trades divided by total position days	0.82	0.55	0.72	0.67	0.69	0.77	0.79	0.67	0.62	0.75	0.72	0.66
Size: Average number of futures long and short contracts held at the end of daily trading	332	175	285	282	357	232	194	237	347	157	938	238
Expirations: Average number of contract expirations held	3.47	1.77	2.54	1.87	1.56	3.74	6.13	1.53	2.28	2.02	2.56	1.81
Net Long: Average net long position divided by average of long and short positions; zero if net short	0.48	0.64	0.66	0.69	0.77	0.50	0.54	0.74	0.60	0.59	0.69	0.66
Net Short: Average net short position divided by average of long and short positions; zero if net long	0.56	0.68	0.64	0.59	0.61	0.49	0.40	0.61	0.50	0.58	0.60	0.54
Panel (B): Distribution of Traders by Business Line												
Commercials (AD,AM,AO,AP)	15.4%	11.7%	28.7%	16.2%	7.2%	29.8%	21.2%	9.1%	19.3%	20.0%	23.7%	16.2%
Swap/Derivatives Dealer (AS)	3.7%	2.7%	1.1%	4.8%	2.3%	4.7%	4.8%	2.4%	3.4%	1.3%	6.8%	1.9%
Floor Broker/Trader (FBT)	9.7%	6.7%	10.5%	12.9%	6.9%	9.2%	8.9%	6.7%	15.9%	11.0%	10.8%	12.1%
Managed Money Trader (MMT)	24.3%	31.1%	15.9%	35.7%	26.5%	26.9%	28.0%	28.1%	30.7%	16.4%	36.1%	24.3%
Other (NRP & specialized)	47.0%	47.8%	43.6%	30.4%	57.2%	29.5%	37.1%	53.6%	30.8%	51.5%	22.6%	45.3%
Panel (C): Representation of Reported Positions												
Percent of All Market OI	92.1%	89.2%	82.1%	79.2%	91.2%	86.9%	94.6%	90.1%	89.0%	80.8%	75.7%	85.6%
Total Reporting Traders	1,830	1,065	3,345	705	1,580	709	1,276	940	857	2,856	545	1,881

Table 3
Overnight Informed Identified Using the False Discovery Rate (FDR) Method

Overnight informed traders are identified using the lagged trading profits and position profit rules to define forecasting success. This table shows the number of such traders found to be significant by the FDR method when the critical value is set at the 5% level of significance in a one-sided test. The informed are identified using close-to-close prices. The unconditional and HM test counts are reported and show the percent of such informed traders relative to all traders in the sample. Also, the percent of daily informed open interest relative to sample daily open interest is shown for the position profits results. The total counts across commodities are shown at the bottom of the table, which also shows the range of critical values arising from applying the FDR criterion to determine the significance of these tests. The sample includes trading between January 2000 to May 2009 and uses all traders who had 30 or more observations on the respective success variable. A liquidity filter is used to remove days in which there was less than 30 contracts traded in a given expiration.

	Lagged Trading Profits				Position Profits					
	Unconditional Test		HM Test		Unconditional Test			HM Test		
Commodity	**Count**	**% Traders**	**Count**	**% Traders**	**Count**	**% Traders**	**% of OI**	**Count**	**% Traders**	**% of OI**
Crude Oil	0	0.0%	0	0.0%	4	0.3%	0.3%	4	0.4%	0.2%
Copper	0	0.0%	0	0.0%	72	7.3%	10.4%	51	8.1%	7.9%
Corn	0	0.0%	0	0.0%	33	1.1%	3.2%	25	1.4%	3.9%
Cotton	0	0.0%	0	0.0%	0	0.0%	0.0%	0	0.0%	0.0%
Gold	0	0.0%	2	0.2%	0	0.0%	0.0%	1	0.1%	0.1%
Heating oil	1	0.2%	1	0.2%	0	0.0%	0.0%	4	0.8%	0.3%
Natural gas	0	0.0%	0	0.0%	4	0.4%	0.3%	4	0.5%	0.4%
Silver	0	0.0%	0	0.0%	93	12.0%	14.3%	0	0.0%	0.0%
Soybean oil	0	0.0%	0	0.0%	27	3.5%	7.4%	1	0.2%	0.4%
Soybeans	0	0.0%	1	0.1%	11	0.5%	0.9%	4	0.2%	0.5%
Sugar	1	0.3%	1	0.4%	0	0.0%	0.0%	0	0.0%	0.0%
Wheat	0	0.0%	0	0.0%	2	0.1%	2.3%	2	0.2%	1.2%
Total	2	0.0%	5	0.1%	246	2.8%	3.3%	96	1.1%	1.2%
Total (less duplicates)	2		5		230			94		
Range of FDR Critical Values	3.58 to 4.03		3.66 to 4.07		2.28 to 3.98			2.59 to 4.30		

Table 4
Characteristics Inferred from Overnight Informed Traders

This table uses the overnight informed results in Table 3 to infer how group characteristics affect a trader's success or non-success as judged by the position profits rule. For these regressions, the discrete dependent variable equals one if the trader is identified by the FDR approach as significantly informed; zero otherwise. The independent variables are defined in Table 2. The Experience, Active, Size, and Expirations variables enter as logarithms. For the business line dummy variables. The model is estimated without a constant term, so the coefficient on each business-type dummy variable represents the full effect of the group. The sample percentage representation of each business type is shown for comparison. The price measure used to judge success is shown at the top of the table. Observations are pooled across commodities with fixed effects defined for each commodity. We adjust for clustering between commodities by trader and use White's (1980) estimator to correct for heteroscedasticity. The coefficents reported here are transformed using the projection defined by equation (8) in the text. The significance level of the underlying coefficient is reported next to the transformed coefficient, where an "*" ("**") indicates significance at the 90% (95%) level of confidence.

Variables	Proportion in Sample	Unconditional Test (1)	(2)	(3)	Proportion in Sample	H-M Test (4)	(5)	(6)
Experience			0.23 **	0.25 **			0.10 *	0.10 *
Active			-0.07 *	-0.07 *			0.16 **	0.12 **
Size			0.08	0.11 *			0.17 *	0.23 **
Expirations			0.02	0.06 **			0.01	0.01
Net Long			-0.06 **	-0.02			-0.23 **	-0.19 **
Net Short			-0.19 **	-0.12 **			-0.28 **	-0.22 **
Commercial	0.21	0.06 **		0.02	0.21	0.06 **		0.07 **
Swaps Dealer	0.03	0.01 *		-0.01	0.03	0.01		0.00
FBT	0.10	0.24 **		0.19 **	0.14	0.40 **		0.27 **
Managed Money	0.25	0.36 **		0.28 **	0.27	0.24 **		0.19 **
Other	0.41	0.33 **		0.42 **	0.36	0.29 **		0.36 **
R-Squared		0.007	0.015	0.02		0.006	0.012	0.018
Sample Size		14518	14518	14518		10037	10037	10037
FDR counts		246	246	246		96	96	96

Table 5
Identifying Intraday Liquidity, Informed, Momentum & Contrarian Traders

This table shows the counts of momentum and contrarian traders as identified by the previous-overnight price change rule and informed, liquidity demanders and suppliers as identified by the triple test. To select momentum (contrarian) traders, the test identifies traders whose change in position moves with (against) the close-to-open price change on the previous overnight. To find informed traders, the triple test identifies traders whose change in open interest moves directly with intraday prices, conversely with the prior open-to-close price and whose end-of-day positions are predictive of the subsequent day's price change. The liquidity traders are selected from the groups that fail to predict the subsequent day's price change. The triple test counts include only traders who also pass the intraday price change test.

	Triple Test						Previous Overnight Test			
	Liquidity Supplier		Liquidity Demander		Informed		Momentum		Contrarian	
Commodity	**Count**	**Percent**	**Count**	**Percent**	**Count**	**Percent**	**Count**	**Percent**	**Count**	**Percent**
Crude Oil	9	0.8%	14	1.3%	7	0.7%	56	4.9%	70	6.1%
Copper	2	0.3%	0	0.0%	9	1.5%	93	14.1%	165	25.0%
Corn	2	0.1%	24	1.2%	28	1.4%	145	6.9%	322	15.4%
Cotton	0	0.0%	16	5.0%	0	0.0%	14	4.1%	16	4.7%
Gold	4	0.5%	8	1.0%	5	0.6%	99	11.4%	108	12.4%
Heating oil	0	0.0%	6	1.2%	3	0.6%	28	5.4%	34	6.6%
Natural gas	6	0.7%	16	1.9%	22	2.7%	67	7.8%	101	11.7%
Silver	6	1.2%	11	2.3%	7	1.4%	56	10.7%	90	17.1%
Soybean oil	3	0.6%	13	2.5%	21	4.1%	55	9.9%	60	10.8%
Soybeans	18	1.2%	17	1.1%	36	2.4%	124	7.5%	114	6.9%
Sugar	0	0.0%	0	0.0%	1	0.3%	9	3.0%	25	8.3%
Wheat	43	4.6%	27	2.9%	19	2.0%	88	8.6%	65	6.4%
Total	93		152		158		834		1170	
Total (less duplicates)	90		115		91		444		912	

Table 6
Effects Inferred from Triple and Previous-Overnight Tests

This table reports estimates of the inverse regression coefficients using the counts identified by the pairs and triple tests. Previous-overnight test results are shown for momentum and contrarian traders and triple test results are shown for liquidity demanders, liquidity suppliers and informed traders. For these regressions, the discrete dependent variable equals one if the trader is identified by the FDR approach as significant; zero otherwise. The independent variables are defined in Table 2. The Experience, Active, Size, and Expirations variables enter in logarithms. The constant is omitted in these regressions. Observations are pooled across commodities with fixed effects defined for each commodity. We adjust for clustering between commodities by trader and use White's (1980) estimator to correct for heteroscedasticity. The coefficents reported here are transformed using the projection defined by equation (15) in the text. The significance level of the underlying coefficient is reported next to the transformed coefficient, where an "*" ("**") indicates significance at the 90% (95%) level of confidence.

		Triple Test to Identify									Previous-Overnight Test to Identify					
	Sample Percent	Liquidity Supplier			Liquidity Demander			Informed			Momentum			Contrarian		
Variables		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
Experience			0.41 **	0.38 **		0.01	0.04		0.10	0.15 *		0.19 **	0.22 **		0.24 **	0.21 **
Active			0.23 **	0.19 **		0.26 **	0.27 **		0.39 **	0.39 **		0.00	0.04		0.14 **	0.12 **
Size			-0.13	-0.06		0.57 **	0.44 **		0.79 **	0.58 **		0.10 *	0.02		0.01	0.06
Expirations			0.08	0.01		-0.40 **	-0.25 **		-0.52 **	-0.36 **		-0.34 **	-0.20 **		0.08 **	0.03 *
Net Long			0.02	0.02		-0.08 **	-0.06 **		0.03	0.02		-0.01	0.00		0.03 **	0.03 **
Net Short			0.09 **	0.08 **		-0.14 **	-0.08 **		-0.08 **	-0.04 *		-0.04 **	-0.02		0.08 **	0.05 **
Commercial	0.25	0.42 **		0.24 **	0.02 *		0.04 **	0.02 *		0.02	0.08 **		0.08 **	0.46 **		0.31 **
Swaps Dealer	0.04	0.08 **		0.05 *	0.07 **		0.05 **	0.17 **		0.13 **	0.03 **		0.03 **	0.04 **		0.02 **
FBT	0.13	0.24 **		0.19 **	0.19 **		0.13 **	0.13 **		0.09 **	0.05 **		0.05 **	0.13 **		0.11 **
Managed Money	0.26	0.07 **		0.09 **	0.52 **		0.37 **	0.53 **		0.34 **	0.56 **		0.37 **	0.13 **		0.13 **
Other	0.33	0.20 **		0.30 **	0.20 **		0.27 **	0.15 **		0.28 **	0.28 **		0.33 **	0.25 **		0.32 **
R-Squared		0.004	0.011	0.012	0.009	0.017	0.021	0.016	0.032	0.043	0.046	0.060	0.076	0.032	0.073	0.083
Sample Size		9845	9845	9845	9845	9845	9845	9845	9845	9845	10544	10544	10544	10544	10544	10544
FDR counts		93	93	93	152	152	152	158	158	158	834	834	834	1170	1170	1170

Table 7

Rank-Sum and t-Tests of Informed and Not-Informed Using Daily Profits

This table compares the daily profits per trader between those identified as informed and not informed in the FDR tests. The p-value for the Wilcoxon rank-sum is shown along with the mean rank-sums for both informed and not informed participants by commodity. The t-test comparing average daily profits per trader is reported below the Wilcoxon results. The p-value for the t-test is computed assuming unequal variances. Panel (A) shows these results for informed traders identified in Table 3 as found by the HM and unconditional position tests using close-to-close prices. Panel (B) shows these results for the intraday informed traders identified in Table 5 by computing the profits for position changes evaluated using midpoint and closing prices. Excluding the overlap between commodities, the sample include 8,921 unique traders.

	Crude oil	Copper	Corn	Cotton	Gold	Heating oil	Natural gas	Silver	Soybean oil	Soybeans	Sugar	Wheat
Panel (A): Overnight Informed Identified in Table 3												
Unconditional Position Test:												
Informed Mean Rank Sum	2,420	2,355	2,426	n.a.	n.a.	n.a.	2,341	2,407	2,387	2,379	n.a.	2,368
Not Informed Mean Rank Sum	2,189	2,244	2,193	n.a.	n.a.	n.a.	2,111	2,192	2,236	2,238	n.a.	2,251
Wilcoxon p-value	0.000	0.002	0.000	n.a.	n.a.	n.a.	0.000	0.000	0.000	0.000	n.a.	0.001
Informed Aver. Daily Profits	$ 33,351	$ 26,499	$ 7,350	n.a.	n.a.	n.a.	$ 39,807	$ 15,390	$ 16,743	$ 12,432	n.a.	$ 12,699
Not Informed Aver. Daily Profits	$ 1,333	$ (4,918)	$ 443	n.a.	n.a.	n.a.	$ (1,596)	$ (10,064)	$ (1,595)	$ (774)	n.a.	$ 891
t-test p-value	0.008	0.012	0.000	n.a.	n.a.	n.a.	0.254	0.089	0.100	0.049	n.a.	0.531
HM Position Test:												
Informed Mean Rank Sum	2,037	2,357	2,391	n.a.	2,102	1,781	2,299	n.a.	1,719	2,342	n.a.	2,266
Not Informed Mean Rank Sum	1,826	2,242	2,228	n.a.	2,060	1,681	2,151	n.a.	1,656	2,220	n.a.	2,225
Wilcoxon p-value	0.000	0.002	0.000	n.a.	0.130	0.003	0.000	n.a.	0.043	0.001	n.a.	0.141
Informed Aver. Daily Profits	$ 45,237	$ 40,179	$ 7,396	n.a.	$ (13,571)	$ 38,651	$ 39,807	n.a.	$ (548)	$ 4,086	n.a.	$ 6,555
Not Informed Aver. Daily Profits	$ (3,401)	$ (726)	$ (156)	n.a.	$ (10,366)	$ (5,693)	$ (8,194)	n.a.	$ (660)	$ 5,760	n.a.	$ (307)
t-test p-value	0.017	0.006	0.003	n.a.	0.798	0.014	0.185	n.a.	0.977	0.890	n.a.	0.210
Panel (B): Intraday Informed Identified in Table 5												
Informed Mean Rank Sum	2,399	1,647	2,198	n.a.	2,592	2,235	2,743	2,504	2,664	2,718	n.a.	2,818
Not Informed Mean Rank Sum	2,169	1,355	1,437	n.a.	1,940	2,366	1,858	2,032	1,953	1,897	n.a.	1,797
Wilcoxon p-value	0.000	0.000	0.000	n.a.	0.000	0.000	0.000	0.000	0.000	0.000	n.a.	0.000
Informed Aver. Daily Profits	$ 24,841	$ 4,764	$ 10,006	n.a.	$ 26,766	$ 7,615	$ 95,885	$ 13,689	$ 4,218	$ 13,110	n.a.	$ 15,488
Not Informed Aver. Daily Profits	$ 9,849	$ 35	$ (210)	n.a.	$ (3,585)	$ 9,358	$ (2,693)	$ 93	$ (1,542)	$ 2,376	n.a.	$ (1,681)
t-test p-value	0.000	0.000	0.000	n.a.	0.000	0.242	0.000	0.000	0.000	0.149	n.a.	0.000