The Impact of Herding on Futures Prices


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We test the prevalence of herding among large speculative traders in futures markets by employing a unique dataset from the U.S. CFTC on individual positions of these traders in thirty-two futures markets covering 2002 - 2006. Using detailed trader level data we test, for the first known time, whether herding exists among hedge funds and other speculative traders, and whether the herding serves to stabilize or destabilize market prices. While we find some mild evidence of herding among hedge funds and other types of speculators we conclude that the magnitude of herding by hedge funds is, on average, similar to that found in equity market studies and that this herding is not destabilizing.

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1. Introduction

In recent years, 'financial herding' has become somewhat of a pejorative phrase within the financial industry. Simply stated, agents herd when they choose to mimic the observed trading behavior of other market participants. A belief that other agents have superior information, as in the informational cascade theories described by Bannerjee (1992) and Bikhchandani et al. (1992), can lead to herd-like behavior.[1] Herding may also occur if agents have common information or views on market fundamentals. These views may be correct, driving prices toward their fundamental values (Lakonishok, Shleifer and Vishny (hereafter, LSV (1992)), or incorrect, which can drive prices away from their fundamental values. Agents may herd if they follow similar trading strategies, such as with "positive feedback trading" whereby agents buy in a rising market and sell in a falling market (DeLong et al. (1994)). Conversely, herding may take place if a contrarian, and quite possibly stabilizing, trading strategy is embarked upon.

We examine herding (following LSV (1992)) in 31 futures markets with data from 2002-2006 that identifies large trader participation on each side of the market. Futures markets offer a rich setting for examining herd behavior. Futures contracts are traded in both floor and electronic settings, allowing us to examine differences in herd behavior under differing degrees and types of trader interaction. We exploit cross-sectional differences that exist among futures contracts to better understand how open interest, trading activity and the mix of traders affect herding as well. Given our data, speculative trading can be more easily identified in futures markets. We identify and exclude natural hedge trades emanating from producers and manufacturers, for instance, removing a source of noise from our herding analysis. Large speculative traders may have greater incentives to herd due to their attempts to infer information about the quality of investment holdings from one another's trades (Banerjee (1992), Bikhchandani et al.

[1] Cascade behavior differs from herding behavior in that it can arise when people choose the same action because all have the same private information. For further discussion on the distinction between herding and information cascades, see Smith and Sorenson (2000) and Celen and Kariv (2004).

(1992)), the basis of evaluation of performance between institutions (Scharfstein and Stein (1990)), or simply by reacting to the same exogenous signals. We examine the sources of herding by floor participants and remote (off-floor) speculators separately. On the floor, futures dealers take active positions based on observable order flow (Ferguson and Mann (2001)), order flow that may give dealers and informational advantage over customers (Manaster and Mann (1996)).[2] This behavior would presumably generate herding among floor participants. Away from the floor, other speculative traders (hedge funds, for instance), may also herd if information acquisition costs make mimicking strategies more attractive.

We compare and contrast herding by floor participants to herding by other speculative traders. We analyze whether the two groups of traders engage in positive feedback trading to determine whether their trading has any impact on price movements and true price discovery mechanisms. We examine whether speculative trading affects market volatility, a concern noted by Elton et al. (1987) and Brorsen and Irwin (1987) who note that hedge fund trading, in particular, is guided by positive feedback (technical) trading systems. Positive feedback trading can be destabilizing if it leads institutions to follow one another into buying overpriced assets and selling underpriced assets, which in turn causes prices to move further from their fundamental values (LSV (1992)). Other studies address the question of whether or not hedge funds stabilize or destabilize market prices and find conflicting results.[3]

Our results suggest that modest herding does occur, on average, and is more prevalent among floor participants. Among remote speculative traders like hedge funds, modest herding exists, but does not destabilize futures markets. We find little evidence of positive feedback trading based on either past day or past week performance, indicating that even though some hedge funds may engage in herding behavior, their behavior may actually stabilize, rather than destabilize futures markets as many have

[2] Locke and Onayev (2007), in turn, link order flow to futures prices.
[3] See Brorsen and Irwin (1987), Dale and Zryen (1996), Edwards (1999), Irwin and Yoshimaru (1999), Brown et al. (2000), Fung and Hsieh (2000), and Brunnermeier and Nagel (2004).

suggested. In fact, we provide evidence which indicates that 'buy' herding often occurs when prices are dropping, while 'sell' herding occurs when prices are rising.

Among stocks, herding by mutual funds has been show to speed the price adjustment process (Wermers (1999)). In derivatives markets, evidence is more sparse.[4] We utilize trader identities from futures markets to show that herding among floor participants and speculative traders off the floor is not destabilizing.

The remainder of this study is crafted as follows. Section II develops a discussion of herding and the importance of hedge fund trading through a review of the recent literature in the area. Section III describes the U.S. Commodity Futures Trading Commission's Large Trader Reporting System (LTRS). In section IV we describe the data in detail and provide summary statistics on hedge fund and floor broker participation in the markets (number of participants, distribution across markets, activity of traders, and incumbency). Section V discusses herding within our two groups of traders. In section VI we examine whether Hedge Funds and FBTs engage in positive feedback trading. Section VII concludes the paper.

II. Herding and Speculation

There are two main groups of theoretical models which attempt to describe herding behavior: rational models which produce information acquisition herding and those models which allow for the divergence of prices from their fundamental values which produce fads or informational cascades. Speculators may play a role in each of these groups, speculating on information in rational models or on the actions of others in fad or cascade models.

Models which produce rational prices and lead to information acquisition herding include those by Froot et al. (1992) and Hirshleifer et al. (1994). Froot et al. (1992) focus on short-term investors who follow types of information likely to be used by other investors since they stand to gain only if other people acting on the same information also trade in that asset. Due to inefficiencies in the market,

[4] The few existing research papers on herding in futures and futures options utilize aggregate Commitment of Trader (COT) data provided by the CFTC with a focus on just one or two markets over very short sample periods. Hartzmark (1987, 1991) employs COT data to examine trading profitability in nine financial and agricultural futures contracts during 1977–1981. Leuthold et al. (1994) conduct a similar study on pork-belly futures.

multiple investors can earn profits from trading on the same piece of information, which may lead to trading on the same side of the market even though no mimicking behavior is involved. In this model investor response to new information is perfectly rational, and herding ceases once all information is absorbed into prices.

Models of informational cascades, fad behavior, and principal-agent herding all allow prices to depart from their fundamental values. Informational cascade models such as those by Banerjee (1992) and Bikhchandani et al. (1992) are based on the assumption that by observing the actions of other agents, investors gain information. Gaining information by watching other agents can be seen as perfectly rational behavior; however, when an investor ignores his own private information and instead relies on observing similar actions among other investors, a cascade is said to have occurred. Cascades may destabilize prices by driving them away from their fundamental values.[5]

Models based on fads evaluate why certain securities or types thereof, become popular for no economic or informational reason. When investors choose to hold large quantities of these securities they create price pressures that may drive up prices. The prices of these securities may also fall dramatically once the assets fall out of fashion. These types of models can be seen in the early works by Dreman (1979) and Friedman (1984).

Principal agent and reputation based models of herding include those by Scharfstein and Stein (1990), Trueman (1994), Zweibel (1995), Prendergast and Stole (1996), Graham (1999), and Maug and Naik (1995). These models are based on the notion that when a principal is uncertain about an agent's capability, the agent will often mimic the behavior of other agents in order to minimize the probability that he will be deemed of poor quality, or preserve the fog of uncertainty about the agent's ability to manage the portfolio. If other agents face similar uncertainty, they too will try to benefit from this behavior, and herding will occur. Mimicking behavior increases with extreme performance if the agent's

[5] Alevy, Haigh and List (2007) run experiments relating to information cascades on CBOT floor/broker traders. Their findings suggest that professional traders make use of private signals to a greater degree than their student counterparts. Furthermore, professionals utilize the *quality* of the public signal to a *greater* extent than do students. Consequently, professionals are involved in weakly fewer cascades overall, and significantly fewer *reverse cascades* (cascades that lead to inferior outcomes).

compensation also depends on the performance of other similar agents in an asset, as buy side herding occurs during periods of price increases and sell herding with price declines. In principal-agent models, individual behavior may be considered rational, but the environment in which the agents operate in may create price pressures that drive prices away from fundmental values.

Empirical tests for herding largely consist of a statistical analysis to determine whether decisions cluster in markets, irrespective of the underlying reasons for such behavior (Bikhchandani and Sharma, (2000)). Although the lack of a unified approach to test for herding makes empirical comparisons difficult, a number of papers apply the herding measure developed by LSV (1992), which we use in order to compare futures markets to other markets. LSV evaluate herding behavior among U.S. money managers (primarily pension funds) and conclude that money managers generally do not herd. They do find herding in smaller stocks, attributed to the relative dearth of information about smaller companies which forces money managers to pay greater attention to other managers trading these firms. Overall, they find that on average if 100 funds were trading, 2.7 more funds traded on the same side of the market than would be expected if money managers made their decisions independently of one another.

Other researchers utilizing the LSV measure find mixed results in other markets and among other traders. Grinblatt et al. (1995) relate herd behavior among mutual fund managers to momentum investment strategies and performance. They find little evidence of herding (an average measure of 2.5), with greater herding in buying past winners than in selling past losers reflecting positive feedback trading strategies. Pirinsky (2002) finds similar herding levels with evidence of reversals, implying that stock prices do not adjust to fundamental values. Wermers (1999) evaluates virtually every mutual fund in existence between 1975-1994 and finds that herding averages a significant 3.4 for the average stock over time He also documents greater herding levels in growth funds, consistent with the tendency for herding in assets for which little is known.

Other research applies the LSV herding measure to emerging stock markets. Choe et al. (1999) find significant herding levels by foreign investors in Korean stocks (with LSV measures around 20) do not destabilize the Korean market. Kim and Wei (1999) also evaluate Korean stock market investors and find that herding is more prevalent among nonresident investors relative to residents. In developing countries, Borensztein and Gelos (2000) calculate an average herding measure of 7.2 among 467 mutual funds and link greater herding levels to markets with more trading and greater liquidity.

Kodres and Pritsker (1996) pioneer the effort to understand herding behavior in U.S. futures markets. Using partially disaggregated data provided by the CFTC, they concentrate on herding among financial institutions in foreign exchange, Eurocrrency and other financial markets during 1992-94. Testing for herding behavior within categories of institutions (e.g., mutual fund, pension funds, commercial banks, etc), they find weak evidence of herding in some markets and among certain categories (dealers and foreign banks herd in foreign exchange markets, for example). As they note, however, financial institutions hold both cash and futures positions that are likely to offset, so that herding in futures alone is relatively uninformative.

Weiner (2000) builds on this work by looking at the non-commericial (speculative) categories in energy markets where non-commercial traders likely hold positions only in futures contracts. He finds little evidence of herding in non-commercial traders in general, and mixed evidence of herding in certain sub-groups of these traders. From a policy viewpoint, concern over the role of herding in market volatility does not appear warranted. These authors, however, fail to accurately categorize all commercial and non-commercial traders (such as hedge funds) to get a clear picture of true herding among groups of traders and did not analyze whether the modest levels of herding were destabilizing in any way. We resolve this problem here by utilizing data from the U.S. CFTC which allows for the accurate classification of market participants.

The available evidence on whether speculators destabilize markets is mixed. Speculators, and hedge funds in particular, have gathered enormous and growing interest in the literature.[6] Fung and Hsieh

[6] Research in hedge fund performance includes Schneeweis and Spurgin (1998), Ackerman et al. (1999), Brown et al. (1999) and Amin and Kat (2003). Baquero et al. (2005) examine fund survival and persistence. Agarwal and Naik (2004) and Gupta and Liang (2005) explore hedge fund capital adequacy while Fung and Hsieh (1997) focus

(2000) consider funds to have exerted a significant market impact during the Asian Exchange Rate Mechanism crises while others determine that funds are not responsible for the Asian crises (see Choe et al. (1998), Fung et al. (2000) and Goetzmann et al. (2000)). More recently, Brunnermeier and Nagel (2004) document that hedge funds did not exert a correcting force on stock prices during the technology bubble and hence question the efficient markets notion that rational speculators always stabilize prices.

Within futures markets, Brorsen and Irwin (1987) find no significant relation between price volatility and "fund positions" in CFTC survey data and Brown et al. (2000) find no link between "fund positions" and falling currency values around the 1997 Asian financial crisis. Both Dale and Zryen (1996) and Irwin and Yoshimaru (1999) find that positive feedback trading in 18 of 36 futures markets did not increase volatility.[7] Irwin and Yoshimaru (1999) also study CFTC survey data and fail to find a significant relation between fund positions and prices. Although these findings are suggestive, researchers generally acknowledge that CFTC survey data is imperfect (labeling numerous trader types as "non-commercial") and note that results from these studies should be interpreted with caution. Our CFTC data, in contrast, identifies specific types of traders. We specifically examine the trades of hedge funds, floor participants and managed money traders—those traders who have the greatest ability (in terms of monitoring other traders' behavior) and capacity (in terms of capital available to move markets) to herd in futures markets.

III. Data Description

The CFTC monitors U.S. futures and options markets through its market surveillance program and since 1922, regulators have been improving the workhorse tool of market surveillance, the Large Trader Reporting System (or LTRS). Under the rules and regulations set out under the Commodity Exchange Act (CEA), the CFTC collects and stores data from daily reports on market data and position information from the exchanges, clearing members, futures commission merchants, foreign brokers and

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on trading styles of hedge funds. Hedge fund data is available through altVest, CISDM, Hedgefund.net, HFR, and TASS.

[7] Other researchers focus on 'small speculators' or locals in futures markets (Manaster and Mann (1996) and Locke and Venkatesh, Locke and Sarkar (2001)), a subset of our floor broker/trader category. ADD TO REFS??

also traders.[8] These reports show the futures and options positions of the reporting traders that hold positions above specific levels set by the CFTC, but generally about 70 – 90% of total open interest is reported in each market.[9] The remainder includes trades by retail and/or relatively inactive traders.

We compile a complete time series of daily data by trader type to measure herding patterns on each day during our sample period from LTRS data. Reportable traders identified by the CFTC are classified as either a "commercial" or "non-commercial" trader. A trader's reported futures positions are determined to be commercial if the trader uses derivative contracts for the purposes of hedging as defined by the CFTC regulations, filing a statement with the CFTC (CFTC Form 40) that the trader is commercially "…engaged in business activities hedged by the use of the futures and option markets." To ensure that the traders are classified consistently and accurately, CFTC market surveillance staff verifies the forms and re-classifies the trader if further information about the trader's involvement with the markets merits action. A few non-reportable positions (calculated by subtracting total long and short reportable positions from the total interest) represent traders who report but are not registered under the CEA The aggregate LTRS data serves as the basis for the CFTC's weekly Commitment of Traders (COT) report, summarizing the percent of open interest held by commercial, non-commercial and non-reportable traders. COT reports are released (for every market in which 20 or more traders hold reportable positions) every Friday based on the prior Tuesday's open interest.[10]

Commercial traders, by definition, likely have hedging objectives so we focus on herding within and among specific non-commercial traders in this study. More specifically, we examine the herding among floor brokers/traders and hedge funds, traders who are likely to have the greatest propensity to herd based on location and/or information acquisition costs. Furthermore, herding among these traders is

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[8] These rules and regulations are published in Title 17, Chapter I of the Code of Federal Regulations.

[9] Reporting levels vary across contracts, e.g. wheat (100 contracts), crude oil (350 contracts), 10-year Treasury notes (1,000 contracts), Euro (400 contracts), etc. The CFTC occasionally adjusts reporting levels to strike a balance between maximizing effective surveillance and minimizing the reporting burden on the industry.

[10] Public availability of this weekly data has made COT reports central to prior studies (e.g., Hartzmark (1991), despite the fact that the data is highly aggregated. The first COT was produced on June 30, 1962. On January 5, 2007, the CFTC began publishing "COT—Supplemental," an enhanced report including aggregate positions of Noncommercial, Commercial and Index Traders in 12 agricultural commodities.

relatively more likely to affect volatility or price stability in futures markets (compared to retail trading, for instance). Our data breaks down aggregate commercial and non-commercial traders into specific trader categories (which enable CFTC surveillance teams to monitor these markets). Although the groupings of specific traders vary across markets, we provide an exhaustive list of CFTC groupings in Table 1. As seen in Table 1, commercial and non-commercial groupings do not include a category of hedge funds *per se*, but many hedge fund complexes operating in futures markets are either advised or operated by Commodity Trading Advisors (CTAs), Commodity Pool Operators (CPOs) and/or and Associated Persons (APs) who may control customer assets.[11] In addition, market surveillance economists at the CFTC also identify managed money traders (MMs) who are known to be managing money on behalf of other investors. To conform to the academic literature and common financial parlance, we refer to CPOs, CTAs, APs and some MMs collectively as hedge funds (see bottom of Table 1), or more generally, off-floor (remote) speculators.

Floor brokers/traders are more readily identifiable in LTRS data. These traders are exchange members or seat lessors who execute trades on the floor. Floor brokers transact either for customers or their own account whereas floor traders only trade for themselves. The traders that we evaluate here meet the trading threshold limits set forth by the CFTC, and typically not only trade in large amounts, but also hold overnight positions. The fact that these participants share common information on the floor of the exchange makes the propensity for herding in this group more likely. In Table 1, floor brokers/traders are listed as floor brokers (FB) and floor traders (FT).

IV. Summary Statistics

We collect four-and-a-half years of daily data (1182 trading days) from the CFTC's LTRS spanning January 1, 2002 through September 9, 2006, for thirty-one futures markets (see Table 2). As

[11] The SEC explicitly defines a hedge fund as an 'entity that holds a pool of securities and perhaps other assets, whose interests are not sold in a registered public offering and which is not registered as an investment company under the Investment Company act" (p.3, SEC (2003)).

noted above, we focus on the herding behavior of hedge funds and floor brokers/traders in this study. The first nineteen markets listed represent nineteen out of twenty of the most heavily traded futures markets during 2006. We include the other twelve markets to examine herding behavior in less active markets. In order to ensure adequate trading activity, we focus on trading in the nearby, first- and second-deferred contracts within each market. Overall, the thirty-one markets account for greater than 90% of all futures volume in each of our sample years. As Figure 1 shows, the cross-sectional variation in volume is significant for these markets, with vast majority of futures volume clustered in the 3-month Eurodollar, e-mini S&P 500 Index, five and ten year T-notes, and U.S. T-bond contracts. Each of the other contract markets comprises less than 5% of overall futures market volume.

Table 2 provides information on the number of unique participants over the time period, as well as the daily average, maximum and minimum number of hedge funds (Panel A) and floor brokers/traders (Panel B) on any given day. As can be seen from Panel A a minimum of 78 hedge funds partipate in each market, and more than 350 unique funds trade corn, soybean, CBOT wheat, and gold contracts during our sample period. Despite these high aggregate figures, the daily average number of hedge funds in these markets range from 10.52 in the mini-Dow to 93.20 in corn. Some evidence suggests that hedge fund trading is clustered over time. Some contracts (the mini-Dow and e-mini Russell 2000) were traded by just one hedge fund on some days but traded by 25 and 57 hedge funds, respectively, on other days in the sample.

Panel B provides parallel statistics for floor brokers/traders. Floor brokers/traders are also active participants in these markets, with each contract traded by a minimum of 56 unique traders (2-year T-Notes). At the active end, more than 245 unique floor brokers/traders funds trade corn, soybean, CBOT wheat, and e-mini S&P500 contracts during our sample period. Similar to hedge fund activity, floor broker/trader activity varies widely from day to day, but each contract averages more than four floor brokers/traders each day. Trading among these participants appears to be clustered as well. At least one floor broker/trader is active every day in each contract but the most active days witness trades from 12 (for 2-year T-Notes) and 134 (for corn) different floor brokers/traders. Variation across time among contracts appears to differ as well. Despite a daily minimum of 11 floor brokers/traders in both corn and cocoa, for instance, the daily maximum for cocoa (35) pales compared to that of corn (134). While both hedge funds and floor participants appear to be active in each of these markets, a comparison of Panels A and B shows that the average number of hedge funds exceeds the number of floor brokers/traders in each individual contract.

Figure 3 illustrates the distribution of hedge funds and floor brokers/traders by the average number of markets in which they held positions during our four-and-a-half year study period. Over half of the hedge funds held positions in four or fewer of these markets during some portion of the period, while about ten percent held positions in 18 or more of the markets. Eight hedge funds held positions in 30 markets at the same time, while no hedge fund trader held a position in all 31 markets at the same time. Almost 90% of floor brokers/traders held positions in three or fewer markets, while less than 1% held positions in 11 or more markets–most floor brokers/traders (over 57%) concentrate in just one market. Only one floor broker/trader held a position in as many as 26 markets at the same time. Floor brokers/traders tend to specialize in one or two markets, while hedge funds tend to hold a relatively more diverse portfolio of futures contracts.

As noted above, the LTRS provides details on end-of-day positions, allowing us to observe daily position changes for each trader category. Figure 3 sheds light on the activity rates of our groups of traders defined by daily trading activity. We define ‘active participants’ as those who changed their positions more than 120 days out of the sample of 1182.[12] As shown in Panel A, an average of 41 hedge funds and floor brokers/traders trade actively in these 31 markets. The market with the highest hedge fund activity rate (35%) is the E-mini S&P 500 index whereas floor brokers/traders are most active in the mini ($5) Dow Jones Industrial Index (47%). Floor brokers/traders, pay to trade on the floor of the exchange. As a result, these traders are more commonly active traders (as can be seen clearly from Figure 4).

[12] The results that follow also hold when we define active participants as those who trade more than 75% of the total number of their days in the market.

Indeed, only in the Japanese Yen and the E-mini NASDAQ 100 markets do we find activity rates for hedge funds exceeding those of floor brokers/traders. Table 3 shows that many hedge fund traders do not trade every day and many hold positions for several days or even months without trading. Most other trader categories change their positions on a much more frequent basis (Haigh et al. (2006)).[13]

VI. Herding

Lakonishok, Shleifer, and Vishny (1992) (LSV) developed a measure of herding for money managers that has become a widely used measure for researchers studying trading behavior. In their study, they evaluate the holdings of 769 tax-exempt funds and look across the universe of stocks held by these money managers to determine whether herding occurs. Here, we utilize the LSV measure of herding, as well as positive feedback, with an application to 32 U.S. futures markets. Rather than evaluation across stocks, our goal is to determine whether herding occurs within futures markets, and, if so, which markets may be more susceptible to herding behavior.

In futures markets, all futures contracts outstanding at any point in time must sum to zero. In other words, for every long there must be a short and it is impossible for the whole market to change position in the same direction. We focus on a subset of traders, hedge funds and floor brokers/traders, and examine the tendency of these groups to trade in the same direction. We study these traders due to the conjecture that hedge funds serve to destabilize prices and the lack of transparency in the hedge fund trading arena may lead funds to attempt to learn from one another by following one anothers trading behavior. We evaluate the measure of herding for both hedge funds and FBTs in order to draw conclusions with regards to whether differences exist between those who manage money and other large speculators in the futures markets.

[13] Although intraday trading could theoretically leave end-of-day positions unchanged, we deem this unlikely. NYMEX (2005) also reports that hedge funds hold positions significantly longer than other participants, which, they say supports the conclusion that hedge funds are non-disruptive source of liquidity to the market.

For our measure of herding we initially evaluate the nearby prices because typically this reflects the majority of open interest in a contract. However, since most traders do not take possession of the underlying asset at expiration of the futures contract we mitigate the effect of traders rolling over their contracts prior to expiration on our measure of herding – something that is not important in measures of herding in stocks. This adjustment is imperative to ensure that spurious results are not being obtained based simply on the fact that these traders *will* appear to move in tandem at the end of each of the contracts due to the liquidation of their positions. This type of herding would be considered spurious herding which is driven by contract expiration rather than trend chasing. Typically, when traders move out of the nearby contract upon expiration, they move into the next deferred contract; therefore we examine herding, not only for the nearby contract, but also for both the first and second deferred contracts combined in order to capture the true relations among these traders. Furthermore, when we examine positive feedback trading we only evaluate the positions of traders in both the nearby and first deferred contracts.

Herding Measure

For a given futures market, *i*, and day, *t*, the herding measure developed by LSV (1992) and applied to futures markets here is as follows:

$$H(i,t) = | p(i,t) - p(t) | - AF(i,t) \qquad (1)$$

where

$$p(i,t) = \frac{B(i,t)}{\left[S(i,t) + B(i,t)\right]},$$

and

$$p(t) = \frac{\sum_{i=1}^{i=N_{it}} B(i,t)}{\left[\sum_{i=1}^{i=N_{it}} S(i,t) + \sum_{i=1}^{i=N_{it}} B(i,t)\right]},$$

and

$$AF(i,t) = E\{| p(i,t) - p(t) |\},$$

where
$S(i,t)$ = the number of traders that are going short in futures market *i* on day *t*
$B(i,t)$ = the number of traders that are going long in futures market *i* on day *t*
$p(i,t)$ = fraction of active futures traders going long in futures market *i* on day *t*
$p(t)$ = total number of future traders going long on day *t* relative to the total number of futures traders active on day *t* across all 32 futures markets
N_{it} = volume of futures contracts traded by futures market participants on day *t*
$AF(i,t)$ = adjustment factor that accounts for the fact that under the null hypothesis of no herding the expected value of $| p(i,t) - p(t) |$ is greater than zero.

B(i,t) and *S(i,t)* are computed from the end of day positions of traders in the LTRS. If a trader is net long for the day *B(i,t)* is increased, whereas if the trader is net short for the day *S(i,t)* is increased by one unit. The adjustment factor is computed assuming a probability of success equal to .5. The adjustment factor will decline as the number of traders increases for a particular contract market.[14]

The above herding measure allows for evaluation of whether hedge funds and FBTs tend to be on the same side of the market in a given market on a given day. In other words, whether a disproportionate number of the traders are either buying or selling the contracts. The LSV measure of herding assumes under a binomial probability distribution function that traders will buy 50% of the time and sell 50% of

[14] To illustrate, assume we have two traders active on a particular day for a particular contract market. The AF for that particular contract market is computed by finding the expected value of $| p(i,t) - p(t) |$, which is the following:

Number of Long Positions (Buy)	Probability	Value	Product
0	0.25	|0/2-0.5| = 0.5	0.125
1	0.50	|1/2-0.5| = 0.5	0.000
2	0.25	|2/2-0.5| = 0.5	0.125
AF			**0.250**

Probability is defined as: $\dfrac{n!*(p)\exp(k)*(1-p)\exp(n-k)}{[(n-k)!*k!}$

As AF = 0.250 in this instance, possible herd values for a futures contract market with two traders are 0.25, -0.25, or 0.25 when the number of traders going long is zero, one or two respectively. To illustrate that the AF measure decreases with the number of traders, consider the case where 5 traders trade a particular contract market:

Number of Long Positions (Buy)	Probability	Value	Product
0	0.0313	|0/5-0.5| = 0.5	0.016
1	0.1563	|1/5-0.5| = 0.3	0.047
2	0.3125	|2/5-0.5| = 0.1	0.031
3	0.3125	|3/5-0.5| = 0.1	0.031
4	0.1563	|4/5-0.5| = 0.3	0.047
5	0.0313	|5/5-0.5| = 0.5	0.016
AF			**0.188**

the time. If this is the case, then no herding is said to exist. If traders are buying (selling) more than they are selling (buying) then the difference between the expected value, or adjustment factor, and the actual purchases (sales) of futures contracts will be significantly different from zero and herding is said to exist.

We further investigate whether herding forms on the buy-side or the sell-side.[15] This is useful to determine the extent of herding by traders going long in futures contracts rather than going short in futures contracts. To do this, we also calculate the following measures: $BH(i,t) = H(i,t) \mid H(i,t)>0$ for buy-side herding and, $SH(i,t) = H(i,t) \mid H(i,t)<0$ for sell-side herding. This will allow us to evaluate the intensity and frequency of buy and sell herding among our groups of traders.

Empirical Results

Tables 6 and 7 present our main results on herding for both hedge funds and FBTs ignoring the roll period (Table 6) and accounting for the roll period (Table 7). Table 6 splits the sample into the contracts being traded, nearby only versus nearby and deferred combined, in order to evaluate the impact of the roll-over period on the herding statistic. The majority of previous studies have combined the positive and negative values of H(i,t) when computing the average level of herding. Sharma, Easterwood & Kumar (2005) differentiate between positive and negative values of H(i,t) in order to examine whether or not there were subsequent reversals by considering stocks with no herding those whose values of H(i,t) are negative since the amount of buying and selling was less in these instances than would have be expected. They then calculate mean herding measures for both buy herding and sell herding. As such, our results are also broken into buy herding, H(i,t)>0, sell herding, H(i,t)<0, and overall herding which consists of the average of all buy and sell herding measures for all thirty-two markets.

Herding in Nearby and Nearby and First Deferred Contracts – Hedge Funds

The left hand panel of Table 6a presents overall, buy and sell herding measures for the nearby contract, the right hand side focuses on the nearby and first deferred contracts combined to account for the

[15] Whereas others have expressed concern (e.g., Wylie (1997)), that a significant herding measure may result, even without herding, solely from the biases of short sale constraints of firms and hence this might explain a bias toward buy side herding rather than sell side herding. In futures markets traders are not faced with such a constraint so our measures would be free from this bias.

fact that many traders will roll out of one contract and into the next at the same rate. The average overall herding measure for the nearby contract is 0.07 and for nearby and first deferred it is 0.09 (see bottom row). These results indicate that if p, the average fraction of changes that are increases, is 0.5, then 57% of all hedge funds in the overall herding category were changing their positions in one direction while 43% were changing their positions in the opposite direction. For the nearby and deferred contracts we see a slightly larger average overall herding measure of 9%. For this combined group we find that 59% of hedge funds in the overall category changed their positions in one direction, and 41% changed in the opposite direction. Obviously when we break herding into buy and sell measures, the buy herd value is larger than the overall and the sell value is less. For instance, the average buy value for the nearby is 0.13 and sell is 0.06.

All of the herding measures are statistically significant, with the exception of overall herding for aluminum and copper in the nearby contract. The largest degree of herding is found in the japanese yen market whereby 66% of japanese yen hedge fund traders were changing their holdings of the contract in one direction while 34% were going in the opposite direction. Forty-four percent of the markets have between 56% and 59% of their holdings moving in the same direction in the nearby contract. In the combined contract we see fifty-percent of the markets' hedge fund traders having between 60% and 67% of their holdings moving in the same direction, with 33-40% moving in the opposite direction. LSV (1992) detected a herding measure of 2.7% of their sample of pension funds, whereas Wermers (1999) found a value of 3.4%. Our average overall measure for the nearby contract is close to Sharma, Easterwood and Kumar's (2005) herding measure of 6.58%, while that of the combined contracts is slightly larger at 9%. Figure 6 provides a visual view of the overall nearby measures of herding broken up by contract market type. Similar levels of herding, with the exception of sugar, are found across the agricultural and soft commodities contract markets. The livestock contracts, as a group seem to exhibit larger degrees of herding than other groups and the financial contracts (not foreign exchange) seem to exhibit the least. In the energy complex, crude oil has the lowest degree of herding with an overall herding measure being just 4%. In twenty-six of the thirty-two contract markets the level of herding is higher or even among hedge funds versus FBTs.

To determine whether hedge fund traders were going long in futures contracts more often than going short (or vice-versa), we partition the overall herding measure into buy and sell herding measures. The overall average herding intensity for buy herding is 13% versus 6% for sell herding in the nearby contract. The results for the nearby and first deferred contracts combined were similar. Further, buy herding dominated sell herding in all thirty-two of the markets; therefore, not only was the intensity of buy herding greater, but also the frequency of buy herding. This is captured in the N statistic which counts the number of days buy herding (greater than zero) versus sell herding (less than zero) was estimated.

If the rollover period causes the herding measures to be artificially inflated we would expect to see a decrease in the measures when we combine the nearby and first deferred net positions. For example, if a trader sells in the nearby and buys in the distant the net position of both contracts would be zero as we pool them together. However, we find that H(i,t) actually increases or remains constant for all but one (Live Cattle) of the markets when compared to the nearby only contract. This indicates that the rollover period does not have an impact on the herding variable, and, as such, the measures of H (i,t) are due to herding among hedge funds and not due to rolling over.

Herding in Nearby and Nearby and First Deferred Contracts - FBTs

For FBTs, as shown in Table 6b, the average overall herding measure is marginally lower than for hedge funds in the nearby contract at 6% and at 7% for the nearby and first deferred. This finding seems consistent with the finding by LSV (1992), Shiller and Pound (1989), Banerjee (1992), and Bikhchandani, Hirshleifer and Welch (1992) that herding may be more prevalent among insitutions rather than among individuals. Again we find all measures statistically significant except the overall herding measures for Aluminium. Copper appears to have the largest amount of herding for the nearby contract, while lean hogs has the highest overall measure for the nearby and first deferred contracts. Forty-one percent of the markets had between 56% and 59% of their holdings moving in the same direction in the nearby contract, which was close to the forty-four percent for hedge funds. For the nearby and first deferred contracts, only twenty-one percent of FBTs had between 60-67% of their holdings moving in the same direction.

The average overall herding intensity for buy herding was 12% in both the nearby and first deferred contracts. For sell herding the intensities measured 6% and -5% for the nearby and first deferred averages respectively, thus pointing to evidence that buy herding is greater than sell herding among FBTs. Further, we find that the rollover period does not significantly impact the herding variable for FBTs with H(i,t) increasing or remaining constant for the majority of the markets when compared to the nearby only contract. Therefore, just as with the hedge fund traders, we can attribute the large measures of H(i,t) to herding among FBTs.

As shown in Figure 6, FBT herding levels are quite uniform across the agricultural and soft commodity contracts and the herding levels are lower (and lower than hedge funds) in the stock index products. The biggest differences between hedge funds and FBTs appear to be in Euro FX, Japanese Yen, Feeder Cattle, Sugar and Silver (hedge funds herd more than FBTs in these markets) and in Copper and Crude Oil (where FBTs herd more than hedge funds).

We examine whether participants moving in and out of the market cause increased price volatility as well. We measure the incumbency of both hedge funds and floor brokers as the percentage of participants that are present in both the first and final 90 days of the sample. On average, across all markets and contracts, 18,4% of hedge funds and 22.5% of floor participants are present at both the beginning and end of the four-and-a-half year sample period. There does not appear to be any identifiable patterns to this incumbency across contracts or participants.

We also measure the frequency of traders exiting and entering these markets where an exit is defined and recorded each time trader positions (long or short) fall below the large trader threshold level (a rough estimate, since the trader has not necessarily liquidated all positions). Floor traders change their positions to levels below the reporting threshold more often than the hedge funds. Across all thirty-one markets the average hedge fund exited (and entered) 9.9 (12.3) times in all of the contracts (nearby, first deferred, or second deferred) and 7.2 (10.1) times in the nearby contract alone.

The pooling of nearby and deferred contracts enable us to account for the fact that many traders predictably roll out of the nearby contract and into the first deferred contract. Given this regular pattern, we account for herding that is likely attributed to this "roll." We also look at herding patterns prior to the roll period by following Gao and Wang (1999). During the pre-roll period traders are not likely to trade in the same direction due to expiration effects of the contract. Herding patterns in nearby contracts during the pre-roll period were similar to those noted above (combining nearby and first deferred contracts).

VII. Feedback Strategies

Measurement of Feedback

Positive feedback trading predicts a relation between the past performance of an asset and the demand for that asset. If traders follow strong positive feedback strategies there is likelihood that prices may be destabilized. This is especially important to examine here due to the finding that herding behavior is occurring within and across groups of traders in the futures markets. To measure the potential to destabilize prices we utilize a measure developed by LSV (1992) known as excess demand. LSV (1992) uses quarerly data on prices whereas we calculate the current day (week) net buying across traders conditional on the past day (week) futures price change.

Two measures of excess demand are calculated, *Dratio* (dollar ratio) and *Nratio* (numbers ratio). For a given futures market, i, the *Dratio* is defined as:

$$Dratio(i) = [\$buys(i) - \$sells(i)]/[\$buys(i) + \$sells(i)],$$

where *$sells(i)* is the total dollar value decreases in futures positions across traders (evaluated at the settlement price for the daily trades, or average weekly settlement price for the weekly measure), and *$buys(i)* is the total dollar value increases in futures positions across traders. The *Nratio* is defined as:

$$Nratio(i) = \#buys(i)/\#active(i),$$

where *#buys(i)* represents the count of traders increasing going long (more long) compared to the previous day(week) and #*active(i)* is the number of traders changing their holdings. The *Nratio* measure represents a 'head count' that allows us to focus on the number of traders that went long or short a contract regardless of the size of the position. These two measures are utilized here because they can yield different results. Traders might, for example, be engaged in positive feedback trading, but those traders doing the opposite (negative feedback trading) might also be changing their position with much larger trades in which case we would see evidence of trend following in the *Nratio* but not in the *Dratio*.

Figures 7 through 10 provide the results of excess demand for the daily and weekly analysis for hedge funds and FBTs based on past day performance, which are broken into quintiles based on the empirical distribution of past daily and weekly performance respectively.[16]

Excess Demand for Hedge Funds

If pure positive feedback trading were to exist, the lower bar (quintile) should be significantly negative (1), the next lower (2) less negative, (3) at zero, (4) positive and (5) significantly positive. From Figure 7 it is clear that in every contract market activity is dominated by either buying or selling across all performance quintiles, and, as such, the trading activity of hedge funds by past day performance provides no indication of pure positive feedback trading. The average feedback measure, across all markets for hedge funds is 0.14 in the lowest quintile (this number should be negative if positive feedback is exhibited). Indeed, for 20 of the 32 markets in quintile (1) we find positive figures indicating that when prices are falling, hedge funds may be herding, but they are buying and not selling. At the other end of the spectrum, we do find a positive excess demand on average. Interestingly, the market with the highest degree of herding (Japanese Yen with a herding measure of 0.16) has an excess demand figure of 0.00 in the highest quintile suggesting no feedback trading and hence no destabilization. In other words, while

[16] The lowest (highest) quintile does not mean prices were falling (rising) – it may mean prices were not rising (falling) as high as those in higher (lower) quintiles.

this market exhibits monotonic increases in excess demand as measured by the Dratio, decreases of holdings always exceed increases even as prices get higher.

For robustness the analysis was also performed over past week performance (not shown). While several of the markets (U.S. t-bonds and cotton) were found to have monotonically increasing levels of excess demand, decreases were found only in the worst performing weekly quintile with increases in demand over all other quintiles. Overall, average excess demand across all markets exhibited increases in holdings always exceeding decreases by both daily and weekly past performance measures, with the increases demonstrating nonmonotonic patterns. If hedge fund traders were destabilizing the futures markets by trend chasing we would expect to see decreases of holdings in the lowest performance quintiles and increases of holdings in the best performing quintiles. We do not observe this using either daily or weekly measures of excess demand.

Similar results on feedback trading are found from the *Nratio* measure of excess demand for hedge funds. From a visual point of view, the graphs should be read in the same manner as the excess demand graphs. While several of the markets have monotonically increasing levels of net buyers, only two, the ten year T-note and Japanese yen, have levels lower than 50% for the worst performing quintiles and greater than 50% for the best performing quintile by both past day and week performance. However both of these markets have net buyers of greater than 50% in only the best performing quintile with 51% and 52% of traders being net buyers in ten year t-notes and Japanese yen respectively. The vast majority of markets have greater than fifty-percent of traders buying across all performance quintiles. From Figure 8 it appears that the Nratio values are the greatest in the metal and energy commodity contracts with the exceptions of natural gas and crude oil. Euro FX, feeder cattle, sugar and KS-wheat have high Nratio statistics, but the levels across the 5 quartiles are not consistent with positive feedback trading. The values for the *Nratio* indicate that hedge funds are, on average across all markets, net buyers independent of the level of past performance. This is not evidence of pure feedback trading, and, as such, using both excess demand and nratio statistics we cannot say that herding among hedge funds, if it is exists, is destabilizing.

Excess Demand for FBTs

The trading activity of FBTs by past day (Figure 9) and past week performance also provides no indication of positive feedback trading. In fact, no market shows monotonic increases in demand based on past performance quintiles. In one market, the japanese yen, based on past week performance do we see negative monotonicity, with purchases in the worst perfoming quintile and sales in the best performing quintile. This indicates, at least for this market, that FBTs are stabilizing, rather than destabilizing, the market by purchasing low performers and selling high performing contracts. On average across all markets, decreases in holdings dominate across all past performance quintiles. Thus, unlike hedge funds, FBTs are selling more than they are purchasing no matter the past performance of the contracts. Figure 9 illustrates this visually for FBTs. In energy markets, for example, this class of speculator is selling when prices are rising, as well as selling when prices are falling. This is counter to hedge funds who were buying when prices were falling as well as buying when prices were rising.

Similar results are found when we evaluate the Nratio measure of excess demand for FBTs. There are no markets which show monotincally increasing levels of demand across past day or week performance quintiles. In fact, it appears that most of the demand remains relatively constant over the performance quintiles. Further, on average, FBTs are neither net sellers nor net buyers, with measures of excess demand relatively close to .5 across all past performance levels.

VIII. Conclusion

In this paper we study herding and positive feedback strategies of six years of end-of-day futures data provided by the U.S. CFTC to examine the extent of herding in and across thirty-two different futures contracts. Our main emphasis is on the evaluation of trading among hedge funds, although we also empirically study the trading activity of floor brokers/traders as a basis of comparison for another group of large traders.

We find some modest evidence of herding for both hedge funds and floor brokers/traders for futures contracts with some markets exhibiting herding measures that are greater than other markets. We include an analysis of both the nearby and nearby and first deferred contracts as well as the roll versus non-roll periods to investigate whether our measures of herding are simply due to the fact that traders will appear to move in the same direction as expiration of the contracts draws near and they roll out of the nearby contracts and into the first deferred contracts to avoid physical delivery. In both cases we find that our values of H(i,t) are robust and due to actual herding behavior among hedge funds and FBTs and not to the rolling over of the contracts.

We also consider whether this herding behavior is causing a destabilization of prices through an examination of positive feedback trading. Using measures of excess demand, we find no evidence that hedge funds destabilize prices, even though they may tend to trade in the same direction. In fact, in many markets they act to stabilize prices by purchasing when prices are both high and low. In the case of the japanese yen market, we find the highest level of herding among hedge funds, yet, we find no evidence that this herding is destabilizing.

This study helps to shed some light on the trading behavior of large groups of traders in futures markets, specifically hedge funds, in a way that other researchers have not been able to do.

Table 1. Grouping of Traders in Commercial and Non-Commercial Categories.

	Commercial		**Non-Commercial**
Code	**Description**	**Code**	**Description**
18	Co-Operative	AP	Associated Person
AD	Dealer/Merchant	CPO	Commodity Pool Operator
AM	Manufacturer	CTA	Commodity Trading Advisor
AO	Agricultural/Natural Resources – Other	FB	Floor Broker
AP	Producer	FCM	Futures Commission Merchant
AS	Commodity Swaps/Derivatives Dealer	FT	Floor Trader
FA	Arbitrageur or Broker/Dealer	IB	Introducing Broker
FB	Non U.S. Commercial Bank	MM	Managed Money
FC	U.S. Commercial Bank		
FD	Endowment or Trust	NR	No Registration
FE	Mutual Fund		
FF	Pension Fund		
FG	Insurance Company		
FH	Hedge Fund		
FM	Mortgage Originator		
FO	Financial – Other		
FP	Managed Account or Pool		
FS	Financial Swaps/Derivatives Dealer		
FT	Corporate Treasurer		
LF	Livestock Feeder		
LO	Livestock – Other		
LS	Livestock Slaughterer		
	Hedge Funds		
	CPO	Commodity Pool Operator	
	CTA	Commodity Trading Advisor	
	AP	Associated Person	
	MM	Managed Money (subset)	

Table 1 lists the trader sub-categories in the CFTC's large-trader reporting system (LTRS). CFTC weekly Commitment of Traders (COT) Reports aggregate these sub-categories in two broad groups (except for agricultural which also has index traders): "Commercials", who have declared an underlying hedging purpose, and "Non-commercials", who have not. "Dealer/Merchant" (AD) includes wholesalers, exporter/importers, crude oil marketers, shippers, etc. "Manufacturer" (AM) includes refiners, fabricators, etc. "Agricultural / Natural Resources – Other" (AO) may include, for example, end users. "Commodity Swaps/Derivatives Dealers" (AS) aggregate all reporting "Swaps/Derivatives Dealers" (FS) and "Arbitrageurs or Broker Dealers" (FA), two categories that were merged in the CFTC's internal reporting system part-way through our sample period. "Hedge Funds" (HF) aggregate all reporting Commodity Pool Operators (CPO), Commodity Trading Advisors (CTAs), "Associated Persons" (APs) controlling customer accounts as well as other "Managed Money" (MM) traders. "Floor Brokers & Traders" (FBT) aggregate all reporting floor brokers and floor traders. NR represents those traders that have not yet been categorized or do not fit any other category. "Non-reporting participants" (NR) are reporting trader who is not registered under the Commodity Exchange Act (CEA). Note: FH under the Commercial category includes hedge funds in financial contracts that are shown to be hedging. This category has very few participants and is not relevant to our study.

Table 2. Daily Speculator Participation in 31 Futures Markets

Total is the count of the number of unique participants within each category that were observed over the time period, while the average gives an idea of the typical presence of that category on an average day. Participation includes participants trading in either the nearby, first deferred, or second deferred contracts.

	Hedge Funds				Floor Brokers/Traders			
Contract Market	Total	Average	Min.	Max.	Total	Average	Min.	Max.
3 Month Eurodollar	304	88.9	52	121	173	32.3	19	49
E-mini S&P 500 Index	262	53.1	3	104	249	42.7	13	65
Ten Year T-Notes	273	62.8	16	108	115	19.3	13	39
T-Notes (5 year)	236	57.2	19	83	100	16.8	8	27
U.S. T-Bonds	213	45.5	11	82	92	15.9	9	26
E-mini NASDAQ 100	290	57.1	6	98	232	37.8	17	55
Corn	411	93.2	2	169	357	75.9	11	134
E-Mini Russell 2000	140	24.1	1	57	90	12.3	1	29
Euro FX	300	53.9	29	78	132	17.4	7	33
Two Year T-Notes	144	24.9	3	50	56	4.9	1	12
Mini ($5) Dow Jones Industrial Index	78	10.5	1	25	142	27.3	1	42
Crude Oil	324	77.9	29	124	190	40.3	25	61
Soybeans	392	89.2	52	135	364	79.9	58	104
30 Day Federal Funds	136	23.6	13	38	77	11.8	3	21
Japanese Yen	235	44.6	20	79	62	8.9	3	14
Gold	354	79.1	34	122	135	31.4	21	46
Sugar #11	222	50.7	17	87	118	26.4	14	49
CBT-Wheat	388	82.4	40	140	246	55.1	37	84
S&P 500 Index	196	28.5	12	48	150	21.4	7	49
Natural Gas	284	66.6	31	104	146	35.8	27	46
Live Cattle	329	72.0	37	127	172	27.4	14	47
Lean Hogs	281	61.2	26	109	129	27.9	13	52
Silver	245	49.3	17	81	81	22.8	11	33
KS-Wheat	187	32.9	9	71	99	19.4	12	31
Cotton	323	74.1	40	129	171	49.6	33	75
Coffee	329	70.7	33	116	193	49.3	30	83
Copper	283	56.5	25	104	86	16.6	3	40
Cocoa	216	40.5	17	81	83	19.3	11	35
Feeder Cattle	159	27.1	9	53	101	17.4	10	28
Unleaded Gas	199	43.0	18	69	86	14.5	10	22
Heating Oil	171	39.9	13	68	88	14.7	9	23

Table 2.a. Daily Average and Maximum and Minimum Number of Hedge Funds Holding Futures in 31 Futures Markets

Futures Contract	Total Number of 'UNIQUE' Participants over the time period		Number of Participants Holding Positions on any given day					
			Average (Std Deviation)		**Minimum**		**Maximum**	
3 Month Eurodollar	304	*200*	88.85(14.04)	*34.03(11.65)*	52	*1*	121	*57*
E-mini S&P 500 Index	262	*261*	53.06(28.10)	*49.49(28.53)*	3	*3*	104	*104*
Ten Year T-Notes	273	*270*	62.84(25.35)	*49.40(30.98)*	16	*1*	108	*106*
T-Notes (5 year)	236	*233*	57.15(15.82)	*44.35(23.99)*	19	*1*	83	*83*
U.S. T-Bonds	213	*210*	45.53(20.27)	*35.54(23.71)*	11	*1*	82	*82*
E-mini NASDAQ 100	290	*286*	57.14(21.86)	*52.51(24.69)*	6	*3*	98	*98*
Corn	411	*372*	93.20(48.04)	*52.74(43.92)*	2	*1*	169	*135*
E-Mini Russell 2000	140	*139*	24.12(18.18)	*22.31(18.11)*	1	*1*	57	*57*
Euro FX	300	*299*	53.88(10.41)	*50.50(15.05)*	29	*1*	78	*77*
Two Year T-Notes	144	*137*	24.85(10.80)	*17.73(12.76)*	3	*1*	50	*50*
Mini ($5) Dow Jones Industrial Index	78	*78*	10.52(6.63)	*9.84 (6.54)*	1	*1*	25	*25*
Crude Oil	324	*303*	77.90(26.32)	*53.68(26.50)*	29	*1*	124	*109*
Soybeans	392	*359*	89.18(17.71)	*43.69(34.38)*	52	*1*	135	*124*
30 Day Federal Funds	136	*97*	23.64(5.30)	*11.92(4.40)*	13	*3*	38	*29*
Japanese Yen	235	*233*	44.57(12.55)	*41.53(15.63)*	20	*1*	79	*79*
Gold	354	*326*	79.12(19.17)	*44.53(35.05)*	34	*1*	122	*114*
Sugar #11	222	*212*	50.66(17.54)	*41.52(20.82)*	17	*1*	87	*86*
CBT-Wheat	388	*354*	82.35(23.43)	*50.03(32.08)*	40	*1*	140	*126*
S&P 500 Index	196	*194*	28.45(9.94)	*26.44(10.63)*	12	*4*	48	*47*
Natural Gas	284	*265*	66.60(15.55)	*46.32(17.31)*	31	*1*	104	*85*
Live Cattle	329	*296*	71.99(21.65)	*32.85(23.41)*	37	*1*	127	*107*
Lean Hogs	281	*261*	61.24(21.60)	*32.05(21.66)*	26	*2*	109	*96*
Silver	245	*231*	49.33(15.52)	*33.35(23.10)*	17	*1*	81	*79*
KS-Wheat	187	*164*	32.92(16.07)	*20.12(14.18)*	9	*1*	71	*57*
Cotton	323	*289*	74.06(17.86)	*41.95(33.36)*	40	*1*	129	*111*
Coffee	329	*308*	70.70(17.15)	*42.16(32.19)*	33	*1*	116	*109*
Copper	283	*49*	56.49(19.57)	*2.86(1.83)*	25	*1*	104	*11*
Cocoa	216	*200*	40.45(13.71)	*24.92(18.68)*	17	*1*	81	*70*
Feeder Cattle	159	*131*	27.11(12.18)	*12.69(9.76)*	9	*1*	53	*45*
Unleaded Gas	199	*181*	42.99(12.61)	*27.87(14.12)*	18	*1*	69	*60*
Heating Oil	171	*160*	39.89(14.61)	*25.44(13.83)*	13	*1*	68	*59*

NOTE: Number of unique participants counts the total number of unique traders within each category that were observed over the time period, while the average gives an idea of the typical presence of that category on an average day. The first number corresponds to participants trading in either the nearby, first deferred, or second deferred contracts, while the second number in italics is for participants in the nearby contract only.

Table 2.b. Daily Average and Maximum and Minimum Number of Floor Brokers/Traders Holding Futures in 31 Futures Markets

Futures Contract	Total Number of Unique Participants over the time period		Number of Participants Holding Positions on any given day					
			Average (Standard Deviation)		Minimum		Maximum	
3 Month Eurodollar	173	*125*	32.32(5.87)	*20.73(7.5663)*	19	*1*	49	*34*
E-mini S&P 500 Index	249	*248*	42.69(9.11)	*41.34(9.0414)*	13	*13*	65	*64*
Ten Year T-Notes	115	*112*	19.32(4.23)	*15.64(7.5922)*	13	*1*	39	*39*
T-Notes (5 year)	100	*99*	16.81(3.91)	*13.77(6.6675)*	8	*1*	27	*27*
U.S. T-Bonds	92	*90*	15.85(2.40)	*13.16(5.3035)*	9	*1*	26	*25*
E-mini NASDAQ 100	232	*227*	37.78(6.27)	*36.55(7.1069)*	17	*7*	55	*50*
Corn	357	*325*	75.91(34.16)	*54.91(34.7303)*	11	*1*	134	*118*
E-Mini Russell 2000	90	*87*	12.26(6.09)	*11.80(5.925)*	1	*1*	29	*26*
Euro FX	132	*131*	17.36(4.64)	*16.52(5.3977)*	7	*1*	33	*32*
Two Year T-Notes	56	*54*	4.89(2.26)	*4.33(2.3148)*	1	*1*	12	*12*
Mini ($5) Dow Jones Industrial Index	142	*142*	27.30(9.03)	*26.73(8.9164)*	1	*1*	42	*42*
Crude Oil	190	*178*	40.34(6.99)	*33.78(10.2953)*	25	*1*	61	*57*
Soybeans	364	*327*	79.85(7.93)	*49.23(27.7759)*	58	*1*	104	*101*
30 Day Federal Funds	77	*60*	11.84(3.43)	*8.70(3.2138)*	3	*1*	21	*18*
Japanese Yen	62	*61*	8.91(1.89)	*8.37(2.40)*	3	*1*	14	*14*
Gold	135	*123*	31.36(4.28)	*19.88(13.9754)*	21	*1*	46	*44*
Sugar #11	118	*114*	26.39(8.25)	*22.04(10.8093)*	14	*1*	49	*49*
CBT-Wheat	246	*218*	55.08(10.40)	*38.75(20.0281)*	37	*1*	84	*81*
S&P 500 Index	150	*149*	21.42(9.66)	*20.87(9.2817)*	7	*7*	49	*47*
Natural Gas	146	*133*	35.79(3.23)	*29.34(5.1955)*	27	*1*	46	*40*
Live Cattle	172	*156*	27.39(6.68)	*18.14(9.3572)*	14	*1*	47	*41*
Lean Hogs	129	*120*	27.88(10.17)	*20.60(8.6004)*	13	*5*	52	*47*
Silver	81	*74*	22.76(4.69)	*15.64(10.2227)*	11	*1*	33	*32*
KS-Wheat	99	*81*	19.43 (3.89)	*13.79(6.0977)*	12	*1*	31	*25*
Cotton	171	*161*	49.59(8.59)	*32.58(20.23)*	33	*1*	75	*74*
Coffee	193	*178*	49.27(10.05)	*31.70(23.1673)*	30	*1*	83	*82*
Copper	86	*56*	16.61(8.46)	*4.82(4.8466)*	3	*1*	40	*26*
Cocoa	83	*77*	19.28(3.46)	*13.56(7.9119)*	11	*1*	35	*34*
Feeder Cattle	101	*79*	17.41(3.55)	*14.87(3.2431)*	10	*8*	28	*24*
Unleaded Gas	86	*82*	14.52(2.18)	*12.74(3.8174)*	10	*1*	22	*22*
Heating Oil	88	*84*	14.74(2.43)	*13.03(3.8568)*	9	*1*	23	*22*

NOTE: Number of unique participants counts the total number of unique traders within each category that were observed over the time period, while the average gives an idea of the typical presence of that category on an average day. The first number corresponds to participants trading in either the nearby, first deferred, or second deferred contracts, while the second number in italics is for participants in the nearby contract only.

Table 3 Participation in the Market for Hedge Funds and Floor Brokers/Traders Holding Futures in 31 Futures Markets

	Hedge Funds			Floor Brokers/Traders		
Futures Contract	# of active participants	# of active days	% active days	# of active participants	# of active days	% active days
3 Month Eurodollar	27 (14%)	307.67	47.20	35 (28%)	391.63	78.60
E-mini S&P 500 Index	92 (35%)	382.45	76.60	98 (40%)	378.83	86.10
Ten Year T-Notes	75 (28%)	350.96	70.40	31 (28%)	435.61	91.90
T-Notes (5 year)	66 (28%)	323.15	65.70	25 (25%)	431.80	90.90
U.S. T-Bonds	50 (24%)	329.12	68.40	28 (31%)	414.93	92.60
E-mini NASDAQ 100	85 (30%)	380.55	71.90	66 (29%)	447.86	81.30
Corn	50 (13%)	231.54	58.80	99 (31%)	390.30	79.00
E-Mini Russell 2000	36 (26%)	321.00	80.40	24 (28%)	355.54	81.50
Euro FX	58 (19%)	354.45	70.60	27 (21%)	427.11	87.50
Two Year T-Notes	17 (12%)	209.88	50.00	9 (17%)	212.44	80.20
Mini ($5) Dow Jones Industrial Index	15 (19%)	388.00	83.80	67 (47%)	319.57	84.10
Crude Oil	80 (26%)	372.08	68.60	70 (39%)	446.80	88.40
Soybeans	61 (17%)	239.07	63.60	103 (32%)	361.76	79.90
30 Day Federal Funds	7 (7%)	230.00	28.30	15 (25%)	281.13	63.00
Japanese Yen	50 (22%)	323.90	66.40	13 (21%)	494.39	86.10
Gold	33 (10%)	232.33	74.50	35 (29%)	352.00	82.20
Sugar #11	45 (21%)	311.24	61.50	42 (37%)	409.79	79.20
CBT-Wheat	51 (14%)	256.26	57.00	65 (30%)	435.52	80.20
S&P 500 Index	37 (19%)	307.05	69.30	39 (26%)	337.13	74.40
Natural Gas	75 (28%)	369.33	71.10	47 (35%)	531.98	84.00
Live Cattle	40 (14%)	295.13	64.00	32 (21%)	427.31	83.20
Lean Hogs	42 (16%)	274.14	65.10	36 (30%)	390.94	76.40
Silver	31 (13%)	261.26	67.40	28 (38%)	394.43	86.80
KS-Wheat	8 (5%)	278.13	62.90	26 (32%)	335.35	77.10
Cotton	36 (13%)	220.08	57.60	65 (40%)	343.69	77.60
Coffee	36 (12%)	234.64	62.90	61 (34%)	331.72	85.30
Copper	2 (4%)	207.00	61.80	6 (11%)	186.17	81.90
Cocoa	23 (12%)	227.78	67.30	29 (38%)	277.03	85.20
Feeder Cattle	13 (10%)	252.39	59.50	22 (28%)	531.73	80.80
Unleaded Gas	43 (24%)	356.95	69.10	24 (29%)	459.79	89.20
Heating Oil	39 (24%)	363.28	68.10	28 (33%)	415.04	89.40
Average	**41 (19%)**	**287.21**	**62.78**	**41 (31%)**	**383.64**	**82.32**

NOTE: Active = participants that actively traded for more than 120 days, very active = participants that also traded more than 75% of their days in the market (there are a total of 1182 trading days). For example, a participant may be in the active group because he changed his positions on 120 days, but if he held passive large positions in the market for an additional 360 days (thus was in the market for a total of 460 days), he will not qualify as a very active trader as his active days constitute only 25% of the total days. The percentage of the number of participants who are active and very active corresponds to the percentage in the nearby or first deferred (in parenthesis) who are active or very active as a percentage of the total number of unique participants trading in all contracts (nearby, first deferred, and second deferred). The % active days are a function of the total number of days that a trader was in the market not the total number of days. For example, in the 3 Month Eurodollar market, the average trader was active for 307.67 days. This represented 47.20% of all days in the markets which meant that the number of days in the market was 785 days.

Table 4.a: Herding Measures: Hedge Funds

Market	Nearby Contract						Nearby and Deferred Contract					
	Overall Herding		Buy Herding		Sell Herding		Overall Herding		Buy Herding		Sell Herding	
	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	
3 Month Eurodollar	0.04***	1044	0.08***	652	-0.04***	392	0.05***	1144	0.10***	747	-0.03***	397
E-mini S&P 500 Index	0.06***	1182	0.10***	783	-0.04***	399	0.07***	1182	0.11***	826	-0.04***	356
Ten Year T-Notes	0.07***	1174	0.12***	853	-0.04***	321	0.08***	1180	0.12***	880	-0.03***	300
T-Notes (5 year)	0.08***	1180	0.13***	843	-0.04***	337	0.10***	1182	0.14***	884	-0.03***	298
U.S. T-Bonds	0.06***	1179	0.11***	803	-0.05***	376	0.08***	1182	0.11***	922	-0.03***	260
E-mini NASDAQ 100	0.08***	1182	0.11***	906	-0.04***	276	0.09***	1182	0.12***	917	-0.03***	265
Corn	0.09***	1073	0.13***	833	-0.07***	240	0.11***	1182	0.14***	998	-0.04***	184
E-Mini Russell 2000	0.04***	1036	0.12***	605	-0.07***	431	0.05***	1037	0.12***	623	-0.07***	414
Euro FX	0.11***	1167	0.14***	976	-0.04***	191	0.12***	1182	0.14***	1046	-0.03***	136
Two Year T-Notes	0.01***	1161	0.10***	549	-0.07***	612	0.03***	1180	0.10***	637	-0.06***	543
Mini ($5) Dow Jones Industrial Index	0.03***	1104	0.13***	608	-0.08***	496	0.04***	1116	0.14***	635	-0.08***	481
Crude Oil	0.04***	1151	0.08***	794	-0.04***	357	0.05***	1173	0.08***	813	-0.03***	360
Soybeans	0.09***	1090	0.14***	838	-0.07***	252	0.10***	1182	0.13***	1010	-0.03***	172
30 Day Federal Funds	0.03***	1182	0.12***	638	-0.07***	544	0.04***	1182	0.09***	717	-0.05***	465
Japanese Yen	0.16***	1171	0.19***	1031	-0.05***	140	0.17***	1182	0.19***	1058	-0.03***	124
Gold	0.10***	755	0.15***	580	-0.07***	175	0.15***	1173	0.17***	1024	-0.05***	149
Sugar #11	0.15***	1148	0.17***	1022	-0.05***	126	0.17***	1171	0.18***	1111	-0.04***	60
CBT-Wheat	0.08***	1058	0.14***	756	-0.05***	302	0.11***	1182	0.14***	971	-0.02***	211
S&P 500 Index	0.03***	1182	0.08***	675	-0.04***	507	0.03***	1182	0.08***	696	-0.04***	486
Natural Gas	0.08***	1140	0.12***	861	-0.04***	279	0.09***	1173	0.12***	912	-0.03***	261
Live Cattle	0.10***	1158	0.14***	896	-0.05***	262	0.08***	1182	0.10***	947	-0.03***	235
Lean Hogs	0.08***	1182	0.13***	841	-0.05***	341	0.10***	1182	0.13***	959	-0.03***	223
Silver	0.14***	889	0.17***	753	-0.06***	136	0.16***	1173	0.18***	1079	-0.04***	94
KS-Wheat	0.09***	923	0.15***	669	-0.07***	254	0.13***	1181	0.17***	964	-0.05***	217
Cotton	0.09***	972	0.16***	687	-0.09***	285	0.14***	1172	0.17***	1033	-0.05***	139
Coffee	0.08***	953	0.15***	654	-0.07***	299	0.14***	1171	0.17***	994	-0.02***	177
Copper	0.01	473	0.15***	208	-0.10***	265	0.07***	951	0.16***	613	-0.10***	338
Cocoa	0.10***	916	0.16***	670	-0.07***	246	0.13***	1171	0.17***	955	-0.03***	216
Feeder Cattle	0.11***	1166	0.17***	925	-0.09***	241	0.12***	1182	0.17***	931	-0.05***	251
Unleaded Gas	0.08***	1135	0.12***	847	-0.06***	288	0.11***	1173	0.13***	1017	-0.03***	156
Heating Oil	0.04***	1124	0.09***	717	-0.05***	407	0.05***	1173	0.09***	790	-0.04***	383
Aluminum	-0.01	18	0.03**	8	-0.03***	10	0.02***	21	0.02***	16	-0.01***	5
AVERAGE	0.07***	1039.63	0.13***	733.78	-0.06***	305.844	0.09***	1127.53	0.13***	866.41	-0.04***	261.125

Note: N represents the number of days that a herding measure could be calculated. For liquid markets, with many participants these days may coincide with an actual herding measure. For example, for the 3 Month Eurodollar of the 1182 trading days in the sample herding could be calculated on 1044 days. In this case 652 days the herding measure was greater than zero (buy herding) and 392 it was less than zero. In total these buy and sell (and overall) herding statistics are staitsically different from zero but it does not mean that everyday a herding measure could be calculated it was statistically significant. For example, out of the 1182 days in the sample, herding could only be calculated 18 times in the aluminum market and this was not significant when both positive (buy) and negative (sell) figures were pooled together. Individually however they are significant.

Table 4.b: Herding Measures: Floor Broker Traders

Market	Nearby Contract						Nearby and Deferred Contract					
	Overall Herding		Buy Herding		Sell Herding		Overall Herding		Buy Herding		Sell Herding	
	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N
3 Month Eurodollar	0.05***	1100	0.11***	705	-0.05***	395	0.06***	1162	0.10***	814	-0.05***	348
E-mini S&P 500 Index	0.01***	1182	0.06***	621	-0.03***	561	0.02***	1182	0.06***	645	-0.03***	537
Ten Year T-Notes	0.06***	1167	0.12***	792	-0.07***	375	0.08***	1180	0.12***	915	-0.04***	265
T-Notes (5 year)	0.04***	1157	0.12***	687	-0.07***	470	0.06***	1182	0.12***	768	-0.05***	414
U.S. T-Bonds	0.04***	1166	0.11***	697	-0.07***	469	0.04***	1182	0.10***	708	-0.05***	474
E-mini NASDAQ 100	0.02***	1182	0.06***	619	-0.03***	563	0.02***	1182	0.06***	622	-0.03***	560
Corn	0.09***	1155	0.12***	874	-0.03***	281	0.08***	1182	0.11***	925	-0.02***	257
E-Mini Russell 2000	0.03***	1169	0.12***	629	-0.07***	540	0.02***	1169	0.11***	627	-0.07***	542
Euro FX	0.03***	1175	0.10***	682	-0.05***	493	0.04***	1182	0.11***	705	-0.05***	477
Two Year T-Notes	0.02***	1038	0.14***	499	-0.09***	539	0.01***	1176	0.15***	513	-0.09***	663
Mini ($5) Dow Jones Industrial Index	0.03***	1106	0.08***	630	-0.04***	476	0.02***	1117	0.07***	637	-0.04***	480
Crude Oil	0.09***	1149	0.12***	891	-0.04***	258	0.11***	1173	0.14***	994	-0.03***	179
Soybeans	0.07***	1167	0.11***	851	-0.04***	316	0.05***	1182	0.08***	825	-0.02***	357
30 Day Federal Funds	0.07***	1179	0.15***	748	-0.08***	431	0.05***	1182	0.12***	715	-0.06***	467
Japanese Yen	0.08***	1161	0.15***	802	-0.07***	359	0.13***	1182	0.19***	909	-0.07***	273
Gold	0.07***	914	0.11***	676	-0.06***	238	0.07***	1173	0.11***	872	-0.04***	301
Sugar #11	0.09***	1148	0.15***	831	-0.07***	317	0.06***	1171	0.11***	780	-0.04***	391
CBT-Wheat	0.08***	1156	0.13***	866	-0.05***	290	0.09***	1182	0.12***	918	-0.03***	264
S&P 500 Index	0.01***	1182	0.07***	615	-0.05***	567	0.02***	1182	0.08***	613	-0.05***	569
Natural Gas	0.02***	1136	0.07***	590	-0.04***	546	0.02***	1173	0.08***	634	-0.04***	539
Live Cattle	0.10***	1155	0.15***	833	-0.05***	322	0.11***	1182	0.14***	1000	-0.04***	182
Lean Hogs	0.07***	1182	0.14***	770	-0.05***	412	0.15***	1182	0.18***	995	-0.05***	187
Silver	0.05***	969	0.12***	575	-0.06***	394	0.11***	1173	0.15***	887	-0.05***	286
KS-Wheat	0.05***	1012	0.11***	631	-0.06***	381	0.08***	1181	0.13***	885	-0.05***	296
Cotton	0.09***	1060	0.14***	741	-0.05***	319	0.09***	1172	0.13***	917	-0.03***	255
Coffee	0.05***	940	0.11***	616	-0.05***	324	0.10***	1171	0.14***	928	-0.03***	243
Copper	0.12***	643	0.22***	429	-0.09***	214	0.09***	1170	0.18***	795	-0.09***	375
Cocoa	0.08***	829	0.14***	568	-0.06***	261	0.11***	1171	0.17***	873	-0.05***	298
Feeder Cattle	0.05***	1182	0.16***	616	-0.06***	566	0.11***	1182	0.14***	946	-0.05***	236
Unleaded Gas	0.05***	1119	0.12***	677	-0.06***	442	0.05***	1173	0.12***	734	-0.05***	439
Heating Oil	0.07***	1126	0.13***	732	-0.06***	394	0.10***	1173	0.15***	860	-0.05***	313
Aluminum	0.00	412	0.03***	223	-0.03***	189	0.00	654	0.04***	271	-0.03***	383
AVERAGE	**0.06*****	**1076**	**0.12*****	**679**	**-0.06*****	**397**	**0.07*****	**1159**	**0.12*****	**788**	**-0.05*****	**370**

Table 5.a: Herding Measures in Non Roll Period v Roll Period in Nearby contract: Hedge Funds

Market	Non Roll						Roll					
	Overall Herding		Buy Herding		Sell Herding		Overall Herding		Buy Herding		Sell Herding	
	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N
3 Month Eurodollar	0.038	522	0.080*	327	-0.034***	195	0.035	522	0.088	325	-0.052	197
E-mini S&P 500 Index	0.057	1132	0.105	751	-0.037	381	0.047	50	0.096	32	-0.039	18
Ten Year T-Notes	0.071***	878	0.105***	654	-0.030***	224	0.079	296	0.154	199	-0.073	97
T-Notes (5 year)	0.080	874	0.123***	630	-0.031***	244	0.089	306	0.160	213	-0.076	93
U.S. T-Bonds	0.068***	883	0.104***	655	-0.037***	228	0.025	296	0.130	148	-0.081	148
E-mini NASDAQ 100	0.077	644	0.116	481	-0.039	163	0.077	538	0.108	425	-0.041	113
Corn	0.116***	561	0.140**	491	-0.050***	70	0.060	512	0.127	342	-0.076	170
E-Mini Russell 2000	0.041	1001	0.120	592	-0.073*	409	0.005	35	0.177	13	-0.096	22
Euro FX	0.115***	1122	0.139	963	-0.030***	159	-0.037	45	0.109	13	-0.096	32
Two Year T-Notes	0.020	773	0.092	397	-0.055	376	-0.013	388	0.119	152	-0.098	236
Mini ($5) Dow Jones Industrial Index	0.034	1040	0.127	574	-0.081*	466	0.028	64	0.139	34	-0.098	30
Crude Oil	0.050***	766	0.077**	567	-0.029***	199	0.032	385	0.090	227	-0.052	158
Soybeans	0.118***	548	0.140	478	-0.028***	70	0.063	542	0.138	360	-0.085	182
30 Day Federal Funds	0.041***	523	0.126**	292	-0.067*	231	0.023	659	0.110	346	-0.073	313
Japanese Yen	0.166***	1103	0.186	1000	-0.036***	103	0.023	68	0.163	31	-0.094	37
Gold	0.130***	469	0.148	422	-0.029***	47	0.040	286	0.147	158	-0.091	128
Sugar #11	0.158***	908	0.174	836	-0.033***	72	0.120	240	0.174	186	-0.068	54
CBT-Wheat	0.105***	541	0.136	438	-0.026***	103	0.057	517	0.135	318	-0.066	199
S&P 500 Index	0.028	1080	0.082	615	-0.043**	465	0.032	102	0.093	60	-0.056	42
Natural Gas	0.093***	638	0.131***	490	-0.032***	148	0.072	502	0.112	371	-0.044	131
Live Cattle	0.086*	259	0.117***	203	-0.026***	56	0.098	899	0.145	693	-0.061	206
Lean Hogs	0.075	472	0.112***	357	-0.037***	115	0.078	710	0.140	484	-0.057	226
Silver	0.157***	549	0.184***	485	-0.047***	64	0.101	340	0.150	268	-0.079	72
KS-Wheat	0.111***	533	0.156	416	-0.046***	117	0.064	390	0.145	253	-0.087	137
Cotton	0.140***	541	0.170***	461	-0.034***	80	0.023	431	0.146	226	-0.113	205
Coffee	0.126***	525	0.155	439	-0.026***	86	0.026	428	0.142	215	-0.091	213
Copper	-0.014**	124	0.132**	46	-0.100	78	0.018	349	0.159	162	-0.104	187
Cocoa	0.123***	515	0.166	406	-0.035***	109	0.067	401	0.155	264	-0.103	137
Feeder Cattle	0.137***	461	0.174*	389	-0.062***	72	0.099	705	0.162	536	-0.102	169
Unleaded Gas	0.101***	555	0.123	477	-0.037***	78	0.054	580	0.123	370	-0.067	210
Heating Oil	0.050***	510	0.088**	360	-0.040***	150	0.032	614	0.100	357	-0.063	257
Aluminum	0.052*	3	0.052*	3	n/a	0	-0.018	15	0.015	5	-0.034	10
AVERAGE	0.086	658	0.127	490	-0.042	167	0.047	382	0.130	243	-0.076	138

Roll is defined as the period when the deferred OI is greater than the nearby. ***,**,* means roll and non roll herding measures are different at the 1%,5% and 10% levels respectively (assuming variances are unequal as the roll period is likely to be more volatile). If the significance level is positioned in the roll (non roll) side it implies that herding measure is greater (in absolute value) than the non roll (roll).

Table 5.b: Herding Measures in Non Roll Period v Roll Period in Nearby contract: Floor Brokers/Traders

Market	Non Roll						Roll					
	Overall Herding		Buy Herding		Sell Herding		Overall Herding		Buy Herding		Sell Herding	
	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N
3 Month Eurodollar	0.062***	589	0.121***	394	-0.057***	195	0.038	511	0.090	311	-0.042	200
E-mini S&P 500 Index	0.013*	1132	0.058	588	-0.034	544	0.028	50	0.060	33	-0.033	17
Ten Year T-Notes	0.082***	878	0.123	663	-0.045***	215	-0.008	289	0.119	129	-0.111	160
T-Notes (5 year)	0.053***	874	0.111***	558	-0.049***	316	0.005	283	0.135	129	-0.104	154
U.S. T-Bonds	0.047***	883	0.103**	560	-0.050***	323	0.008	283	0.126	137	-0.102	146
E-mini NASDAQ 100	0.017	644	0.064	335	-0.034	309	0.016	538	0.062	284	-0.035	254
Corn	0.068***	561	0.105***	396	-0.021***	165	0.102	594	0.139	478	-0.048	116
E-Mini Russell 2000	0.030	1134	0.114	613	-0.069	521	0.039	35	0.152	16	-0.057	19
Euro FX	0.035***	1122	0.097	655	-0.051***	467	-0.005	53	0.098	27	-0.112	26
Two Year T-Notes	0.012***	771	0.139	351	-0.095	420	0.042	267	0.153	148	-0.095	119
Mini ($5) Dow Jones Industrial Index	0.028	1042	0.081	592	-0.042	450	0.025	64	0.067	38	-0.035	26
Crude Oil	0.111***	766	0.137***	648	-0.032***	118	0.037	383	0.087	243	-0.049	140
Soybeans	0.044***	548	0.069***	404	-0.025***	144	0.088	619	0.144	447	-0.057	172
30 Day Federal Funds	0.065	521	0.156	321	-0.082**	200	0.070	658	0.147	427	-0.072	231
Japanese Yen	0.088***	1103	0.153	778	-0.070	325	0.010	58	0.137	24	-0.079	34
Gold	0.083***	470	0.111	379	-0.037***	91	0.055	444	0.115	297	-0.068	147
Sugar #11	0.111***	908	0.154**	713	-0.046***	195	0.015	240	0.131	118	-0.097	122
CBT-Wheat	0.097***	542	0.126	440	-0.030***	102	0.073	614	0.131	426	-0.060	188
S&P 500 Index	0.014	1080	0.073**	564	-0.050	516	0.022	102	0.094	51	-0.051	51
Natural Gas	0.024	638	0.078*	333	-0.036	305	0.017	498	0.069	257	-0.039	241
Live Cattle	0.101	259	0.131***	215	-0.042	44	0.094	896	0.159	618	-0.050	278
Lean Hogs	0.159***	472	0.204***	388	-0.048	84	0.019	710	0.080	382	-0.053	328
Silver	0.061***	570	0.118	370	-0.045***	200	0.022	399	0.111	205	-0.071	194
KS-Wheat	0.053	533	0.105***	353	-0.048***	180	0.044	479	0.126	278	-0.068	201
Cotton	0.089	541	0.134***	397	-0.034***	144	0.081	519	0.155	344	-0.065	175
Coffee	0.062***	525	0.098***	378	-0.029***	147	0.043	415	0.128	238	-0.072	177
Copper	0.136	146	0.233	105	-0.112**	41	0.113	497	0.215	324	-0.079	173
Cocoa	0.072	515	0.126***	353	-0.046***	162	0.082	314	0.156	215	-0.080	99
Feeder Cattle	0.137***	461	0.205***	339	-0.051**	122	0.001	721	0.097	277	-0.059	444
Unleaded Gas	0.058***	555	0.119	360	-0.056**	195	0.034	564	0.111	317	-0.064	247
Heating Oil	0.086***	510	0.146***	358	-0.056**	152	0.049	616	0.122	374	-0.064	242
Aluminum	0.012	46	0.043***	25	-0.024	21	0.001	366	0.029	198	-0.032	168
AVERAGE	0.066	667	0.120	435	-0.048	232	0.039	409	0.117	243	-0.066	165

Roll is defined as the period when the deferred OI is greater than the nearby. ***,**,* means roll and non roll herding measures are different at the 1%,5% and 10% levels respectively (assuming variances are unequal as the roll period is likely to be more volatile). If the significance level is positioned in the roll (non roll) side it implies that herding measure is greater (in absolute value) than the non roll (roll).

Figure 1: Percentage of Futures Volume for 2006

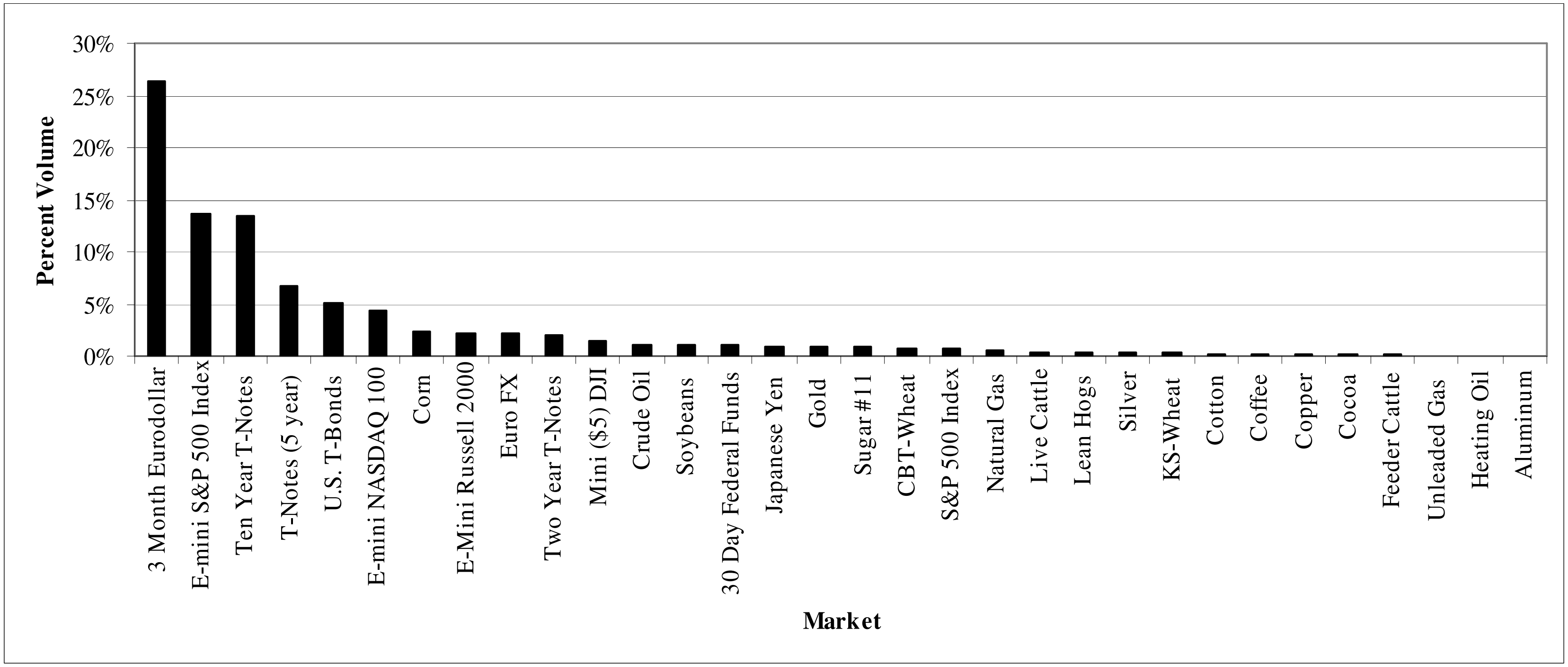


Figure 2: Average Number of Particpants Holding Positions on any Given Day

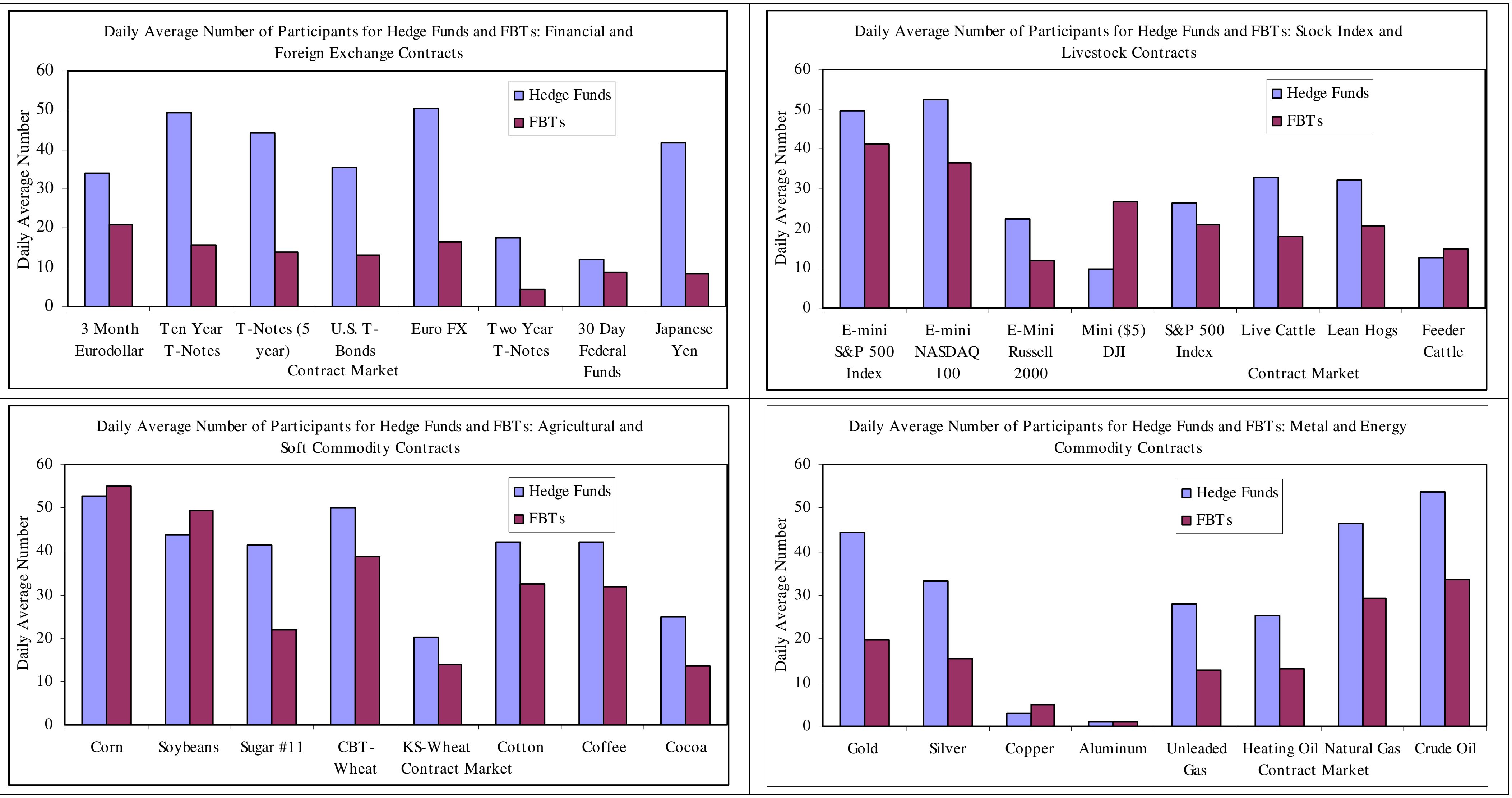
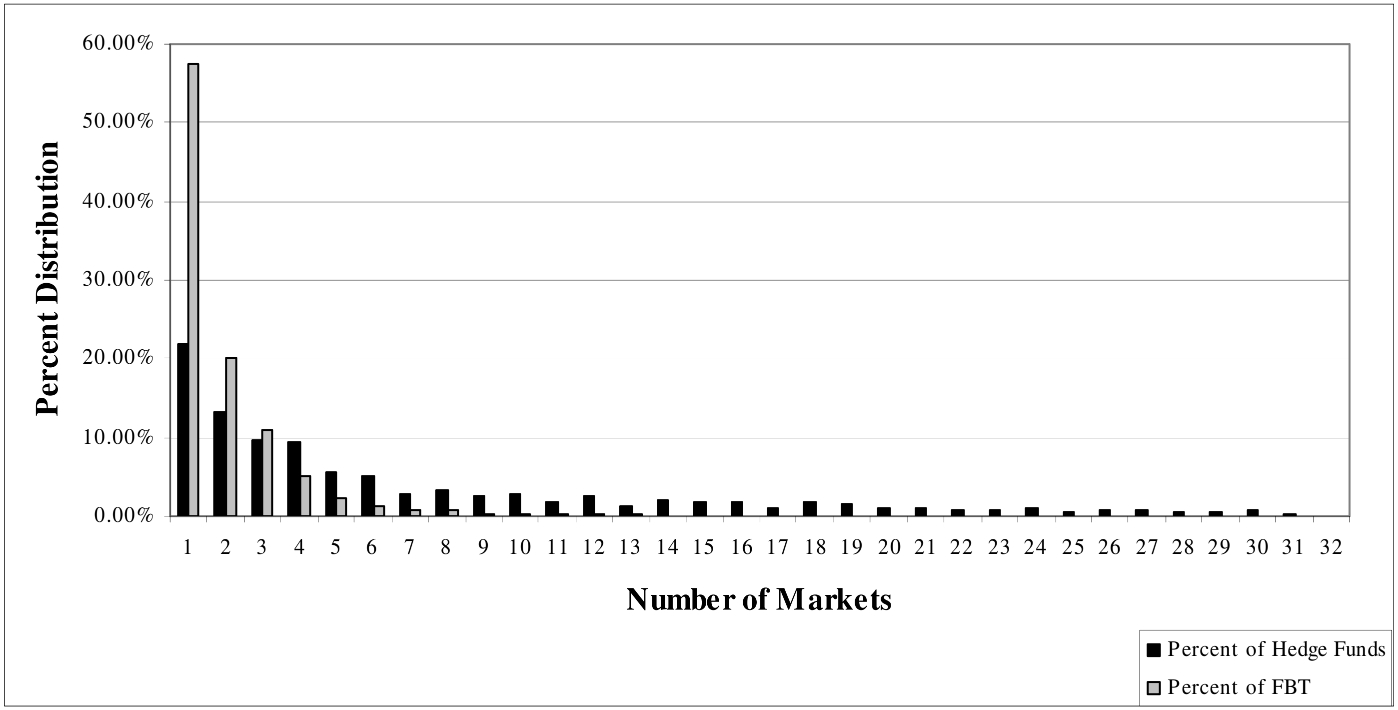
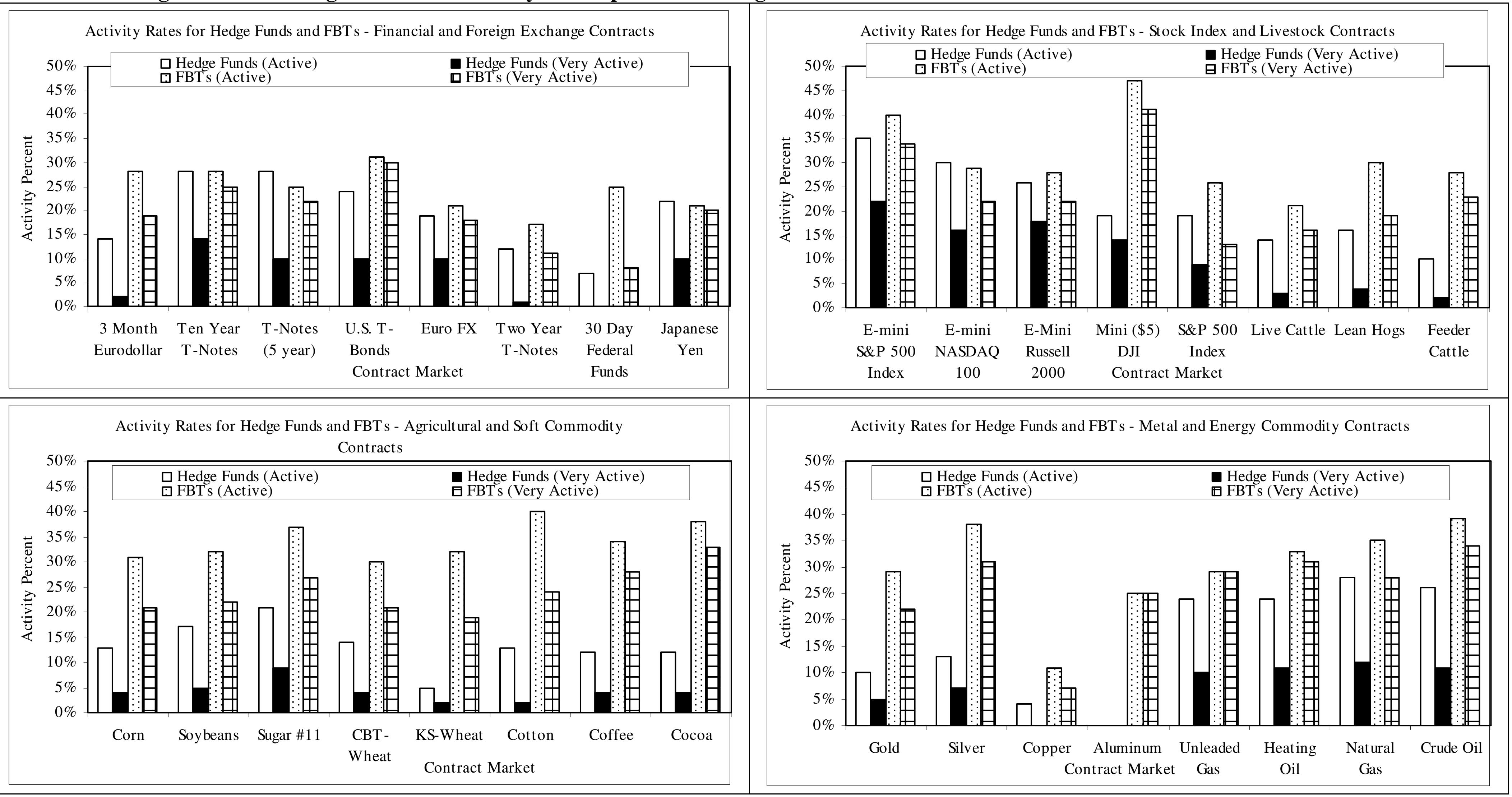


Figure 3: Percentage Distribution of Hedge Funds vs. Floor Brokers/Traders



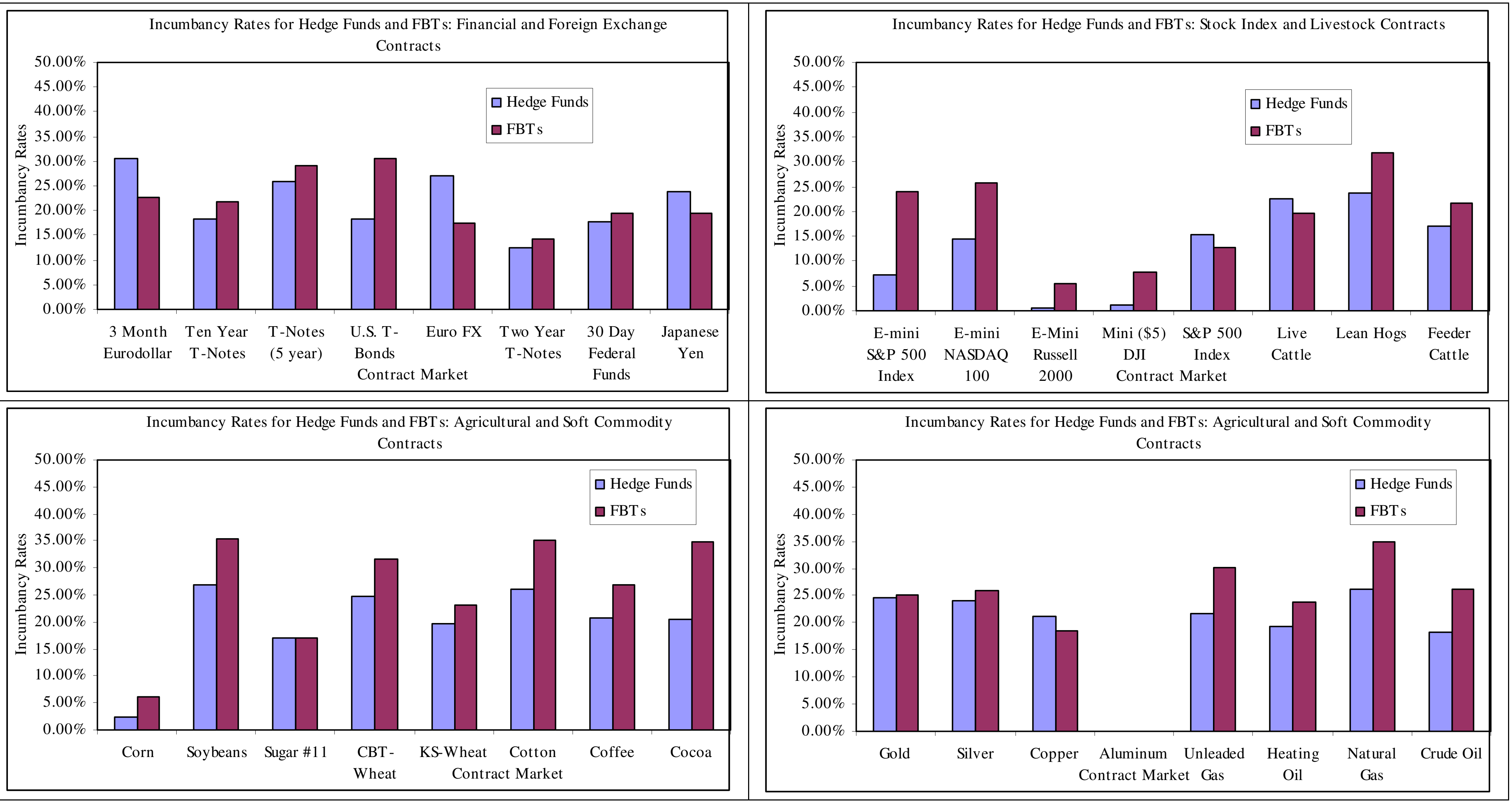
This figure presents the distribution of hedge funds and floor brokers/traders across the 32 futures markets. For example, almost 60% of FBTs only trade in one futures market on average. No hedge fund or floor broker traded in all 32 markets at the same time.

Figure 4: Percentage of Active and Very Participation for Hedge Funds vs. Floor Brokers/Traders



Active = participants that actively traded for more than 120 days, very active = participants that also traded more than 75% of their days in the market (there are a total of 1182 trading days). For example, a participant may be actice if they changed their positions for 120 days but if he held passive large positions in the market for an additional 360 days he would not qualify as a very active trader as his active days only constitute 25% of the total days.

Figure 5: Percent Incumbency for Hedge Funds vs. Floor Brokers/Traders



Incumbency is the percentage of participants present for at least one day in the last 90 days of the sample who were also present for at least one day in the first 90 days of the sample period.

Figure 6: Herding Levels for Hedge Funds vs. Floor Brokers/Traders

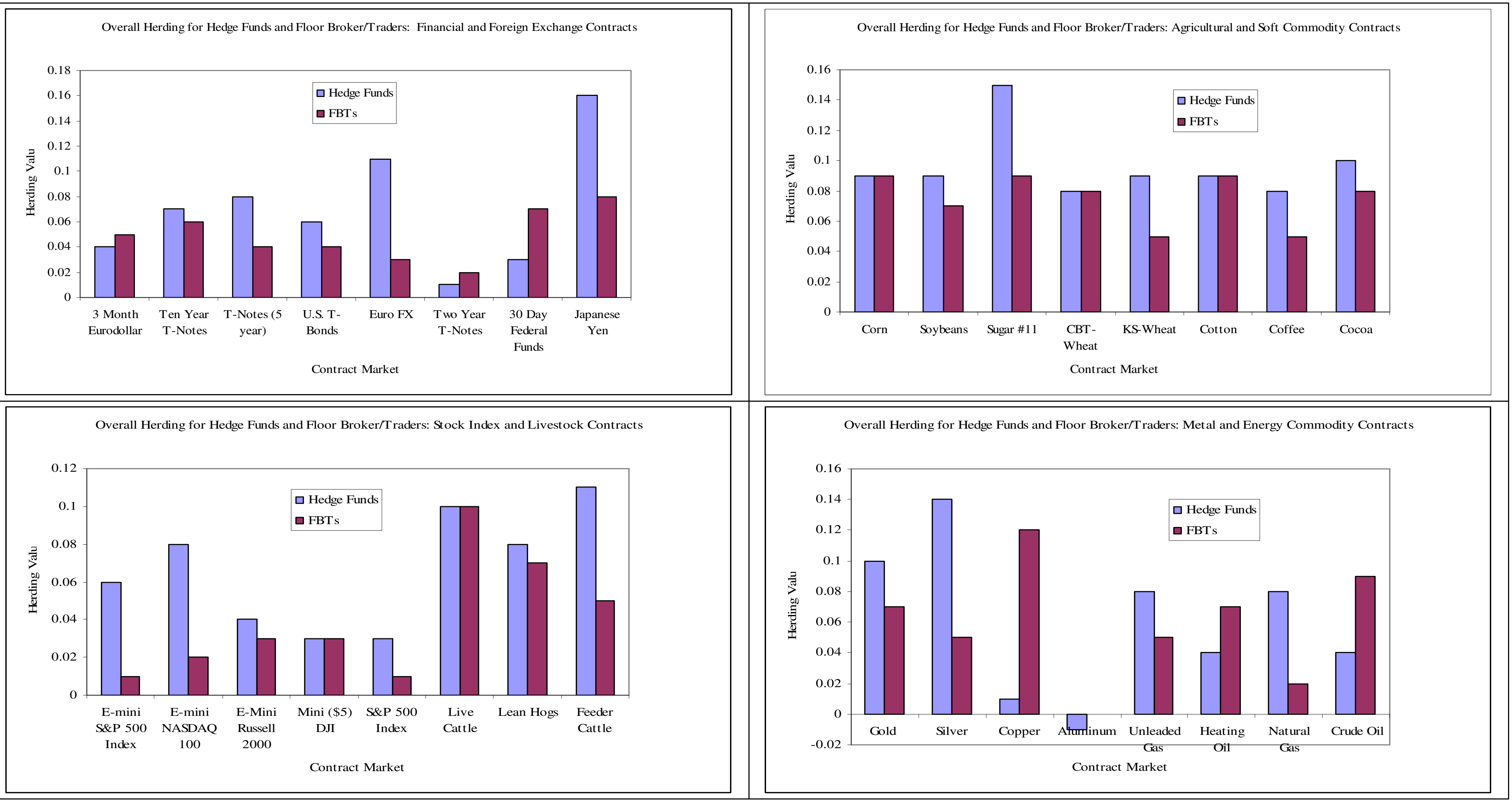


Figure 7: Positive Feedback Measure of Excess Demand by Past Day for Hedge Funds

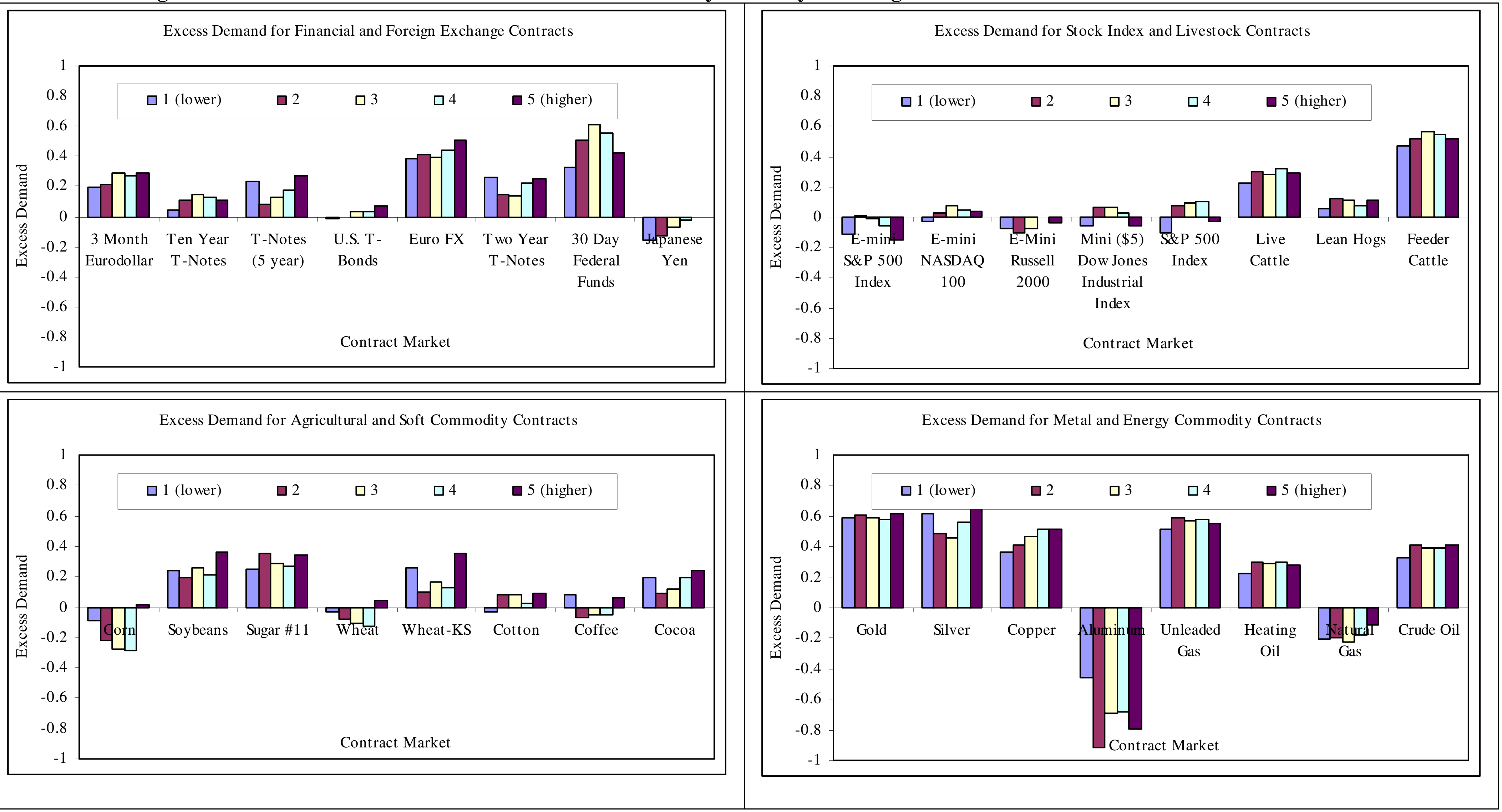


Figure 8: Positive Feedback Measure of NRatio by Past Day for Hedge Funds

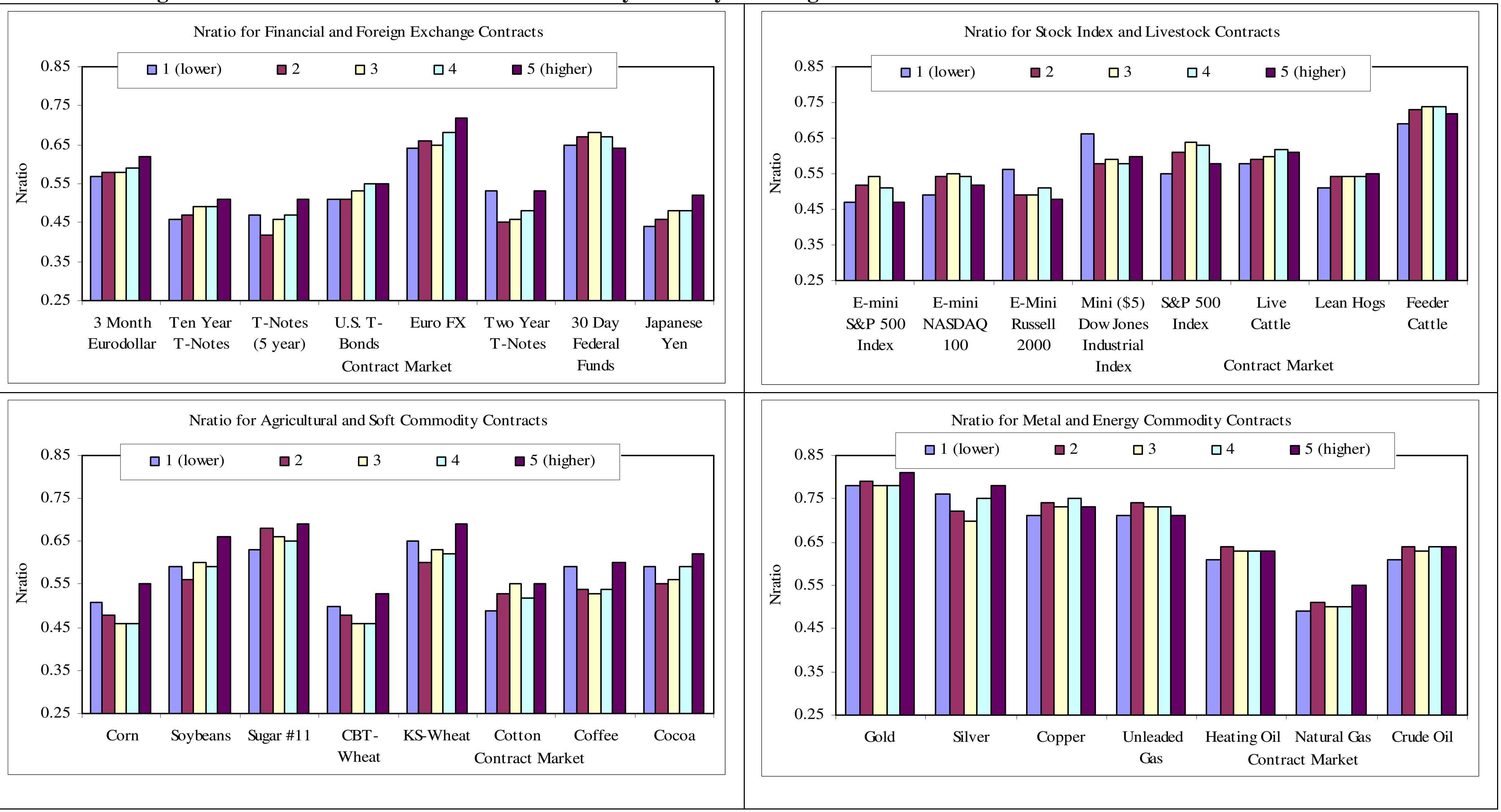
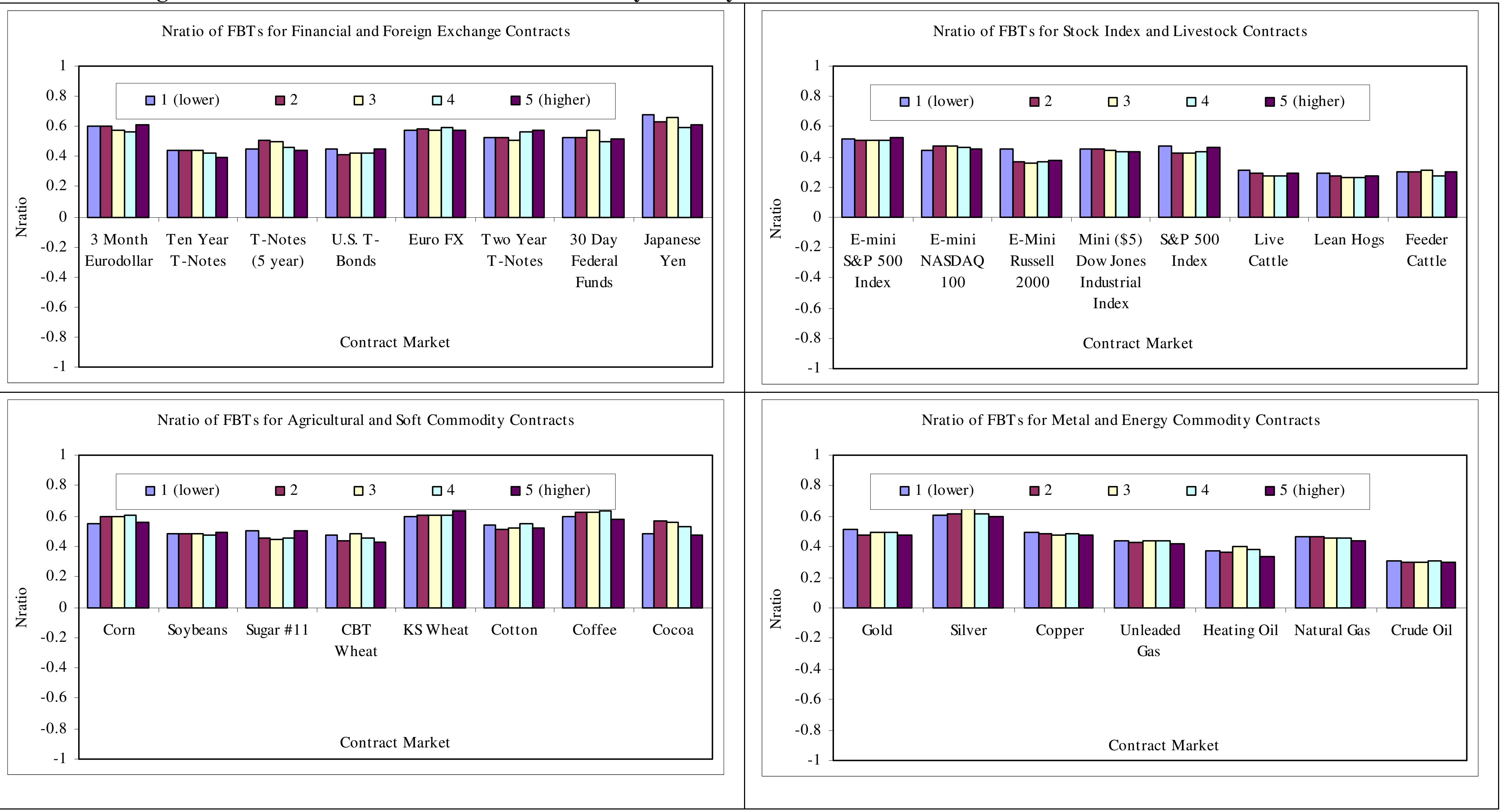


Figure 9: Positive Feedback Measure of Excess Demand by Past Day for FBTs

Figure 10: Positive Feedback Measure of NRatio by Past Day for FBTs



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