# Speculators, Prices and Market Volatility

Celso Brunetti Bahattin Büyükşahin Jeffrey H. Harris

## Abstract

We employ data over 2005-2009 which uniquely identify categories of traders to test whether speculators like hedge funds and swap dealers cause price changes or volatility. We find little evidence that speculators destabilize financial markets. To the contrary, speculative trading activity largely reacts to market conditions and reduces volatility levels, consistent with the hypothesis that speculators provide valuable liquidity to the market. These results hold across a variety of products and suggest that hedge funds (with approximately constant risk tolerance as in Deuskar and Johnson [2010]) improve overall market quality.

Key Words: Speculation, hedge funds, swap dealers, realized volatility, price

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* **Brunetti**: John Hopkins University, 100 International Drive, Baltimore, MD, 21202. Email: celsob@jhu.edu. **Büyükşahin**: International Energy Agency, Reu de la Fèdèration, 75739, Paris. Email: bahattin.buyuksahin@iea.org. **Harris**: University of Delaware, Newark, DE 19716, Tel: (302) 831-1812. Email: harrisj@lerner.udel.edu.

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*"The oil market, born in Texas, is behaving like a bucking bronco again. Prices that careened from $147 a barrel in mid-2008 to $31 … have jumped back to around $70 in recent days. …, politicians are again blaming speculators for this unruly behaviour."* The Economist, June 18, 2009

# I. Introduction

The role of speculators in financial markets has been the source of considerable interest and controversy in recent years. As the recent financial crisis demonstrates, failures within the financial system can have devastating effects in the real economy, elevating concerns about the trading behavior of financial market participants, particularly those operating outside of the public eye. The burgeoning hedge fund industry, for instance, operates largely outside of the U.S. Securities and Exchange Commission (SEC) jurisdiction, with few public reporting requirements. Likewise, swap dealers operate in relatively opaque over-the-counter (OTC) markets, fueling anxiety about their influence as well.[1]

Concerns about hedge fund and swap dealer trading activities also find support in theory where noise traders, speculative bubbles and herding can drive prices away from fundamental values and destabilize markets (see, for instance, Shleifer and Summers [1990], de Long et al. [1990], Lux [1995] and Shiller [2003]). Conversely, traditional speculative stabilizing theory (Friedman [1953]) suggests that profitable speculation must involve buying when the price is low and selling when the price is high so that irrational speculators or noise traders trading on irrelevant information will not survive in the market place. Indeed, Deuskar and Johnson (2010) demonstrate significant gains to supplying liquidity in the S&P 500 index futures markets.

Ultimately the question of whether these speculative groups destabilize markets or simply supply needed liquidity becomes an empirical issue. In this paper, we analyze the trading of both hedge funds and swap dealers in futures markets from 2005 through 2009 to test how speculative trading affects market prices and volatility. The futures markets offer us a unique view on this question, since speculative groups are easily identified in U.S. futures markets data and a number of futures markets have experienced significant price fluctuations in recent years. The U.S. Commodity Futures Trading Commission

[1] The 2010 Dodd-Frank financial reform legislation prescribes various oversight measures for swap dealers and requires hedge funds to register with the SEC as investment advisers. Hedge funds will provide information about their trades and portfolios as necessary to assess systemic risk.

(CFTC) collects daily position data from all large market participants, classifying traders by line of business and separating commercial (hedgers) traders (like manufacturers, producers and commercial dealers) from non-commercial (speculative) traders (like hedge funds, floor traders and swap dealers). We specifically analyze the crude oil, natural gas, corn, three-month Eurodollar and eMini-Dow futures markets to assess the impact of speculative trading on market prices and volatility. Each of these markets has experienced significant price changes during the recent financial crisis, thereby providing a unique opportunity to examine how speculative trade affects prices and market volatility.

Importantly, futures markets have experienced significant increases in speculative participation from both hedge funds and swap dealers during the past decade. Concurrent with the growth in overall open interest, hedge fund participation in futures markets has grown in recent years. Likewise, as over-the-counter financial markets have experienced increased risk, swap dealers writing OTC contracts increasingly hedge their OTC exposure with futures products (Büyükşahin et al. [2010]). Swap dealers also service the vast majority of commodity index trading, a business that has grown more than 10-fold from 2003 to 2009. The increased participation of these traders has fueled claims that these speculators destabilize markets.[2] Despite these concerns, there is limited empirical research on how speculative trading activity impacts prices and volatility (presumably since data on speculative trading is scarce).[3]

We jointly examine proprietary CFTC data on speculator positions and futures market prices. Consistent with Friedman (1953), we find that speculative activity does not generally affect returns, but consistently reduces volatility. More specifically, we implement multivariate Granger-causality tests examining lead-lag relations, and instrumental variables examining contemporaneous causal relations, between daily futures market returns and positions of the five most prominent types of market participants in each market. Hedge fund activity does not Granger-cause any other variable in the system. Conversely, hedge funds react to position changes of other market participants. In line with Keynes (1923) and Deuskar and Johnson (2010), these results suggest that hedge funds provide liquidity to the market by taking positions opposite to other market participants.

[2] In fact, responding to public concerns about increased speculative positions, the CFTC has failed to increase Federal speculative position limits for many agricultural futures since 2006.

[3] Indeed, even as we identify speculator positions, swap dealers and hedge funds taking apparent speculative positions may simply be hedging OTC exposures. One caveat to our analysis is that we document the effects of speculator positions, not necessarily speculation *per se*.

To assess the impact of speculative activity on risk, we construct daily realized volatility measures from high-frequency data and run Granger-causality tests between realized volatility and positions of the five most prominent trader categories as well.[4] We find that both swap dealer and hedge fund activities Granger-cause volatility, but as impulse response functions demonstrate, the effect of these traders is to *reduce* volatility. Additionally, we find that hedge fund and swap dealer position changes generally serve to reduce contemporaneous market volatility. This result is of particular importance since lower volatility implies a reduction in the overall risk of these futures markets. Importantly, the trading activities of prominent speculators—swap dealers and hedge funds—generally serve to stabilize prices during the most recent financial crisis, enhancing the ability of futures markets to serve as venues for transferring risk.

Our results are robust to using herding as an alternative metric of speculative activity as well. We explore the lead-lag relations between herding and both returns and volatility and consistently fail to find evidence that speculative activity systematically affects prices or volatility. Consistent with our main results based on net trader positions, hedge fund herding is not destabilizing, but actually reduces market volatility.

Hedge fund trading has been examined during several crisis events, including the 1992 European Exchange Rate Mechanism crisis and the 1994 Mexican peso crisis (Fung and Hsieh [2000]), the 1997 Asian financial crisis (Brown et al. [2000]), the Long Term Capital Management financial bailout (Edwards [1999]) and the technology bubble (Brunnermeier and Nagel [2004] and Griffin et al. [2010]). In some episodes, hedge funds were deemed to have significant exposures which probably exerted market impact, while in others they were unlikely to be destabilizing. In contrast to the mixed evidence on speculation in individual markets over relatively short periods of time, our detailed data over many markets during 2005-2009 yields the consistent results that hedge funds largely stabilize markets.

Although our results address speculative trading more generally, the comprehensive nature of our data speak to the value that speculators offer to the risk management function of futures markets. In this regard, our findings comport with Hirshleifer (1989, 1990), who shows that speculation lowers hedge premia by filling the imbalance between long and short hedging demand. Although we do not measure hedge premia directly,

[4] Similarly, Büyükşahin and Harris (2010) focus on various lead-lag relations for positions and returns in the crude oil market.

speculative activity that reduces volatility levels will, in turn, reduce the cost of hedging. Our analysis shows that speculators take the opposite position of hedgers and reduce market volatility. Likewise, our results comport with Deuskar and Johnson's (2010) supposition that investors with constant risk tolerance (e.g. hedge funds) can trade profitably against flow-driven liquidity shocks.

Numerous studies find that futures markets tend to lead cash markets in terms of price discovery (e.g. Hasbrouck [2003]). Our results suggest that the informative futures market trades in these studies likely do not emanate from speculators. Rather, we find that commercial dealer and merchant trades lead to increased volatility levels, consistent with these traders bringing fundamental information about the underlying commodity to the futures markets.

The remainder of the paper proceeds as follows. In section II we describe our data. In section III we analyze contemporaneous correlation between return, volatility, and the five most important categories of market participants in the crude oil, natural gas, corn, three-month Eurodollars and eMini-Dow futures markets. In section IV we analyze Granger-causality tests between trader positions and rate of return as well as positions and volatility. In section V we analyze contemporaneous causality between volatility and traders positions, and in section VI we measure herding and investigate whether herding affects prices and volatility. We conclude in section VII.

## II. Data

Our analysis draws upon three different data sets sampled from January 3, 2005 through March 19, 2009: 1) daily futures returns; 2) high frequency transaction data for computing realized volatility measures; and 3) daily futures positions of the most important categories of market participants in each market.[5] The New York Mercantile Exchange (NYMEX) crude oil and natural gas contracts represent the largest energy markets, the Chicago Board of Trade (CBOT) corn futures the largest agriculture market, the Chicago Mercantile Exchange (CME) three-month Eurodollar futures contract is the most widely-traded U.S. interest rate futures product, and the CBOT eMini-Dow one of the largest U.S. equity futures markets.[6]

[5] High frequency data for corn begins on August 1, 2006.
[6] Appendix provides descriptive details about these five contracts.

The variety across contracts allows us to analyze the role of speculators in markets which have each experienced dramatic price changes during our sample period. As Figure I, Panel A shows, during our sample, crude oil futures rise from about $42 to a staggering $146 in July 2008 before dropping back to $42 at the end of our sample. Natural gas futures change dramatically a number of times, more than doubling from $6 to $15 at the end of 2005, returning to $6 in 2006, and doubling again to $13 in 2008 before settling below $4 in March 2009. Similarly, corn futures more than doubled from under $4 to over $8 in 2008 before dropping back near $4 by the end of our sample. Conversely, since the inception of the so-called sub-prime crisis, the three-month Eurodollar futures market has experienced a decline in open interest from a peak of 12 million to 9 million contracts during our sample period. Likewise, the sub-prime crisis has generally weighed heavily on the eMini-Dow futures market as well. Although these markets do not experience the same precipitous rise and fall relative to the physical commodities, they both experience significant volatility episodes and have active hedge fund participation.

For each market we concentrate on the nearby contract (closest to delivery). Before maturity (the expiration date), most market participants either close out positions or roll over positions from the nearby contract (March 2005, say) to the next-to-nearby contract (June 2005). This rolling behavior generates seasonality in the data. To mitigate these problems, we consider the nearby contract until its open interest falls below that of the next-to-nearby contract and account for seasonality in our tests. In this regard our data totally excludes futures delivery periods so that the relations we find in this paper are not subject to (nor do we capture) price changes driven by delivery mechanisms.

### *II.A. Futures Market Return Data*

We obtain futures prices from both electronic and open outcry sessions. Crude oil, natural gas, corn and Eurodollar futures contracts are dually-traded electronically and via open outcry. We analyze daily position changes reported at the close of open outcry sessions (the Eurodollar continues trading electronically around the clock). The CBOT eMini-Dow futures are only traded electronically.

We compute daily returns for each contract using settlement prices set daily by the exchange at the market close.[7] In particular, we construct daily returns as $r_t = p(t) - p(t-1)$, where $p(t)$ is the natural logarithm of the settlement price on day *t*. On the days we switch contracts from the nearby to the next-to-nearby, both $p(t)$ and $p(t-1)$ refer to the next-to-nearby contract.

The five markets we examine represent a diverse set of returns over this sample period. Table I, column 1, reports summary statistics for returns. Daily returns on crude oil have a negative mean (-11.6 percent annually), a positive median, high standard deviation and mean revert. The unconditional distribution is non-Gaussian with negative skew and kurtosis above three.[8] Natural gas exhibits a significant negative mean daily returns (–47 percent annually) and a very large standard deviation (the largest of the five markets). The unconditional distribution of the daily natural gas returns is also non-Gaussian. Corn displays the highest average returns over the sample (6.3 percent annually). Not surprisingly, daily Eurodollar returns average close to zero with a very low standard deviation. Eurodollar returns also exhibit mean reversion and excess kurtosis. eMini-Dow returns, reflecting the sub-prime crisis, have negative daily average (11 percent annually), negative skew and excess kurtosis.

*II.B. High Frequency Transaction Data and Realized Volatility*

Each of these products represents very liquid markets—the median intertrade duration for each is less than one second. From transaction data provided by the CFTC we construct realized volatility measures. For crude oil and natural gas, we consider transactions from both the electronic platform and the traditional pit (pit trading declined from 100 percent to less than 30 percent of volume during our sample period). In the corn market we only utilize electronic transactions since the vast majority of transactions occur on the electronic platform and the intraday pit trading data contain several types of recording errors that persist throughout our sample period, including late reports, canceled trades, and inaccurate prices that we detect as statistical anomalies. For the Eurodollar

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[7] We exclude trading days abbreviated by holidays to ensure that the market is open for at least five (three for corn) trading hours.

[8] For each variable in Table I we also compute skewness, kurtosis, Jarque-Bera normality tests, autocorrelation up to order 100, and augmented Dickey-Fuller non-stationarity tests. To conserve space, we only report a subset of the descriptive statistics.

market, we consider both electronic and pit transactions that take place when the pit is open (and liquidity concentrates).

Realized volatility measures constructed with high frequency data can be biased by market microstructure noise. This noise likely varies significantly over time, given the wide range of prices experienced by these markets during our sample period. In this paper we apply three approaches to overcome this problem and, for the sake of brevity, report only results for the Zhang et al. (2005) *two scales realized volatility* (TSRV) estimator.[9] The *two scales realized volatility* estimator is quite simple. Let $\{p(\tau)\}_{\tau\in t}$ be the natural logarithm of the price process over the time interval $t$, and let $[a,b]\subset t$ be a compact interval (we use one trading day) which is partitioned in $m$ subintervals. For a given $m$, the $i$th intraday subinterval is given by $[\tau_{i-1,}^m, \tau_i^m]$, where $a=\tau_0^m<\tau_1^m<...\tau_m^m=b$, and the length of each intraday interval is given by $\Delta_i^m=\tau_i^m-\tau_{i-1}^m$. The intraday returns are defined as $r_i^m=p\left(\tau_i^m\right)-p\left(\tau_{i-1}^m\right)$ where $i=1,2,...,m$. Realized volatility on day $t$ is the sum of squared intraday returns sampled at frequency $m$.

$$RV_t^m=\sum_{i=1}^{m}\left(r_i^m\right)^2 \tag{1}$$

Starting from the first observation, we set $m$=$s$ transactions and compute RV using equation (1).[10] Then, starting from the second observation we re-compute RV using equation (1) and iterate to the third observation, the fourth, and continue through all available transactions for the day (with $m$ unchanged). We then average the realized volatility estimators obtained on the subintervals. Sampling at the relatively low frequency dramatically reduces the effect of market microstructure noise, while the variation of the estimates is lessened by the averaging.

We then apply equation (1) to all observations (sampling at the highest possible frequency, $m$=$1$) to obtain a consistent estimate of the variance of the market microstructure noise ($RV^{all}$). The last step in the *two scales realized volatility* estimator corrects for the bias of the noise by subtracting the noise variance from the average estimator

[9] Alternatively, the Barndorff-Nielsen et al. (2008) kernel estimator and the Andersen et al. (2001) low frequency sampling approach yield qualitatively similar results.
[10] We choose the optimal sampling frequency $m$ based on monthly volatility signature plots (Andersen et al. [2000]).

$$RV_t^{TSRV} = \frac{1}{k}\sum_{j=1}^{k} RV_{t,j}^{m} - \gamma RV_t^{all} \tag{2}$$

where $k$ denotes the number of subintervals of size $m$ and $\gamma$ is the ratio between $m$ and the total number of observations in the trading day.

Table I, column 2, provides descriptive statistics for our realized volatility estimates. Energy and corn markets both show a very high average volatility and a high variation in volatility levels. This is perhaps not surprising, given that our sample is constructed to include markets experiencing dramatic price changes. The Eurodollar market exhibits the lowest volatility. Notably, all realized volatility measures are stationary and highly persistent.

Figure I depicts prices and *two scales realized volatility* measures for our five markets over time. Generally speaking, we see increased volatility during periods of market decline. Crude oil, Eurodollars and equities (eMini-Dow) exhibit higher volatility in the last part of our sample, likely linked to uncertainty about the sub-prime crisis and the subsequent recession. Conversely, natural gas and corn exhibit relatively high variability throughout our sample period.

*II.C. Market Participant Positions*

For each market we obtain individual trader positions from the CFTC's Large Trader Reporting System (LTRS) which identifies daily positions of individual traders classified by line of business.[11] LTRS data represents approximately 70 to 90 percent of total open interest in each market, with the remainder comprised of small traders. The LTRS data identifies growth in speculative positions concurrent with the dramatic swings in prices for these commodities during our sample period. For example, hedge fund and swap dealer positions in crude oil markets have grown 100 and 50 percent, respectively, during our sample period.

For each market we concentrate on the five largest categories of market participants, with hedge funds and floor brokers/traders common to all five markets. Swap dealers are significant participants in crude oil, natural gas and corn. In these markets we

[11] CFTC reporting thresholds strike a balance between effective surveillance and reporting costs with reporting thresholds during our sample period of 350 contracts for crude oil, 200 contracts for natural gas, 250 contracts for corn, 3,000 contracts for Eurodollars, and 1,000 contracts for the eMini-Dow. Aggregate LTRS data comprises the CFTC's weekly public Commitment of Traders Reports by broad trader classifications (*producer/merchants*, *swap dealers*, *managed money traders,* and *other non-commercials*).

also analyze dealers/merchants (which include wholesalers, exporters/importers, shippers, etc.) and manufacturers (for crude oil and corn, including fabricators, refiners, etc.) or producers (for natural gas). For the Eurodollar market, we analyze commercial arbitrageurs or broker/dealers, non-U.S. commercial banks and U.S. commercial banks. For the eMini-Dow we analyze arbitrageurs or broker/dealers, other financial institutions, and hedge funds that are known to be hedging (on behalf of commercial entities, for instance).

Given our focus on the effects of speculation, we specifically analyze and examine the positions of commodity swap dealers and hedge funds. Although there is no precise definition of hedge funds in futures markets, many hedge fund complexes are registered with the CFTC as Commodity Pool Operators, Commodity Trading Advisors, and/or Associated Persons who may control customer accounts. CFTC market surveillance staff also identifies other participants who are known to be managing money. Accordingly, we define hedge funds to include these four categories.[12]

As noted above, commodity swap dealers use derivative markets to manage price exposure from OTC swaps and transactions with commodity index funds. Index funds are increasingly used by large institutions to diversify portfolios with commodities—by June 2008, the notional value of commodity index investments tied to U.S. futures exchanges exceeded $160 billion. These funds hold significant long-only positions, primarily in near-term futures contracts.

For each market, we consider the number of contracts held in long (or short) positions, the net futures positions (futures long minus futures short), and net total positions (the sum of net futures positions and the net, delta-adjusted, option positions) of each trader category. Columns three through seven in Table I show descriptive statistics for changes in the net futures positions for each market participant category organized by market. We emphasize position changes as measures of trading activity. In crude oil, natural gas and corn markets, where swap dealers are most active, both mean and median swap dealer position changes are negative, indicating an overall reduction in their positions. Likewise, across all markets, hedge fund position changes are negative over our sample period as well. The standard deviation of position changes among both swap dealers and hedge funds is very high, indicating that these groups change positions often and/or by large amount (as might be expected from speculative trading groups).

[12] For completeness, we verify the funds in these four categories are indeed hedge funds with characterizations of these funds in the press.

Table II shows the five trader categories in each market comprise at least half and up to four-fifths of the total open interest in each market. The participation rate of each trader category varies by long and short position. Merchants, producers and manufacturers are primarily short, consistent with the needs of these market participants to hedge long positions in the underlying commodity. Swap dealers hold an average of 40 percent of long positions in crude oil, natural gas and corn, consistent with large long positions taken on behalf of commodity index funds. Interestingly, hedge funds hold large positions on both the long and short sides of all five markets, suggesting that hedge fund activity is more heterogeneous than other trader categories.

## III. Unconditional Contemporaneous Correlations

We first examine the link between trader positions and both returns and volatility with an analysis of the correlation coefficients. Table III reports correlation coefficients between returns and volatility, and change in positions. Merchant positions are negatively correlated with the returns of crude oil, natural gas and corn, and positively correlated with natural gas volatility.

Examining speculators, we find no evidence of a contemporaneous link between swap dealer positions and returns. Swap dealer activity is positively linked to crude oil volatility but negatively linked to natural gas volatility. Hedge fund position changes are positively correlated with returns. However, hedge fund activity is not significantly correlated with volatility. Hedge fund and swap dealer position changes are generally negatively correlated with other trader positions, suggesting that both of these speculative trader groups provide liquidity to other market participants.

The simple correlation analysis provides three main results. First, swap dealer activity is largely unrelated to returns and volatility. Second, hedge fund activity is positively correlated with returns but uncorrelated with volatility. Third, the correlation between position changes of hedge funds and swap dealers with other market participants is always negative. Speculators, by taking positions opposite to hedgers, serve to provide liquidity in derivatives markets.

## IV. Do Trader Position Changes Granger-Cause Returns or Volatility?

Although suggestive, correlation analysis does not establish any causal or lead/lag relation between trader position changes and either returns or volatility. We formally test for Granger causality between position changes and both returns and volatility in the context of Vector Autoregressive (VAR) models using Generalized Method of Moments (GMM) with Newey-West robust standard errors.[13] Although we only report results for the optimal lag-length in each specification, these results are robust and hold regardless of the lag structure in the VAR.[14]

### *IV.A. Returns and Trader Position Changes*

We are particularly interested in testing whether swap dealer and hedge fund activity Granger-cause returns and/or volatility, but to better characterize the dynamics of these markets we also present tests for the interactions among trader groups. For brevity we do not include all parameters in the model, but rather focus on the significance of the Granger causality tests. Tables IV and V provide p-values for Granger-non-causality tests in both directions. In the upper right quadrant (column titled 'All') we test whether each variable is Granger-caused by all the other variables in the system. In the lower quadrant (row titled 'Total') we test whether each variable Granger-causes any other variable in the system. The null hypothesis is that of Granger-non-causality—i.e. a p-value greater than five percent indicates failure to reject the null. Where we find evidence that trader position changes Granger-cause either returns or volatility, we provide impulse-response results in Figures II and III.

Table IV presents Granger-causality tests between returns and position changes for each of the five markets. Panel A presents results for crude oil. Returns on the crude oil market are not Granger-caused by collective position changes of these traders (p-value=0.199), nor by any individual trader group. On the other hand, prior returns strongly Granger-cause positions of each individual trader group and of the full set of traders (p-value=0.000). Hedge funds do appear to be unique in that hedge funds are the only group

[13] We find no evidence of cointegrating vectors between variables used in the VAR for Granger non-causality tests. For brevity, we only report results for net futures positions but results are qualitatively similar for long futures positions, short futures positions and net total (futures and options) positions. Results for levels are nearly identical.
[14] Given heteroskedasticity and serial correlation, we use Wald tests rather than Akaike (AIC) or Schwartz Information Criteria (SIC) to select the optimal lag-length (which always exceeds that selected by AIC and SIC).

which does not jointly Granger-cause (at 5 percent significance level) any other variable in the system. This implies that hedge fund activity does not provide any useful information for predicting either returns or the positions of other traders at the one day horizon. Conversely, hedge fund activity is Granger-caused by the system (p-value=0.000). Swap dealer activity, on the other hand, both Granger-causes and is Granger-caused by the other variables in the system.

Panel B reports Granger-causality test results (p-values) for returns and position changes for the natural gas market. As with crude oil, we find that natural gas returns are not Granger-caused by trader position changes (p-value=0.571). However, position changes are Granger-caused by returns (p-value=0.000). The system significantly Granger-causes hedge fund activity (p-value=0.000), but hedge fund activity does not Granger-cause the system (p-value=0.240). Hedge funds largely react to market conditions but hedge fund position changes do not lead price changes or position changes of other traders. Similar to the crude oil market, swap dealer activity in natural gas both Granger-causes and is Granger-caused by returns and position changes of other traders. Conversely, natural gas producer activity appears to strongly influence the positions of other traders.

Corn returns appear to be largely insulated from changes in lagged trader positions (see Panel C). Similar to the energy markets, hedge fund activity in corn is Granger-caused by the system (p-value=0.000) but does not Granger-cause the system (p-value=0.158). This is also true for swap dealer activity (p-values=0.000 and 0.563, respectively). More noticeably, corn manufacturer activity Granger-causes hedge fund, swap dealer and floor trader activity.

Panel D of Table IV reports Granger-causality tests for the Eurodollar market. In line with other markets, returns are not Granger-caused by positions (p-value=0.478). In contrast to other markets, however, Eurodollar returns do not Granger-cause position changes (p-value=0.495), perhaps reflecting the fact that trading positions are more dispersed in this market. Interestingly, hedge fund activity responds to the other variables in the system (p-value 0.001) but does not lead any other variable in the system (p-value 0.411).

In the eMini-Dow market we have two hedge fund categories: commercial funds (hedgers) and the more common speculative funds (see Panel E). eMini-Dow returns are Granger-caused by trader positions (p-value=0.026) and vice versa (p-value=0.038). Financial institution and hedge fund activities appear to be the driving force behind the connection between position changes and returns in the eMini-Dow market. Interestingly, commercial fund activity does not significantly lead eMini-Dow returns. However, hedge fund activity significantly leads the system of returns and other trader positions (p-value=0.008).

To further explore how hedge fund and other trader position changes affect eMini-Dow returns, we compute impulse-responses depicting the 10-day return response to a one standard deviation innovation in position changes.[15] As Figure II shows, the trading activity of speculative hedge funds and dealer/arbitrageurs contribute to reversing the negative trend in the eMini-Dow returns over our sample period. That is, although hedge fund position changes lead price changes, the effect of net hedge fund purchases is not to Granger-cause price increases, but rather to temper price declines. On the other hand, other financial institutions and floor broker/trader activities appear to contribute to the negative trend in stock returns during our sample period.[16]

*IV.B. Volatility and Trader Position Changes*

Table V reports Granger-causality tests for volatility and trader position changes. For volatility, we use the logarithmic *two scales realized volatility* measure in transaction time (described in Section II).[17] Panel A shows that position changes (p-value=0.000) Granger-cause volatility in the crude oil market. There is also a feedback effect from volatility to trader position changes (p-value=0.007). Both swap dealer and hedge fund position changes appear to lead volatility in the crude oil market.

Panel B of Table V reports results for the natural gas market. Natural gas volatility is marginally (at 10 percent level) Granger-caused by trader activity (p-value=0.052), but trader activity is not Granger-caused by volatility (p-value=0.344). Merchants, producer and swap dealer position changes significantly lead changes in other variables in the system, with the strongest connection between trader positions rather than with volatility. In fact, all other trader position changes strongly lag position changes of natural gas

[15] We follow Pesaran and Shin's (1998) *generalized impulse responses* which are invariant to the ordering of the VAR variables and do not require shocks to be orthogonal. Impulse responses generated with Cholesky decompositions with several variable orderings are similar. Response standard errors are computed with 1,000 Monte Carlo replications.

[16] These results also hold separately during the run-up in the eMini-Dow (January 2005 – August 2007) and through the eMini-Dow decline (September 2007 – March 2009).

[17] We confirm that logarithmic realized standard deviation is approximately Gaussian (see Andersen et al. [2003]). Our results are robust to alternative realized volatility measures as well.

producers. As with our results examining returns above, hedge fund activity is largely unrelated to volatility or other trader position changes in the natural gas market.

For the corn market (Panel C) we find evidence of two-way Granger-causality between trader position changes and volatility. Swap dealer and hedge fund activity do not Granger-cause the system (p-values=0.158 and 0.148, respectively), but their activity significantly lags other variables in the system (p-value=0.000 for both). As with the analysis of returns above, manufacturer position changes significantly lead the position changes of both swap dealers and hedge funds in the corn market.

Volatility in the Eurodollar market (Panel D) is Granger-caused by trading activity (p-value=0.025), with the strongest link to hedge funds (p-value=0.007). In fact, hedge fund position changes also strongly lead position changes of both non-U.S. banks and brokers. Broker activity feeds back to hedge fund position changes as well (p-value=0.002). Overall, however, Eurodollar volatility shows no sign of Granger-causing the position changes of traders in this market (p-value=0.239).

Similar to most other markets eMini-Dow volatility is Granger-caused by the full set of trader position changes (p-value=0.007) but there is evidence of only a marginal feed-back effect (p-value=0.110). Notably, eMini-Dow volatility is also significantly led by arbitrageur and speculative hedge fund position changes (p-values=0.042 and 0.043, respectively). Hedge fund activity also significantly leads arbitrageur position changes.

Given the consistent connection between trader position changes and volatility, we present impulse-responses for each market in Figure III. We are particularly interested in the response of volatility to a shock to commodity swap dealer and hedge fund activity shown in the two graphs to the far right. An unexpected positive shock to swap dealer positions is associated with a significant reduction of volatility in the crude oil and natural gas markets (Panels A and B) and a marginal reduction of volatility in the corn market (Panel C). Likewise, an unexpected one-standard deviation increase in hedge fund activity significantly reduces volatility in the crude oil (Panel A) and eMini-Dow (Panel E) markets and marginally reduces volatility in the corn (Panel C) and the Eurodollar (Panel D) markets. These facts provide further evidence that speculators generally do not destabilize markets, but rather serve to buffet volatility brought to bear by other traders.

In fact, these impulse-response functions demonstrate that shocks to merchant (hedger) position changes have a positive impact on volatility in crude oil and natural gas markets. Likewise, an unexpected increase in financial institution activity also increases volatility in the eMini-Dow market. These results are perhaps not surprising, since commercial traders are commonly thought to bring fundamental information about the commodity to the futures market, information that would thus generate higher volatility.

It is interesting to contrast the impulse responses for the eMini-Dow presented in Figures II and III. Hedge funds and arbitrageurs that change positions against the return trend (Figure II) are the same traders which significantly reduce market volatility (Figure III, Panel E). Conversely, financial institutions and floor traders that trade with the return trend have a short-term, positive effect on volatility.

Our analysis of Granger-causality suggests that speculation does not destabilize prices across a variety of markets during historically volatile times. Although Granger-causality tests have limitations our results are very robust, holding for both position levels and changes, various volatility measures, and in numerous VAR specifications.

## V. Contemporaneous Volatility and Trader Position Changes

The above Granger-causality tests are based on a precise temporal structure: we test whether a variable on day $t$ helps predicting another variable the next day, $t+1$. However, given that these markets are very liquid and active, it is perhaps likely that position changes and volatility occur contemporaneously. To explore this possibility we test for a contemporaneous causal relation between realized volatility and trader positions with the following equation:

$$RV_{i,t} = \alpha_i + \beta_{i,j}|\Delta TP_{i,j,t}| + \sum_{s=1}^{22} \zeta_{i,k} RV_{i,t-k} + \varepsilon_{i,t} \qquad (1)$$

where $RV_{i,t}$ is the (log) *two scales realized volatility* in market $i$ at time $t$, $|\Delta TP_{i,j,t}|$ is the (absolute value of the) trading position changes of trader group $j$ in market $i$ at time $t$, $\varepsilon_{i,t}$ is an error term assumed to be uncorrelated with lag values of realized volatility but not necessarily with $|\Delta TP_{i,j,t}|$. The large number of lags of $RV_{i,t}$ covers the trading days of the past month.

We are particularly interested in the parameter $\beta$ which measures the contemporaneous impact of trading activity on volatility. However, $|\Delta TP_{i,j,t}|$ and $\varepsilon_{i,t}$ may be correlated because position changes may be endogenous. For instance, high volatility may induce speculators to change positions so that simple OLS estimates of $\beta$ may be biased. To overcome this problem we adopt a set of instruments which are correlated with $|\Delta TP_{i,j,t}|$ but uncorrelated with $\varepsilon_{i,t}$. The instrument we propose is the change in the number of traders reporting position changes, by group, in each market each day, $\Delta NT_{i,j,t}$. We test the validity of the instruments with an F-test using Stock and Yogo (2005) critical values and then estimate Equation (1) using Limited Information Maximum Likelihood (LIML).[18]

Table VI reports estimation results for the instrumental variable regressions. These results are in line with the Granger-causality tests above. Interestingly merchant activity increases volatility in the crude oil and natural gas markets (but not in corn). These effects are economically significant. In fact, a unit change in merchant positions increases volatility by 38 and 23 basis points in the crude oil and natural gas markets, respectively. Likewise, floor broker activity increases volatility by 25 basis points in crude oil and four basis points in the eMini-Dow market. Financial institution activity also increases volatility by four basis points in the eMini-Dow market.

Notably, swap dealer activity is largely unrelated to contemporaneous volatility. More importantly, perhaps, is the fact that a unit change in hedge fund activity reduces crude oil volatility by 40 basis points, reduces natural gas volatility by 7 basis points, and reduces eMini-Dow volatility by 13 basis points. We find little evidence that hedge fund activity destabilizes these markets, but rather reduces contemporaneous volatility in futures markets.

## VI. Herding as an Alternative Speculation Metric

The aggregation of speculative positions by hedge fund and commodity index trader groupings might obscure the impact of individual traders within the group. That is, since we measure aggregate positions by trader group, the results above do not distinguish between a market with many traders going long (short) and a market with one dominant long (short) position that influences the net long (short) position of the group. To disentangle the effects of one dominant trader from a group of traders on the same side of the market, we calculate the herding measure developed by Lakonishok et al. (1992). In this regard, we explore whether our results reflect speculator behavior more generally, or perhaps reflect the activity of a dominant speculator. We consider the herding metric an alternative measure of speculative activity that excludes effects of a dominant trader.

[18] LIML is less sensitive to weak instruments than two-stage least squares estimation. In order for the actual size of the LIML test to be no greater than 10% (15%), the F-statistics should exceed 16.38 (8.96). The F-test reveals that the change in the number of reporting traders is a valid instrument. We also estimate the model for positions in levels and obtain similar results.

The herding metric measures the difference between the number of net buyers from each trader category and the number of net buyers across all markets each day (with an adjustment factor that accounts for the number of active traders in each category). The herding measure captures the propensity for individual traders to trade on the same side of the market, a specific form of speculation, to the extent that herding captures mimicking behavior within the group.

Table VII shows mean values for the herding measure. The mean values for each commodity are fairly small, but statistically different from zero. For example, in the crude oil market, the average herding for hedge funds is 1.1 percent, implying that 51.1 percent of hedge funds increased positions while 48.9 percent decreased positions on the average day. The largest average values for the herding measure are in the natural gas market for swap dealers (8 percent), in the corn market for merchants (8.83 percent), and in the eMini-Dow for other financial institutions (-12.6 percent) and commercial funds (-12.5 percent).[19]

Table VII also shows the daily correlations of herding with returns and volatility for each of the five markets. Notably, we see that herding among hedge funds and swap dealers is, when significant, negatively related to volatility, indicating that hedge fund and swap dealer herding is mainly countercyclical. Interestingly, hedge fund and swap dealer herding is positively linked to rate of returns (except for hedge funds in natural gas and swap dealers in crude oil). These results suggest that the Granger-causality results we document above stem more generally from hedge fund position changes and not from a dominant hedge fund.

Contrary to herding among speculative groups, merchant and floor broker herding is highly correlated with returns and volatility. In particular, herding among merchants is negatively linked to rate of returns but positively linked to volatility in the crude oil and natural gas markets. In these markets, however, the economic effect of merchant herding is relatively small and given the fact that information arrival can lead to clustering of traders on one side of the market (and hence, a higher herding measure), these correlations are only suggestive. Herding among floor brokers is  negatively correlated with volatility for the crude oil and corn markets but positively correlated with returns in the crude oil, natural gas and corn markets.

[19] By comparison, Lakonishok et al. (1992) document herding of 2.7 percent among equity money managers. Boyd et al. (2010) examine herding in futures markets in more detail.

To investigate the effects of herding on returns and volatility, we run Granger-non-causality tests (similar to those reported in Section IV) using herding as an alternative measure of speculative activity. We find no significant link between returns and herding in any of the five markets we analyze. However, Granger-causality results for volatility and herding show a feed-back effect between volatility and herding measures for the crude oil, corn and eMini-Dow markets.[20] To further investigate this issue, we compute generalized impulse responses and present results in Figure IV. A one standard deviation shock to hedge fund herding has almost no significant effect on volatility, except in crude oil where herding among hedge funds serves to reduce volatility levels (Panel A). Interestingly, an unexpected shock to herding among hedge funds increases volatility levels in the Eurodollar market. Swap dealer herding does not impact volatility, while a shock to merchant herding increases volatility levels only in the natural gas and corn markets.

## VII. Conclusion

We employ a unique dataset that allows us to precisely identify positions of market participants in five actively-traded and recently volatile futures markets to investigate whether speculation moves prices and/or increases market volatility. Through correlations, Granger-causality tests, and contemporaneous tests with instrumental variables, we find that speculative groups like hedge fund and commodity swap dealer position changes do not lead price changes, but rather lead to reduced market volatility. As a whole, these speculative traders provide liquidity and do not destabilize futures markets.

Importantly, these results hold uniformly across a variety of financial and commodity futures products over recent periods when turmoil in financial markets has generated historically high levels of volatility. Indeed our results hold both for periods when prices trend upward and also for periods where prices drop significantly and market volatility spikes. Our results are also robust to measuring speculation by the total net positions taken by hedge funds and swap dealers and by herding among hedge funds and to various alternative volatility metrics.

These results are consistent Deuskar and Johnson's (2010) conjecture that investors with constant risk tolerance (like hedge funds perhaps) can trade profitably against flow-driven shocks. Indeed, the increased positions taken in recent years by hedge funds and

[20] For herding, we are unable to identify a valid instrument to replicate results from Section V.

swap dealers across a wide variety of futures markets may simply reflect a rational profit motive. These speculative groups have not been destabilizing markets, but rather have served to dampen volatility during the recent financial crisis.

Although we do not rule out the possibility that traders might attempt to (or actually succeed to) move prices and increase volatility over short intervals of time, we find no systematic, deleterious link between the trades of hedge funds or swap dealers and either returns or volatility. Hedge fund trading, in fact, is commonly related to returns and volatility, but in a beneficial sense—hedge funds commonly provide liquidity in futures markets, reducing market volatility. In general, speculators like hedge funds and swap dealers should not be viewed by hedgers as adversarial agents. Rather, speculative trading activity serves to reduce market volatility and provides the necessary liquidity for the proper functioning of financial markets.

## References


Andersen, Torben, Tim Bollerslev, Francis X. Diebold, and Heiko Ebens. 2001. "The Distribution of Realized Stock Return Volatility." *Journal of Financial Economics* 61 (July): 43-76.

Andersen, Torben, Tim Bollerslev, Francis X. Diebold, and Paul Labys. 2000. "Great Realizations." *Risk* 13 (March): 105-108.

Andersen, Torben, Tim Bollerslev, Francis X. Diebold, and Paul Labys. 2003. "Modeling and Forecasting Realized Volatility." *Econometrica* 71 (March): 579-625.

Barndorff-Nielsen, Ole E., Peter R. Hansen, Asger Lunde, and Neil Shephard. 2008. "Designing Realized Kernels to Measure the ex post Variation of Equity Prices in the Presence of Noise." *Econometrica* 76 (November): 1481-1536.

Boyd, Naomi, Bahattin Büyükşahin, Michael S. Haigh, and Jeffrey H. Harris. 2010. "The Prevalence, Sources and Effects of Herding in Futures Markets." Working paper, Commodity Futures Trading Commission.

Brown, Steven J., William N. Goetzmann, and James M. Park. 2000. "Hedge Funds and the Asian Currency Crisis of 1997." *Journal of Portfolio Management* 26 (Summer): 95-101.

Brunnermeier, Markus K., and Stefan Nagel. 2004. "Hedge Funds and the Technology Bubble." *Journal of Finance* 59 (October): 2013-2040.

Büyükşahin, Bahattin, Michael S. Haigh, Jeffrey H. Harris, Michel Robe, and James Overdahl. 2010. "Fundamentals, Trading Activity and Derivative Pricing." Working paper, Commodity Futures Trading Commission.

Büyükşahin, Bahattin, and Jeffrey H. Harris. 2010. Do Speculators Drive Crude Oil Futures Prices? *Energy Journal*. Forthcoming.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann. 1990. "Noise Trader Risk in Financial Markets." *Journal of Political Economy* 98 (August): 704-738.

Deuskar, Prachi, and Timothy C. Johnson. 2010. "Market Liquidity and Flow-Driven Risk." University of Illinois at Urbana-Champaign Working Paper.

Edwards, Franklin R. 1999. "Hedge Funds and the Collapse of Long Term Capital Management," *Journal of Economic Perspectives* 13 (Winter): 189-210.

Friedman, Milton. 1953. "The Case for Flexible Exchange Rates." In Essays in Positive Economics, University of Chicago Press, Chicago, 157-203.

Fung, William, and David A. Hsieh. 2000. "Measuring the Market Impact of Hedge Funds." *Journal of Empirical Finance*, 7 (May): 1-36.

Griffin, John M., Jeffrey H. Harris, Tao Shu and Selim Topaloglu, 2010, "Who Drove and Burst the Tech Bubble?," Working Paper.

Hasbrouck, Joel. 2003. "Intraday Price Formation in U.S. Equity Index Markets."*Journal of Finance* 58 (December): 2375-2400.

Hirshleifer, David A. 1989. "Determinants of Hedging and Risk Premia in Commodity Futures Markets." *Journal of Financial and Quantitative Analysis* 24 (September): 313-331.

Hirshleifer, David A. 1990. "Hedging Pressure and Futures Price Movements in a General Equilibrium Model." *Econometrica* 58 (March): 411-428.

Keynes, John M. 1923. "Some Aspects of Commodity Markets." Manchester Guardian Commercial, Reconstruction Supplement, in *The Collected Writings of John Maynard Keynes, Vol. 12*. London: Macmillan.

Lakonishok, Josef., Andrei. Shleifer and Robert W. Vishny. 1992. The impact of institutional trading on stock prices. *Journal of Financial Economics* 32, 23–43.

Lux, Thomas. 1995. "Herd Behaviour, Bubbles and Crashes." *The Economic Journal* 105 (July): 881-896

Pesaran, H. Hashem, and Yongcheol Shin. 1998. "Generalized Impulse Response Analysis in Linear Multivariate Models." *Economics Letters* 58 (January): 17-29.

Shiller, Robert J. 2003. "From Efficient Markets Theory to Behavioral Finance." *Journal of Economic Perspectives* 17 (Winter): 83-104.

Shleifer, Andrei and Lawrence H. Summers. 1990. "The Noise Trader Approach to Finance." *The Journal of Economic Perspectives* 4 (Spring): 19-33.

Stock, James H., and Motohiro Yogo. 2005. Testing for Weak Instruments in Linear IV Regression, in D.W.K. Andrews and J.H. Stock, eds., *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, Cambridge: Cambridge University Press, 80–108.

Zhang, Lan, Per A. Mykland, and Yacine Aït-Sahalia. 2005. "A Tale of Two Time Scales: Determining Integrated Volatility with Noisy High Frequency Data." *Journal of the American Statistical Association* 100 (December): 1394-1411.

## Table I: Descriptive Statistics

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Panel A: Crude Oil – January 2005-March 2009 – 1047 obs. | | | | | | | |
| | Returns | Volatility | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund |
| Mean | -0.046 | 3.803 | -64.21 | 512.7 | 146.62 | -159.69 | -1285 |
| Median | 0.059 | 2.171 | 306.0 | 272.0 | 18 | -492 | -1295 |
| Std.Dev. | 2.514 | 4.556 | 6783 | 3162 | 2228.9 | 8207.6 | 6644 |
| Panel B: Natural Gas – January 2005-March 2009 – 1053 obs. | | | | | | | |
| | Returns | Volatility | Merchant | Producer | Floor Broker | Swap Dealer | Hedge Fund |
| Mean | -0.188 | 5.278 | 89.89 | 6.549 | 64.73 | -381.8 | -70.39 |
| Median | -0.157 | 3.927 | 26.00 | 0.000 | 39.00 | -510.0 | -246.0 |
| Std.Dev. | 3.056 | 4.465 | 1429 | 428.4 | 1442 | 2867 | 3423 |
| Panel C: Corn – August 2006-March 2009 – 646 obs. | | | | | | | |
| | Returns | Volatility | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund |
| Mean | 0.025 | 3.153 | 868.2 | -116.6 | -208.0 | -328.7 | -362.8 |
| Median | 0.000 | 2.535 | 830.5 | -152.5 | -151.5 | -620.0 | -423.3 |
| Std.Dev. | 2.303 | 2.306 | 6669 | 1400 | 4191 | 7937 | 6918 |
| Panel D: Eurodollar – January 2005-May 2008 – 1045 obs. | | | | | | | |
| | Returns | Volatility | Arbitrageur | US Banks | Floor Broker | Non US Banks | Hedge Fund |
| Mean | 0.000 | 0.003 | -555.1 | 476.9 | 933.4 | 202.3 | -35.45 |
| Median | 0.000 | 0.001 | 16.00 | 443.0 | 686.0 | 115.0 | -1148 |
| Std.Dev. | 0.059 | 0.005 | 15625 | 13035 | 14571 | 12341 | 25395 |
| Panel E: Mini-Dow – January 2005-May 2008 – 1038 obs. | | | | | | | |
| | Returns | Volatility | Arbitrageur | Other Fin'l. | Floor Broker | Com'l. Funds | Hedge Fund |
| Mean | -0.044 | 1.303 | 116.7 | 12.16 | 15.66 | -77.66 | -45.63 |
| Median | 0.043 | 0.363 | 222.0 | 10.00 | -65.50 | -3.000 | -28.00 |
| Std.Dev. | 1.442 | 3.189 | 2912 | 547.1 | 1972 | 1750 | 2707 |

*Notes. Volatility refers to the two-scale realized volatility estimator of Zhang et al.(2005). Trader positions refer to net (futures long minus futures short) daily changes.*

## Table II: Long/Short Percentage of Total Open Interest

Panel A: Crude Oil

| | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Funds | Total Mean | Total Max | Total Min |
|---|---|---|---|---|---|---|---|---|
| Long | 0.074 | 0.010 | 0.021 | 0.417 | 0.233 | 0.754 | 0.878 | 0.524 |
| Short | 0.296 | 0.102 | 0.048 | 0.064 | 0.224 | 0.734 | 0.849 | 0.576 |

Panel B: Natural Gas

| | Merchant | Producer | Floor Broker | Swap Dealer | Hedge Funds | Total Mean | Total Max | Total Min |
|---|---|---|---|---|---|---|---|---|
| Long | 0.074 | 0.008 | 0.024 | 0.385 | 0.286 | 0.777 | 0.912 | 0.623 |
| Short | 0.159 | 0.027 | 0.046 | 0.069 | 0.567 | 0.868 | 0.999 | 0.686 |

Panel C: Corn

| | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Funds | Total Mean | Total Max | Total Min |
|---|---|---|---|---|---|---|---|---|
| Long | 0.053 | 0.034 | 0.058 | 0.413 | 0.198 | 0.756 | 0.847 | 0.611 |
| Short | 0.437 | 0.048 | 0.087 | 0.016 | 0.159 | 0.746 | 0.845 | 0.634 |

Panel D: Eurodollar

| | Arbitrageur | US Bank | Floor Broker | Non-US Bank | Hedge Fund | Total Mean | Total Max | Total Min |
|---|---|---|---|---|---|---|---|---|
| Long | 0.143 | 0.037 | 0.043 | 0.088 | 0.125 | 0.435 | 0.680 | 0.211 |
| Short | 0.241 | 0.073 | 0.020 | 0.127 | 0.122 | 0.584 | 0.798 | 0.391 |

Panel E: eMini-Dow

| | Arbitrageur | Other Fin'l | Floor Broker | Com'l Fund | Hedge Fund | Total Mean | Total Max | Total Min |
|---|---|---|---|---|---|---|---|---|
| Long | 0.295 | 0.015 | 0.107 | 0.163 | 0.098 | 0.677 | 0.873 | 0.346 |
| Short | 0.280 | 0.028 | 0.149 | 0.059 | 0.082 | 0.599 | 0.803 | 0.274 |

*Notes. Total Mean, Max, Min refers to mean, maximum and minimum, respectively, of the sum of the open interest of the five categories of market participants in each market. It indicates the percentage of total open interest jointly held by these five categories of traders.*

## Table III: Correlations – Net Futures Positions

| Panel A: Crude Oil | | | | | |
|---|---|---|---|---|---|
| | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund |
| Returns | -0.061* | -0.139** | -0.082** | 0.051 | 0.319** |
| Volatility | -0.032 | -0.051 | 0.021 | 0.062* | -0.031 |
| Manufacturer | 0.251** | 1 | | | |
| Floor Broker | 0.023 | 0.038 | 1 | | |
| Swap Dealer | -0.644** | -0.411** | -0.182** | 1 | |
| Hedge Fund | -0.231** | -0.232** | -0.119** | -0.252** | 1 |

| Panel B: Natural Gas | | | | | |
|---|---|---|---|---|---|
| | Merchant | Producer | Floor Broker | Swap Dealer | Hedge Fund |
| Returns | -0.184** | -0.199** | -0.231** | 0.019 | 0.181** |
| Volatility | 0.074** | 0.052 | 0.008 | -0.062* | 0.022 |
| Producer | 0.092** | 1 | | | |
| Floor Broker | 0.143** | 0.051 | 1 | | |
| Swap Dealer | -0.341** | -0.173** | -0.181** | 1 | |
| Hedge Fund | -0.082** | -0.081** | -0.301** | -0.621** | 1 |

| Panel C: Corn | | | | | |
|---|---|---|---|---|---|
| | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund |
| Returns | -0.372** | -0.289** | 0.052 | 0.002 | 0.451** |
| Volatility | 0.011 | -0.051 | 0.081* | -0.071 | -0.011 |
| Manufacturer | 0.342** | 1 | | | |
| Floor Broker | 0.052 | 0.023 | 1 | | |
| Swap Dealer | -0.543** | -0.229** | -0.459** | 1 | |
| Hedge Fund | -0.512** | -0.311** | -0.091** | -0.129** | 1 |

| Panel D: Eurodollar | | | | | |
|---|---|---|---|---|---|
| | Arbitrageurs | US Bank | Floor Broker | Non-US Bank | Hedge Fund |
| Returns | -0.202** | 0.041 | 0.011 | -0.073** | 0.192** |
| Volatility | -0.042 | 0.009 | -0.017 | 0.01 | -0.026 |
| US Bank | -0.082** | 1 | | | |
| Floor Broker | -0.024 | -0.061* | 1 | | |
| Non-US Bank | -0.073** | -0.013 | 0.122** | 1 | |
| Hedge Fund | -0.331** | -0.219** | 0.131** | -0.091** | 1 |

| Panel E: eMini-Dow | | | | | |
|---|---|---|---|---|---|
| | Arbitrageur | Other Fin'l. | Floor Broker | Com'l. Funds | Hedge Fund |
| Returns | 0.13** | -0.301** | -0.104** | 0.001 | 0.212** |
| Volatility | -0.01 | -0.011 | -0.031 | 0.019 | 0.003 |
| Other Financial | -0.09** | 1 | | | |
| Floor Broker | -0.06* | 0.029 | 1 | | |
| Com'l. Funds | -0.12** | 0.021 | -0.481** | 1 | |
| Hedge fund | -0.50** | -0.253** | -0.227** | 0.003 | 1 |

*Notes. Asterisks mark rejection at the 5%(**) and 10% (*) significance levels, respectively, indicating that the correlation coefficients are significantly different from zero.*

**Table IV: Granger non-Causality Test: Returns and Changes in Net Futures Positions**

Panel A: Crude Oil – Optimal Lag-Length (5)

| | Returns | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund | All |
|---|---|---|---|---|---|---|---|
| Returns | | 0.253 | 0.211 | 0.218 | 0.362 | 0.533 | 0.199 |
| Merchant | 0.000** | | 0.317 | 0.420 | 0.011** | 0.016** | 0.000** |
| Manufacturer | 0.000** | 0.004** | | 0.052* | 0.000** | 0.003** | 0.000** |
| Floor Broker | 0.017** | 0.353 | 0.416 | | 0.011** | 0.252 | 0.000** |
| Swap Dealer | 0.001** | 0.195 | 0.000** | 0.217 | | 0.590 | 0.000** |
| Hedge Fund | 0.013** | 0.427 | 0.433 | 0.380 | 0.030** | | 0.000** |
| Total | 0.000** | 0.001** | 0.000** | 0.067* | 0.000** | 0.086* | |

Panel B: Natural Gas – Optimal Lag-Length (3)

| | Returns | Merchant | Producer | Floor Broker | Swap Dealer | Hedge Fund | All |
|---|---|---|---|---|---|---|---|
| Returns | | 0.448 | 0.403 | 0.345 | 0.503 | 0.666 | 0.571 |
| Merchant | 0.206 | | 0.013** | 0.913 | 0.009** | 0.841 | 0.000** |
| Producer | 0.124 | 0.301 | | 0.908 | 0.000** | 0.303 | 0.000** |
| Floor Broker | 0.019** | 0.106 | 0.001** | | 0.194 | 0.308 | 0.000** |
| Swap Dealer | 0.000** | 0.385 | 0.000** | 0.502 | | 0.535 | 0.000** |
| Hedge Fund | 0.036** | 0.025** | 0.000** | 0.889 | 0.652 | | 0.000** |
| Total | 0.000** | 0.000** | 0.000** | 0.923 | 0.000** | 0.240 | |

Panel C: Corn – Optimal Lag-Length (5)

| | Returns | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund | All |
|---|---|---|---|---|---|---|---|
| Returns | | 0.285 | 0.777 | 0.823 | 0.799 | 0.394 | 0.442 |
| Merchant | 0.004** | | 0.388 | 0.591 | 0.544 | 0.892 | 0.002** |
| Manufacturer | 0.633 | 0.745 | | 0.899 | 0.910 | 0.861 | 0.960 |
| Floor Broker | 0.799 | 0.056* | 0.001** | | 0.059 | 0.047* | 0.000** |
| Swap Dealer | 0.355 | 0.607 | 0.000** | 0.352 | | 0.948 | 0.000** |
| Hedge Fund | 0.240 | 0.327 | 0.001** | 0.957 | 0.101 | | 0.000** |
| Total | 0.101 | 0.018** | 0.000** | 0.483 | 0.563 | 0.158 | |

Panel D: Eurodollar – Optimal Lag-Length (4)

| | Returns | Arbitrageur | US Bank | Floor Broker | Non-US Bank | Hedge Fund | All |
|---|---|---|---|---|---|---|---|
| Returns | | 0.174 | 0.203 | 0.165 | 0.226 | 0.315 | 0.478 |
| Arbitrageur | 0.380 | | 0.727 | 0.051* | 0.671 | 0.924 | 0.144 |
| US Bank | 0.254 | 0.511 | | 0.139 | 0.861 | 0.27 | 0.196 |
| Floor Broker | 0.731 | 0.020** | 0.173 | | 0.439 | 0.228 | 0.239 |
| Non-US Bank | 0.381 | 0.897 | 0.001** | 0.100 | | 0.654 | 0.000** |
| Hedge Fund | 0.548 | 0.005** | 0.301 | 0.005** | 0.594 | | 0.001** |
| Total | 0.495 | 0.000** | 0.001** | 0.004** | 0.169 | 0.411 | |

Panel E: eMini-Dow – Optimal Lag-Length (3)

| | Returns | Arbitrageur | Other Fin'l. | Floor Broker | Com'l. Fund | Hedge Fund | All |
|---|---|---|---|---|---|---|---|
| Returns | | 0.057* | 0.010** | 0.471 | 0.221 | 0.071 | 0.026** |
| Arbitrageur | 0.097* | | 0.818 | 0.658 | 0.590 | 0.007** | 0.000** |
| Other Fin'l. | 0.165 | 0.261 | | 0.171 | 0.518 | 0.191 | 0.232 |
| Floor Broker | 0.237 | 0.762 | 0.219 | | 0.918 | 0.350 | 0.521 |
| Com'l. Fund | 0.07* | 0.588 | 0.000** | 0.434 | | 0.283 | 0.000** |
| Hedge Fund | 0.09* | 0.102 | 0.444 | 0.250 | 0.332 | | 0.004** |
| Total | 0.038** | 0.089* | 0.000** | 0.362 | 0.360 | 0.008** | |

*Notes. The table reports p-values of the Granger-causality test. Asterisks mark rejection at the 5% (**) and 10% (*) significance levels, respectively, indicating evidence of Granger causality.*

## Table V: Granger non-Causality Test: Volatility and Changes in Net Futures Positions

Panel A: Crude Oil – Optimal Lag-Length (5)

| | Volatility | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund | All |
|---|---|---|---|---|---|---|---|
| Volatility | | 0.066* | 0.062* | 0.025** | 0.001** | 0.072* | 0.000** |
| Merchant | 0.223 | | 0.209 | 0.117 | 0.064* | 0.000** | 0.000** |
| Manufacturer | 0.556 | 0.000** | | 0.023** | 0.000** | 0.000** | 0.000** |
| Floor Broker | 0.063 | 0.124 | 0.394 | | 0.098* | 0.596 | 0.000** |
| Swap Dealer | 0.001** | 0.185 | 0.000** | 0.242 | | 0.557 | 0.000** |
| Hedge Fund | 0.079* | 0.453 | 0.086* | 0.284 | 0.028** | | 0.000** |
| Total | 0.007** | 0.000** | 0.000** | 0.001** | 0.000** | 0.000** | |

Panel B: Natural Gas – Optimal Lag-Length (3)

| | Volatility | Merchant | Producer | Floor Broker | Swap Dealer | Hedge Fund | All |
|---|---|---|---|---|---|---|---|
| Volatility | | 0.974 | 0.476 | 0.066* | 0.065* | 0.667 | 0.052* |
| Merchant | 0.951 | | 0.001** | 0.996 | 0.014** | 0.865 | 0.000** |
| Producer | 0.169 | 0.105 | | 0.975 | 0.000** | 0.244 | 0.000** |
| Floor Broker | 0.477 | 0.154 | 0.001** | | 0.286 | 0.344 | 0.000** |
| Swap Dealer | 0.391 | 0.538 | 0.000** | 0.819 | | 0.139 | 0.000** |
| Hedge Fund | 0.044 | 0.015** | 0.000** | 0.976 | 0.354 | | 0.000** |
| Total | 0.344 | 0.002** | 0.000** | 0.879 | 0.000** | 0.437 | |

Panel C: Corn – Optimal Lag-Length (5)

| | Volatility | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund | All |
|---|---|---|---|---|---|---|---|
| Volatility | | 0.711 | 0.892 | 0.174 | 0.266 | 0.330 | 0.020** |
| Merchant | 0.034** | | 0.337 | 0.439 | 0.147 | 0.893 | 0.010** |
| Manufacturer | 0.222 | 0.722 | | 0.940 | 0.816 | 0.795 | 0.868 |
| Floor Broker | 0.011** | 0.022* | 0.000** | | 0.046** | 0.045** | 0.000** |
| Swap Dealer | 0.431 | 0.774 | 0.000** | 0.246 | | 0.906 | 0.000** |
| Hedge Fund | 0.839 | 0.168 | 0.001** | 0.973 | 0.234 | | 0.000** |
| Total | 0.004** | 0.013** | 0.000** | 0.500 | 0.158 | 0.148 | |

Panel D: Eurodollar – Optimal Lag-Length (5)

| | Volatility | Arbitrageur | US Bank | Floor Broker | Non-US Bank | Hedge Fund | All |
|---|---|---|---|---|---|---|---|
| Volatility | | 0.053* | 0.085* | 0.058* | 0.104 | 0.007** | 0.025** |
| Arbitrageur | 0.278 | | 0.192 | 0.668 | 0.370 | 0.279 | 0.059* |
| US Bank | 0.642 | 0.015** | | 0.285 | 0.754 | 0.211 | 0.373 |
| Floor Broker | 0.054* | 0.573 | 0.147 | | 0.592 | 0.047** | 0.084* |
| Non-US Bank | 0.575 | 0.153 | 0.021** | 0.079* | | 0.001** | 0.000** |
| Hedge Fund | 0.111 | 0.846 | 0.196 | 0.002** | 0.946 | | 0.002** |
| Total | 0.239 | 0.015** | 0.001** | 0.000** | 0.198 | 0.000** | |

Panel E: eMini-Dow– Optimal Lag-Length (4)

| | Volatility | Arbitrageur | Other Fin'l | Floor Broker | Com'l. Fund | Hedge Fund | All |
|---|---|---|---|---|---|---|---|
| Volatility | | 0.042** | 0.162 | 0.909 | 0.270 | 0.043** | 0.007** |
| Arbitrageur | 0.741 | | 0.799 | 0.651 | 0.153 | 0.008** | 0.001** |
| Other Fin'l. | 0.370 | 0.590 | | 0.275 | 0.640 | 0.335 | 0.435 |
| Floor Broker | 0.016** | 0.583 | 0.213 | | 0.118 | 0.530 | 0.011** |
| Com'l. Fund | 0.069* | 0.138 | 0.000** | 0.474 | | 0.389 | 0.000** |
| Hedge Fund | 0.359 | 0.134 | 0.770 | 0.325 | 0.348 | | 0.043** |
| Total | 0.110 | 0.089* | 0.000** | 0.617 | 0.010** | 0.008** | |

*Notes. The table reports p-values of the Granger-causality test. Asterisks mark rejection at the 5% (**) and 10% (*) significance levels, respectively, indicating evidence of Granger causality.*

## Table VI: OLS and IV Estimates of Realized Volatility on Trader Positions

| | | | | | | |
|---|---|---|---|---|---|---|
| | | **Panel A: Crude Oil** | | | | |
| | | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund |
| OLS | Coeff. | 3.52e-4** | 2.11e-4 | 6.24e-4** | -2.29e-4** | -2.44e-4 |
| | | (9.22e-5) | (1.99e-4) | (2.19e-4) | (7.64e-5) | (9.33e-4) |
| | $R^2$ (%) | 77.59 | 77.29 | 77.37 | 77.46 | 77.41 |
| IV | Coeff. | 2.71e-4** | 6.18e-5 | 5.41e-4** | -1.20e-4 | -2.88e-4** |
| | | (1.01e-4) | (2.05e-4) | (2.73e-4) | (9.17e-5) | (8.31e-5) |
| | F-Stat | 113.1 | 46.08 | 9.948 | 321.5 | 16.38 |
| | | **Panel B: Natural Gas** | | | | |
| | | Merchant | Producer | Floor Broker | Swap Dealer | Hedge Fund |
| OLS | Coeff. | 2.07e-3** | 4.74e-4 | -1.91e-4 | -9.02e-4** | 2.41e-4 |
| | | (8.93e-4) | (2.95e-4) | (8.17e-4) | (4.53e-4) | (3.13e-4) |
| | $R^2$ (%) | 32.75 | 32.39 | 32.39 | 32.65 | 32.42 |
| IV | Coeff. | 1.76e-3* | -1.26e-4 | -2.94e-4 | -6.43e-4 | -8.29e-05** |
| | | (9.73e-4) | (2.54e-3) | (7.63e-4) | (5.19e-4) | (3.60e-5) |
| | F-Stat | 34.40 | 17.72 | 8.6691 | 117.67 | 43.11 |
| | | **Panel C: Corn** | | | | |
| | | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund |
| OLS | Coeff. | 5.44e-5 | -4.50e-4 | 3.38e-4 | -1.86e-4 | 3.63e-5 |
| | | (1.51e-4) | (7.12e-4) | (2.50e-4) | (1.31e-4) | (1.60e-4) |
| | $R^2$ (%) | 45.74 | 45.76 | 45.89 | 45.91 | 45.73 |
| IV | Coeff. | 1.37e-5 | -5.11e-4 | 2.95e-4 | -1.45e-4 | -3.57e-5 |
| | | (1.66e-4) | (7.55e-4) | (2.84e-4) | (1.72e-4) | (1.53e-4) |
| | F-Stat | 33.38 | 12.276 | 14.082 | 70.70 | 10.092 |
| | | **Panel D: Eurodollar** | | | | |
| | | Arbitrageur | US Bank | Floor Broker | Non-US Bank | Hedge Fund |
| OLS | Coeff. | -2.08e-4** | -1.82e-4 | 5.22e-5 | 1.18e-4 | 2.12e-5 |
| | | (9.36e-5) | (1.12e-4) | (1.00e-4) | (1.18e-4) | (5.78e-5) |
| | $R^2$ (%) | 62.55 | 62.46 | 62.37 | 62.40 | 62.36 |
| IV | Coeff. | 2.26e-4** | -1.76e-4 | 5.86e-5 | 1.17e-4 | 2.51e-5 |
| | | (1.02e-4) | (1.31e-4) | (7.45e-5) | (1.07e-4) | (6.23e-5) |
| | F-Stat | 1.6155 | 1.5651 | 15.827 | 3.4869 | 14.396 |
| | | **Panel E: eMini-Dow** | | | | |
| | | Arbitrageur | Other Financial | Floor Broker | Com'l Fund | Hedge Fund |
| OLS | Coeff. | -1.07e-3** | 8.91e-3** | 1.29e-3* | -3.66e-5 | -1.22e-4 |
| | | (4.12e-4) | (2.50e-3) | (6.88e-4) | (7.83e-4) | (5.02e-4) |
| | $R^2$ (%) | 86.45 | 86.56 | 86.43 | 86.38 | 86.44 |
| IV | Coeff. | -1.10e-3* | 8.92e-3** | 1.30e-3* | -2.48e-5 | -1.42e-3** |
| | | (5.76e-4) | (2.73e-3) | (7.98e-4) | (9.29e-4) | (4.86e-4) |
| | F-Stat | 21.111 | 18.735 | 5.8920 | 10.619 | 50.442 |

*Notes. The tables reports OLS and Instrumental Variables estimates of the contemporaneous effect of trader position changes (in absolute value) on volatility. Asterisks mark rejection at the 5% (**), and 10% (*) significance levels, respectively, indicating that the coefficients are significantly different from zero. The F-statistics in excess of 8.96 indicates that the change in the number of reporting traders is a valid instrument.*

## Table VII: Lakonishok, Shleifer and Vishny (1992) Measure of Herding

| | | | | | |
|---|---|---|---|---|---|
| | | | Panel A: Crude Oil | | |
| | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund |
| Mean | 0.011** | -0.026** | 0.000 | 0.011** | 0.011** |
| Corr. Ret. | -0.208** | 0.065** | 0.217** | -0.104** | 0.241** |
| Corr. Vol. | 0.303** | -0.029 | -0.170** | -0.100** | -0.229** |
| | | | Panel B: Natural Gas | | |
| | Merchant | Producer | Floor Broker | Swap Dealer | Hedge Fund |
| Mean | 0.042** | 0.021** | 0.002 | 0.080** | 0.050** |
| Corr. Ret. | -0.361** | -0.105** | 0.086** | 0.138** | -0.095** |
| Corr. Vol. | 0.220** | -0.029 | 0.085** | -0.047 | 0.005 |
| | | | Panel C: Corn | | |
| | Merchant | Manufacturer | Floor Broker | Swap Dealer | Hedge Fund |
| Mean | 0.098** | 0.032** | 0.004 | 0.011** | 0.020** |
| Corr. Ret. | 0.375** | 0.026 | 0.115** | 0.122** | 0.228** |
| Corr. Vol. | -0.256** | -0.037 | -0.104** | -0.058 | -0.107** |
| | | | Panel D: Eurodollar | | |
| | Arbitrageur | US Banks | Floor Broker | Non US Banks | Hedge Fund |
| Mean | 0.012** | 0.023** | 0.001 | 0.010** | 0.012** |
| Corr. Ret. | -0.086** | 0.017 | -0.003 | -0.054 | 0.160** |
| Corr. Vol. | -0.056 | -0.001 | -0.035 | 0.048 | 0.048 |
| | | | Panel E: eMini-Dow | | |
| | Arbitrageur | Other Fin. | Floor Broker | Com'l. Funds | Hedge Fund |
| Mean | -0.029** | -0.126** | 0.006 | -0.125** | -0.040** |
| Corr. Ret. | 0.012 | -0.109** | -0.085** | -0.021 | 0.004 |
| Corr. Vol. | -0.013 | -0.046 | -0.001 | 0.047 | 0.011 |

*Notes. 'Mean' refers to the arithmetic mean of the herding measure. 'Corr.Ret.' refers to the correlation between herding measures and rate of returns. 'Corr.Vol.' refers to the correlation between herding measures and volatility. Asterisks mark rejection at the 5% (**), and 10% (*) significance levels, respectively, indicating that the coefficients are significantly different from zero.*

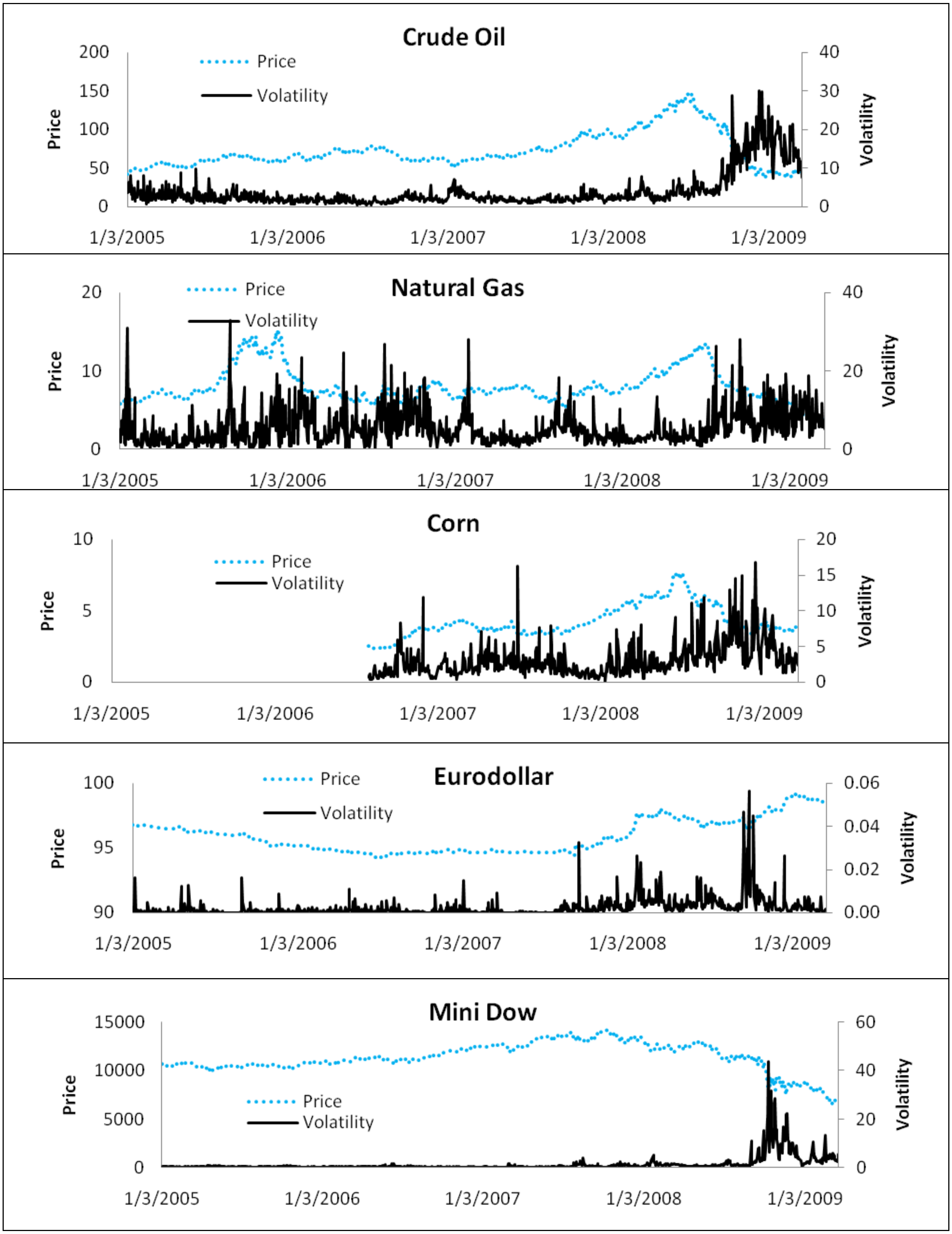


**Figure I: Price and Realized Volatility**

The figure plots prices and realized volatility over the sample period January 2005 – March 2009.

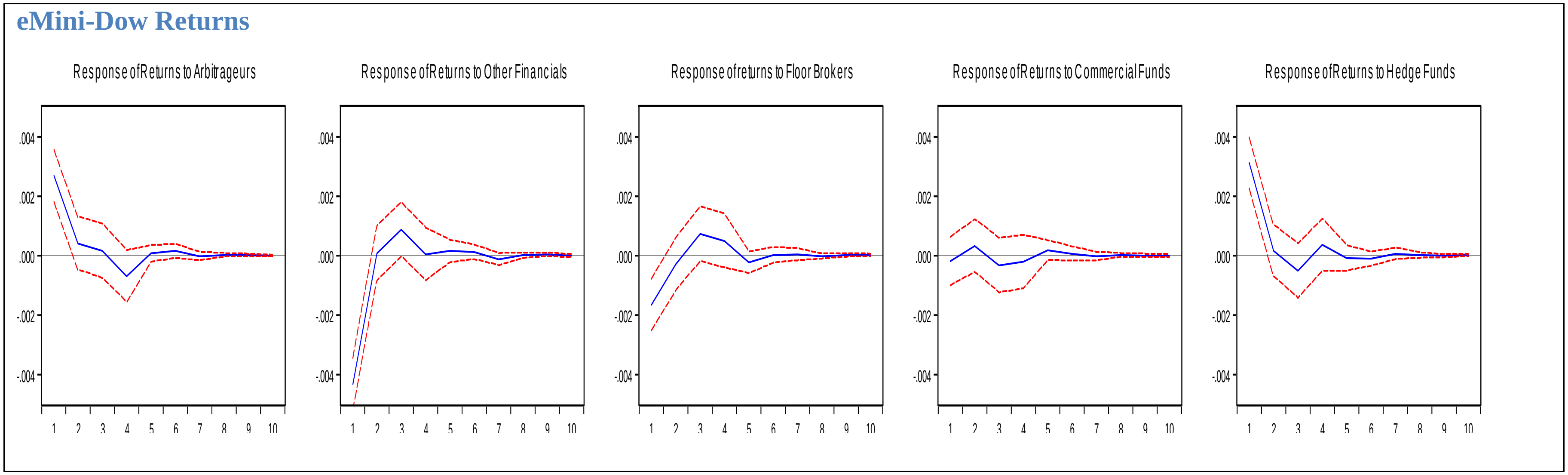


**Figure II: Impulse Response of Returns**

The figure plots generalized impulse responses of returns to one standard deviation innovations in trader position changes for the eMini-Dow futures market.

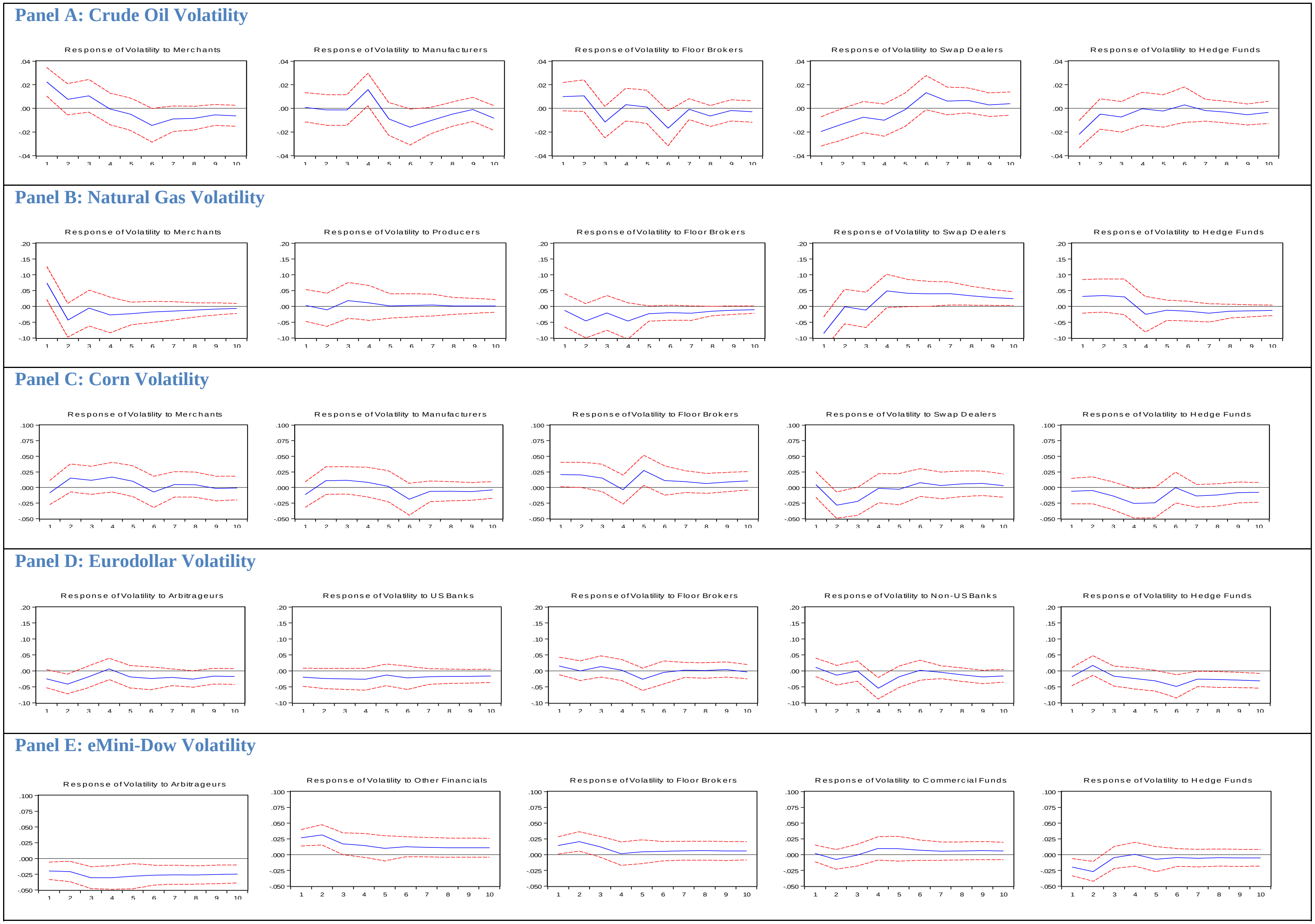


**Figure III: Generalized Impulse Response of Volatility**

The figure plots generalized impulse response of realized volatility to one standard deviation innovations in trader position changes.

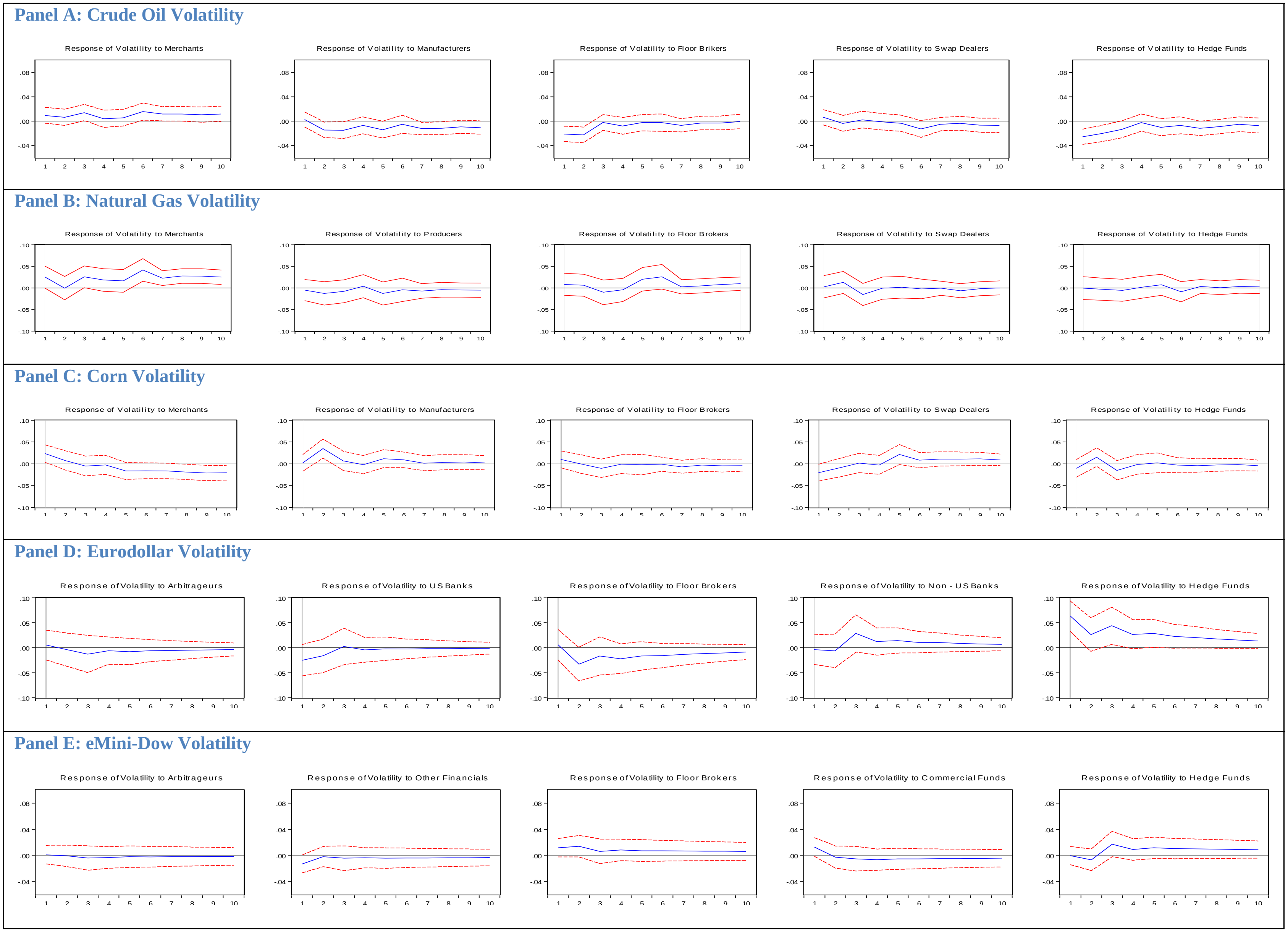


**Figure IV: Generalized Impulse Response of Volatility to Herding Measures**

The figure plots generalized impulse response of realized volatility to one standard deviation innovations in herding measures.

## Appendix: **Contract Specifications**

| | Crude Oil (CL) | Natural Gas (NG) | Corn (C) | EuroDollars (ED) | eMini-Dow (YM) |
|---|---|---|---|---|---|
| Exchange | NYMEX | NYMEX | CBOT | CME | CBOT |
| Trading Unit | 1000 US barrel | 10,000 mmBtu | 5000 bushels | Eurodollar time deposit having a principal value of 1 million with a 3-month maturity | 1 mini-sized Dow futures |
| Trading Hours (EST): | | | | | |
| Open Outcry: | 9:00 am-2:30pm | 9:00am-2:30pm | 10:30am-2:15pm | 8:20am-3pm | N/A |
| Electronic | 6:00pm-5:15pm | 6:00pm-5:15pm | 7:00pm-7am and 10:30am-2:15pm | 6:00pm-5:00pm | 6:00pm-4:15pm, and 4:30pm-5:30pm |
| Trading months | Consecutive months in the current year and the next five years as well as June and December contracts are beyond sixth year | Consecutive months in the current year and the next twelve years | Dec, Mar, May, Jul and Sep | Mar, Jun, Sep, Dec, forty months in March quarterly cycle, and the four nearest serial contract months | Mar, Jun, Sep, Dec |
| Minimum Price Fluctuations | $0.01 per barrel ($10 per contract) | $0.01 per mmBtu ($10 per contract) | 1/4 cent/bushel ($12.50/contract) | $12.50 per contract<br><br>($6.25 for nearest expiring contract) | Minimum price increment is one index point (equal to $5 per contract). |
| Settlement Type | Physical | Physical | Physical | Cash | Cash |
| Last Trading Day | Trading terminates at the close of business on the third business day prior to the 25th calendar day of the month preceding the delivery month. | Trading terminates three business days prior to the first calendar day of the delivery month. | The business day prior to the 15th calendar day of the contract month. | Futures trading shall terminate at 5:00a.m. (Chicago Time on the second London bank business day before the third Wednesday of the contract month. | Trading can occur up to 8:30 a.m. on the 3rd Friday of the contract month. |
| Daily average (max-min) number of contract traded | 39,498 (182,330-837) | 7,943 (61,860-302) | 21,041* (96,391-942) | 8,355 (33,641-725) | 73,022* (321,700-1,110) |

*Notes. Asterisk indicates that electronic trading occurs only during times when open outcry is trading (9:30am – 4:00pm EST for eMini-Dow).*