Speculators, Prices and Market Volatility

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Abstract

We employ detailed trader data over 2005-2009 from the U.S. Commodity Futures Trading Commission (CFTC) to test whether speculators—hedge funds and swap dealers—cause price movements or volatility in futures markets. We find little evidence that speculator trades destabilize futures markets. To the contrary, speculative trading activity largely reacts to past-day events and reduces volatility levels, consistent with the hypothesis that speculators provide valuable liquidity to the market.

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

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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

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. The U.S.

[1] The 2010 Dodd-Frank financial reform legislation proscribes various oversight measures for swap dealers.

Commodity Futures Trading Commission (CFTC) collects daily position data from all large market participants, classifying traders by line of business and separating commercial 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 2003-2009. 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 between daily futures market returns and positions of the five most

[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*.

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.

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. 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. 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 alternative specifications where we employ OLS and instrumental variables to explain the contemporaneous causal relation between realized volatility and changing trader positions as well. We find that hedge fund and swap dealer position changes generally serve to reduce contemporaneous market volatility. We also explore the lead-lag relations between herding (as an alternative metric of speculative activity) and both returns and volatility and consistently fail to find evidence that speculative activity systematically affects prices or volatility. In fact, 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 speak to 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. Although we do not measure hedge premia directly, speculative activity that reduces volatility levels will, in turn, reduce the cost of hedging. 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.[4] Our results suggest that the informative futures market trades in these studies likely do not emanate from speculators. Interestingly we find that commercial dealer and merchant trades lead to increased volatility levels. These results are consistent with commercial dealers and merchants bringing fundamental information about the underlying commodity to the futures markets.

The remainder of the paper proceeds as follows. In section I we describe our data. In section II 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 III we analyze Granger-causality tests

[4] See Hasbrouck (2003).

between trader positions and rate of return as well as positions and volatility. In section IV we analyze contemporaneous causality between volatility and traders positions and in section V we measure herding and investigate whether herding affects prices and volatility. We conclude in section VI.

I. 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]

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 1, 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

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

back near $4 by the end of our sample. Many have attributed these price movements to speculative activity.[7]

Conversely, since the inception of the so-called sub-prime crisis, interest rate markets have experienced a decline in open interest. The Eurodollar futures market is no exception. During our sample, the open interest for three-month Eurodollar futures declined from a peak of 12 million to 9 million contracts. Likewise, the sub-prime crisis has generally weighed heavily on the eMini-Dow futures market as well. We include these markets for a richer cross-section of futures activity where speculators remain active.

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. 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.

A. Futures Market Return Data

We obtain futures prices from both electronic and open outcry sessions. Both crude oil and natural gas futures contracts are dually-traded electronically and via open outcry. Corn futures trade on both the open outcry and electronic platforms. While Eurodollar futures trade via open outcry during the day, electronic trading occurs around the clock. Importantly, our analysis includes daily position changes reported at the close of open outcry sessions, but includes

[7] Indeed, during our sample period Amaranth, a hedge fund, has been formally charged with manipulating natural gas prices. While our results apply generally, we do not analyze specific traders or short-term events such as are typically pursued in manipulation cases.

changes across all trading platforms. 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.[8] 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% annually), a positive median, high standard deviation and mean revert. The unconditional distribution is non-Gaussian with negative skew and kurtosis above three. Natural gas exhibits a significant negative average daily returns (-47% 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% 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% annually), negative skew and excess kurtosis.

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

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

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 pit trading data can be problematic. For instance, the corn pit data we analyzed 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 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. 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 ith 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 in day t is the sum of squared intraday returns sampled at frequency m.

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

[9] Alternatively, using the Barndorff-Nielsen et al. (2008) kernel estimator and the Andersen et al. (2001) low frequency sampling approach yields qualitatively similar results. These results are available upon request.

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

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

where k denotes the number of subintervals of size m and γ 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 1 depicts prices and *two scales realized volatility* measures for our five markets over time. 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

[10] We choose the optimal sampling frequency m based on monthly volatility signature plots - see Andersen et al. (2000). Details on this procedure available upon request.

recession. Conversely, natural gas and corn exhibit relatively high variability throughout our sample period.

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. In the crude oil, natural gas and corn markets, we also analyze dealers/merchants (which include wholesalers, exporters/importers, shippers, etc.), commodity swap dealers, 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.

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

[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*).

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.[13] 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 by large amount (as might be expected from speculative trading groups).

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

[12] For completeness, we check the names of the funds in these four categories with those identified as hedge funds in press reports, and verify that our classifications concur with characterizations of these funds in the press.

[13] To conserve space we only report results for the net futures positions. Results for futures short, futures long and net total positions are qualitatively similar and available upon request.

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.

II. 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 also negatively correlated with crude oil volatility. Conversely, merchant positions are positively correlated with natural gas and corn volatility.

Examining speculators, we find no evidence of a contemporaneous link between swap dealer positions and returns. Swap dealer activity is negatively correlated with corn and natural gas volatility, but positively correlated with crude oil volatility. Hedge fund position changes are positively correlated with returns. However, hedge fund activity, when significant (for crude oil, natural gas and eMini-Dow), is negatively 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 but is negatively linked to volatility. Second, hedge fund activity is positively correlated with returns but weakly negatively correlated with volatility. Third, the correlation between position changes of hedge funds and swap dealers with other market participants is always negative.

III. Do Changing Trader Positions Cause Returns or Volatility?

Although suggestive, correlation analysis does not establish any causal relation between trader positions and either returns or volatility. We formally test for Granger causality between trader positions and returns, and trader positions and volatility in the context of Vector Autoregressive (VAR) models using Generalized Method of Moments (GMM) and Newey-West robust standard errors to accommodate heteroskedasticity and serial correlation in our variables.[14] We only report results for the optimal lag-length in each specification, although these results are robust and hold regardless of the lag structure in the VAR.[15]

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, although we also present tests for the interactions of each trader group. 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—a p-value greater than five percent

[14] 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. We report only results for the change in positions. Results for levels are nearly identical.
[15] We use Wald tests to select the optimal lag-length (i.e. test for the significance of the parameters of each lag). Given heteroskedasticity and serial correlation in our data, we could not rely on standard Akaike (AIC) and Schwartz Information Criteria (SIC). The optimal lag-length is always higher than that selected by AIC and SIC.

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 Figure 2.

Table IV presents Granger-causality tests between returns and position changes for each of the five markets we study. Panel A presents results for crude oil. Returns on the crude oil market are not Granger-caused by position changes of the full set of traders (p-value=0.199), nor of any individual trader group. On the other hand, 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 which does not jointly Granger-cause any other variable in the system (p-value=0.086). This implies that hedge fund activity does not provide any useful information for predicting either returns or the positions of other traders. 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 do not affect prices or the positions 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 other traders. In addition, natural gas producer activity appears to strongly influence the positions of other traders.

Corn returns appear to be largely insulated from changes in trader positions (see Panel C). Similar to the energy markets, hedge fund activity 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 (AM) 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 is caused by the other variables in the system (p-value 0.001) but hedge fund activity 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 hedgers and speculator (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 activity appears to be the driving force behind the connection between position changes and returns. Interestingly, commercial hedge fund activity does not exhibit significant effects on eMini-Dow returns. To further explore how trader position changes affect eMini-Dow returns, we compute impulse-responses depicting the 10-day return response to a one standard deviation innovation in trader position changes (see Figure 2, Panel A).[16] As Figure 2 shows, the trading activity of speculative hedge funds and dealer/arbitrageurs contribute to reversing the negative trend in the eMini-Dow over our sample period. On the other hand, financial institution (other financial) and floor broker/trader activities appear to contribute to the negative trend in stock returns during our sample period.[17]

B. Volatility and Trader Position Changes

[16] 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 and thus, not reported. Response standard errors are computed with 1,000 Monte Carlo replications.

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

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 I).[18] 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 influence volatility in the crude oil market.

Panel B of Table V reports results for the natural gas market. Natural gas volatility is marginally not Granger-caused by trader activity (p-value=0.052), nor is trader activity Granger-caused by volatility (p-value=0.344). For the corn market (Panel C), however, we find evidence of two-way Granger-causality between trader position changes and volatility. Swap dealer and hedge fund activity Granger-cause no variable in the system (p-values=0.158 and 0.148, respectively), but are caused by the other variables in the system (p-value=0.000 for both). Volatility in the Eurodollar market (Panel D) is Granger-caused by trading activity (p-value=0.025), including hedge fund. Notably, Eurodollar trader activity is not significantly affected by volatility. Similarly, eMini-Dow volatility is Granger-caused by positions (Panel E, p-value=0.007) and also by speculative hedge fund positions (p-value=0.043). Likewise, eMini-Dow trader activity is not significantly affected by volatility.

Given the consistent connection between trader position changes and volatility, we present impulse-responses for each market in Figure 2. We are particularly interested in the response of volatility to a shock to commodity swap dealer and hedge fund activity. The second column indicates that swap dealers significantly reduce volatility in the crude oil and natural gas markets (Panels B and C) and marginally reduce volatility in the corn market (Panel D). Likewise, hedge fund activity reduces volatility in the crude oil (Panel B) and eMini-Dow (Panel

[18] We confirm that logarithmic realized standard deviation is approximately Gaussian (see Andersen et al. (2003)). Our results are robust to the different measures of realized volatility considered.

F) markets (with no significant effect in the other markets). Notably, arbitrageurs/brokers also significantly reduce volatility in the Eurodollar and eMini-Dow markets. These facts provide further evidence that speculators do not destabilize markets, but rather serve to buffet volatility brought to bear by other traders, and in the spirit of Friedman (1953), buy when the price is falling and sell when the price is rising.

In fact, these impulse-response functions demonstrate that merchant (hedger) position changes have a positive impact on volatility in crude oil and natural gas markets. Likewise, 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, thus generating higher volatility.

It is interesting to contrast the impulse responses for the eMini-Dow presented in Figures 2. Hedge funds and arbitrageur/dealers that change positions against the return trend are the same traders which significantly reduce market volatility. 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 between returns and trader activities yields two main results. First, returns are not Granger-caused by position changes, with the notable exception in the stock market where we find that speculative hedge fund activity has a positive impact on a bearish market; speculative activity actually reverses the trend in the equity market. Second, hedge fund activity does not Granger-cause returns and/or positions of other market traders, but it is in fact Granger-caused by the other variables in the system. These results are particularly important since they suggest that speculation does not destabilize prices across a variety of markets during historically volatile times. Speculation in general, and hedge fund activity more specifically, seems to respond to market conditions but does not move the market nor the trading activity of other traders. Although Granger-causality tests have limitations, our results are very robust. Using position levels and changes with various volatility measures in numerous VAR specifications, we consistently find that speculator positions do not systematically lead price changes.

Does speculation increase market volatility? It is possible that speculation activity may have no impact on prices, but it might have an impact on market volatility. With the exception of corn, we find that speculative trading activity leads to significantly lower volatility. In particular, hedge fund activity is linked to lower volatility. Likewise, commodity swap dealers appear to reduce volatility in the crude oil and natural gas markets.

IV. Contemporaneous Volatility and Trader Position Changes

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 may be that causation occurs contemporaneously within the same trading day. Therefore we also test for a contemporaneous causal relation between realized volatility and trader positions with the following equation:

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

where $RV_{i,t}$ is the (log) *two scales realized volatility* in market i at time t, $\Delta TP_{i,j,t}$ is 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 β which measures the 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 β 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. We then estimate Equation (1) using Limited Information Maximum Likelihood (LIML) procedure.[19]

Table VI reports estimation results for the instrumental variable regressions which are in line with the Granger-causality analysis above. Interestingly merchant activity increases volatility in the crude oil and natural gas markets (but not in corn). Likewise, floor broker activity increases volatility in the crude oil and eMini-Dow markets. Financial institution activity also increases volatility in the eMini-Dow market.

Notably, swap dealer activity is largely unrelated to contemporaneous volatility, and where significant in OLS specifications, swap dealer activity is associated with lower volatility levels. More importantly, perhaps, is the fact that hedge fund activity has a significant negative impact on volatility in the crude oil, natural gas and eMini-Dow markets. We find little evidence that swap dealer or hedge fund activity destabilize these markets. On the contrary, swap dealer and hedge fund activity is more likely to reduce contemporaneous volatility in futures markets.

V. 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

[19] 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.

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. [20] We consider the herding metric an alternative measure of speculative activity that excludes effects of a dominant trader.

The herding metric measures the difference between the number of net buyers (or sellers) from each trader category 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 hedge funds (index 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. We only compute herding for floor brokers/traders and hedge funds since traders that hedge seldom change positions, making the herding measure for hedgers largely undefined at the daily level.

Table VII shows mean and median values for the herding measure. The mean value for each commodity and for both floor brokers/traders and hedge funds are fairly small, but statistically different from zero. For example, in the crude oil market, the average herding for hedge funds is 4.42%, implying that 54.42% of hedge funds increased positions while 45.58% decreased positions on the average day. The largest average value for the herding measure is in the corn market for floor brokers/traders (8.83%).[21] Median herding metrics are always lower than the average, suggesting a positive skew to the data and that some days exhibit markedly higher herding.

Table VIII shows the daily correlations of herding with price changes and volatility for each of the five markets. Notably, we see that herding among hedge funds is largely negatively related to returns and volatility, indicating that hedge fund herding is largely countercyclical and commonly stabilizes market prices. These results suggest that the Granger-causality results we

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

document above stem more generally from hedge fund position changes and not from a dominant hedge fund. Herding among floor brokers/traders is also negatively correlated with volatility for the crude oil, natural gas and corn markets. However, floor broker/trader herding is positively correlated to returns in the crude oil, Eurodollar and eMini-Dow markets.

To further investigate the effects of speculation on returns and volatilities, we run Granger-non-causality tests (similar to those reported in Section III), using herding as an alternative measure of speculative activity. We find no significant link between returns and the herding among floor brokers/traders or hedge funds in any of the five markets we analyze.

Table IX reports Granger-causality results for volatility and herding. For crude oil, natural gas and corn there is some limited evidence that volatility is Granger-caused by herding among these trader groups. To further investigate this issue, we compute generalized impulse responses and present results in Figure 3. For floor brokers/traders a one standard deviation shock to herding does not have any significant impact on volatility. Likewise, a one standard deviation shock to hedge fund herding has almost no significant effect on volatility. However, when hedge fund herding does have a significant effect, the herding among hedge funds serves to reduce volatility levels (see panels B and C).

VI. 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 instrumental variable approaches, we find that speculative groups like hedge funds and commodity swap dealers do not cause prices to change, but rather serve to reduce market volatility. As a whole, these speculative traders provide liquidity and do not destabilize futures markets, but more commonly make market prices more robust and less volatile.

Our results are robust to different metrics of speculation. We first measure speculation by the total net positions taken by hedge funds and swap dealers. Additionally, we also compute herding metrics among hedge funds and floor brokers/traders as an alternative look at speculative activity.

These results are consistent with the conjecture in Deuskar and Johnson (2010) that investors with constant risk tolerance can trade profitably against flow-driven shocks. Indeed, the increased positions taken in recent years by hedge funds and swap dealers across a wide variety of futures markets may simply reflect a rational profit motive. Being subject to regulatory oversight and weekly public reporting should yield confidence that these speculative groups have not been destabilizing markets, but rather have served to dampen volatility.

Although we do not rule out the possibility that a single trader might attempt to (or actually succeed to) implement trading strategies that 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 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, and Jeffrey H. Harris. 2010. "The Role of Speculators in the Crude Oil Futures Market." Working paper, Commodity Futures Trading Commission.

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.

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.

Gao, Andre H., and George H.K. Wang. 1999. "Modeling Nonlinear Dynamics of Daily Futures Price Changes." *Journal of Futures Markets* 19 (May): 325-351.

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.

——. 2008. "Interagency Task Force: Interim Report on Commodity Markets: Interim Report on Crude Oil." Report, Commodity Futures Trading Commission.

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	ΔMerchant	ΔManufacturer	ΔFloor Broker	ΔSwap Dealer	ΔHedge Fund
Mean	-0.0463	3.8032	-64.214	512.65	146.62	-159.69	-1285.2
Median	0.0588	2.1706	306	272	18	-492	-1295
Std.Dev.	2.5143	4.5557	6782.5	3161.8	2228.9	8207.6	6644.2
Panel B – Natural Gas – January 2005-March 2009 – 1053 obs.							
	Returns	Volatility	ΔMerchant	ΔProducer	ΔFloor Broker	ΔSwap Dealer	ΔHedge Fund
Mean	-0.1882	5.2782	89.888	6.5489	64.730	-381.77	-70.391
Median	-0.1569	3.9265	26	0.0000	39	-510	-246
Std.Dev.	3.0563	4.4653	1429.4	428.41	1441.9	2867.1	3423.4
Panel C – Corn – August 2006-March 2009 – 646 obs.							
	Returns	Volatility	ΔMerchant	ΔManufacturer	ΔFloor Broker	ΔSwap Dealer	ΔHedge Fund
Mean	0.0251	3.1528	868.23	-116.57	-208.02	-328.67	-362.75
Median	0.0000	2.5354	830.50	-152.5	-151.5	-620	-423.32
Std.Dev.	2.3031	2.3062	6668.9	1400	4191.12	7937.1	6918.2
Panel D – Eurodollar – January 2005-May 2008 – 1045 obs.							
	Returns	Volatility	ΔArbitrageur	ΔUS Banks	ΔFloor Broker	ΔNon US Banks	ΔHedge Fund
Mean	0.0003	0.0025	-555.1	476.92	933.44	202.29	-35.448
Median	0.0000	0.0010	16	443	686	115	-1148
Std.Dev.	0.0591	0.0046	15625	13035	14571	12341	25395
Panel E – Mini-Dow – January 2005-May 2008 – 1038 obs.							
	Returns	Volatility	ΔArbitrageur	ΔOther Fin.	ΔFloor Broker	ΔCom'l. Funds	ΔHedge Fund
Mean	-0.0438	1.3029	116.74	12.156	15.663	-77.655	-45.628
Median	0.0435	0.3634	222	10	-65.5	-3	-28
Std.Dev.	1.4420	3.1887	2912.3	547.07	1971.9	1749.6	2707

Volatility: two-scale realized volatility in transaction time, Zhang, Mykland and Aït-Sahalia (2005). Δ refers to first difference.

Table II: Long/Short Percentage of Total Open Interest

Panel A – Crude Oil

	Merchant	Manufacturer	Floor Broker	Swap Dealer	Hedge Fund	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 Fund	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 Fund	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	0.1427	0.0369	0.0428	0.0877	0.1250	0.4351	0.6799	0.2113
Short	0.2413	0.0732	0.0201	0.1274	0.1220	0.5840	0.7981	0.3911

Panel E – eMini-Dow

	Arbitrageur	Other Fin.	Floor Broker	Com'l. Funds	Hedge Fund	Total Mean	Total Max	Total Min
Long	0.2946	0.0148	0.1074	0.1625	0.0979	0.6772	0.8725	0.3463
Short	0.2800	0.0282	0.1493	0.0592	0.0819	0.5987	0.8029	0.2739

Total Mean, Max, Min: mean, maximum and minimum of the sum of the open interest of the five categories of market participants. It indicates the percentage of total open interest jointly held by these five categories.

Table III: Correlations – Net Futures Positions

Panel A – Crude Oil

	Merchant	Swap Dealer	Manufacturer	Floor Broker	Hedge Fund
Returns	-0.06	0.05	-0.14*	-0.08*	0.32*
Volatility	-0.03	0.06	-0.05	0.02	-0.03
Swap Dealer	-0.64*	1.00			
Manufacturer	0.25*	-0.41*	1.00		
Floor Broker	0.02	-0.18*	0.04	1.00	
Hedge Fund	-0.23*	-0.25*	-0.23*	-0.13*	1.00

Panel B – Natural Gas

	Merchant	Swap Dealer	Producer	Floor Broker	Hedge Fund
Returns	-0.18*	0.02	-0.20*	-0.23*	0.18*
Volatility	0.07*	-0.06*	0.05	0.01	0.02
Swap Dealer	-0.34*	1.00			
Producer	0.09*	-0.17*	1.00		
Floor Broker	0.14*	-0.18*	0.05	1.00	
Hedge Fund	-0.08*	-0.62*	-0.08*	-0.30*	1.00

Panel C – Corn

	Merchant	Swap Dealer	Manufacturer	Floor Broker	Hedge Fund
Returns	-0.37*	0.00	-0.29*	0.05	0.45*
Volatility	0.01	-0.07	-0.05	0.08*	-0.01
Swap Dealer	-0.54*	1.00			
Manufacturer	0.34*	-0.23*	1.00		
Floor Broker	0.05	-0.46*	0.02	1.00	
Hedge Fund	-0.51*	-0.13*	-0.31*	-0.09*	1.00

Panel D – Eurodollar

	Arbitrageurs	Non-US Bank	US Bank	Floor Broker	Hedge Fund
Returns	-0.20*	-0.07*	0.04	0.01	0.19*
Volatility	-0.04	0.01	0.01	-0.02	-0.03
Non-US Commercial Bank	-0.07*	1.00			
US Commercial Bank	-0.08*	-0.01	1.00		
Floor Broker	-0.02	0.12*	-0.06	1.00	
Hedge Fund	-0.33*	-0.09*	-0.22*	0.13*	1.00

Panel E – eMini-Dow

	Arbitrageur	Com'l. Funds	Other Fin.	Floor Broker	Hedge Fund
Returns	0.13*	0.00	-0.30*	-0.10*	0.21*
Volatility	-0.01	0.02	-0.01*	-0.03	0.00
Commercial Funds	-0.12*	1.00			
Other Financial	-0.09*	0.02	1.00		
Floor Broker	-0.06*	-0.48*	0.03	1.00	
Hedge fund	-0.50*	-0.00	-0.25*	-0.23*	1.00

* significance at 10% level.

Table IV: Granger non-Causality Test: p-values – Returns and Changes in Net Futures Positions

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

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

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

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

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

	Returns	Merchant	Manufacturer	Swap Dealer	Floor Broker	Hedge Fund	All
Returns		0.285	0.777	0.799	0.823	0.394	0.442
Merchant	0.004*		0.388	0.544	0.591	0.892	0.002*
Manufacturer	0.633	0.745		0.910	0.899	0.861	0.960
Swap Dealer	0.355	0.607	0.000*		0.352	0.948	0.000*
Floor Broker	0.799	0.056	0.001*	0.059		0.047*	0.000*
Hedge Fund	0.240	0.327	0.001*	0.101	0.957		0.000*
Total	0.100	0.018*	0.000*	0.563	0.483	0.158	

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

	Returns	Arbitrageur	US Bank	Non-US Bank	Floor Broker	Hedge Fund	All
Returns		0.174	0.203	0.226	0.165	0.315	0.478
Arbitrageur	0.380		0.727	0.671	0.051	0.924	0.144
US Bank	0.254	0.511		0.861	0.139	0.270	0.196
Non-US Bank	0.381	0.897	0.001*		0.100	0.654	0.000*
Floor Broker	0.731	0.020*	0.173	0.439		0.228	0.239
Hedge Fund	0.548	0.005*	0.301	0.594	0.005*		0.001*
Total	0.495	0.000*	0.001*	0.169	0.004*	0.411	

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

	Returns	Arbitrageur	Other Fin.	Com'l. Fund	Floor Broker	Hedge Fund	All
Returns		0.057	0.010*	0.221	0.471	0.071	0.026*
Arbitrageur	0.097		0.818	0.590	0.658	0.007*	0.000*
Other Fin.	0.165	0.261		0.518	0.171	0.191	0.232
Com'l. Fund	0.070	0.588	0.000*		0.434	0.283	0.000*
Floor Broker	0.237	0.762	0.219	0.918		0.350	0.521
Hedge Fund	0.090	0.102	0.444	0.332	0.250		0.004*
Total	0.038*	0.089	0.000*	0.360	0.362	0.008*	

*indicates rejection of the null of non-Granger causality at 5% level.

Table V: Granger non-Causality Test: p-values – Volatility and Changes in Net Futures Positions

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

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

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

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

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

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

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

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

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

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

* indicates rejection of the null of non-Granger causality at 5% level.

Table VI: OLS and IV Estimates of Realized Volatility on Trader Positions (1st Diff.)

		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-06*
		(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 Fin.	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-3)	(9.29e-4)	(4.86e-4)
	F-Stat	21.111	18.735	5.8920	10.619	50.442

* and ** indicate significance at 5% and 10% level.

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

	Crude Oil		Natural Gas		Corn		Eurodollar		eMini-Dow	
	Floor Broker	Hedge Fund	Floor Broker	Hedge Fund	Floor Broker	Hedge Fund	Floor Broker	Hedge Fund	Floor Broker	Hedge Fund
Mean	0.0405**	0.0442**	0.0224**	0.0635**	0.0883**	0.0501**	0.0469**	0.0130**	0.0485**	0.0723**
	(0.0025)	(0.0019)	(0.0022)	(0.0025)	(0.0048)	(0.0037)	(0.0028)	(0.0029)	(0.0024)	(0.0034)
Median	0.0223	0.0379	0.0106	0.0494	0.0431	0.0386	0.0000	0.0000	0.0375	0.0715

Standard errors in parentheses. ** and * indicate significance at 5% and 10% level, respectively.

Table VII: Correlations - Herding Measures

	Crude Oil		Natural Gas		Corn		Eurodollar		eMini-Dow	
	Floor Broker	Hedge Fund	Floor Broker	Hedge Fund	Floor Broker	Hedge Fund	Floor Broker	Hedge Fund	Floor Broker	Hedge Fund
Return	0.09**	-0.04*	0.02	-0.09**	0.02	-0.01	0.05*	0.03	0.06*	-0.02
Volatility	-0.10**	-0.03	-0.08**	-0.14**	-0.09**	-0.15**	0.04	0.07**	0.02	0.01

**and * indicate significance at 5% and 10% level, respectively.

Table IX: Granger non-Causality Test: p-values – Volatility and Herding

	Volatility	Floor Broker	Hedge Fund	All
	Panel A: Crude Oil – Optimal Lag-Length (3)			
	Volatility	Floor Broker	Hedge Fund	All
Volatility		0.006*	0.807	0.043*
Floor Broker	0.633		0.245	0.429
Hedge Fund	0.278	0.071		0.112
Total	0.350	0.003*	0.448	
	Panel B: Natural Gas – Optimal Lag-Length (2)			
	Volatility	Floor Broker	Hedge Fund	All
Volatility		0.941	0.020*	0.099
Floor Broker	0.495		0.173	0.308
Hedge Fund	0.587	0.428		0.524
Total	0.563	0.776	0.016*	
	Panel C: Corn – Optimal Lag-Length (3)			
	Volatility	Floor Broker	Hedge Fund	All
Volatility		0.282	0.015*	0.044*
Floor Broker	0.618		0.012*	0.026*
Hedge Fund	0.432	0.159		0.310
Total	0.652	0.131	0.001*	
	Panel D: Eurodollar – Optimal Lag-Length (2)			
	Volatility	Floor Broker	Hedge Fund	All
Volatility		0.749	0.594	0.804
Floor Broker	0.183		0.535	0.438
Hedge Fund	0.318	0.295		0.295
Total	0.217	0.520	0.572	
	Panel E: eMini-Dow – Optimal Lag-Length (3)			
	Volatility	Floor Broker	Hedge Fund	All
Volatility		0.324	0.548	0.497
Floor Broker	0.448		0.001*	0.004*
Hedge Fund	0.737	0.580		0.751
Total	0.617	0.516	0.005*	

* indicates significance at the 5% or lesser level.

Figure 1: Price and Realized Volatility

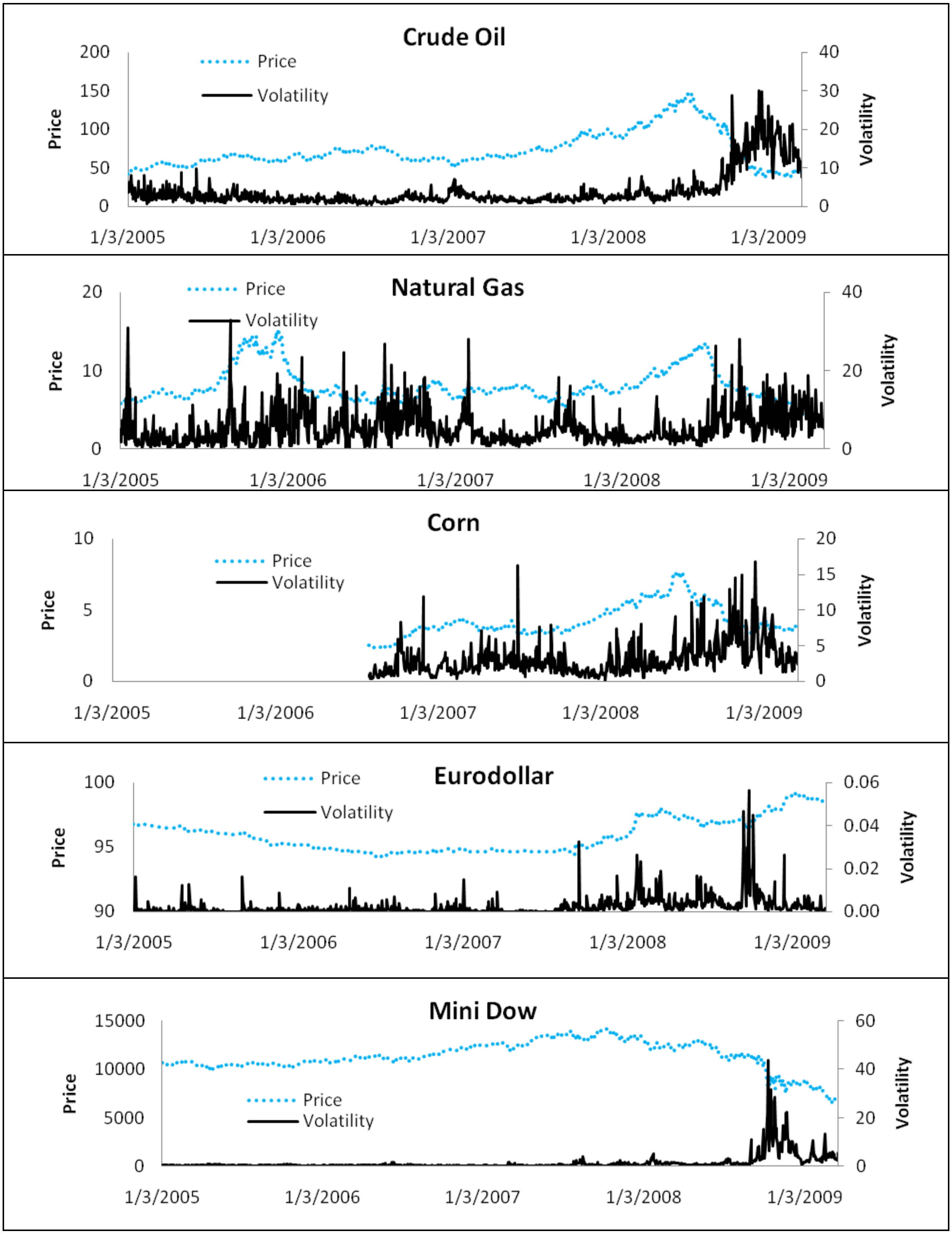
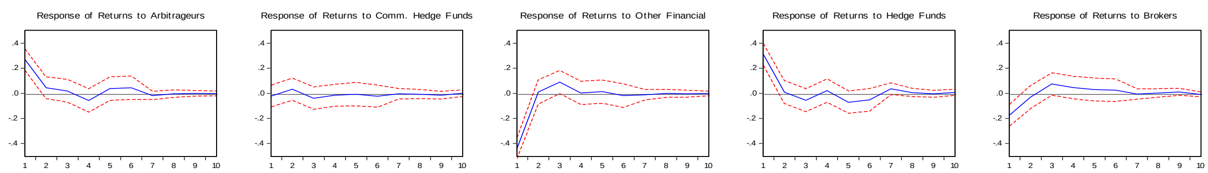


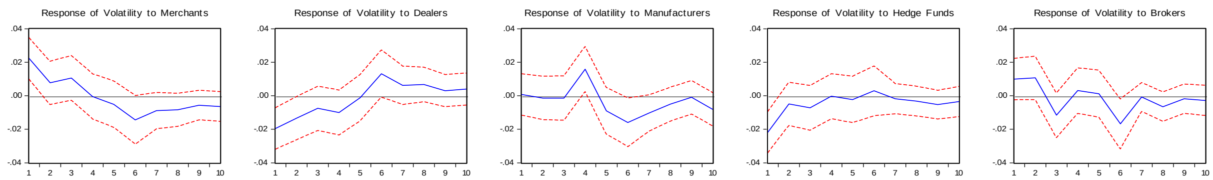
Figure 2

Generalized Impulse Response of Volatility/Returns to One S.D. Innovations in Traders Positions in First Difference

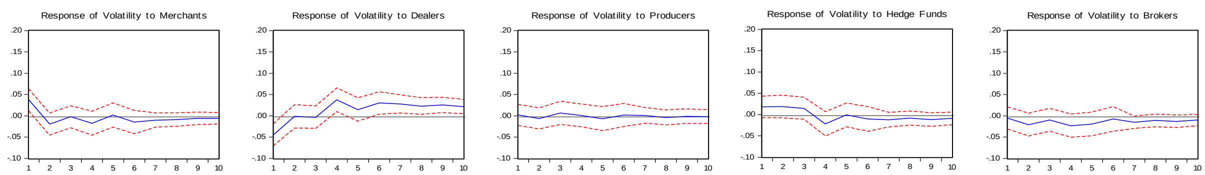
Panel A: eMini-Dow Returns



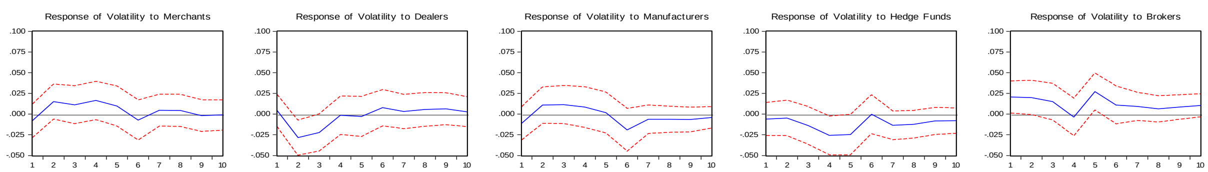
Panel B: Crude Oil Volatility



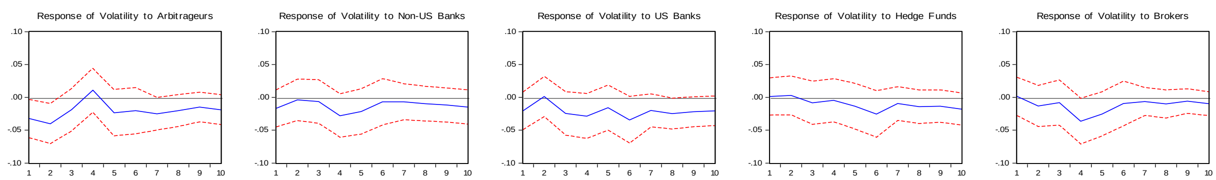
Panel C: Natural Gas Volatility



Panel D: Corn Volatility



Panel E: Eurodollar Volatility



Panel F: eMini-Dow Volatility

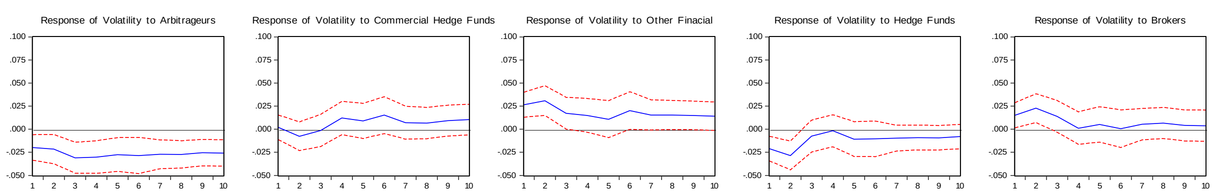
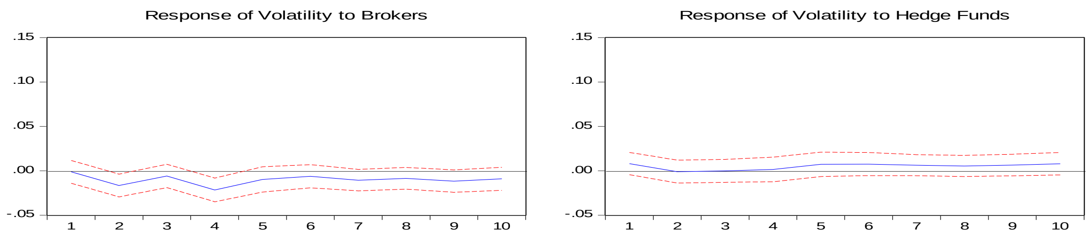
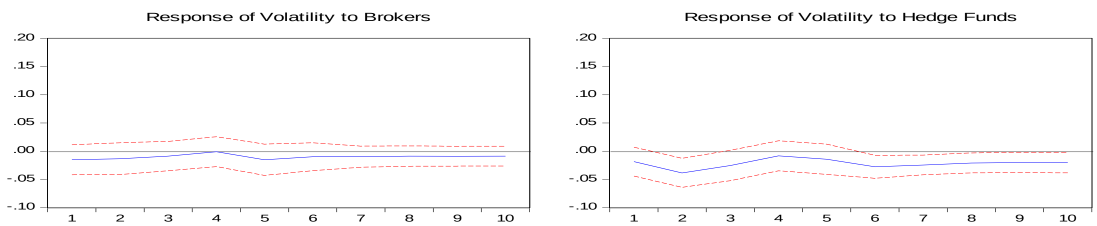


Figure 3
Generalized Impulse Response of Volatility to One S.D. Innovations in Herding Measures

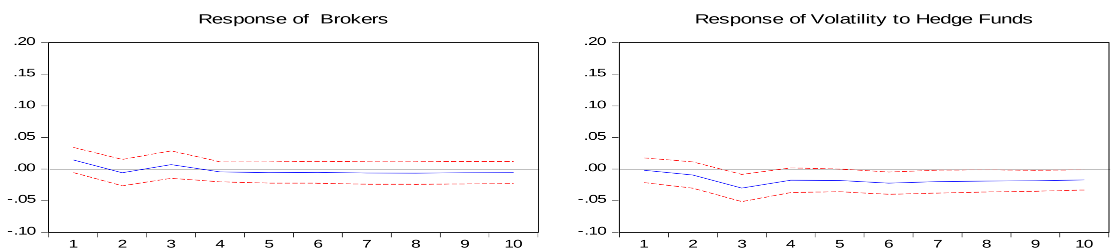
Panel G: Crude Oil Volatility



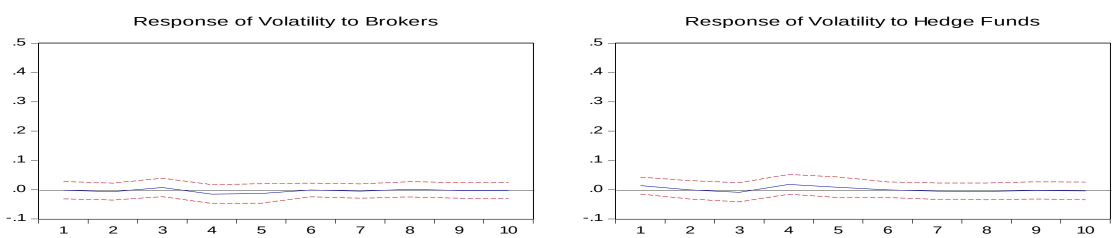
Panel H: Natural Gas Volatility



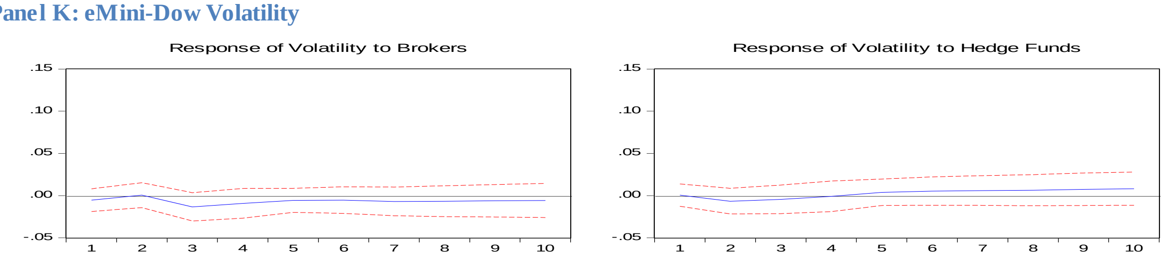
Panel I: Corn Volatility



Panel J: Eurodollar Volatility



Panel K: eMini-Dow Volatility



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: Electronic	 9:00 am-2:30pm 6:00pm-5:15pm	 9:00am-2:30pm 6:00pm-5:15pm	 10:30am-2:15pm 7:00pm-7am and 10:30am-2:15pm	 8:20am-3pm 6:00pm-5:00pm	 N/A 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 ($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)

* Electronic trading only during times when open outcry is trading (9:30am – 4:00pm EST for eMini-Dow).