Is Speculation Destabilizing?

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Abstract: The possibility that speculative trading destabilizes or creates a volatile market is frequently debated. To test the hypothesis that speculative trading is destabilizing we employ a unique dataset from the U.S. Commodity Futures Trading Commission (CFTC) on individual positions of speculators. While others have used a more aggregated version of our data, here we test, for the first known time, whether speculators cause, in a forecasting sense, price movements and volatility in futures markets and, therefore, destabilize markets. Our findings provide evidence that speculative trading in futures markets is not destabilizing. In particular, speculative trading activity reduces volatility levels.

Key Words: Speculation, hedge fund, swap dealer, realized volatility, price, Granger-causality

JEL Codes: C3, G1

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"[…] there is no question that speculators […] have pushed prices beyond the supply-demand fundamentals and into an era of speculative bubble in oil markets […] hedge funds are exploiting recently deregulated energy trading markets to manipulate energy prices."
Tyson Slocum, Director, Public Citizen's Energy Program,
Capital Hill Hearing Testimony, July 11, 2008

"[…] swap dealers […] convinced institutional investors that commodity futures were an asset class that would deliver 'equity like returns' […] the result has been a titanic wave of speculative money that has flowed into the commodities futures markets and driven up prices dramatically."
Adam K. White, Director, Research White Knight Research & Trading
Capital Hill Hearing Testimony, July 10, 2008

1. Introduction

The role of speculators, in particular hedge funds, in futures markets has been the source of considerable interest as well as controversy, in recent years. The traditional speculative stabilizing theory of Friedman (1953), that profitable speculation must involve buying when the price is low and selling when the price is high, has come under strong criticism. The critique originates from the observation that trading behavior of hedge funds and other large speculators can increase the fragility of financial markets leading to a potential destabilization of the broader market system. Two of the most important functions of futures markets are the transfer of risk and price discovery. In a well functioning futures market, hedgers, who are trying to reduce their exposure to price risk, will trade with someone who is willing to accept the risk by taking opposing positions. By taking the opposing positions, these traders facilitate the needs of hedgers to mitigate their price risk, while also adding to overall trading volume, which contributes to the formation of liquid and well-functioning markets. One important development in futures markets in recent years is the increased participation of speculators. In addition to traditional speculators such as hedge funds, other financial institutions, such as commodity swap dealers, have entered commodity futures markets. These institutions view commodities as a distinct *asset class* and allocate a portion of the portfolios they manage into futures contracts tied to commodity indices. The increased participation of traditional speculators as well as other financial institutions in futures markets[1] has led to claims that the trading activities of these speculators

[1] Buyuksahin *et al*. (2009) show that the amount of money invested globally in commodity indices has been steadily growing and that the percentage participation of hedge funds and swap dealers in futures and options on futures has also been growing.

destabilize markets. Despite these accusations, there has been surprisingly limited research on how speculative trading activity may impact prices and volatility. On the one hand this is particularly remarkable given the fact that this class of trader is controversial; on the other hand a lack of data stands in the way of a formal study of speculative trading in markets.

The available evidence on the effects of speculation activity is mixed. Speculators, and hedge funds in particular, have been examined in several financial distresses, including the 1992 European Exchange Rate Mechanism (ERM) crisis, and the 1994 Mexican peso crisis (Fung and Hsieh, 2000[2]); the 1997 Asian financial crisis (Brown, Goetzman and Park, 2000); and perhaps most famously the financial bailout of Long Term Capital Management (Edwards, 1999). In some episodes, hedge funds were deemed to have significant exposures and more than likely exerted market impact, whereas in other episodes they were unlikely to have contributed to destabilization. Brunnermeier and Nagel (2004) in their study of hedge funds and the technology bubble concluded that those funds did not exert a correcting force on stock prices during the bubble and hence question the efficient markets notion that rational speculators stabilize prices.

The limited nature of the previous literature on the market impact of speculators can be attributed to the difficulty of obtaining data on their trading activities. We do not face this problem. In fact, in this paper we employ the Commodity Futures Trading Commission (CFTC) Large Trader Reporting System that allows us to identify positions of each trader category in each futures contract for every contract maturity on each day. We use unique, highly disaggregated, precisely defined, position-level data in five different futures markets collected by the US CFTC. These markets are crude oil and natural gas in energy futures markets, corn in agricultural futures markets, and three-month Eurodollars and mini-Dow in financial futures markets. Choosing commodities and other financial derivatives from different sectors allows us to analyze the role of speculators in a variety of markets. The choice of these markets is uniquely made. Crude oil, natural gas and corn have experienced an amazing increase in price followed by a sudden reduction. We investigate whether these price movements are caused by speculation activity.

The three-month Eurodollar contract is the most heavily traded futures contract in the United States. This market is experiencing high volatility due to the current sub-prime crisis. Here we would like to investigate what is the role of speculative activity in the highly volatile interest rate market. Finally, the mini-Dow is chosen to represent the market-wide

[2] Fung and Hsieh (2000) analyze the impact of hedge funds in several events including the 1994 Mexican crisis.

overall stock market index. We are, therefore, covering a broad spectrum of assets traded in organized exchanges.

The data period considered in the paper runs from January 2005 until March 2009. We select this time period because it covers two important episodes: 1. the rise and the subsequent decline in commodity price (especially, energy markets); and 2. the sub-prime crisis. Our analysis, therefore, provides insights on the role exerted by speculation activity during these important events.

Contrary to common claims, we find that speculative activity does not affect prices. In addition, we find that speculation activity actually reduces volatility. Specifically, we analyze, in a simple multivariate framework, Granger-causality between the daily rate of returns of the above mentioned futures contracts and the daily positions of the five most important categories of market participants in these markets. With the exception of the stock market (mini-Dow), the results unambiguously show that hedge fund activity does not Granger-cause returns. In particular, hedge fund activity does not Granger-cause any other variable in the system but it is Granger-caused by the other variables in the system. Our results suggest that, by taking the reverse positions of other market participants, hedge funds provide liquidity to the market.

Furthermore, to assess the impact of speculative activity on risk, we construct *realized volatility* measures from high frequency data, and run Granger-causality tests between volatility and positions of the five most important trader categories in the crude oil, natural gas, corn, Eurodollar and mini-Dow futures contracts. We find evidence that swap dealer and hedge fund activities Granger-cause volatility. We, therefore, analyze impulse response functions and find that swap dealer and hedge fund activity reduces volatility. This result is of particular importance. Lower levels of volatility imply a reduction in the overall risk of the markets analyzed. Trading activities of swap dealers, in commodity markets, and hedge funds, in all five markets considered in our study, stabilize prices and, therefore, help these markets to perform their risk transfer function.

Our paper contributes to a reach literature. Empirically, the relationship between trader positions and price movement in futures markets has been studied using a highly aggregated public report produced by the CFTC called Commitments of Traders (COT). Brorsen and Irwin (1987) find no significant relation between price volatility and hedge fund positions in COT data, and Brown et al (2000) find no link between fund positions and falling currency values around the 1997 Asian financial crisis. Irwin and Yoshimaru (1999) also fail to find a link between funds positions and prices. Although these findings are suggestive, researchers generally acknowledge that CFTC COT data is highly aggregated; therefore results from these studies should be interpreted with caution. Recent research using disaggregated data from the CFTC Large Trading Reporting System provides further evidence on the relationship between trader positions and price movements. Irwin and Holt (2004) use CFTC data on large hedge funds and commodity trading advisors for the six-month period from April 1994 to October 1994, for 13 different futures markets. They find a small but positive relationship between trading volume and volatility. Yet, their study suffers from the aggregation problem since they used total hedge fund position as a proxy for nearby position. Haigh, Hranaiova and Overdahl (2007) also adopted CFTC data to analyze the relationship between positions of different trader categories and price movements. Using daily data from August 2003 to August 2004 for crude oil and natural gas futures markets, they find that hedge funds enhance the price discovery function of futures markets.[3] They use directed graph analysis and focus only on the return process while we consider both returns and volatility and adopt a different methodology. We also employ a richer data set in terms of both markets analyzed and time period covered.

Our results are also linked to a vast theoretical literature that starts with Friedman (1953). This theory predicts that profitable speculation has a stabilizing effect, since speculators buy when the price is low, therefore, increasing depressed prices, and sell when the price is high, therefore, decreasing inflated prices. According to Friedman's theory, speculation activity smoothes the price process. Our results confirm this view. Moreover, we find evidence that hedge funds take the opposite positions with respect to other market participants, therefore providing liquidity to the market. This is in line with Keynes' (1923) view that speculators fill hedgers' demand-supply imbalances and provide liquidity to the market. Our results are also linked to the work of Hirshleifer (1989, 1990). In a general equilibrium framework, he shows that speculation lowers hedge premia. We do not measure hedge premia directly. However, we find that speculation activity reduces volatility levels and lower volatility levels reduce the cost of hedging.

The remainder of the paper proceeds as follows. In section 2 we describe our data. In section 3 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 mini-Dow futures markets. In section 4 we analyze Granger-causality tests between trader positions and rate of return as well as positions and volatility. We conclude in section 5.

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[3] Boyd, Buyuksahin, Haigh and Harris (2009) employ the same data set to analyze the existence of herding among hedge funds. They find that the degree of herding in futures markets is similar to equity markets and that the moderate level of herding in futures markets serves to stabilize prices.

2. Data

We select futures contracts that represent a broad spectrum of assets traded in futures markets: energy (crude oil and natural gas), agriculture (corn), interest rates (Eurodollar) and stocks (mini-Dow).

We analyze a considerable amount of data covering the period of January 3, 2005 (August 1, 2006 for corn)[4] through March 19, 2009. During this time period, the role of speculators has been heavily criticized. This is particularly true for energy and agricultural markets. In fact, at the beginning of our sample, the futures price of crude oil is just over $42, then reaches the staggering price of $146 in July 2008 and goes back to $42 at the end of our sample (see Figure 1, row 1). Natural gas also experiences great price variability, during our sample. Prices move up from $6 to $15 at the end of 2005, and then return back to $6 in 2006, moved up again to $13 in 2008 and settle below $4 in March 2009 (see Figure 1, row 2). The corn market also experienced a sharp increase in price (from $5 to $16) followed by a sharp decline, during our sample. Many have attributed these price movements to speculative activity.[5]

For each market analyzed, we use three different data sets: 1) daily futures rate of returns; 2) high frequency transaction data which we employ for computing realized volatility measures; and 3) data on daily net futures positions of the most important categories of market participants in each market.

We use futures market data for several reasons. First, futures prices are readily available on a tick-by-tick basis. Second, the contracts we analyze are very actively traded, and transactions costs are lower in futures markets. Third, the CFTC collects data on the market participants' positions for futures and options but not for the cash market. Fourth, numerous studies find that futures markets tend to lead cash markets in terms of price discovery.[6] This last point is very important as we focus on the impact of speculation activity on prices and volatility.

For each market we concentrate on the nearby contract (closest to delivery). Before maturity (the expiration date), market participants roll over their positions from the nearby contract (March 2005, say) to the next-to-nearby contract (June 2005). This behavior generates some type of seasonality in the data. To mitigate these problems, the roll-over strategy adopted in this paper is to switch to the new contract when the open interest of the nearby contract (March 2005) is lower than the open interest of the next-to-nearby contract

[4] High frequency data for corn are not available before August 2006.

[5] Indeed, in the natural gas market over the sample period analyzed, a hedge fund (Amaranth) has been formally charged with market manipulation.

[6] See Hausbrouk (2003).

(June 2005).[7] Futures contracts rarely involve physical delivery. In fact, they are closed before maturity. The roll-over strategy employed in this paper may also solve the delivery distortion problems caused by the need of market participants to close their positions before the nearby contract expires.

In what follows we describe the data in some detail.

2.1 Futures Market Return Data

Table 1 provides an overview of the five selected contracts. Crude oil and natural gas are listed on the New York Mercantile Exchange (NYMEX). Crude oil is the world's most actively traded commodity and the light sweet crude oil traded on NYMEX is the most liquid futures contract on a physical commodity. Natural gas accounts for almost a quarter of U.S. energy consumption, and the natural gas futures contract traded on NYMEX is widely used as a national and international benchmark price. Energy futures contracts are traded on both an electronic platform and an open auction. Daily settlement prices refer to the prevailing price at 2:30 pm EST, when the open auction closes.[8] Futures contracts on corn are traded on the Chicago Board of Trade (CBOT). Corn is becoming increasingly important for the production of bio-fuel (ethanol). Trading on both the open outcry and electronic platform starts at 10:30am and ends at 2:15pm EST (there is also an additional electronic trading session from 7:00pm to 7:00am EST). We compute daily returns using settlement prices which are set by the exchange at the close of the trading day (2:15pm EST). The Eurodollar futures contract is listed on the Chicago Mercantile Exchange (CME) and is the most widely traded interest rate futures product in the US. Eurodollar deposits[9] play a major role in the international capital market, and are considered the benchmark interest rate for corporate funding. The market is open from 8:20am to 3:00pm EST for floor trading, while the electronic trading on Globex occurs between 6:00pm (the previous day) and 5:00pm EST. The settlement price is derived from trades and quotes occurring between 2:59pm and 3:00pm EST on Globex. The last market considered is the mini-Dow futures, which is traded on CBOT. Mini-Dow futures provide a way to efficiently gain exposure to the Dow Jones 30 index, using a small-sized electronic contract (each point is worth $5). The contract trades only electronically on Globex from 6:00pm (the previous day) until 4:15pm EST (there is also an additional session from 4:30pm to 5:30pm EST).

Daily returns are constructed as $r_t = p(t) - p(t-1)$, where $p(t)$ is the natural logarithm of the settlement price in day *t*. When we switch contract from the nearby

[7] See Gao and Wang (1999).
[8] We only consider days when the market is open for at least five (three for corn) trading hours.
[9] Eurodollars are defined as U.S. dollars deposited in commercial banks outside of the U.S.

position to the next-to-nearby position, $p(t)$ and $p(t-1)$ refer to the next-to-nearby contract. Table 2, column one, reports summary statistics for the return processes. Daily returns on crude oil have a negative mean (-11.6% annually) and high standard deviation. The unconditional distribution is non-Gaussian with negative skew and kurtosis in excess of three. The negative first-order autocorrelation indicates mean reversion. Natural gas exhibits a significant negative average daily return (-47% annually) and a very large standard deviation (the largest of the five markets). The unconditional distribution of the daily rate of returns on natural gas is non-Gaussian. Corn displays the highest average daily rate of return over the sample (6.3% annually). The standard deviation dominates the mean and the unconditional distribution is close to a Gaussian. Not surprisingly, the Eurodollar interest rate has a very low standard deviation and daily average close to zero. The Eurodollar returns also exhibit significant first order autocorrelation and excess kurtosis. Returns on the mini-Dow have negative daily average (11% annually), negative skew and excess kurtosis. The standard deviation of futures returns on the mini-Dow is higher than that of the Eurodollar but lower than that of energy products and corn, confirming that, over our sample, commodity markets experience large price variations. The negative return for the mini-Dow is mainly due to the sub-prime srisis and the recession that followed soon after the crisis.

2.2 High Frequency Transaction Data

To construct realized volatility measures, we obtained transaction data from the Commodity Futures Trading Commission. At the end of each trading day, the CFTC receives data on all transactions that occurred in futures and options directly from the exchanges.

For crude oil and natural gas we consider transactions in both the electronic platform and the traditional pit. Energy markets started to trade electronically on September 5th 2006. After that day, most of the transactions take place in the electronic platform. However, there is still a 30 percent of volume traded on the pit. We, therefore, constructed realized volatility measures considering all transactions that took place between 9:00 am and 2:30pm EST (see Table 1).

In the corn market we only utilize electronic transactions that took place between 10:30am and 2:15pm EST. In fact, in this market the majority of transactions occur on the electronic platform. Pit trading is sometimes infrequent and pit transaction data are somehow problematic. Electronic trading on corn starts on August 1st 2006, this is when our sample starts.

For the Eurodollar market we construct realized volatility measures considering both electronic and pit transactions that took place between 8:20am and 3:00pm EST. The mini-Dow is only traded electronically, and we consider transactions that took place between 9:30am and 4:00pm EST, when traded volume is the highest and when the market for the underline stocks is most actively trading.

We are dealing with very liquid markets. Crude oil and mini-Dow, for example, have several days where the number of transactions is over 150,000 (see last row of Table 1). The median intertrade duration for all the markets analyzed, is zero seconds.[10]

The use of high frequency data for constructing realized volatility measures could be problematic given the bias produced by market microstructure noise. Several solutions have been proposed to overcome this problem. In this paper we follow three approaches. Barndorf-Nielsen *et al.* (2008) propose a kernel estimator where the bias correction is achieved by taking into account the autocorrelation structure of high frequency data. The second approach we follow is that of Andersen *et al.* (2001) where the bias correction is achieved by sampling at relatively lower frequencies. The last approach we implement is developed by Zhang *et al.* (2005) and is referred to in the literature as *two scales realized volatility*. The results of our analysis are qualitatively the same regardless of the realized volatility estimator adopted. To conserve space, we only report results for the two scales realized volatility estimator.[11] Here we describe this estimator in some detail and to do so we need to introduce some notation.

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 which is partitioned in m subintervals. In our setup the interval $[a,b]$ is a trading day. For a given m, the ith intraday subinterval is given by $[\tau_{i-1,}^m, \tau_i^m]$, where $a=\tau_0^m<\tau_1^m<\ldots\tau_m^m=b$, 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 $i=1,2,\ldots,m.$ Realized volatility in day t is the sum of squared intraday returns sampled at frequency m

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

The two scales realized volatility estimator is quite simple. Starting from the first observation, set m=300 transactions, say, and compute RV using equation (1). Then, starting from the second observation re-compute RV using equation (1) (m is unchanged).

[10] Our high frequency data contain information up to the second, but actual transactions are recorded in hundredths of a second (centiseconds) or thousands of a second (milliseconds).

[11] Results for the other realize volatility estimators are available from the authors.

In this way, even if m is set to a given sampling frequency, we still make use of all available observations (transactions). We then average the estimators obtained on the subintervals. Sampling at a relatively lower frequency (say, 5-minute, in calendar time, or every 300 transactions in transaction time) dramatically reduces the effect of market microstructure noise. This benefit is now retained, while the variation of the estimates will be lessened by the averaging. When applying equation (1) to all observations (i.e. sampling at the highest possible frequency, $m=1$), we obtain a consistent estimate of the variance of the market microstructure noise. The last step in the two scales realized volatility estimator is to correct for the bias of the noise, by subtracting from the average estimator the noise variance

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

where k denotes the number of subintervals of size m and, therefore, the number of realized volatilities computed using equation (1) and setting m to a lower frequency; γ is a ratio between m and the total number of observations in $[a,b]$; and RV^{all} refers to the realized volatility measure in (1) computed using all available data in the interval $[a,b]$. Intraday returns can be constructed using different sampling schemes. In our framework, $\tau_{i,m}$ denotes the time of a transaction. We, therefore, compute the two scales realized volatility measure in transaction time (for example, sampling every 300 transactions). In order to implement equation (2), we need to choose m, the sampling frequency. *Volatility signature plots*[12] provide valuable information about the bias in RV measures in (1) and about optimally choosing m in order to correct that bias. For each asset, we construct volatility signature plots for each month in our sample and then select m.[13]

Figure 1 depicts prices and two scales realized volatility measures for the five assets analyzed in the paper. Crude oil, interest rates (Eurodollar) and the stock market (mini-Dow) exhibit high volatility in the last part of our sample, after the sub-prime crisis hits the economy. We may conjecture that these markets are strongly linked to the overall *status* of the economy. The uncertainty about the sub-prime crisis and the recession is clearly evident in the volatility of these assets. Natural gas and corn also exhibit higher volatility towards the end of our sample, but these volatility levels are comparable to those computed in the first part of our sample.

Table 2, column 2, provides descriptive statistics for RV. Energy and corn markets show both a very high average volatility and a high variation in volatility levels. This is not

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[12] Volatility signature plots show average daily realized volatility measures, computed using equation (1), against sampling frequencies m - see Andersen, Bollerslev, Diebold and Labys (2000).
[13] Details on this procedure can be obtained from the authors.

surprising, given that we are indeed covering the period where commodity markets experience dramatic price increases. The lowest volatility is in the Eurodollar market followed. All realized volatility measures are stationary and highly persistent.

2.3 Market Participants' Positions

The CFTC monitors U.S. futures and options on futures markets through its market surveillance program, and since the 1920s, the CFTC (and its predecessors) has been utilizing the central tool of market surveillance known as the Large Trader Reporting System (LTRS). Following the Commodity Exchange Act (CEA), the CFTC collects and stores data from daily reports on market data and position information from the Futures Commission Merchants (FCM's), foreign brokers, exchanges, clearing members, and also traders. These reports show the positions of traders that hold contracts above specific levels set by the CFTC. These large trader reporting levels include crude oil, 350 contracts; natural gas, 200 contracts; corn, 250 contracts; Eurodollar, 3,000 contracts; and mini-Dow, 1,000 contracts. The total amount of all trader positions reported to the CFTC represents approximately 70 – 90 percent of total open interest in any market, while the remainder are traders who generally trade a small number of contracts, known as Non-Reportable Positions (NRP).[14]

When a trader is identified to the CFTC, the trader is classified either as a *commercial* or *non-commercial*. A trader's reported futures position is determined to be commercial if the trader uses futures contracts for the purposes of hedging as defined by CFTC regulations. The non commercial category includes participants who are not involved in the underlying cash business – otherwise known as speculators and include hedge funds, floor brokers/traders and so forth (see Exhibit 1 in the appendix).[15]

The Commitment of Traders Report (COT), which utilizes data from the LTRS, provides a summary of highly aggregated traders' position (commercial, noncommercial and NRP) as of the close of business on Tuesday for each market in which at least 20 traders hold positions. Information released to the public in the form of the COT is highly aggregated, but the disaggregated LTRS enables the CFTC surveillance team to monitor

[14] Occasionally, the CFTC will raise or lower the reporting levels in specific markets with the objective of striking a balance between maximizing effective surveillance and minimizing the reporting burden on the futures industry.

[15] Specifically, a reportable trader gets classified as commercial by filing a statement with the CFTC (using the CFTC Form 40) that he is commercially "…engaged in business activities hedged by the use of the futures and option markets." However, to ensure that the traders are classified consistently and with utmost accuracy, CFTC market surveillance staff in the regional offices checks the forms and re-classifies the trader by collecting further information about the trader's involvement in the markets.

individual participants and/or a specific group of market participants. It is these detailed groupings within the commercial and non-commercial categories that we analyze in this study. Active groupings of participants vary across contract markets but an exhaustive list of participants can be found in Exhibit 1 in the appendix.

Two categories of market participants deserve further discussion: commodity swap dealers and hedge funds. We start with the latter.

There is no consensus on the exact definition of a hedge fund in futures markets and the CEA, the statute governing futures trading, does not define hedge funds.[16] Accordingly, there is not a requirement that hedge funds be categorized in the LTRS. Despite this, many hedge fund complexes are registered as Commodity Pool Operators (CPOs),[17] Commodity Trading Advisors (CTAs)[18] and/or Associated Persons (APs),[19] who may control customer accounts. In addition to these three categories of traders, market surveillance staff at the CFTC identifies other participants who are not registered in any of these three categories but are known to be managing money (MM). These four categories combined are defined as being the hedge fund category (see bottom of Exhibit 1 in the appendix). We actually check the names of the funds in these four categories with those listed in press reports as hedge funds, and we find that many of the large CPOs, CTAs, APs and MMs are generally considered to be hedge funds and hedge fund operators. As such, and to conform with the academic literature and common financial parlance, we refer to these four categories collectively as hedge funds in our study.

In commodity markets, commercial commodity swap/derivatives dealers (henceforth, swap dealers), play an important, albeit controversial, role. This category of market participants uses derivative markets for two main reasons: i) to manage their price

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

[17] "Commodity Pool Operator (CPO): A person engaged in a business similar to an investment trust or a syndicate and who solicits or accepts funds, securities, or property for the purpose of trading commodity futures contracts or commodity options. The commodity pool operator either itself makes trading decisions on behalf of the pool or engages a commodity trading advisor to do so."
Source: Glossary of the CFTC (http://www.cftc.gov/educationcenter/glossary/index.htm).

[18] "Commodity Trading Advisor (CTA): A person who, for pay, regularly engages in the business of advising others as to the value of commodity futures or options or the advisability of trading in commodity futures or options, or issues analyses or reports concerning commodity futures or options."
Source: Glossary of the CFTC (http://www.cftc.gov/educationcenter/glossary/index.htm).

[19] "Associated Person (AP): An individual who solicits or accepts (other than in a clerical capacity) orders, discretionary accounts, or participation in a commodity pool, or supervises any individual so engaged, on behalf of a futures commission merchant, an introducing broker, a commodity trading advisor, a commodity pool operator, or an agricultural trade option merchant."
Source: Glossary of the CFTC (http://www.cftc.gov/educationcenter/glossary/index.htm).

exposure originating from their over-the-counter (OTC) business; and ii) to manage their transactions with commodity index funds. These funds are often employed by pension funds and other large institutions that seek diversification by investing in commodities. For this reason commodity index funds hold significant long-only positions, especially in near-term futures contracts. The controversy regarding swap dealers owes to the fact that they are classified as commercial traders (i.e. hedgers) - indeed these market participants are hedging their price exposure - but they are often trading to fulfill the needs of commodity index funds that are entering commodity markets to have an exposure in these markets. Over our sample, commodity index funds have experienced a significant growth.[20]

For each market, we consider four types of traders' information: i) number of contracts held in long positions by a specific trader category (futures long); ii) number of contracts held in short positions by a specific trader category (futures short); iii) the difference between futures long and futures short positions (net futures positions); and iv) net total positions which accounts for both the net futures positions and the net (delta adjusted) option positions of each trader. To conserve space we report only results for the net futures positions. However, results for futures short, futures long and net total positions[21] are qualitatively similar to those obtained with the net futures positions.

For each market we concentrate on the five largest categories of market participants. Hedge funds (HF) and floor brokers/traders (FBT) are common to the five markets analyzed. According to the CFTC definition, these two categories of market participants are non-commercial – i.e. speculators. In the crude oil, natural gas and corn markets, we analyze dealers/merchants (AD) – which include wholesalers, exporters/importers, shippers, etc.; swap dealers (AS) – see discussion above; and manufacturers[22] (AM) – which includes fabricators, refiners, etc.; and producers (AP)[23]. For the Eurodollar market, in addition to hedge funds and floor brokers/traders, we study the positions of commercial arbitrageurs or broker/dealers (FA), non-U.S. commercial banks (FB) and U.S. commercial banks (FC).[24] It is not surprising that domestic and foreign banks are very active in this market. Finally, the hedger categories for the mini-Dow are arbitrageurs or broker/dealers (FA), financial institutions other than those already classified (FO), and hedge funds (FH) – hedge funds that are shown to be hedging.

[20] By June 2008, the notional value of commodity index investments tied to U.S. futures exchanges exceeded 160 billion dollars (CFTC, 2008).
[21] These results are available from the authors.
[22] For crude oil and corn.
[23] For natural gas.
[24] For a definition of broker, dealer, floor trader and floor broker, we refer the interested reader to the glossary of the CFTC, which can be found on line at http://www.cftc.gov/educationcenter/glossary/index.htm.

Table 1 shows descriptive statistics for the level and first difference of the net futures positions of each category of market participants organized by market. Dealers and merchants (AD) are net short over our sample, while swap dealers are net long. This is to be expected given that commodity index funds hold long positions. Hedge funds are net long in crude oil, corn, Eurodollar and mini-Dow, but net short in natural gas. Positions in levels are stationary for all markets but the Eurodollar. This market, in fact, is experiencing a reduction in volume and open interest since the inception of the sub-prime crisis. Interestingly, hedge fund positions in the Eurodollar market are stationary, indicating that these market participants are not fleeing the market. Positions in levels exhibit strong autocorrelation. Positions in levels measure the stock hold by each market participants in each market and are, therefore, a measure of stock. To measure trading activity (flow) we compute change in positions. Swap dealers exhibit negative mean and median indicating an overall reduction in their positions. This is also true for hedge funds. Swap dealers (AS) and hedge funds (HF) exhibit high standard deviation in change in positions - .i.e. they are changing their positions often and by large amounts.

Table 3 shows the participation rate of each trader category in each market as percentage of the total open interest. While in Table 2 we analyze net futures positions of market traders, in Table 3 we concentrate on the long and the short components of trader positions. Dealers and merchants (AD) are mainly short. This is in line with the needs of these market participants to hedge their positions in the underlying commodity. Swap dealers hold 40 percent of the long positions in all commodities analyzed. Interestingly, hedge funds hold large positions in all five markets, and they are present on both sides of the market (long and short positions). The last column of Table 3 shows the percentage (mean, maximum and minimum) of total open interest held by the five categories of market traders over our sample. Even if we only consider five categories of traders in each market, we cover most of the total open interest traded on these markets.

We proceed with the correlation analysis.

3. Unconditional Contemporaneous Correlation

Our preliminary analysis of the relationship between returns, volatility, and trader positions begins by computing correlation coefficients. Table 4 reports, for each market, correlation coefficients between returns, realized volatilities, and the positions of the five categories of traders analyzed. The top number refers to the positions in levels, while the bottom number refers to the change in positions. Positions for dealers/merchants (AD) are negatively correlated with rate of returns and positively linked to volatility of natural gas and corn but negatively linked to volatility of crude oil. There is no evidence of a contemporaneous link between swap dealer positions, either in levels or first difference, and rate of returns. Swap dealer activity seems to move in the opposite direction of volatility in the corn and the natural gas markets but is positively link to volatility levels in the crude oil market. Hedge funds have a positive correlation with returns. This implies that hedge fund positions move in the same direction as the market. It is also interesting to note that hedge fund activity is negatively linked to volatility. An increase in hedge fund activity is associated with lower volatility levels. Finally, swap dealer activity and hedge fund activity is negatively linked to other traders' positions. This may suggest that by taking the opposite position with respect to the other market traders, swap dealers and hedge funds may provide liquidity to the market. This is in line with the results of Haigh, Hranaiova and Overdahl (2005) who study the interaction between traders in the natural gas and crude oil futures markets. They find that hedge funds provide liquidity to hedgers. This is also in line with the theory of speculation as described in Keynes and Hicks, which postulates that speculator positions should offset any imbalance of hedger positions.

The simple correlation analysis provides three main results. First, swap dealer activity is not contemporaneously correlated with returns and is negatively linked to volatility. Second, hedge fund activity is positively correlated with returns but negatively correlated with volatility. Third, the correlation between hedge fund positions and positions of the other market traders is always negative. The same result also holds for swap dealers.

4. Granger-Causality Analysis

The concept of Granger-causality relates to predictions – x_t is Granger-causal for z_t if x_t contains useful information for predicting z_t. This definition of causality is practical but has limitations. In fact, the notion of causality is an old one and goes back to the ancient Greek philosophy - Aristotle distinguishes between cause and effect: a cause is an event that produces an effect. Unfortunately, Granger-causality does not allow us to distinguish between causes and effects. Nonetheless, Granger-causality is easy to compute and provides useful information as to whether a trader activity prompts, in a forecasting sense, price movements and/or *vice versa*.

We test for Granger causality in the context of Vector AutoRegression (VAR) models. Since the variables exhibit heteroskedasticity and serial correlation, we estimate VAR models using the Generalized Method of Moments (GMM) and Newey-West robust standard errors. We estimate four different sets of VARs. In the first we consider rate of returns and positions in levels; in the second we employ rate of returns and change in positions; in the third we utilize volatility and positions in levels; in the last we consider volatility and change in positions.[25] We only report results for the optimal lag-length.[26] However, we would like to emphasize that these results are very robust and hold regardless of the lag structure in the VAR.

4.1 Crude Oil

Table 5 provides the results (p-values) of Granger-non-causality tests. The last column and the last row of the Table are labeled "all". In the last column we test whether each variable is Granger-caused by all the other variables in the system - i.e. are returns (volatilities) Granger-caused by positions? The last row is, on the other hand, testing whether each variable is Granger-causing any other variable in the system. In other words, we are testing whether each variable is jointly Granger-causing the remaining variables in the system. Here we are particularly interested in testing whether swap dealer activity and hedge fund activity are Granger-causal for returns and volatility. The null hypothesis is that of Granger-non-causality - a p-value greater than 5 percent indicates failure to reject the null.

Panels A and B in Table 5 refer to Granger-causality tests between rates of returns and positions in levels, and in their first difference, respectively. We obtain some interesting results. Returns on the crude oil market are not Granger-caused by positions (the p-value is equal to 0.148 for levels and 0.199 for change in positions). On the other hand, returns Granger-cause positions (the p-value is 0.000). When jointly testing whether hedge funds Granger-cause returns or any other variable in the system, we fail to reject the null. In fact, hedge fund activity is the only variable which is not jointly Granger-causing any other variable in the system (the p-value 0.181 in panel A and 0.086 in panel B) at 5 percent significance level. This implies that hedge fund positions do not provide any useful information for predicting returns or positions of other traders. Moreover, hedge fund activity is Granger-caused by the system (the p-value is 0.000 for both levels and change in positions). If we pair this result with the negative correlation between hedge fund positions and positions of the other traders, it is reasonable to conjecture that by taking the opposite side in the market (negative correlation), hedge funds are providing liquidity to the market.

[25] We only report results for net futures positions. However, we perform the same analysis also for long futures positions, short futures positions and net total (future and options) positions.

[26] We select the optimal lag-length using a series of Wald tests (i.e. testing for the significance of the parameters of each lag). Given the problems of heteroskedasticity and serial correlation in our data, we could not rely on standard Akaike (AIC) and Schwartz information criteria (SIC). Wald tests do not pose any penalty to less parsimonious specifications, unlike AIC and SIC. Therefore, the optimal lag-length selected is always higher than that selected by AIC and SIC. However, the results do hold even when using AIC and SIC.

Our results for swap dealers indicate a feedback effect: swap dealer positions are Granger-caused by the other variables in the system and Granger-cause these variables.

The last two panels in Table 5 report Granger-causality tests for volatility and traders' positions (panel C refers to positions in levels while panel D refers to change in positions). A stylized empirical finding in the realized volatility literature is that logarithmic realized standard deviation is approximately Gaussian. Our realized volatility measures confirm this finding.[27] In fact, in modeling realized volatility measures in the context of VARs, it is customary to use logarithmic realized standard deviation – e.g. Andersen *et al*. (2006). In our analysis we use the three measures of realized volatility described in Section 2 and their logarithm realized standard deviations counterparts. To conserve space, we only report results for logarithmic two scales realized standard deviation in transaction time.[28]

Panels C and D show that positions, including those of swap dealers and hedge funds, Granger-cause volatility. There is also a feedback effect from volatility to traders' positions. Therefore, it seems that swap dealer and hedge fund trading, among others, are moving volatility levels in the crude oil market. To further investigate this issue we compute impulse responses. Pesaran and Shin (1998), proposed a technique, termed "generalized impulse responses", which is invariant to the ordering of the variable in the VAR and does not require shocks to be orthogonal. Assume that there is a one-standard deviation shock to the k-th variable; generalized impulse responses are then computed by applying a variable specific Cholesky factor which is derived by placing the k-th variable at the top of the Cholesky ordering. Figure 2, row 1, depicts generalized impulse responses of volatility to one standard deviation innovation in the level of traders' positions in the crude oil futures market, for the VAR with 5 lags.[29] We are particularly interested in the response of volatility to a standard deviation shock to commodity swap dealer activity and hedge fund activity. The second column in row 1 indicates that swap dealers have no impact on volatility. Interestingly, the fourth column in row 1 provides evidence of a short-lived and statistically significant reduction in volatility. In other words, a shock in hedge fund activity reduces volatility. It is also worth noting that positions of dealers and merchants (hedgers) have a positive impact on volatility levels (i.e. they increase volatility).

[27] Results not reported.

[28] Our results are robust to the different measures of realized volatility considered.

[29] This is the optimal lag-length. Generalize impulse responses for VARs with 4-1 lags are very similar to those reported in Figure 2. Response standard errors are computed with 1,000 Monte Carlo replications in EViews 6. On the horizontal axis is the number of days after the shock, in this instance 10 days.

We also compute impulse responses using the classic Cholesky decomposition which is very sensitive to the order of the variables in the VAR. To mitigate this problem we consider several orderings of the variables and always find results similar to those reported above.[30]

Figure 3 row 1 illustrates impulse responses of volatility to a standard deviation shock to change in positions. Swap dealer activity and hedge fund activity have a negative impact on volatility – i.e. the trading of these two market participants reduces volatility levels. There is also some evidence that dealers and merchants (commercial AD) swell volatility.[31]

4.2 Natural Gas

Table 6, panels A and B, report Granger-causality test results (p-values) for returns and positions in levels, as well as returns and change in positions, respectively. We find that rate of returns in the natural gas industry are not Granger-caused by positions, both in levels (p-value 0.486) and first difference (p-value 0.571), but positions are Granger-caused by rate of returns (p-value 0.001 for positions in levels and 0.000 for change in positions). Swap dealer positions are Granger-caused and Granger-cause the other positions in the system. There is also evidence that the system is Granger-causing hedge fund activity, but hedge fund activity is not Granger-causing the system. It seems that hedge funds are reacting to market conditions, and there is no indication that hedge fund activity is moving prices and/or positions of other traders. These results are qualitatively similar to those obtained in the crude oil market.

Panel C in Table 6 shows Granger-causality tests for volatility and positions in levels. Volatility is Granger-caused by traders' positions (p-value 0.016), including hedge funds. There is no evidence of a feed-back effect from volatility to trading activity (p-value 0.633). Figure 2, row 2, shows generalized impulse responses of volatility to a standard deviation shock in trader positions. Swap dealers and hedge funds have a short-lived negative impact on volatility, in the sense of a reduction of volatility levels (see second and fourth columns in Figure 2, row 2). On the other hand, it appears that dealers and merchants (AD) and producers (AP) increase volatility levels.

The last panel in Table 6 refers to Granger-causality tests for volatility and change in trader positions. The results suggest that volatility is marginally not Granger-caused by

[30] Impulse responses using the classic Cholesky decomposition are also calculated for all the other markets studied in this paper. Results from Cholesky decomposition are similar to generalized impulse responses; therefore we do not report them in this paper.

[31] For the change in positions we also compute impulse responses using Cholesky decompositions and several orderings of the variables. We always obtain qualitatively similar results.

trading activity (p-value 0.052) and does not Granger-cause trading activity (p-value 0.344). Similarly to what we find in the crude oil market, there is evidence that hedge fund trading is Granger-caused by the trading of the other market participants but is not causing, in a forecasting sense, any variable in the system. Figure 3, row 2, confirms our findings. In fact, hedge fund activity does not have any impact on volatility (fourth graph); swap dealers seem to slightly reduce volatility (second graph); while dealers and merchants seem to increase volatility levels.

4.3 Corn

Rate of returns on corn appear to not be affected by trader positions and by the change in trader positions. In fact, Table 7 shows that returns are not Granger-caused by the trading activity of the five largest categories of traders. Similar to the results for the energy market, hedge fund activity is Granger-caused by the system but does not Granger-cause the system. This is also true for swap dealer activity in panels B (change in positions).

There is evidence of a feed-back effect between volatility and trader positions. Hedge fund activity is non-causal for the system (p-values 0.070 and 0.148 in Table 7, panels C and D, respectively) but is caused by the other variables in the system. Similar results also hold for swap dealer positions in the last panel, where changes in positions are considered. Impulse responses in Figures 2 and 3, row 3, show that hedge fund activity and swap dealer activity do not have a significant effect on volatility.

4.4 Eurodollar

Since the inception of the so-called sub-prime crisis, interest rate markets experienced a decline in open interest. The Eurodollar futures market is no exception.[32] However, it still remains the most liquid futures market in the US in terms of traded volumes. For four of the trader types analyzed, net positions (futures or futures and futures equivalent options) are non-stationary (the ADF test fails to reject the null of stationarity). We, therefore, only analyze changes in positions. Table 8 reports Granger-causality tests for the Eurodollar market. In line with the previous results, rate of returns is not Granger-caused by positions (p-value 0.478). Interestingly, hedge fund activity is caused by the other variables in the system (p-value 0.001) but does not Granger-cause any variable in the system (p-value 0.411).

[32] During our sample, futures-only three-month Eurodollars open interest declined from a peak of 12 million contracts to 9 million contracts.

Similar to the results for crude oil and natural gas, it seems that volatility in the Eurodollar market is Granger-caused by trading activity (p-value 0.025). In particular, there is evidence that hedge fund activity is causal to volatility (p-value 0.007). To further investigate this issue, we compute generalized impulse responses. Figure 3, row 4, shows that four of the five trader categories (including hedge funds) have no effect on the Eurodollar volatility while commercial arbitrageurs and brokers/dealers (FA) seem to reduce risk in this market.

4.5 Mini-Dow

The last market we analyze is the mini-Dow. In this market we have two hedge fund categories: hedgers (commercial FH) and speculators (non-commercial HF). It is interesting, then, to compare how hedge funds behave when entering the market for different purposes.[33]

The results for this market are, in part, different from those obtained in the other markets analyzed. In fact, rates of return (see Table 9, panels A and B) are Granger-caused by trader positions. This is a feedback effect. Returns also cause, in a forecasting sense, positions. It also appears from panel B (change in positions) that speculative hedge fund activity is responsible for this causal effect. Positions of commercial hedge funds (hedgers) seem to affect rates of return when considering the levels of the positions (p-value 0.000); this is no longer the case when considering changes in positions (p-value 0.360). Since this is the first market analyzed where rates of return are Granger-caused by positions, we also investigate impulse responses. Figure 2, row 4 (positions in levels), and Figure 3, row 5 (change in positions), depict generalized impulse responses of mini-Dow returns to a shock in market positions. Speculative hedge fund activity has a positive impact on returns in the sense that it increases return levels. During the time period analyzed, the Dow index, first increases from a level of 10,750 to 14,200 in the second half of 2007 and then declines after the beginning of the sub-prime crisis and reaches 6,500 at the end of our sample. On average, the Dow experienced a negative return over our sample (11% on an annual basis). Trading activity of speculative hedge funds (HF) and commercial arbitrageurs and brokers and dealers (FA), contribute to reverse the negative trend. On the other hand, commercial financial institutions (FO) and floor brokers/traders (FBT) appear to contribute to the

[33] Among the five markets analyzed, commercial hedge funds hold significant positions only in the mini-Dow.

trend.[34] Interestingly, commercial hedge funds (FH) exhibit no significant impact on returns.

Now we turn our attention to the volatility of the mini-Dow. Table 9, panels C and D, show that volatility is Granger-caused by positions (including those of commercial and non-commercial hedge funds) but not *vice versa*. In line with the results for volatility dynamics described above, speculative hedge fund activity reduces volatility. It is interesting to contrast the graphs in the last two rows of Figures 2 and 3. Traders that increase rate of returns and reverse the trend (speculative hedge funds and arbitrageurs and brokers and dealers), decrease volatility; while traders that decreased returns (financial others), have a net positive effect on volatility. According to classical theory (Friedman, 1953) a speculator should buy when the price is falling and sell when the price is rising. This implies a trend reversal. Speculative hedge fund activity in this market does seem to reverse the trend. Moreover, speculation from hedge funds reduces the risk level in this market. We also notice a difference between the effects of trading activity of commercial hedge funds (hedgers) and non-commercial hedge funds (speculators). The latter category reverses the trend and reduces volatility levels while the former does not have any significant effect on returns and volatility.

4.6 Main Findings

Is speculation activity causing price movements in energy, agricultural, and financial markets?

The analysis of Granger-causality between returns and trader activities yields two main results. First, returns are not Granger-caused by positions. The only exception is the stock market where we find that speculative hedge fund activity has a positive impact on a bearish market. Therefore, the answer to the above question is negative for most markets analyzed and when we have evidence of a causal effect on returns, we find that speculation activity reverses the trend. Second, hedge fund activity is not Granger-causal for returns and/or positions of the other market traders, but it is Granger-caused by the other variables in the system. Once again, the stock market behaves differently. These results are particularly important for the issue we analyze in this paper. In fact, they suggest that speculation activity does not destabilize prices, even in markets and times when prices reach historical highs. Speculation activity, in general, and hedge fund activity, in particular, seems to be responsive to market conditions but is not moving the market, nor is it generating trading activity from other traders. We are aware that Granger-causality

[34] These results hold for the sub-periods January 2005 – August 2007, and September 2007 – March 2009.

tests have limitations. However, our results are very robust. Using different data filtrations (levels and first differences) and different VAR specifications, we always find that speculation activity does not move prices and, in the case of hedge funds, does not cause trading activity by other market participants. These findings are in line with previous literature. Irwin and Yoshimaru (1999), and Fung and Hsieh (2000), for example, find no evidence that hedge fund activity has an impact on market prices. The previous literature, however, analyzes highly aggregated data while we are able to precisely identify specific categories of traders. In this respect, our results are noteworthy.

Overall, the above results seem to provide support to the traditional Keynes-Hicks paradigm on the stabilizing role of speculation in financial markets.

Is speculation activity increasing risk? It is, in fact, possible that speculation activity may not have any impact on prices but it might have an impact on market volatility.

With the exception of the corn market, we find that trading activity Granger-causes volatility. In particular, there is evidence of causality from hedge fund activity to volatility. Further investigation, *via* generalized impulse responses, shows a statistically significant reduction in volatility. In other words, a shock in hedge fund activity reduces volatility. These results are very robust. In fact, we adopt three measures of realized variance and three measures of logarithmic realized standard deviation, and unambiguously find that if hedge fund activity is causal, in a Granger sense, for volatility, this causal relationship implies that hedge fund trading reduces volatility levels. Similar results also apply to commodity swap dealers in the crude oil and natural gas markets. Lower levels of volatility imply that markets are less risky. Less volatile markets are more attractive and perform their role of risk transfer. This implies a reduction in the hedge premia, as predicted by Hirshleifer (1989, 1990).

6. Conclusion

Is speculation activity destabilizing? Our analysis clearly shows that this is not the case. We employ a unique dataset that allows us to precisely identify positions of market participants in five futures markets. By adopting a very simple but well-established technique, Granger-causality, we investigate whether speculation activity is moving prices and increasing volatility. In general, we find that speculation activity is not causing any price movement, but it has some impact on risk: it reduces risk. We are not ruling out the possibility that a single trader (of any category of market participants) might implement trading strategies that move prices and increase volatility. However, as a whole, speculation does not seem to destabilize futures markets. The role of speculation activity in financial markets is very important because it allows hedgers to find counterparties to hedge their positions and, in general, it allows markets to perform their institutional role. Therefore, speculators, in general, and hedge funds, in particular, should not be seen as sinful agents. In fact, we find that speculative trading activity has beneficial effect on markets.

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Table 1
Contract Specifications

	Crude Oil (CL)	Natural Gas (NG)	Corn (C)	EuroDollars (ED)	Mini-Dow (YM)
Exchange	NYMEX	NYMEX	CBOT	CME	CBOT
Trading Unit	1000 US barrel	10000 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	$).01 (1cent) per barrel ($10 per contract)	$0.01 (1cent) 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 mini-Dow).

Table 2
Descriptive Statistics

Panel A – Crude Oil (CL) – January 2005-March 2009 – 1047 obs.

	Returns	Volatility	AD	ΔAD	AS	ΔASP	AM	ΔAM	FBT	ΔFBT	HF	ΔHF
Mean	-0.0463	3.8032	-61509	-64.214	98528	-159.69	-24744	512.65	-7134.2	146.62	241.29	-1285.2
Median	0.0588	2.1706	-61580	306	94960	-492	-25603	272	-7185	18	1729	-1295
St.Dev.	2.5143	4.5557	25713	6782.5	34882	8207.6	12033	3161.8	8941.7	2228.9	27127	6644.2
Skew	-0.1671	2.7523	-0.4610	-0.2125	0.4544	0.0349	0.0441	0.5096	0.2030	0.3287	-0.1201	-0.9053
Kurt	6.4251	10.812	3.7731	5.0029	3.3507	3.8687	2.7207	4.8302	4.5732	4.9581	2.2813	9.9187
AC(1)	-0.0878	0.8653	0.9201	0.3441	0.9281	0.4697	0.9125	0.2846	0.8913	-0.0502	0.9346	0.0058
AC(20)	-0.0344	0.7717	0.3377	0.1519	0.1230	0.3021	0.5321	0.2352	0.1854	0.0898	0.5793	0.0874
ADF	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0005	0.0000	0.0000	0.0000

Panel B – Natural Gas (NG) – January 2005-March 2009 – 1053 obs.

	Returns	Volatility	AD	ΔAD	AS	ΔAS	AP	ΔAP	FBT	ΔFBT	HF	ΔHF
Mean	-0.1882	5.2782	-8148.8	89.888	33214	-381.77	-1923.8	6.5489	-2373.2	64.730	-29401	-70.391
Median	-0.1569	3.9265	-6887	26	30503	-510	-1663	0.0000	-2318	39	-26874	-246
St.Dev.	3.0563	4.4653	7681.6	1429.4	20148	2867.1	2486.1	428.41	3937.6	1441.9	17628	3423.4
Skew	0.0966	1.9158	-0.2588	-0.0081	0.4349	-1.4249	-0.4238	1.3370	0.0564	0.0119	-0.4023	0.5964
Kurt	4.4262	8.3137	2.2316	5.2892	2.4758	7.6439	3.1552	17.7895	3.2987	8.5135	2.9345	6.3237
AC(1)	0.0243	0.3783	0.9498	0.2503	0.9602	0.5307	0.9312	0.2635	0.8767	-0.1286	0.9589	0.1562
AC(20)	0.0085	0.1789	0.2467	0.0009	-0.1129	-0.1683	0.2740	0.0077	0.0869	0.0308	0.1582	-0.0480
ADF	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000	0.0006	0.0000	0.0000	0.0000

Panel C – Corn (C) – August 2006-March 2009 – 646 obs.

	Returns	Volatility	AD	ΔAD	AS	ΔASP	AM	ΔAM	FBT	ΔFBT	HF	ΔHF
Mean	0.0251	3.1528	-191899	868.23	196425	-328.67	-6447.3	-116.57	-14321	-208.02	23135	-362.75
Median	0.0000	2.5354	-203709	830.50	205261	-620	-6107	-152.5	-12516	-151.5	25989	-423.32
St.Dev.	2.3031	2.3062	67578	6668.9	71087	7937.1	8007.7	1400	22989	4191.12	43765	6918.2
Skew	-0.1967	2.0833	0.5545	0.2677	-0.0321	0.5368	0.1272	0.4963	0.1265	0.0566	-0.0142	-0.2288
Kurt	3.6168	9.4042	2.8670	4.9924	2.3532	7.5340	2.7922	5.6987	2.7297	6.5418	3.0761	5.8681
AC(1)	0.0150	0.5290	0.9877	0.3853	0.9817	0.6226	0.9608	0.0966	0.9615	0.2368	0.9735	0.1433
AC(20)	-0.0537	0.3394	0.5264	-0.1450	0.5056	-0.0474	0.2556	-0.0006	0.4445	0.0094	0.4496	0.0326
ADF	0.0000	0.0000	0.0057	0.0000	0.0092	0.0000	0.0000	0.0000	0.0003	0.0000	0.0005	0.0000

Panel D – Eurodollar (ED) – January 2005-May 2008 – 1045 obs.

	Returns	Volatility	FA	ΔFA	FB	ΔFB	FC	ΔFC	FBT	ΔFBT	HF	ΔHF
Mean	0.0003	0.0025	-158630	-555.1	-65481	202.29	-56801	476.92	35828	933.44	9133.9	-35.448
Median	0.0000	0.0010	-130246	16	-29143	115	-68800	443	31921	686	-6448	-1148
St.Dev.	0.0591	0.0046	267864	15625	161298	12341	79341	13035	79327	14571	136728	25395
Skew	0.0148	5.3308	-0.1450	-0.5426	-0.7453	0.6446	0.5171	-1.3694	0.0735	0.1726	0.2378	0.2737
Kurt	9.6360	44.024	1.6864	6.3110	2.8785	13.700	2.8395	23.445	2.5369	38.096	2.5501	11.422
AC(1)	0.1048	0.5459	0.9950	-0.0084	0.9912	0.1369	0.9764	0.0555	0.9707	-0.2504	0.9741	-0.0556
AC(20)	0.0170	0.2102	0.9044	-0.0420	0.7853	0.0596	0.6550	-0.0065	0.6158	0.0932	0.5627	0.0245
ADF	0.0000	0.0000	0.1690	0.0000	0.1541	0.0000	0.0539	0.0000	0.3201	0.0000	0.0008	0.0000

Panel E – Mini-Dow (YM) – January 2005-May 2008 – 1038 obs.

	Returns	Volatility	FA	ΔFA	FH	ΔFH	FO	ΔFO	FBT	ΔFBT	HF	ΔHF
Mean	-0.0438	1.3029	525.22	116.74	10093	-77.655	-1126.4	12.156	-3844.4	15.663	2334.3	-45.628
Median	0.0435	0.3634	-561	222	631.5	-3	-786	10	-4228	-65.5	1489.5	-28
St.Dev.	1.4420	3.1887	15248	2912.3	20662	1749.6	2465.9	547.07	12523	1971.9	10066	2707
Skew	0.5730	6.2088	0.1955	-0.3305	1.2705	-0.4312	-1.3895	0.3450	-0.4860	0.8132	-0.2248	-0.1709
Kurt	20.355	55.944	2.9972	8.5299	3.7821	46.097	6.6388	11.3671	3.8928	30.838	2.4640	7.9691
AC(1)	-0.1346	0.7544	0.9712	0.0407	0.9936	0.1505	0.9673	-0.0508	0.9464	-0.0539	0.9575	-0.1820
AC(20)	-0.0245	0.5054	0.4724	-0.0348	0.9259	-0.0311	0.4832	-0.0161	0.6726	-0.0107	0.7098	0.0249
ADF	0.0000	0.0148	0.0007	0.0000	0.0084	0.0000	0.0276	0.0000	0.0196	0.0000	0.0001	0.0000

ADF: augmented Dickey-Fuller unit root test (p-values). Volatility: two-scale realized volatility in transaction time, Zhang, Mykland and Aït-Sahalia (2005). AD: dealer/merchant; AS: commodity swap dealer; AM: manufacturer; AP: producer; FA: arbitrageurs or brokers/dealers; FB: non U.S. commercial bank; FC: U.S. commercial bank; FF: pension funds; FH: hedge funds (commercial); FO: financial – other; FBT: floor broker/trader; HF: hedge fund (non-commercial). Δ refers to first difference.

Table 3
Long/Short Percentage of Total Open Interest

Panel A – Crude Oil (CL)

	AD	AS	AM	FBT	HF	Total Mean	Total Max	Total Min
Long	0.074	0.417	0.010	0.021	0.233	0.754	0.878	0.524
Short	0.296	0.064	0.102	0.048	0.224	0.734	0.849	0.576

Panel B – Natural Gas (NG)

	AD	AS	AP	FBT	HF	Total Mean	Total Max	Total Min
Long	0.074	0.385	0.008	0.024	0.286	0.777	0.912	0.623
Short	0.159	0.069	0.027	0.046	0.567	0.868	0.999	0.686

Panel C – Corn (C)

	AD	AS	AM	FBT	HF	Total Mean	Total Max	Total Min
Long	0.053	0.413	0.034	0.058	0.198	0.756	0.847	0.611
Short	0.437	0.016	0.048	0.087	0.159	0.746	0.845	0.634

Panel D – €/$ (ED)

	FA	FB	FC	FBT	HF	Total Mean	Total Max	Total Min
Long	0.1427	0.0877	0.0369	0.0428	0.1250	0.4351	0.6799	0.2113
Short	0.2413	0.1274	0.0732	0.0201	0.1220	0.5840	0.7981	0.3911

Panel E – Mini-Dow (YM)

	FA	FH	FO	FBT	HF	Total Mean	Total Max	Total Min
Long	0.2946	0.1625	0.0148	0.1074	0.0979	0.6772	0.8725	0.3463
Short	0.2800	0.0592	0.0282	0.1493	0.0819	0.5987	0.8029	0.2739

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

Table 4
Correlations – Net Futures Positions

Panel A – Crude Oil (CL)

	AD	AS	AM	FBT	HF
Returns	-0.04 -0.06	0.03 0.05	-0.08* -0.14*	0.01 -0.08*	0.10* 0.32*
Volatility	-0.22* -0.03	0.11* 0.06	0.26* -0.05	-0.09* 0.02	0.02 -0.03*
AS	-0.51* -0.64*	1.00			
AM	0.25* 0.25*	-0.32* -0.41*	1.00		
FBT	0.10* 0.02	-0.36* -0.18*	-0.03 0.04	1.00	
HF	-0.29* -0.23*	-0.41* -0.25*	-0.32* -0.23*	-0.01 -0.13*	1.00

Panel B – Natural Gas (NG)

	AD	AS	AP	FBT	HF
Returns	-0.06* -0.18*	0.02 0.02	-0.02 -0.20*	-0.14* -0.23*	0.04 0.18*
Volatility	0.12* 0.07*	-0.01 -0.06*	0.19* 0.05	-0.03 0.01	-0.09* 0.02
AS	-0.10* -0.34*	1.00			
AP	0.22* 0.09*	-0.21* -0.17*	1.00		
FBT	-0.13* 0.14*	-0.45* -0.18*	0.11* 0.05	1.00	
HF	-0.27* -0.08*	-0.85* -0.62*	-0.07* -0.08*	0.23* -0.30*	1.00

Panel C – Corn (C)

	AD	AS	AM	FBT	HF
Returns	-0.02 -0.37*	0.05 0.00	-0.03 -0.29*	-0.06 0.05	0.00 0.45*
Volatility	0.32* 0.01	-0.38* -0.07	-0.07 -0.05	0.15* 0.08*	-0.05 -0.01
AS	-0.69* -0.54*	1.00			
AM	-0.09* 0.34*	-0.27* -0.23*	1.00		
FBT	0.02 0.05	-0.55* -0.46*	0.39* 0.02	1.00	
HF	-0.64* -0.51*	0.01 -0.13*	0.19 -0.31*	0.22* -0.09*	1.00

Panel D – Eurodollar (ED)

	FA	FB	FC	FBT	HF
Returns	-0.20*	-0.07*	0.04	0.01	0.19*
Volatility	-0.04	0.01	0.01	-0.02	-0.03
FB	-0.07*	1.00			
FC	-0.08*	-0.01	1.00		
FBT	-0.02	0.12*	-0.06	1.00	
HF	-0.33*	-0.09*	-0.22*	0.13*	1.00

Panel E – Mini-Dow (YM)

	FA	FH	FO	FBT	HF
Returns	0.04 0.13*	0.05 0.00	-0.06* -0.30*	-0.06* -0.10*	0.08* 0.21*
Volatility	-0.17* -0.01	-0.20* 0.02	0.16* -0.01*	0.16* -0.03	-0.20* 0.00
FH	-0.32* -0.12*	1.00			
FO	0.09* -0.09*	-0.02 0.02	1.00		
FBT	-0.11* -0.06*	-0.48* -0.48*	-0.31* 0.03	1.00	
HF	-0.24* -0.50*	0.47 -0.00	-0.17* -0.25*	-0.47* -0.23*	1.00

* significance at 10% level. The top number refers to net futures positions in levels while the bottom number refers to the first difference. The €/$ positions in levels are not stationary. Therefore, no correlation is reported.

Table 5
Granger non-Causality Test: p-values –Crude Oil (CL)

Panel A: Returns and Net Futures Positions in Levels – Optimal Lags-Length (5)

	Returns	AD	AS	AM	FBT	HF	All
Returns		0.546	0.621	0.276	0.091	0.624	0.148
AD	0.000*		0.026*	0.226	0.492	0.058	0.000*
AS	0.004*	0.402		0.000*	0.155	0.645	0.000*
AM	0.000*	0.012*	0.000*		0.025*	0.023*	0.000*
FBT	0.035*	0.371	0.108	0.288		0.350	0.000*
HF	0.021*	0.199	0.009*	0.142	0.264		0.000*
All	0.000*	0.002*	0.000*	0.000*	0.008*	0.181	

Panel B: Returns and Net Futures Positions in First Difference – Optimal Lags-Length (4)

	Returns	AD	AS	AM	FBT	HF	All
Returns		0.253	0.362	0.211	0.218	0.533	0.199
AD	0.000*		0.011*	0.317	0.420	0.016*	0.000*
AS	0.001*	0.195		0.000*	0.217	0.590	0.000*
AM	0.000*	0.004*	0.000*		0.052	0.003*	0.000*
FBT	0.017*	0.353	0.011*	0.416		0.252	0.000*
HF	0.013*	0.427	0.030*	0.433	0.380		0.000*
All	0.000*	0.001*	0.000*	0.000*	0.067	0.086	

Panel C: Volatility and Net Futures Positions in Levels – Optimal Lags-Length (5)

	Volatility	AD	AS	AM	FBT	HF	All
Volatility		0.191	0.064	0.086	0.063	0.127	0.001*
AD	0.024*		0.089	0.188	0.093	0.001*	0.000*
AS	0.000*	0.206		0.000*	0.540	0.841	0.000*
AM	0.340	0.000*	0.000*		0.018*	0.023*	0.000*
FBT	0.035*	0.089	0.088	0.468		0.206	0.000*
HF	0.052	0.272	0.004*	0.064	0.148		0.000*
All	0.000*	0.000*	0.000*	0.000*	0.000*	0.004*	

Panel D: Volatility and Net Futures Positions in First Difference – Optimal Lags-Length (5)

	Volatility	AD	AS	AM	FBT	HF	All
Volatility		0.066	0.001*	0.062	0.025*	0.072	0.000*
AD	0.223		0.064	0.209	0.117	0.000*	0.000*
AS	0.001*	0.185		0.000*	0.242	0.557	0.000*
AM	0.556	0.000*	0.000*		0.023*	0.000*	0.000*
FBT	0.063	0.124	0.098	0.394		0.596	0.000*
HF	0.079	0.453	0.028*	0.086	0.284		0.000*
All	0.007*	0.000*	0.000*	0.000*	0.001*	0.000*	

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

Table 6
Granger non-Causality Test: p-values –Natural Gas (NG)

Panel A: Returns and Net Futures Positions in Levels – Optimal Lags-Length (4)

	Returns	AD	AP	AS	FBT	HF	All
Returns		0.629	0.578	0.426	0.205	0.796	0.483
AD	0.357		0.004*	0.031*	0.961	0.301	0.000*
AP	0.104	0.097		0.000*	0.805	0.053	0.000*
AS	0.000*	0.163*	0.000*		0.495*	0.311	0.000*
FBT	0.010*	0.098*	0.000*	0.275		0.219	0.000*
HF	0.044	0.049*	0.000	0.395	0.957		0.000*
All	0.001*	0.000*	0.000*	0.000*	0.847	0.061	

Panel B: Returns and Net Futures Positions in First Difference – Optimal Lags-Length (3)

	Returns	AD	AP	AS	FBT	HF	All
Returns		0.448	0.403	0.503	0.345	0.666	0.571
AD	0.206		0.013*	0.009*	0.913	0.841	0.000*
AP	0.124	0.301		0.000*	0.908	0.303	0.000*
AS	0.000*	0.385	0.000*		0.502	0.535	0.000*
FBT	0.019*	0.106	0.001*	0.194		0.308	0.000*
HF	0.036*	0.025*	0.000*	0.652	0.889		0.000*
All	0.000*	0.000*	0.000*	0.000*	0.923	0.240	

Panel C: Volatility and Net Futures Positions in Levels – Optimal Lags-Length (4)

	Volatility	AD	AP	AS	FBT	HF	All
Volatility		0.393	0.119	0.557	0.080	0.037*	0.016*
AD	0.839		0.001*	0.025*	0.993	0.654	0.000*
AP	0.168	0.053		0.000*	0.631	0.147	0.000*
AS	0.725	0.112	0.000*		0.476	0.121	0.000*
FBT	0.763	0.004*	0.000*	0.353		0.063	0.000*
HF	0.325	0.023*	0.000*	0.173	0.991		0.000*
All	0.633	0.000*	0.000*	0.000*	0.806	0.051	

Panel D: Volatility and Net Futures Positions in First Difference – Optimal Lags-Length (3)

	Volatility	AD	AP	AS	FBT	HF	All
Volatility		0.974	0.476	0.065	0.066	0.667	0.052
AD	0.951		0.001*	0.014*	0.996	0.865	0.000*
AP	0.169	0.105		0.000*	0.975	0.244	0.000*
AS	0.391	0.538	0.000*		0.819	0.139	0.000*
FBT	0.477	0.154	0.001*	0.286		0.344	0.000*
HF	0.044	0.015*	0.000*	0.354	0.976		0.000*
All	0.344	0.002*	0.000*	0.000*	0.879	0.437	

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

Table 7
Granger non-Causality Test: p-values –Corn (C)

Panel A: Returns and Net Futures Positions in Levels – Optimal Lags-Length (5)

	Returns	AD	AM	AS	FBT	HF	All
Returns		0.358	0.847	0.634	0.863	0.650	0.462
AD	0.032*		0.280	0.100	0.433	0.921	0.001*
AM	0.914	0.600		0.000*	0.922	0.792	0.000*
AS	0.072	0.310	0.000*		0.062	0.689	0.000*
FBT	0.801	0.138	0.001*	0.220		0.045*	0.000*
HF	0.313	0.131	0.003*	0.059	0.962		0.001*
All	0.228	0.007*	0.000*	0.000*	0.134	0.078	

Panel B: Returns and Net Futures Positions in Levels – Optimal Lags-Length (5)

	Returns	AD	AM	AS	FBT	HF	All
Returns		0.285	0.777	0.799	0.823	0.394	0.442
AD	0.004*		0.388	0.544	0.591	0.892	0.002*
AM	0.633	0.745		0.910	0.899	0.861	0.960
AS	0.355	0.607	0.000*		0.352	0.948	0.000*
FBT	0.799	0.056	0.001*	0.059		0.047*	0.000*
HF	0.240	0.327	0.001*	0.101	0.957		0.000*
All	0.100	0.018*	0.000*	0.563	0.483	0.158	

Panel C: Volatility and Net Futures Positions in Levels – Optimal Lags-Length (5)

	Volatility	AD	AM	AS	FBT	HF	All
Volatility		0.273	0.923	0.678	0.152	0.164	0.008*
AD	0.041*		0.220	0.083	0.233	0.898	0.001*
AM	0.103	0.645		0.000*	0.884	0.666	0.000*
AS	0.544	0.665	0.000*		0.044*	0.778	0.000*
FBT	0.198	0.038*	0.000*	0.267		0.047*	0.000*
HF	0.726	0.117	0.004*	0.138	0.991		0.001*
All	0.012*	0.003*	0.000*	0.000*	0.103	0.070	

Panel D: Volatility and Net Futures Positions in First Difference – Optimal Lags-Length (5)

	Volatility	AD	AM	AS	FBT	HF	All
Volatility		0.711	0.892	0.266	0.174	0.330	0.020*
AD	0.034*		0.337	0.147	0.439	0.893	0.010*
AM	0.222	0.722		0.816	0.940	0.795	0.868
AS	0.431	0.774	0.000*		0.246	0.906	0.000*
FBT	0.011*	0.022*	0.000*	0.046*		0.045*	0.000*
HF	0.839	0.168	0.001*	0.234	0.973		0.000*
All	0.004*	0.013*	0.000*	0.158	0.500	0.148	

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

Table 8
Granger non-Causality Test: p-values – Eurodollar (ED)

Panel A: Returns and Net Futures Positions in First Difference – Optimal Lags-Length (4)

	Returns	FA	FC	FB	FBT	HF	All
Returns		0.174	0.203	0.226	0.165	0.315	0.478
FA	0.380		0.727	0.671	0.051	0.924	0.144
FC	0.254	0.511		0.861	0.139	0.270	0.196
FB	0.381	0.897	0.001*		0.100	0.654	0.000*
FBT	0.731	0.020*	0.173	0.439		0.228	0.239
HF	0.548	0.005*	0.301	0.594	0.005*		0.001*
All	0.495	0.000*	0.001*	0.169	0.004*	0.411	

Panel B: Volatility and Net Futures Positions in First Difference – Optimal Lags-Length (5)

	Volatility	FA	FC	FB	FBT	HF	All
Volatility		0.053	0.085	0.104	0.058	0.007*	0.025*
FA	0.278		0.192	0.370	0.668	0.279	0.059
FC	0.642	0.015*		0.754	0.285	0.211	0.373
FB	0.575	0.153	0.021*		0.079	0.001*	0.000*
FBT	0.054	0.573	0.147	0.592		0.047*	0.084
HF	0.111	0.846	0.196	0.946	0.002*		0.002*
All	0.239	0.015*	0.001*	0.198	0.000*	0.000*	

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

Table 9
Granger non-Causality Test: p-values – Mini-Dow (YM)

Panel A: Returns and Net Futures Positions in Levels – Optimal Lags-Length (2)

	Returns	FA	FO	FH	FBT	HF	All
Returns		0.082	0.074	0.652	0.672	0.127	0.036*
FA	0.089		0.184	0.696	0.377	0.026*	0.000*
FO	0.188	0.083		0.000*	0.023*	0.046*	0.000*
FH	0.022*	0.493	0.000*		0.494	0.756	0.000*
FBT	0.813	0.469	0.314	0.826		0.672	0.228
HF	0.064	0.146	0.185	0.444	0.150		0.003*
All	0.011*	0.108	0.000*	0.000*	0.063	0.080	

Panel B: Returns and Net Total Positions in First Difference – Optimal Lags-Length (3)

	Returns	FA	FO	FH	FBT	HF	All
Returns		0.057	0.010*	0.221	0.471	0.071	0.026*
FA	0.097		0.818	0.590	0.658	0.007*	0.000*
FO	0.165	0.261		0.518	0.171	0.191	0.232
FH	0.070	0.588	0.000*		0.434	0.283	0.000*
FBT	0.237	0.762	0.219	0.918		0.350	0.521
HF	0.090	0.102	0.444	0.332	0.250		0.004*
All	0.038*	0.089	0.000*	0.360	0.362	0.008*	

Panel C: Returns and Net Futures Positions in Levels – Optimal Lags-Length (4)

	Volatility	FA	FO	FH	FBT	HF	All
Volatility		0.053	0.061	0.224	0.712	0.079	0.002*
FA	0.829		0.519	0.534	0.631	0.004*	0.003*
FO	0.116	0.441		0.000*	0.086	0.357	0.000*
FH	0.264	0.756	0.000*		0.460	0.239	0.000*
FBT	0.267	0.968	0.319	0.983		0.451	0.239
HF	0.601	0.145	0.460	0.311	0.442		0.050*
All	0.397	0.258	0.000*	0.000*	0.294	0.005*	

Panel D: Volatility and Net Futures Positions in First Difference – Optimal Lags-Length (4)

	Volatility	FA	FO	FH	FBT	HF	All
Volatility		0.042*	0.162	0.270	0.909	0.043*	0.007*
FA	0.741		0.799	0.153	0.651	0.008*	0.001*
FO	0.370	0.590		0.640	0.275	0.335	0.435
FH	0.069	0.138	0.000*		0.474	0.389	0.000*
FBT	0.016*	0.583	0.213	0.118		0.530	0.011*
HF	0.359	0.134	0.770	0.348	0.325		0.043*
All	0.110	0.089	0.000*	0.010*	0.617	0.008*	

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

Figure 1
Price and Realized Volatility

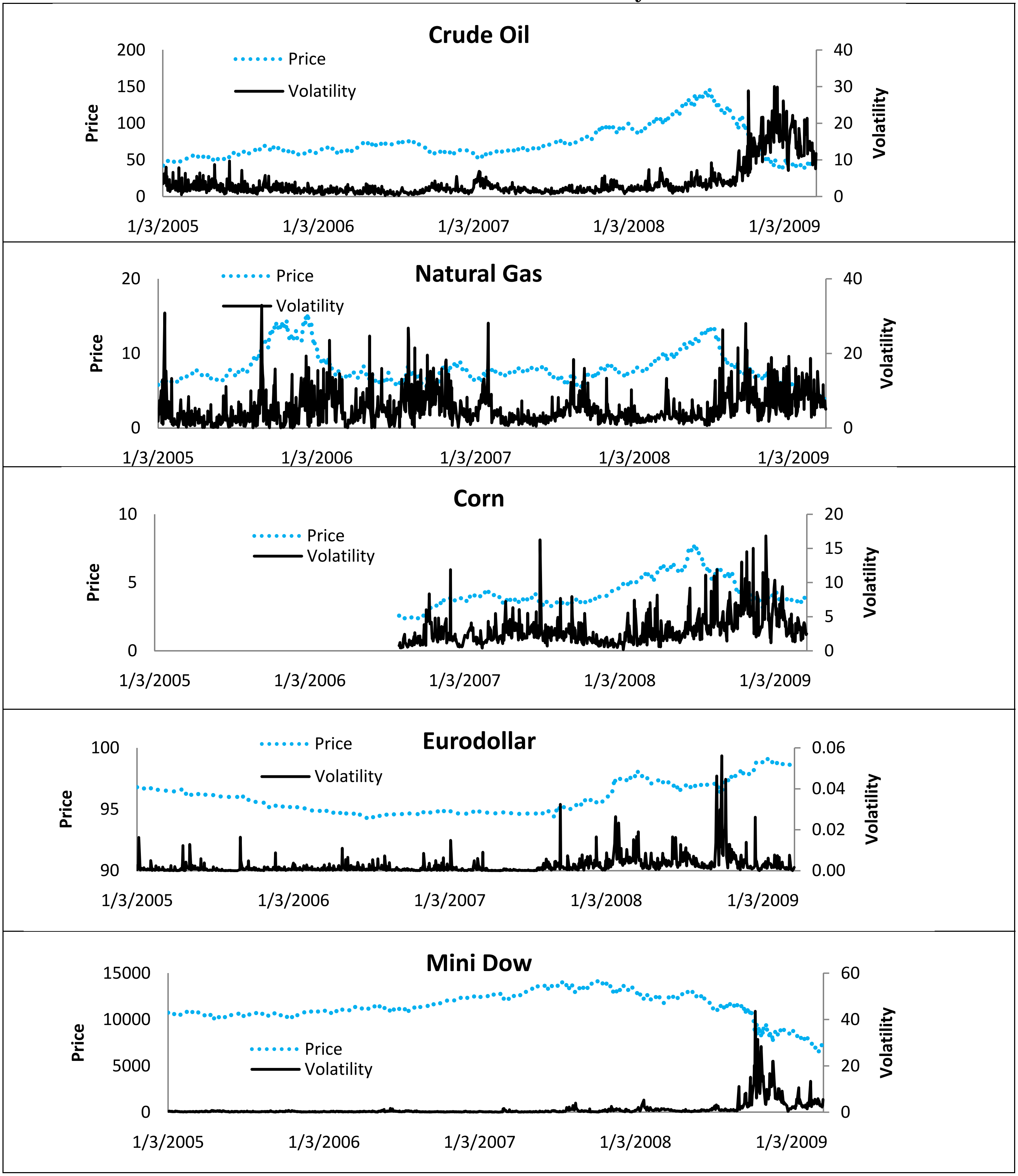


Figure 2

Generalized Impulse Response of Volatility/Returns to One S.D. Innovations in Trader Positions in Levels

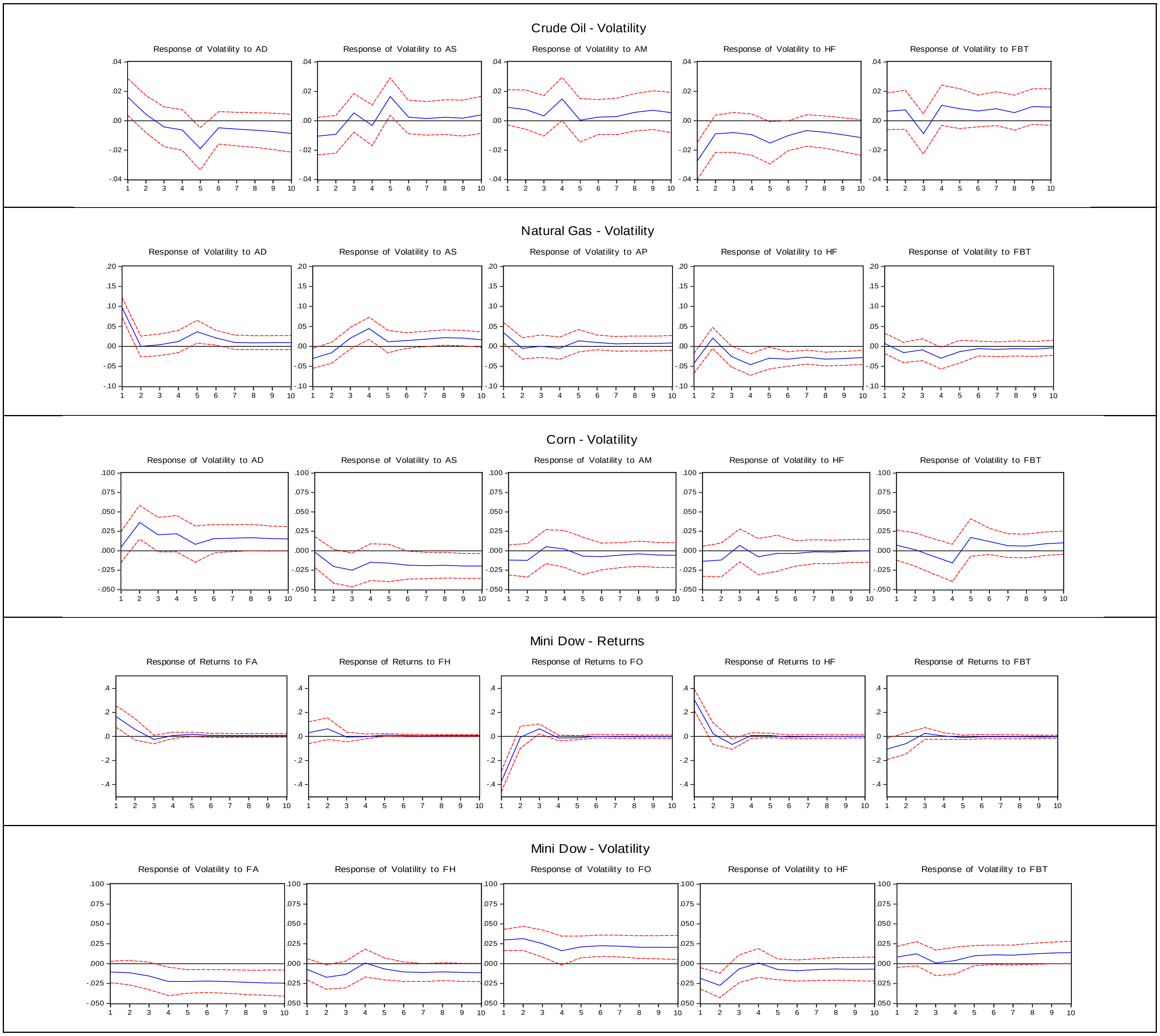
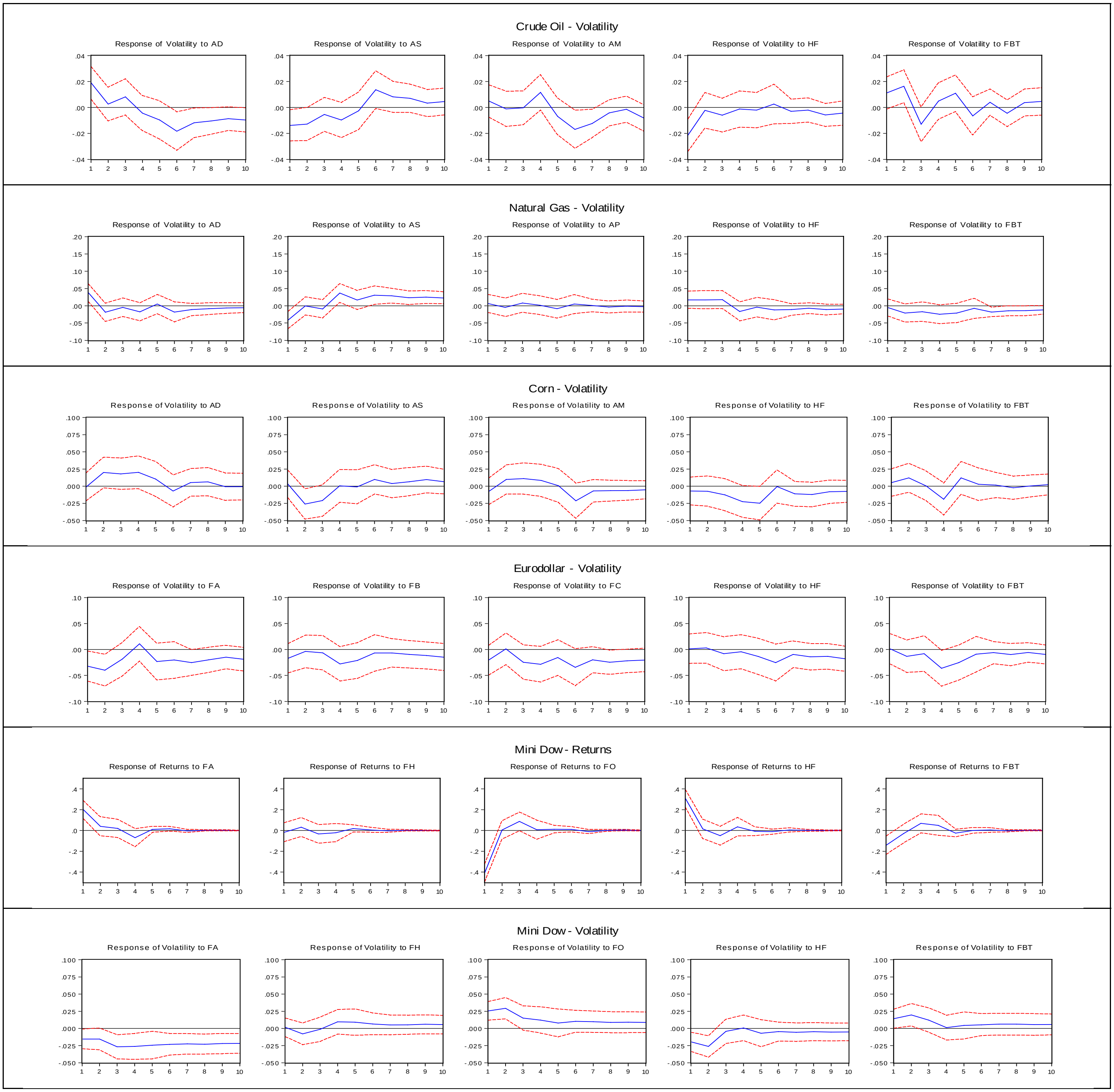


Figure 3

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



Appendix

List of the trader sub-categories in the CFTC's large-trader reporting system (LTRS)

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

Hedge Funds (HF)

CPO	Commodity Pool Operator
CTA	Commodity Trading Advisor
AP	Associated Person
MM	Managed Money (subset)

Floor Broker and Traders (FBT)

FB	Floor Broker
FT	Floor Trader

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