The Dynamics of Trading in Commodity Futures

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Abstract

We examine weekly trading imbalances for speculators and small investors in the commodity futures market and their price and volatility effects over the period 1986-2012. First, speculators behave like short term momentum traders and long-term contrarians. Their imbalances are positively autocorrelated and positively cross-autocorrelated with small investor imbalances, consistent with their 'riding the wave' caused by small traders. Speculators sell (buy) to a greater extent after their long (short) positions have become larger, especially when volatility is elevated: this is consistent with their being risk averse. Small trader imbalances also follow speculator imbalances of a given sign, and display mean reversion and volatility aversion, but both are weaker than for speculators. Second, imbalances have positive and significant permanent price effects, which are larger for speculators. Further analysis suggests that the price impact of speculator imbalances is smaller when they act as suppliers of liquidity to hedgers. Finally, price volatility is related positively to lagged small trader imbalances, supportive of noise trader effects, and negatively to the lagged variability of speculator imbalances, which is inconsistent with speculator activity promoting futures market volatility. Our results are broadly similar in extreme market conditions. The picture that emerges from our analysis is that speculators are risk averse, short-term oriented, liquidity providers with trades that are, in general, not destabilizing. Our work contributes to the debate on the effects of trading, especially by speculators, and the need for new regulatory initiatives.

Keywords: Speculation; Trading; Futures Markets; Futures Prices; Commodities

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1 Introduction

Commodity markets are an important sector of the real economy in which producers, consumers, and dealers meet and trade in a competitive environment. In addition to the presence of a large physical market, for most commodities there is usually a deep and active derivatives market in which participants trade for hedging and also for speculative purposes.

The increased participation in these markets of traditional speculators as well as of recent entrants into commodities trading, such as investment banks and hedge funds, has potentially provided benefits in the form of improved risk sharing. But it has also led regulators and practitioners to worry that such speculative trading can destabilize markets, and cause undesirable price volatility. Additionally, recent spikes in futures prices[4] have prompted a spirited debate about the role of speculative trading in price formation. As speculative behavior is thought to be related to market instability (Brunnermeier and Pedersen, 2009) and systemic risk (Acharya and Naqvi, 2011), the dynamics of speculative trading are of interest to regulators and market participants in general.

In this paper, we study futures trading activity and its relation to price changes and price volatility. In contrast to the extant literature, which studies specific investor groups or commodities or short time periods, we analyze trading activity for a comprehensive sample of unrelated[5] groups of commodities over the 1986–2012period, the longest period for which trading data are available.

Our analysis focuses on three questions. First, we examine the determinants of trader imbalances. Second, we estimate the price impact of order imbalances, focusing on the extent to which speculator trades move prices. Third, we explore the relation between imbalances and futures price volatility. We study these relations unconditionally and also in extreme market conditions: high uncertainty, tight funding constraints, high sentiment and good macro-economic states. This conditional analysis is important because trading activity,

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[4] In July 2008 the price of crude oil increased to $147/bbl. and declined dramatically soon thereafter. Such booms and busts can potentially impose large costs on consumers. The importance of such effects in the real economy has stimulated debate on the factors that drive such large price changes (Hooker (1996), Rotemberg and Woodford (1996), Hamilton (2003), Sauter and Awerbuch (2003)).

[5] Prices are unrelated in the sense that their supply or demand cross-elasticities are almost equal to zero.

especially speculator orders, might have small effects on average, but these effects could be pronounced in times of market stress.

Our sample of 26 commodities includes *grains* (corn, soybeans, wheat, soybean oil, soybean meal, wheat KC, wheat Minn, and oats), *energy* (crude oil, natural gas, gasoline and heating oil), *livestock* (feeder cattle, lean hogs, and live cattle), *metals* (gold, silver, copper, platinum and palladium), *food and fiber* (sugar, cocoa, coffee, cotton, frozen orange juice, and lumber). The source of the trading data is the weekly Commitments of Traders (COT) reports published by the U.S. Commodity Futures Trading Commission (CFTC). These reports breakdown futures contract open interest into commercial (*hedgers* that include dealers, producers and manufacturers), non-commercial (*speculators* that include hedge funds and commodity trading firms), and *small* trader positions. Our measure of net demand is the change in net interest (long minus short open interest), available in aggregated form by trader type. This is the analog of equity market order imbalance. We combine the COT data with data on weekly futures returns and other market and macroeconomic data.

We start by studying imbalances. During our sample period, speculators behave like momentum traders, chasing high weekly returns, and contrarians in the long-term, selling after high six month returns. Speculator imbalances are positively autocorrelated, consistent with order splitting, and positively cross-autocorrelated with small investor imbalances, consistent with their 'riding the wave' caused by small trades. Last, speculators sell (buy) to a greater extent after their long (short) positions have become larger, and especially when volatility is elevated: this suggests a desire to return to more neutral positions and is consistent with speculators being risk averse. Small trader imbalances, too, follow speculator imbalances of a given sign. Their imbalances display mean reversion and some volatility aversion, but both are weaker than in the case of speculators.

We next examine how imbalances affect prices. We find a positive relation between returns and contemporaneous imbalances from both speculators and small traders, and a negative relation to lagged imbalances. The contemporaneous and lagged relations are stronger for speculator imbalances, as is the permanent (long run) effect. Thus, while there is evidence of liquidity related reversals in prices (e.g. due to inventory effects), information appears to play prominent role in explaining why speculator trading affects prices.

An issue in interpreting the price impact results unambiguously is that prices are the outcome of the interaction of demand and supply. It is possible that, at times, speculators supply liquidity to hedgers, who aggressively demand liquidity. At such times, the price impact of speculator imbalances should be small. We address this possibility by introducing an interaction term for the case when speculative imbalances are large. The logic behind this test is that hedgers are likely to place larger trades (e.g.around the time the crop is harvested). If speculators facilitate these trades, the price impact of speculator imbalances should be lower than unconditionally. The coefficient on the interaction term is negative and significant. This result suggests that, although speculators move prices significantly when they demand liquidity (the unconditional case), the price impact of their trades is smaller when they act as suppliers of liquidity to hedgers.[6]

Recent commodity price volatility has renewed interest among academics, practitioners and policy makers in the role and impact of derivatives traders, especially speculators, in these markets.[7] We contribute to the debate by exploring the effect of speculator and small trader imbalances on volatility. We find that volatility is related positively to the lagged small trader imbalance and negatively to the lagged variability of speculator imbalances. Noise trader risk is a possible explanation for the positive association between volatility and the small trader imbalance. The negative coefficient on speculator imbalance variability is inconsistent with speculator activity promoting futures market volatility.

We carry out several checks to confirm that our results are robust. We add other control variables to our models, including proxies for fundamentals such as global economic growth. Our conclusions are unchanged. The coefficients on the proxies for fundamentals have the expected signs. Furthermore, a potential explanation for our findings is the recent increase in financialization of commodity markets: non-information based investments by retail and institutional investors who buy commodities for portfolio allocation reasons, reportedly starting in the early 2000s. Several observers and policymakers (e.g. Masters, 2008) have expressed the concern that these investments might have caused unwarranted

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[6] The positive coefficient on speculator imbalances suggests that speculators are viewed as informed traders. The fact that the interaction coefficient is negative suggests that the price impact declines in certain circumstances.

[7] See for example Dinceler, Khokher, and Simin (2005), NYMEX (2005), Erb and Harvey (2006), Miffre and Rallis (2007), Haigh, Hranaiova, and Overdahl (2007), Interagency Task Force on Commodity Markets (2008), Büyükşahin, Haigh, Harris, Overdahl, and Robe (2008), Khan, Khokher, and Simin (2008), Gorton, Hayashi, and Rouwenhorst (2008), Büyükşahin and Harris (2009), Acharya, Ramadorai, and Lochstoer (2010), Stoll and Whaley (2010), and de Roon and Szymanowska (2010).

price increases and excessive price volatility. We repeat all our tests for the sub-period ending in 2000 and find similar results. Therefore, financialization does not appear to be the driving force behind the patterns we uncover.

Our analysis of extreme market conditions is instructive. The reversion in speculator positions is stronger in extreme market conditions, regardless of whether conditions are good or bad. The stronger reversion when funding is tight (TED is high) is consistent with the 'financial distress' hypothesis (see Cheng, Kirilenko and Xiong, 2012): financial traders reduce their participation in the market after suffering losses. More generally, however, speculators appear to recognize extreme conditions and reduce their market participation. We also find that, during turbulent periods, there is stronger feedback from small investor imbalances to speculator imbalances.[8] The permanent price impact of speculator imbalances and the effect of imbalance variability on price volatility are broadly unchanged in extreme conditions. These results suggest that speculator trades are, in general, not destabilizing.

Our work is closely related to Cheng, Kirilenko and Xiong (2012), who look at the interplay between the net demands of commercial hedgers and non-commercial speculators in commodity futures. They find that after the financial crisis erupted in September 2008, distressed commodity index traders and hedge funds demanded liquidity from commercial hedgers rather than providing liquidity to them. That is, the authors find that during normal times, speculators accommodate hedgers' needs, i.e. absorb risk from them by taking long positions in futures contracts, whereas during crises (high VIX) hedgers absorb the risk that speculators want to unload. Their focus is therefore on the interaction between net demands and (distressed) market conditions. Our work differs from theirs in our focus on the interplay of net demand, prices and volatility.

Our paper is also related to Hong and Yogo (2012), who provide a theoretical model in which open interest is more informative than futures prices. Their results suggest that open interest is pro-cyclical, correlated with both macroeconomic activity, and predicts commodity and bond returns. Our paper departs from theirs in that we contrast the

[8] Both results are consistent with Brunnermeier and Nagel (2004), who study hedge fund behavior during the dot-com bubble.

determinants and effects of speculatorand small trader net interest, whereas they examine open interest as a whole.

The rest of the paper is organized as follows. Section 2 describes the data and methods. Section 3 analyzes the determinants of trading imbalances. Section 4 and Section 5 examine the pricing and volatility effects of imbalances. Section 6 discusses robustness tests and extensions. Section 6 concludes.

2 Data and Sample

2.1 Commitments of Traders Reports (COT)

Our data source for trading positions is the Commitments of Traders (COT) reports provided by the Commodity Futures Trading Commission (CFTC), which monitors U.S. futures and options trading through its market surveillance program. Following the Commodity Exchange Act (CEA), the CFTC collects and stores data on the positions (open interest)for markets in which 20 or more traders hold positions equal to or above the reporting levels established by the CFTC.[9]

The COT reports break down futures market open interest into commercial ('hedgers'), non-commercial ('speculators') and non-reportable positions. Each contract has someone on the short as well as on the long side. Therefore open interest is equal to the sum of all long positions or equivalently of all short positions.

A reportable trader is classified as commercial by filing a statement with the CFTC (using the CFTC Form 40) that he is *commercially*[10] "…engaged in business activities hedged by the use of the futures and option markets[...] This would include production, merchandising, or processing of a cash commodity, asset/liability risk management by depository institution, security portfolio risk management, etc." To ensure that these traders are classified consistently and accurately, CFTC market surveillance staff in the

[9] The reporting levels generally range from 50 to 200 contracts. Information on reporting levels is available at http://www.gpo.gov/fdsys/pkg/CFR-2013-title17-vol1/xml/CFR-2013-title17-vol1-sec15-03.xml.

[10] *Commercial traders* include the following categories of traders: Co-Operative, Dealer/Merchant, Manufacturer, Agricultural/Natural Resources – Other, Producer, Commodity Swaps/Derivatives Dealer, Arbitrageur or Broker/Dealer, Non U.S. Commercial Bank, U.S. Commercial Bank, Endowment or Trust, Mutual Fund, Pension Fund, Insurance Company, Hedge funds in financial contracts that are shown to be hedging, Mortgage Originator, Financial – Other, Managed Account or Pool, Financial Swaps/Derivatives Dealer, Corporate Treasurer, Livestock Feeder, Livestock – Other, Livestock Slaughterer.

regional offices verifies the forms and collects further information about the trader's involvement in the markets.

All other large traders who do not meet these criteria are classified as *Non Commercial*[11]*Traders*. Non-commercials have no underlying cash business and are hence treated as speculative traders betting on the price of a commodity rising or falling. Finally, *Small traders* consist of traders whose positions do not exceed the CFTC reporting levels. Consequently, their position is calculated in the COT reports as the difference between total open interest and the total of all reporting positions. As the name implies, these are usually small, typically retail, traders.

The Commitment of Traders Report (COT)provides a summary of aggregated positions of the three trader groups as of the close of business on Tuesday. Prior to 1991, the CFTC compiled the reports once a month, reflecting thesepositions as of the last trading day in the month. From 01/91 to 10/92 the CFTC compiled the COT report twice a month, reflecting the holdings on the 15th of the month (or the previous trading day if that day was a holiday or weekend) and the last trading day of the month. From 10/16/92[12] to the present, the CFTC compiles the data weekly, reflecting the holdings as of the close of each Tuesday. The data are released electronically to the public every Friday at 3:30 P.M and show the holdings as of the previous Tuesday. For example, the COT report released 12/22/00 (a Friday) contains the holdings as of 12/19/00 (the prior Tuesday).

2.2 Commodities sample

We obtain daily futures prices and open interest (the number of "open" contracts in the market) on 26 commodities from 5 sectors (energy, grains, livestock, food and fiber, and metals) for a period of 27 years that begins in January 1986 and extends through June 2012. Our datasource is Pinnacle Data Corp.

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[11] *Non-commercial* traders include the following: Associated Person, Commodity Pool Operator, Commodity Trading Advisor, Floor Broker, Futures Commission Merchant, Floor Trader, Introducing Broker, Managed Money.

[12] Even though the CFTC only published monthly COT reports from 1/15/86 to 10/16/92, semi-monthly data are available for this period. In January of 1991, the CFTC began using a new computer program that compiled the data on a semi-monthly basis. In conjunction with this release, they ran their historical data (going back to 1986) through the new program. This created the semi-monthly reports before 1991.

The *energy* sector contains four commodities: crude oil, natural gas, gasoline and heating oil. Crude oil is the most important component of this sector because heating oil and gasoline are refined oil products, whose prices move closely with crude oil prices. The *grains* sector contains eight commodities: corn, soybeans, wheat, soybean oil, soybean meal, wheat KC, wheat Minn, and oats. These grains are used as food for humans and animals. The *food and fiber* sector is a mix of tropical products that are grown primarily in tropical and subtropical regions: sugar, cocoa, coffee, cotton, frozen orange juice, and lumber. It is common practice to classify them together in one sector, although the links between them are not as close as in other sectors. The *livestock* sector has three commodities: feeder cattle, lean hogs, and live cattle. They are primarily for human consumption. The *metals* sector contains five commodities: gold, silver, copper, platinum and palladium. They are used as both investments and inputs for industrial production.

Futures prices are collected on all nearest and second nearest contracts. The nearest contract is held until the end of the month prior to the maturity month. At the end of that month, the position is rolled over to the second nearest contract, which is again held until the month-end prior to the maturity month. Futures returns are calculated using the prices of the contract being held. These returns are then measured weekly, from Tuesday-Tuesday, to match the frequency of the open interest data.

2.3 Net Interest: Construction and Characteristics

Much research has been devoted to exploring the relation between stock price movements and trading activity. A large literature has studied the association between stock market returns and volume (e.g. Gallant et al., 1992; Hiemstra and Jones, 1994; Lo and Wang,2000; see also the studies summarized in Karpoff, 1987). More recent studies have examined *order imbalance*, the difference between buyer-initiated and seller-initiated trades (e.g. Chordia et al., 2002; Chordia and Subrahmanyam, 2004). There are at least two reasons why order imbalance can predict returns beyond volume. First, a large order imbalance can lead to price overshooting and subsequent reversals as market-makers re-establish desired inventory positions. In addition, if order imbalances signal informed investor interest, they can predict future returns (Kyle, 1985; Glosten and Milgrom,1985).

Using the open interest positions in the COT reports, we build a measure of trading activity to approximate order imbalance. First, we compute the net long position as the difference between long and short positions for each trader type. Second, we compute the weekly difference in the net long position. Therefore, our measure of trading activity is the change in the net long position for each trader type and we interpret this number as order imbalance or order flow.

Table 1 reports details on open interest for each commodity, separately by the type of trader. Energy is by far the most actively-traded group of commodities. The commodities with the highest trading volume are crude oil (ranked first by some distance), natural gas, gold, corn, heating oil and soybeans. The least liquid commodities are lumber, oats, orange juice, feeder cattle and platinum. Hedgers account for the bulk of the open interest for most commodities. Speculators are activein metals (gold, silver and platinum; consistent with anecdotal evidence on their activities), and also (relative to hedgers) in orange juice, lumber and feeder cattle. Interestingly, small investor open interest is sizeable forseveral commodities and is the highest of the three groups for lumber, oats and silver.

Figure 1 plots the *gross* interest (long plus short open interest) for the three trader categories. The measure plotted is constructed by adding long and short positions for each commodity and each type ofinvestor, and averaging this across all commodities. The first interesting observation is that the gross interest originating from hedgers is five times larger than that from speculators or small traders. It exhibits a steady upward trend until2005, when it almost doubles,followed by a crash in 2008, with the start of the recent financial crisis, and a recovery to pre-crisis levelsin 2011. Second, small investor gross interest is relatively constant throughout our sample period. It exceeds speculator gross interest up to 2003, after which the latter increases substantially. Figure 1 and Table 1 suggest that although small trader positions are not large individually, collectively their position is significant. Their activity therefore is potentially relevant in price determination, and we will examine this question in the following sections. Finally, the rapid expansion of both hedging and speculative trading after 2003 indicates the financialization of the industry in the mid-2000s.

Figure 2 plots the *net* interest (long minus short open interest) for the three trader categories. The measure is constructed by subtracting the total short position from the total long position for each commodity and each trader type, and averaging this across all commodities. First, commercial hedgers in the aggregate tend to be net short in commodity futures. This is consistent with the conjecture initially proposed by Keynes (1930) and Hicks (1939) that most hedgers have long positions in the underlying asset and hedge by holding short futures positions. On the other hand, speculators, who accommodate this net short position, are on average net long. Finally, small traders are typically net short after 2003, in contrast to their net long position throughout 1980s and 1990s.

We compute the correlation in order imbalances (*imbalances* for short) for the three types of traders by commodity (these are not tabulated to save space). For every commodity, the correlation between hedger and speculator order imbalances is strongly negative (between -0.7 and -0.9), while that between speculator and small trader imbalances is positive, although generally modest (values below 0.2). The large negative correlation between hedger and speculator imbalancesis potentially mechanical, driven by twofacts: these two trader groups tend to dominate the market; and small trader positions are stable over time. It is also consistent with demand for immediacy from one group of traders being quickly accommodated by the other major group. We attempt to disentangle such dynamic links in Section 6.1. Due to the magnitude of this negative correlation, we include only speculatorand small trader order flow in our subsequent pricing regressions.

3 Determinants of Net Interest

Microstructure theory suggests that informed traders impact prices (Kyle, 1985; Glosten andMilgrom, 1985). Further, trades that differ in terms of immediacy and size will also impact prices differently. Since it is likely that the groups of traders we study are differentially informed and have distinct trading motives, their orders should have different price impacts.[13]

With a view to understanding what moves prices in the futures markets and the role of each market participant in the process, we analyze the dynamic relationship between trading and returns sequentially. First, in this section,we explore the determinants of order imbalances. In Section 4, we estimate the price impact of order imbalance. Section 5 examines the impact of trading on futures volatility. We run all specifications as pooled OLS

[13] For the effects of institutional and individual trades see e.g. Keim and Madhavan(1995), Chan and Lakonishok(1995), Griffin, Harris and Topaloglu (2003), Boehmer and Kelley (2005), Jones and Lipson (2004), and Kaniel, Saar and Titman (2004).

regressions, pooled across commodities and through time (we examine separate industry groups in Section 6). To facilitate the comparison of coefficient estimates across trader types, the dependent and independent variables are demeaned and standardized. For each observation of a variable we subtract the time-series mean of the variable, and scale the result by its time-series standard deviation. Therefore, the coefficients can be interpreted as the change in the dependent variable (measured in standard deviations) resulting from a one standard deviation change in the explanatory variables.

We model imbalances as a functionof commodity and market characteristics, estimating the following specification for speculators (we estimate an identical model for small traders, i.e. with $\Delta NetOI^{i}_{small}(t)$ as the dependent variable):

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\begin{aligned}
\Delta NetOI^{i}_{spec}(t) = a_0 &+ a_1\Delta NetOI^{i}_{spec}(t-1) + a_2 NetOI^{i}_{spec}(t-1) + a_3 NetOI^{i}_{spec}(t-1) \\
&\times \sigma^{i}_{ST}(t-1) + a_4 NetOI^{i}_{spec}(t-1) \times \sigma^{i}_{LT}(t-1) + a_5\Delta NetOI^{i}_{small}(t-1) \\
&+ a_6 NetOI^{i}_{small}(t-1) + a_7 NetOI^{i}_{small}(t-1) \\
&\times \sigma^{i}_{ST}(t-1) + a_8 NetOI^{i}_{small}(t-1) \times \sigma^{i}_{LT}(t-1) + a_9 R^{i}_{ST}(t-1) + a_{10} R^{i}_{LT}(t-1) \\
&+ a_{11}\sigma^{i}_{ST}(t-1) + a_{12}\sigma^{i}_{LT}(t-1) + a_{13} R^{M}(t-1) + a_{14} ContractDummy + u^{i}(t)
\end{aligned}
\qquad (1)
$$

where $NetOI^{i}_{spec}(t)$ and $\Delta NetOI^{i}_{spec}(t)$ are the weekly levels and changes in the net long position (the difference between the long and short positions) for speculators. $R^{i}_{ST}(t-1)$, $R^{i}_{LT}(t-1)$, $\sigma^{i}_{ST}(t-1)$ and $\sigma^{i}_{LT}(t-1)$ are lagged short term and long term returns and volatilities for commodity i, $R^{M}(t-1)$ is the lagged futures market return where the weight for each commodity return is its open-interest. The short term measures are defined over the previous week, and the long term measures are computed over the previous six months with a one month gap relative to week *t*. Volatility is calculated as the weekly or six monthly average of the daily log(P_{high}/P_{low}) as in Parkinson (1980). *Contract dummy* is an indicator equal to 1 for the weeks in which contracts are rolled over.

Table 2 reports the slope coefficients and p-values computed from robust standard errors clustered at the level of the group. We start with the determinants of speculative positions in **Panel A**. Due to the high correlation between short-term and long-term volatility, we present two models that separate the two volatility variables. Our first result is familiar. We find a positive coefficient of 0.118 on the lagged order imbalance, suggesting persistence in trading positions. This finding lines up with empirical research from the equity markets showing that order imbalances are persistent, a fact consistent with order splitting by traders to minimize the price impact.

There is an interesting contrast in the coefficients on the lagged short-term and long-term returns. The first is positive and significant (0.170): the fact that speculators trade in the direction of prior-week returns is consistent withtheir acting as momentum traders. The second coefficientis negative and significant (-0.037), whichis consistent with speculators takinglong termprofits.The coefficients on short-term and long-term volatility are not significant. Nor is the contract dummy.

The coefficient on the lagged net position is negative and significant (-0.084), suggesting that large positions tend to be reduced, i.e. long positions are followed by selling. This reversion in positions is consistent with risk aversion: speculators are reluctant to hold large positions for extended periods. Interacting the net position with volatility, we find a negative and significant coefficient (-0.048). This reinforces the previous result on speculator risk aversion: when speculators are net long and volatility in commodity prices is high, they react by decreasing their positions even further. We obtain similar results when we interact the net position with long-term (six-month) volatility instead of short-term volatility.

Finally, we find evidence of feedback between the two groups of traders. The coefficient on the lagged small trader position is positive and significant, so speculators follow small trades with trades of the same sign. This is consistent with research documenting that sophisticated traders have incentives to 'ride the wave' (Brunnermeierand Nagel, 2004). Overall, the model has a respectable adjusted R-squared of 8.2%.

Turning to the determinants of small trader positions (**Panel B**), we see a negative coefficient on the lagged net position (-0.116), which is in fact larger than the coefficient for speculators (-0.084). This suggests that small traders are more risk averse than speculators, a conclusion we think is plausible. Small trader imbalances follow the lagged speculator imbalances. However, the negative coefficient on the interaction of the net long position of speculators and long-term commodity volatility means that, when speculators are long and volatility is high, small traders tend to sell in the next period. This is consistent with herding behavior, i.e. with small traders choosing the same trades as those of speculators. There is weak evidence that small traders increase their positions following high futures market returns (p-value of 0.13); there is no such evidence of return chasing for speculators. Interestingly, we do not find a similar volatility effect for small traders as for speculators: although the coefficients signs are the same, they are not significant. Also, note the lower explanatory power of 2.6% for small traders.

Overall, we find similarities in the trading behavior of speculators and small investors but also notable differences.[14] We now examine whether these differences translate into differences in price and volatility outcomes.

4 Trading and Prices

In this section we ask how weekly imbalances impact prices. An important concern is the possibility of reverse causality between returns and order imbalances. We rely on market microstructure theory that suggests a causal link from order flow to prices, an implication that follows fromboth inventory models (Stoll, 1978; Ho and Stoll, 1981) and asymmetric-information models (Glosten and Milgrom, 1985; Kyle, 1985). Therefore, we model returns as follows:

$$\begin{aligned} R^i\ (t) = a_0 + a_1 \Delta NetOI^i_{spec}(t) + a_2 \Delta NetOI^i_{small}(t) \\ + a_3 NetOI^i_{spec}(t-1) + a_4 NetOI^i_{small}(t-1) + a_5 \Delta NetOI^i_{spec}(t) \\ \times NetOI^i_{spec}(t-1) + a_6 \Delta NetOI^i_{small}(t) \times NetOI^i_{small}(t-1) + a_7 NetOI^i_{spec}(t \\ -1) \times \sigma^i_{ST}(t-1) + a_8 NetOI^i_{small}(t-1) \times \sigma^i_{ST}(t-1) + a_9 NetOI^i_{spec}(t-1) \\ \times \sigma^i_{LT}(t-1) + a_{10h} NetOI^i_{small}(t-1) \times \sigma^i_{LT}(t-1) + a_{11} R^i_{ST}(t-1) \\ + a_{12} R^i_{LT}(t-1) + a_{13} \sigma^i_{ST}(t-1) + a_{14} \sigma^i_{LT}(t-1) + a_{15} R^M(t-1) \\ + a_{16} ContractDummy + u^i(t) \end{aligned} \tag{2}$$

where $R^i(t)$ is the return for commodity i, $NetOI^i_{type}(t)$and $\Delta NetOI^i_{type}(t)$ are the weekly levels and changes in net long positions (as defined previously) for each type of investor (type = speculators and small). The remaining variables are the same as in equation (1), and, as before, we estimate the model as a pooled OLS regression. **Table 3** reports the slope coefficients and p-values computed using robust standard errors clustered at the group level. The dependent and independent variables are demeaned and standardized using their time series means and standard deviations.

[14] A possible explanation for the similarities in trading behavior between small traders and speculators is that in order to avoid disclosure, speculators split their orders to fall below the CTFC reporting thresholds, and therefore trade as small traders. However, this is inconsistent with the fact that there are numerous differences in the coefficients on the explanatory variables for speculator and small trader imbalances. Thus, we do not think this explanation fits our results.

First, we find that both speculator and small investor imbalances have positive and significant price impacts (coefficients of 0.340 and 0.128 in Column 1).The size of the coefficients shows that speculator imbalances have a stronger price effect than small trader imbalances. The positive relation between return and contemporaneous imbalances could reflect information or liquidity effects.

We test whether the price impact is information or liquidity driven by adding the previous week's imbalances to the model. Under the liquidity explanation, we expect a negative coefficient on lagged imbalances as prices overshoot in response to imbalances and subsequently correct. Column (3) shows that the coefficient on lagged imbalances is negative: -0.085 for speculators and -0.016 for small traders. This negative coefficient implies that, consistent with the liquidity explanation, prices partially revert during the following trading week. The fact that the reversal is larger for speculator imbalances is also reasonable because they tend to place larger trades. These results imply that the positive contemporaneous relation between price change and order imbalance is in part due to liquidity. Nevertheless, the combined or permanent effects of imbalances (captured by the sum of the contemporaneous and lagged coefficients) are still positive and significant: 0.26 and 0.11 for speculator and small trader imbalances. This suggests that the information effects of order imbalances are large relative to the inventory effects.

We also find a positive and significant coefficient on lagged order imbalance, $NetOI^i_{type}(t-1)$, which suggests that the overall size of speculator and small investor positions move prices, beyond effects related to imbalances. Thus, for instance, when speculators or small traders have larger net long positions, prices tend to increase—this is consistent with scarcity or inventory effects. The effect is stronger for speculators (0.045) than for small traders (0.012). It is interesting that, when we interact imbalances with the previous week's net positions ($\Delta NetOI^i_{type}(t) \times NetOI^i_{type}(t-1)$), we obtain a negative and significant coefficient for speculators (-0.030). This effect means that the price impact is lower when speculators sell (buy) from larger initial net long (short) positions. It is consistent with other investors realizing the risk reduction motivation of speculators, and reducing their assessment of the information content of trades placed at such times.

We also explore the impact of the net position when volatility is high. We find the coefficients on the interaction terms $NetOI^i_{spec}(t-1) * \sigma^i\,(t-1)$ to be positive, suggesting more extreme price changes associated with larger net speculator positions and high volatility. The coefficient is 0.106 when the net position is interacted with short term volatility and 0.167 when it is interacted with long term volatility. The corresponding coefficients for small trader net positions are insignificant.

Finally, we find that the lagged commodity return is negative and significant (-0.067), indicative of illiquidity effects unrelated to trading. The coefficient on the contemporaneous market return, which serves as a control for general price movements, is positive and significant (0.319).

The results in this section suggest that, on average, price changes are associated with the trades of both speculators and small traders. Both sets of trades create relatively minor liquidity related reversals, and therefore have large permanent effects on the price. The effects of speculator trades are considerably stronger than those of small investors, consistent with their greater size and informational advantage.The next section examines whether these trades have an effect on volatility.

5 Trading and Price Volatility

The influence of speculators has led to substantial research and controversy. The effects of speculators, hedge funds in particular, have been examined during several turbulent episodes, including the 1992 European Exchange Rate Mechanism (ERM) crisis (Obstfeld, 1996), the 1994 Mexican peso crisis (Fung and Hsieh, 2000), the 1997 Asian financial crisis (Brown, Goetzmann, and Park, 2000), and the financial bailout of Long Term Capital Management (Edwards, 1999). The evidence from these studies on whether speculators destabilized markets is mixed.

We contribute to this debate by examining the relation between trading and subsequent volatility.In order to addresswhether trading by each group of investors impacts volatility, we estimate the following model for volatility:

$$\begin{aligned}\sigma^i(t) = a_0 &+ a_1 NetOI^i_{spec}(t-1) + a_2 NetOI^i_{small}(t-1) + a_3 \Delta NetOI^i_{spec}(t-1) \\ &+ a_4 \Delta NetOI^i_{small}(t-1) + a_5\left[\Delta NetOI^i_{spec}(t-1)\right]^2 + a_6\left[\Delta NetOI^i_{small}(t-1)\right]^2 \\ &+ a_7 \sigma^i_{ST}(t-1) + a_8 \sigma^i_{LT}(t-1) + a_9 ContractDummy + u^i(t)\end{aligned} \quad (3)$$

where $\sigma^i_{ST}(t-1)$and $\sigma^i_{LT}(t-1)$ are short term (prior week) and long-term (six month, skipping one month)volatility of commodity *i* (calculated as the respective averages of the daily log(P_{high}/P_{low})), and the other variables are defined as in specifications (1) and (2).

The results are presented in **Table 4**. As a benchmark, column (1) has a simple model where weekly volatility is regressed on lagged short-term and long-term volatilities. The coefficients are positive and significant, 0.57 on short-term volatility and 0.23 on long-term volatility. These coefficients line up with the large literature showing that volatility is persistent (e.g. see Schwert, 1989).

We then add trading variables to this base model. In column (2), the coefficients on $NetOI^i_{spec}(t-1)$ and $NetOI^i_{small}(t-1)$ are 0.010 and 0.008, respectively, and neither is statistically significant. Therefore, the size of speculator net positions does not appear to be associated with higher volatility in the following week. Nor is the size of the small trader net position. Column (3) adds order imbalances, $\Delta NetOI^i_{spec}(t-1)$ and $\Delta NetOI^i_{small}(t-1)$, to the model in (2). The coefficient on the speculator imbalance is not significant. That on small trader imbalance is positive and marginally significant, possibly pointing to noise trader risk associated with greater small trader participation for the commodity.

We add squared imbalances, $\left[\Delta NetOI^i_{spec}(t-1)\right]^2$and $\left[\Delta NetOI^i_{small}(t-1)\right]^2$, to the model in column (2). Shown in column (4), the coefficients on squared imbalances are negative (-0.017 and -0.005) and significant. These coefficients suggest that large buying *or* selling activity hasa stabilizing effect on next period's volatility, and this effect is especially strong for speculator trades. Therefore, this evidence suggests that speculators' trading activity in the commodity markets may stabilize prices, as suggested by Friedman (1953), and help these markets better perform their risk transfer function.

In models (2) through (4), the coefficients on volatility are virtually unchanged. Thus, volatility persistence is not explained by futures trading activity. Curiously, the coefficient on the contract dummy is negative and significant.

The key result in this section is that squared speculator imbalances have a negative effect on subsequent volatility, a finding inconsistent with speculator activity promoting volatility. Rather, this result suggests that speculator actions can be an important channel for volatility reduction.

6 Robustness Checks and Extensions

In this section, we run tests to further understand the dynamics of traders' positions and pricing effects. First, we explore the effect of large imbalances. Second, we add controls for macroeconomic fundamentals. Third, we study the extent to which speculative trading and its pricing effects are determined by extreme market conditions. Finally, we re-estimate the model at the industry level and examine time effects.

6.1 Large Imbalances

Our analysis in the previous sections confirms that speculator and small trader imbalances contain information that affects commodity prices even after controlling for other factors. However, it is possible that it is the trades of hedgers impact prices under certain circumstances—and our analysis incorrectly attributes the price changes to the investors who trade with hedgers. Specifically, it is possible that, at times, speculators supply liquidity to hedgers, who aggressively demand liquidity. At such times, the price impact of speculator imbalances should be small.

We address this possibility and study instances in which trading patterns may differ between hedgers and speculators. It is likely that speculators place frequent but smaller trades, while hedgers place infrequent and larger trades. Therefore, if speculators and small traders accommodate the trades of hedgers, we should expect to see a smaller price impact for speculators and small traders when imbalances are large.

To test this hypothesis, we estimate our model by adding an interaction term that captures the effect of speculative trading when speculator imbalances are large. Therefore we estimate the following model:

$$\begin{aligned} R^{i}\ (t) = {} & a_0 + a_1 \Delta NetOI^{i}_{spec}(t) + a_2 \Delta NetOI^{i}_{small}(t) + a_3 \left|\Delta NetOI^{i}_{spec}(t)\right| \times \left[\Delta NetOI^{i}_{spec}(t)\right] \\ & + a_4 \left|\Delta NetOI^{i}_{small}(t)\right| \times \left[\Delta NetOI^{i}_{small}(t)\right] + + a_5 R^{i}_{ST}(t-1) + a_6 R^{i}_{LT}(t-1) \\ & + a_7 \sigma^{i}_{ST}(t-1) + a_8 \sigma^{i}_{LT}(t-1) + a_9 R^{M}(t) + a_{10} ContractDummy + u^{i}(t) \end{aligned} \quad (4)$$

where $R^{i}(t)$ is the weekly return for commodity i, and all other variables are defined as in previous specifications (1), (2) and (3). In this specification, the large trade effect is captured by $\left|\Delta NetOI^{i}_{type}(t)\right|$. Hence, we want to test whether the interaction of $\Delta NetOI^{i}_{type}(t)$ with

$\left|\Delta NetOI^i_{type}(t)\right|$, has a negative coefficient. We retain our prior controls: lagged commodity returns and volatilities, as well as market return.

The results are presented in **Table 5**. As before, the coefficients on $\Delta NetOI^i_{spec}(t)$ and $\Delta NetOI^i_{small}(t)$ are both positive, 0.445 and 0.193, pointing to apositive price impact for speculators and small traders. On the other hand, the coefficients on $\left|\Delta NetOI^i_{type}(t)\right| \times \Delta NetOI^i_{type}(t)$ are negative (-0.126 for speculators and -0.080 for small traders) and significant. This indicates that larger imbalances of either sign are associated with a smaller price impact. Focusing on speculator imbalances, for which the effect is larger, this negative coefficient suggests that larger speculator trades are viewed as less likely to convey significant information. This is consistent with the conjecture that speculators, when serving as liquidity providers to hedgers, benefit in form of a lower price impact.

6.2 Economic Fundamentals

We next investigate whether our previous results on the determinants of imbalances and their price and volatility effects are robust to the inclusion of additional macroeconomic controls. This is important since commodity demand and prices are especially sensitive to global and local economic conditions. Accordingly, we add two controls for macroeconomic conditions – growth in industrial production and stock market returns—in both developed and emerging countries to our main specification fortrading determinants, pricing effects and volatility. We choose these measures because industrial production growth directly measures economic output while stock market returns are a leading indicator of future economic conditions.[15] The two measures are constructed as equally weighted averages across developed (U.S., Canada, France, Germany, UK, Japan) and emerging countries (Brazil, China, India, Korea, Mexico, Philippines, Russia). The measures are monthly, and we use the lagged full-month values as controls in our specifications.

Table 6 reports the estimates. When we include only the proxies for macroeconomic activity, the explanatory power for all three specifications is very low, less than 0.001. Examining determinants of traders' positions, we find that higher industrial production growth in developed countries has a positive effect on speculator imbalances (i.e.

[15] In unreported results, we add developed and emerging market indices based on CPI inflation and exchange rates versus the U.S. dollar to the model, but these variables are not significant.

speculators increase their net long position). However, we do not find a similar effect for small trader imbalances. The coefficients on the other independent variables are similar to their values in Table 2.

Turning to the price impact and volatility results, we see that the coefficients on the macro-economic variables are occasionally significant. For instance, industrial production growth has a positive relation with returns and negative relation with future volatility. However, once we include trading variables the significance of the macro controls goes away. Yet the coefficients on imbalances in the price impact regression are virtually unchanged. Similarly, the coefficient on squared imbalances in the volatility model is similar to its value in Table 4.

In sum, our previous results on the determinants and pricing effects of speculator and small investor imbalances are unchanged. This suggests that there is information in trading that is not associated with fundamentals.

6.3 Market Conditions

We explore trading patterns and pricing effects in extreme market conditions: high uncertainty based on the VIX, tight funding based on the TED spread, high sentiment based on the Baker and Wurgler (2006) sentiment index, and economic expansion based on the CFNAI (Chicago Fed National Activity Index).

First, we use VIX as an indicator of market uncertainty. Starting in 1993, the Chicago Board Options Exchange (CBOE) published its VIX index. It reflects market expectations of the 30-day volatility implied in equity index options. For the period preceding 1993, we use the “old" VIX (now VXO), a measure based on S&P 100 index of at-the-money put and call prices. We use the TED spread, or the difference between three-month LIBOR and the three-month U.S. T-bill yield, as a measure of funding constraints. LIBOR includes a premium for credit risk in the interbank loan market, while the three-month T-bill is free of default risk. Higher values of TED signify tighter credit conditions (for instance, TED reached a high in excess of 4% in October 2008, during the subprime crisis). High values of VIX and TED signify poor market conditions.

Third, we use the Baker and Wurgler (2006) sentiment index to capture investor sentiment in the economy. The index is based on the common variation (identified using principal components analysis) of six underlying proxies for sentiment: the closed-end fund discount, NYSE share turnover, the number of average first-day returns on IPOs, the equity share in new issues, and the dividend premium. The fourth measure is the Chicago Fed National Activity Index (CFNAI), a monthly index designed to gauge overall economic activity. The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity.[16] It is constructed to have an average value of zero and a standard deviation of one, and a positive index reading corresponds to growth above trend and a negative reading to growth below trend. Research has found that the CFNAI provides a useful gauge on current and future economic activity and inflation in the United States. High values of SENT and CFNAI signify good market conditions.

We re-estimate the model for investor imbalances, price impact and price volatility using only periods when the four variables are above their 90th percentile cutoff. **Table 7** reports the estimates. **Panel A** reports the results for imbalances. Our findings are similar to those obtained for the baseline model except for the coefficient on lagged net open interest. Speculators tend to reduce their positions even more sharply during extreme market conditions, regardless of whether conditions are good or bad. For instance, the coefficient on lagged net interest is -0.194 when VIX is high compared with -0.084 in the baseline model. The stronger reversion when uncertainty is high (high VIX) or funding is tight (TED is high) is consistent with the 'financial distress' hypothesis (see Cheng et al, 2012): financial traders reduce their market participation after suffering losses.[17] More generally, however, speculators appear to recognize extreme conditions and reduce their participation level. Thus, extreme conditions also appear to promote speculator risk aversion. We find a stronger feedback effect between the two trader groups during periods of high VIX or TED.

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[16] These 85 economic indicators are drawn from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories.The details on the construction of CFNAI are available at the Federal Reserve Bank of Chicago website.

[17] An alternative explanation (see Cheng et al, 2012) based on "hedging pressure" implies that increased uncertainty exposes commercial hedgers to a greater wedge between costs of external and internal financing and greater default risk, and provides greater incentives for them to hedge their commodity price risks. Therefore times of high uncertainty would lead hedgers to increase their net short positions. In order for the market to clear financial investors would have to increase their net long positions as well. Our finding of a reduction in net long speculator positions during times of high market uncertainty is inconsistent with the hedging pressure hypothesis.

Panel B reports the price impact results. We find that the price impact is slightly lower during periods of high VIX or TED, and significantly higher in periods of high SENT or CFNAI. Reversals are also stronger in high SENT or CFNAIperiods and lower in high VIX or TED periods. Consequently, the net (permanent) effect is similar to that in the baseline model. **Panel C** reports results for volatility. We find that the coefficients on $\left[\Delta NetOI^{i}_{spec}(t-1)\right]^{2}$ are more negative in extreme market states than in the baseline model.

6.4 Industries

Finally, we explore whether our results hold across industries by estimating models (1) – (3) for each of the five groups of commodities in our sample. **Table 8** reports the results. **Panel A** shows the industry specific estimates for trader imbalances. First, we see consistency across all groups, especially for one of our main variables of interest, the lagged net position: the negative coefficient on this variable implies reversals in traders' net positions in the week after an increase in their net position. Short term momentum and long term reversals are present for all commodities except for the energy group.

Panel B reports the results for price impact. Our previous results on price impact hold for all groups except for energy. It is interesting to note that the Energy group has the highest coefficient on the market return (0.626), suggesting that this group moves with the market. Thus, the fact that imbalances have a much lower impact in the energy group is somewhat reasonable. **Panel C** reports the results for volatility. We find that speculator trading variability has a negative sign for all groups, which is significant for grains, livestock and metals. Overall, these results show that our findings are not specific to a specific group of commodities.

6.5 Time Effects

A potential explanation for our findings is the recent increase in the financialization of commodity markets: non-information based commodity investments by retail and institutional investors who buy commodities for portfolio allocation reasons. The argument made is that, starting in the early 2000s, recognition of the potential diversification benefits prompted rapid growth in commodity investments. Commodity futures have emerged as a new asset class for many financial institutions and led to a massive inflow of capital intocommodity funds.Several observers and policymakers (see e.g. Masters, 2008) have expressed the concern that such investments might have caused unwarranted increases in the cost of energy and food and induced excessive price volatility.To address this concern, we repeat all our tests for the subperiod ending in 2000 and find similar results. Therefore, financialization does not appear to be the driving factor behind the patterns we uncover.

7 Conclusions

In this paper, we examine weekly trading imbalances for speculators and small investors in the commodity futures market over the period 1986-2012, as well as their price and volatility effects. We study the determinants of weekly imbalances for the two groups of traders and then relate returns and volatility to speculator and small trader imbalances.

We uncover several results of interest. First, speculators behave like short term momentum traders, chasing returns from the prior week, but as long-term contrarians, selling after prices have risen over the prior six months. Their imbalances are positively autocorrelated, consistent with order splitting, and positively cross-autocorrelated with small investor imbalances, consistent with their ‘riding the wave’ caused by small traders. Speculators sell (buy) to a greater extent after their long (short) positions have become larger, especially when volatility is elevated: this points tospeculators being risk averse. Small trader imbalances also follow speculator imbalances of a given sign, and display mean reversion and volatility aversion, but both effects are weaker than in the case of speculators.

Second, imbalances have positive and significant permanent price effects, which are larger for speculators. Further analysis based on the size of the imbalances suggests that the price impact of speculator and small trader imbalances is smaller when they act as suppliers of liquidity to hedgers. Finally, price volatility is related positively to lagged small trader imbalances, supportive of noise trader effects, and negatively to the lagged variability of speculator imbalances, which is inconsistent with speculator activity promoting futures market volatility.

Our results survive a range of robustness checks. We also study extreme market conditions (high volatility and tight funding conditions, for instance), and our results are similar. Last, we estimate our models in industry groups and reach similar conclusions.

Our work is relevant in light of the continuing debate on the effects of trading, especially by speculators, and the need for new regulatory initiatives to possibly curb such trades.Our analysis indicates that there are similarities and differences in the trading behavior of speculators and small traders. Of greater significance, the picture that emerges from our results is that speculators are mainly risk averse, short-term oriented, liquidity providers, and their trades that are, in general, not destabilizing.

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Figure 1: Trends in Gross Positions. The figure plots the gross interest (long + short) averages by type of investor. The types of investors are Commercials (Hedgers), Non-Commercials (Speculators) and Small Traders. The sample period is 01/01/1986-30/06/2012.

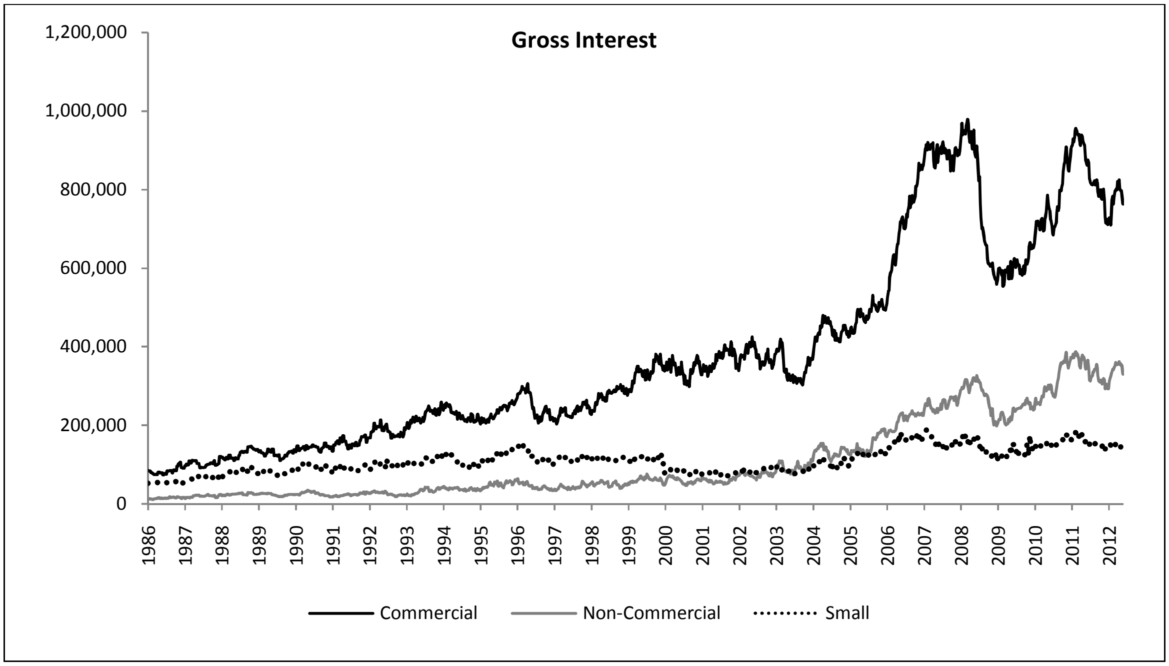

Figure 2: Trends in Net Positions. The figure plots the net interest (long - short) averages by type of investor. The types of investors are Commercials (Hedgers), Non-Commercials (Speculators) and Small Traders. The sample period is 01/01/1986-30/06/2012.

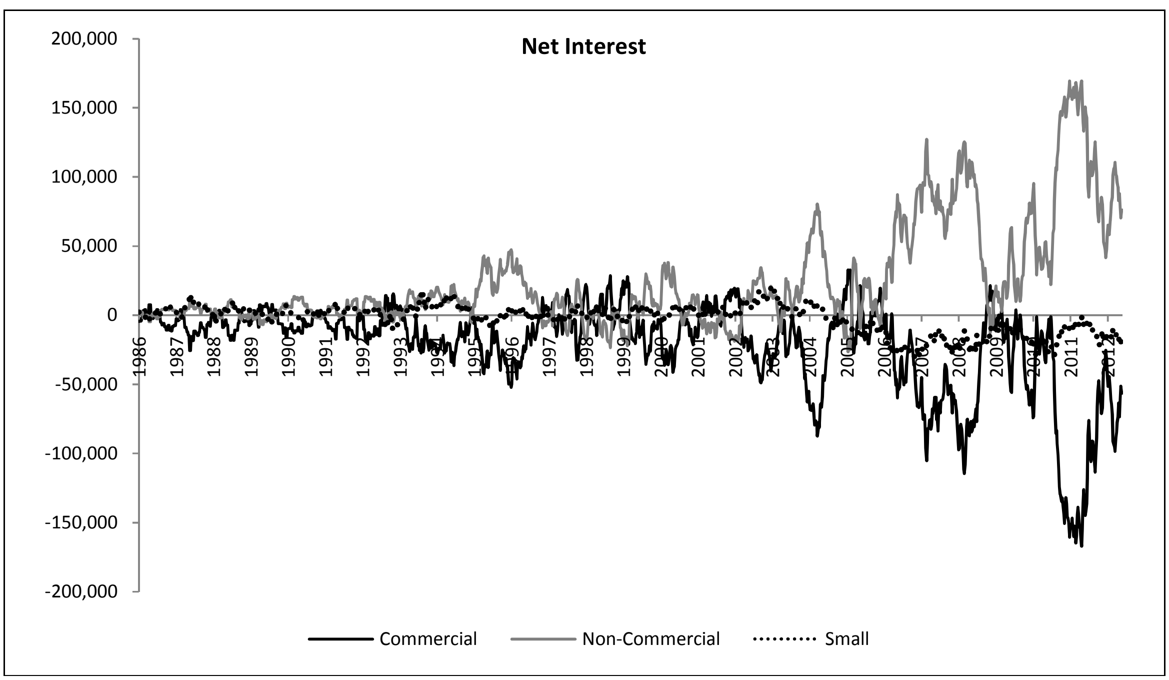

Table 1: Characteristics of the Commitment of Traders Positions. We report summary statistics for 26 commodities at a weekly frequency. The basket of commodities is grouped in Energy, Food and Fiber, Grains, Livestock, and Metals. The types of investors are Hedgers (Commercials), Speculators (Non-Commercials) and Small Traders. The sample period is from 01-Jan-1986 to 30-Jun-2012.

Group	Ticker	Commodity	Hedgers	Speculators	Small	Volume	Open Interest
ENERGY	CL	Crude Oil	368,041	88,489	70,502	219,189	527,033
	NG	Natural Gas	241,728	52,426	54,622	103,425	348,776
	RB	Gasoline	31,425	82,013	55,026	44,021	168,465
	HO	Heating Oil	89,648	18,147	37,147	47,083	144,942
FOOD and FIBER	SB	Sugar	151,533	65,438	51,418	40,506	268,389
	CC	Cocoa	55,763	19,459	10,968	9,112	86,190
	CT	Cotton	48,506	19,509	14,130	11,836	82,145
	KC	Coffee	33,302	16,790	10,558	11,606	60,651
	JO	Frozen Orange Juice	9,785	7,015	4,764	2,491	21,563
	LB	Lumber	1,262	1,478	2,037	1,008	4,778
GRAINS	C	Corn	264,554	127,267	101,770	60,935	493,590
	S	Soybeans	97,763	55,666	51,396	46,741	204,825
	W	Wheat	82,292	35,129	28,979	20,302	146,399
	BO	Soybean Oil	70,147	28,211	29,813	21,566	128,172
	SM	Soybean Meal	54,685	22,547	32,177	22,051	109,409
	KW	Wheat KC	32,996	15,366	14,623	9,245	62,985
	MW	Wheat Minn	12,799	3,856	7,238	4,031	23,894
	O	Oats	4,246	2,243	4,852	1,338	11,340
LIVESTOCK	LC	Live Cattle	54,878	35,838	30,601	19,571	121,317
	LH	Live Hogs	30,345	18,572	15,443	11,823	64,360
	FC	Feeder Cattle	5,990	6,000	5,933	2,717	17,923
METALS	GC	Gold	88,945	75,343	43,791	62,252	208,078
	SI	Silver	25,229	31,393	32,160	23,165	88,782
	HG	Copper	36,326	18,122	15,695	15,126	70,142
	PL	Platinum	4,952	7,556	4,629	3,140	17,136
	PA	Palladium	2,504	4,195	1,804	1,040	8,503

Table 2: Determinants of Traders' Positions

The table reports estimates from the following regression model (equation 1 in the text):

$$\begin{aligned}\Delta NetOI^i_{spec}(t) = {} & a_0 + a_1 \Delta NetOI^i_{spec}(t-1) + a_2 NetOI^i_{spec}(t-1) + a_3 NetOI^i_{spec}(t-1) \\ & \times \sigma^i_{ST}(t-1) + a_4 NetOI^i_{spec}(t-1) \times \sigma^i_{LT}(t-1) + a_5 \Delta NetOI^i_{small}(t-1) \\ & + a_6 NetOI^i_{small}(t-1) + a_7 NetOI^i_{small}(t-1) \times \sigma^i_{ST}(t-1) + a_8 NetOI^i_{small}(t-1) \\ & \times \sigma^i_{LT}(t-1) + a_9 R^i_{ST}(t-1) + a_{10} R^i_{LT}(t-1) + a_{11} \sigma^i_{ST}(t-1) + a_{12} \sigma^i_{LT}(t-1) \\ & + a_{13} R^M(t-1) + a_{14} ContractDummy + u^i(t)\end{aligned} \tag{1}$$

where $NetOI^i_{type}(t)$ and $\Delta NetOI^i_{type}(t)$ are the weekly levels and changes in net long positions (i.e. the difference between the long and short positions) for each type of investor (speculators or non-commercial and small). $R^i_{ST}(t-1)$, $R^i_{LT}(t-1)$, $\sigma^i_{ST}(t-1)$ and $\sigma^i_{LT}(t-1)$ are the short term and long term returns and volatilities for commodity i, $R^M(t-1)$ is the lagged futures market return weighted by open-interest. The short term measures are defined over the previous week, and the long term measures are built over the last six month with one month non-overlapping windows relative to week *t*. Volatility is calculate as a weekly or a six months average of the daily log(P_{high}/P_{low}). Contract dummy is an indicator equal to 1 for the weeks in which the contracts are rolled over. The model is estimated as a pooled OLS regression. The table reports the slope coefficients and p-values computed using robust standard errors clustered at the level of the group. Both the dependent and the independent variables are demeaned and standardized using the entire time series means and standard deviations, respectively. The sample period is from 01-Jan-1986 to 30-Jun-2012.

	Panel A: SPEC		**Panel B: SMALL**	
	(1)	**(2)**	**(3)**	**(4)**
Intercept	0.002	0.002	0.000	0.000
	[0.715]	[0.725]	[0.971]	[0.982]
$\Delta NetOI^i_{spec}(t-1)$	**0.118**	**0.119**	**0.050**	**0.050**
	[0.004]	**[0.004]**	**[0.041]**	**[0.044]**
$\Delta NetOI^i_{small}(t-1)$	**0.055**	**0.055**	-0.039	-0.039
	[0.011]	**[0.011]**	[0.265]	[0.266]
$NetOI^i_{spec}(t-1)$	**-0.084**	**-0.066**	-0.021	0.008
	[0.005]	**[0.039]**	[0.464]	[0.592]
$NetOI^i_{small}(t-1)$	-0.018	-0.034	**-0.116**	**-0.138**
	[0.333]	[0.156]	**[0.002]**	**[0.002]**
$NetOI^i_{spec} t-1 \ * \ \sigma^i_{ST}(t-1)$	**-0.048**		0.002	
	[0.027]		[0.937]	
$\mathrm{NetOI}^i_{small}(t-1) \ * \ \sigma^i_{ST}(t-1)$	0.007		-0.013	
	[0.491]		[0.534]	
$NetOI^i_{spec}(t-1) * \sigma^i_{LT}(t-1)$		**-0.064**		**-0.029**
		[0.056]		**[0.111]**
$NetOI^i_{small}(t-1) * \sigma^i_{LT}(t-1)$		**0.024**		0.010
		[0.085]		[0.656]
$R^i_{ST}(t-1)$	**0.170**	**0.170**	0.035	0.035
	[0.001]	**[0.001]**	[0.377]	[0.378]
$R^i_{LT}(t-1)$	**-0.037**	**-0.038**	-0.024	-0.025
	[0.003]	**[0.001]**	[0.186]	[0.189]
$\sigma^i_{ST}(t-1)$	0.005		-0.001	
	[0.398]		[0.866]	
$\sigma^i_{LT}(t-1)$		0.006		-0.004
		[0.470]		[0.834]
$R^M(t-1)$	-0.002	-0.002	0.031	0.031
	[0.846]	[0.853]	[0.120]	[0.127]
Contract Dummy	-0.014	-0.015	0.003	0.003
	[0.746]	[0.740]	[0.949]	[0.954]
Adj. R^2	0. 082	0. 082	0.026	0.025

Table 3: Price Impact

The table reports parameter estimates from the following regression (equation 2 in the text):

$$
\begin{aligned}
R^{i}\ (t) = a_0 + a_1 \Delta NetOI^{i}_{spec}(t) + a_2 \Delta NetOI^{i}_{small}(t) + a_3 \left|\Delta NetOI^{i}_{spec}(t)\right| \times \left[\Delta NetOI^{i}_{spec}(t)\right] \\
+ a_4 \left|\Delta NetOI^{i}_{small}(t)\right| \times \left[\Delta NetOI^{i}_{small}(t)\right] + + a_5 R^{i}_{ST}(t-1) + a_6 R^{i}_{LT}(t-1) \\
+ a_7 \sigma^{i}_{ST}(t-1)\ + a_8 \sigma^{i}_{LT}(t-1) + a_9 R^{M}(t) + a_{10} ContractDummy + u^{i}(t)
\end{aligned} \tag{2}
$$

where $R^i(t)$ is the return for commodity $i, NetOI^{i}_{type}(t)$ and $\Delta NetOI^{i}_{type}(t)$ are the weekly levels and changes in net long positions (i.e. the difference between the long and short positions) for each type of investor (speculators or non-commercial and small). $R^{i}_{ST}(t-1)$, $R^{i}_{LT}(t-1)$, $\sigma^{i}_{ST}(t-1)$ and $\sigma^{i}_{LT}(t-1)$ are the short term and long term returns and volatilities for commodity i, $R^{M}(t-1)$ is the lagged futures market return weighted by open-interest. The short term measures are defined over the previous week, and the long term measures are built over the last six month with one month non-overlapping windows relative to week t. Volatility is calculate as a weekly or a six months average of the daily $\log(P_{high}/P_{low})$. Contract dummy is an indicator equal to 1 for the weeks in which the contracts are rolled over. The model is estimated as a pooled OLS regression. The table reports the slope coefficients and p-values computed using robust standard errors clustered at the level of the group. Both the dependent and the independent variables are demeaned and standardized using the entire time series means and standard deviations, respectively. The sample period is from 01-Jan-1986 to 30-Jun-2012.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	0.000	0.001	0.001	0.000	0.001	0.001
	[0.912]	[0.497]	[0.862]	[0.891]	[0.841]	[0.817]
$\Delta NetOI^{i}_{spec}(t)$	**0.340**		**0.354**	**0.366**	**0.259**	**0.198**
	[0.001]		**[0.001]**	**[0.000]**	**[0.001]**	**[0.002]**
$\Delta NetOI^{i}_{small}(t)$	**0.128**		**0.131**	**0.123**	**0.129**	0.043
	[0.016]		**[0.013]**	**[0.018]**	**[0.010]**	[0.393]
$\Delta NetOI^{i}_{spec}(t-1)$		**-0.037**	**-0.085**	**-0.084**	**-0.085**	**-0.083**
		[0.019]	**[0.009]**	**[0.009]**	**[0.009]**	**[0.009]**
$\Delta NetOI^{i}_{small}(t-1)$		-0.002	**-0.016**	**-0.016**	**-0.016**	**-0.016**
		[0.703]	**[0.105]**	**[0.104]**	**[0.101]**	**[0.102]**
$NetOI^{i}_{spec}(t-1)$			**0.045**	**0.044**	**0.046**	**0.045**
			[0.001]	**[0.001]**	**[0.001]**	**[0.001]**
$NetOI^{i}_{small}(t-1)$			**0.012**	**0.012**	**0.012**	**0.011**
			[0.058]	**[0.057]**	**[0.069]**	**[0.073]**
$\Delta NetOI^{i}_{spec}(t) *\ NetOI^{i}_{spec}(t-1)$				**-0.030**		
				[0.085]		
$\Delta NetOI^{i}_{small}(t)\ *\ NetOI^{i}_{small}(t-1)$				0.022		
				[0.158]		
$NetOI^{i}_{spec}(t-1)\ *\ \sigma^{i}_{ST}(t-1)$					**0.106**	
					[0.055]	
$NetOI^{i}_{small}(t-1) *\ \sigma^{i}_{ST}(t-1)$					0.003	
					[0.928]	
$NetOI^{i}_{spec}(t-1) *\ \sigma^{i}_{LT}(t-1)$						**0.167**
						[0.043]
$NetOI^{i}_{small}(t-1) *\ \sigma^{i}_{LT}(t-1)$						0.092
						[0.236]
$R^{i}_{ST}(t-1)$	**-0.062**	**0.035**	**-0.032**	**-0.033**	**-0.037**	**-0.037**
	[0.009]	**[0.075]**	**[0.031]**	**[0.031]**	**[0.022]**	**[0.019]**
$R^{i}_{LT}(t-1)$	**0.029**	**-0.016**	0.005	0.006	0.007	0.007
	[0.029]	**[0.023]**	[0.538]	[0.502]	[0.417]	[0.405]
$\sigma^{i}_{ST}(t-1)$	0.013	0.013	0.014	0.013	0.012	
	[0.480]	[0.472]	[0.467]	[0.474]	[0.391]	
$\sigma^{i}_{LT}(t-1)$	-0.001	-0.003	-0.004	-0.003		0.004
	[0.949]	[0.821]	[0.788]	[0.806]		[0.684]
$R^{M}(t-1)$	**0.319**	**0.395**	**0.316**	**0.317**	**0.316**	**0.314**
	[0.016]	**[0.010]**	**[0.017]**	**[0.017]**	**[0.017]**	**[0.018]**
Contract Dummy	0.000	-0.007	-0.003	-0.002	-0.003	-0.004
	[0.986]	[0.483]	[0.909]	[0.944]	[0.885]	[0.860]
Adj. R^2	0.288	0.157	0.296	0.297	0.298	0.300

Table 4: Price Volatility

The table reports estimates from the following regression model (equation 3 in the text):

$$\sigma^{i}(t) = a_0 + a_1 NetOI^{i}_{spec}(t-1) + a_2 NetOI^{i}_{small}(t-1) + a_3 \Delta NetOI^{i}_{spec}(t-1) + a_4 \Delta NetOI^{i}_{small}(t-1) + a_5\left[\Delta NetOI^{i}_{spec}(t-1)\right]^2 + a_6\left[\Delta NetOI^{i}_{small}(t-1)\right]^2 + a_7\sigma^{i}_{ST}(t-1) + a_8\sigma^{i}_{LT}(t-1) + a_9 ContractDummy + u^{i}(t) \tag{3}$$

where $\sigma^{i}(t)$ is the weekly volatility of commodity *i,* $NetOI^{i}_{type}(t)$ and $\Delta NetOI^{i}_{type}(t)$ are the weekly levels and changes in net long positions (i.e. the difference between the long and short positions) for each type of investor (speculators or non-commercial and small). $R^{i}_{ST}(t-1)$, $R^{i}_{LT}(t-1)$, $\sigma^{i}_{ST}(t-1)$ and $\sigma^{i}_{LT}(t-1)$ are the short term and long term returns and volatilities for commodity i, $R^{M}(t-1)$ is the lagged futures market return weighted by open-interest. The short term measures are defined over the previous week, and the long term measures are built over the last six month with one month non-overlapping windows relative to week *t*. Volatility is calculate as a weekly or a six months average of the daily log(P_{high}/P_{low}). Contract dummy is an indicator equal to 1 for the weeks in which the contracts are rolled over. The model is estimated as a pooled OLS regression. The table reports the slope coefficients and p-values computed using robust standard errors clustered at the level of the group. Both the dependent and the independent variables are demeaned and standardized using the entire time series means and standard deviations, respectively. The sample period is from 01-Jan-1986 to 30-Jun-2012.

	(1)	**(2)**	**(3)**	**(4)**
Intercept	**0.007**	**0.007**	**0.007**	**0.007**
	[0.003]	**[0.003]**	**[0.003]**	**[0.004]**
$NetOI^{i}_{spec}(t-1)$		0.010	0.010	0.012
		[0.637]	[0.638]	[0.535]
$NetOI^{i}_{small}(t-1)$		0.008	0.007	0.008
		[0.429]	[0.459]	[0.469]
$\Delta NetOI^{i}_{spec}(t-1)$			-0.003	
			[0.519]	
$\Delta NetOI^{i}_{small}(t-1)$			**0.014**	
			[0.076]	
$[\Delta NetOI^{i}_{spec}(t-1)]^2$				**-0.017**
				[0.021]
$[\Delta NetOI^{i}_{small}(t-1)]^2$				-0.005
				[0.164]
$\sigma^{i}_{ST}(t-1)$	**0.570**	**0.569**	**0.569**	**0.572**
	[0.001]	**[0.001]**	**[0.001]**	**[0.001]**
$\sigma^{i}_{LT}(t-1)$	**0.231**	**0.231**	**0.231**	**0.229**
	[0.001]	**[0.001]**	**[0.001]**	**[0.001]**
Contract Dummy	**-0.061**	**-0.061**	**-0.061**	**-0.061**
	[0.000]	**[0.000]**	**[0.000]**	**[0.000]**
Adj. R^2	0.530	0.530	0.530	0.530

Table 5: Price Impact Identification

The table reports estimates from the following regression model (equation 4 in the text):

$$R^i\ (t) = a_0 + a_1 \Delta NetOI^i_{spec}(t) + a_2 \Delta NetOI^i_{small}(t) + a_3 \left|\Delta NetOI^i_{spec}(t)\right| \times \left[\Delta NetOI^i_{spec}(t)\right] + a_4 \left|\Delta NetOI^i_{small}(t)\right| \times \left[\Delta NetOI^i_{small}(t)\right] + + a_5 R^i_{ST}(t-1) + a_6 R^i_{LT}(t-1) + a_7 \sigma^i_{ST}(t-1)\ + a_8 \sigma^i_{LT}(t-1) + a_9 R^M(t) + a_{10} ContractDummy + u^i(t) \tag{4}$$

where $R^i(t)$ is the weekly return for commodity i, $NetOI^i_{type}(t)$ and $\Delta NetOI^i_{type}(t)$ are the weekly levels and changes in net long positions (i.e. the difference between the long and short positions) for each type of investor (speculators or non-commercial and small). $R^i_{ST}(t-1)$, $R^i_{LT}(t-1)$, $\sigma^i_{ST}(t-1)$ and $\sigma^i_{LT}(t-1)$ are the short term and long term returns and volatilities for commodity i, $R^M(t-1)$ is the lagged futures market return weighted by open-interest. The short term measures are defined over the previous week, and the long term measures are built over the last six month with one month non-overlapping windows relative to week t. Volatility is calculate as a weekly or a six months average of the daily log(P_{high}/P_{low}). Contract dummy is an indicator equal to 1 for the weeks in which the contracts are rolled over. The model is estimated as a pooled OLS regression. The table reports the slope coefficients and p-values computed using robust standard errors clustered at the level of the group. Both the dependent and the independent variables are demeaned and standardized using the entire time series means and standard deviations, respectively. The sample period is from 01-Jan-1986 to 30-Jun-2012.

	(1)	**(2)**
Intercept	0.000	0.000
	[0.998]	[0.911]
$\Delta NetOI^i_{spec}(t)$	**0.445**	**0.449**
	[0.001]	**[0.001]**
$\Delta NetOI^i_{small}(t)$	**0.193**	**0.195**
	[0.011]	**[0.012]**
$\left\|\Delta NetOI^i_{spec}(t)\right\|\ x\ \left[\Delta NetOI^i_{spec}(t)\right]$		**-0.126**
		[0.004]
$\left\|\Delta NetOI^i_{small}(t)\right\|\ x\ \left[\Delta NetOI^i_{small}(t)\right]$		**-0.080**
		[0.015]
$R^i_{ST}(t-1)$	**-0.062**	**-0.068**
	[0.009]	**[0.007]**
$R^i_{LT}(t-1)$	**0.029**	**0.031**
	[0.029]	**[0.030]**
$\sigma^i_{ST}(t-1)$	0.013	0.014
	[0.480]	[0.457]
$\sigma^i_{LT}(t-1)$	-0.001	-0.001
	[0.949]	[0.952]
$R^{\mathrm{M}}(t)$	**0.319**	**0.315**
	[0.016]	**[0.017]**
$Contract\ Dummy$	0.000	-0.001
	[0.986]	[0.980]
Adj. R^2	0.288	0.295

Table 6: Traders' Positions, Pricing Effects and Fundamentals

The table reports estimates from regression models in equation (1), (2) and (3) with controls for macroeconomic activity. $NetOI^i_{type}(t)$and$\Delta NetOI^i_{type}(t)$ are the weekly levels and changes in net long positions (i.e. the difference between the long and short positions) for each type of investor (speculators or non-commercial and small). $R^i_{ST}(t-1)$,$R^i_{LT}(t-1)$,$\sigma^i_{ST}(t-1)$ and $\sigma^i_{LT}(t-1)$ are the short term and long term returns and volatilities for commodity i, $R^M(t-1)$ is the lagged futures market return weighted by open-interest. The short term measures are defined over the previous week, and the long term measures are built over the last six months with one month non-overlapping windows relative to week *t*. Volatility is calculate as a weekly or a six months average of the daily log(P_{high}/P_{low}). Contract dummy is an indicator equal to 1 for the weeks in which the contracts are rolled over. *Industrial Production and Stock Index* are computed as monthly equally weighted averages of log values corresponding to each group of Developed countries (U.S., Canada, France, Germany, UK, Japan) and Emerging countries (Brazil, China, India, Korea, Mexico, Philippines, Russia). The model is estimated as a pooled OLS regression. The table reports the slope coefficients and p-values computed using robust standard errors clustered at the level of the group. Both the dependent and the independent variables are demeaned and standardized using the entire time series means and standard deviations, respectively. The sample period is from 01-Jan-1986 to 30-Jun-2012.

PANEL A: Positions		**SPEC**			**SMALL**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	0.002	0.000	0.002	0.000	0.000	0.000
	[0.712]	[0.496]	[0.711]	[0.979]	[0.523]	[0.957]
$\Delta NetOI^i_{spec}(t-1)$	**0.118**		**0.117**	**0.049**		**0.049**
	[0.004]		**[0.004]**	**[0.043]**		**[0.043]**
$\Delta NetOI^i_{small}(t-1)$	**0.055**		**0.055**	-0.039		-0.039
	[0.011]		**[0.011]**	[0.266]		[0.266]
$NetOI^i_{spec}(t-1)$	**-0.123**		**-0.123**	**-0.019**		**-0.019**
	[0.001]		**[0.001]**	**[0.109]**		**[0.107]**
$NetOI^i_{small}(t-1)$	-0.013		-0.013	**-0.128**		**-0.129**
	[0.464]		[0.423]	**[0.001]**		**[0.001]**
$R^i_{ST}(t-1)$	**0.170**		**0.170**	0.035		0.035
	[0.001]		**[0.001]**	[0.377]		[0.377]
$R^i_{LT}(t-1)$	**-0.039**		**-0.042**	-0.025		-0.026
	[0.002]		**[0.002]**	[0.170]		[0.199]
$\sigma^i_{ST}(t-1)$	-0.006		-0.005	0.002		0.002
	[0.594]		[0.684]	[0.915]		[0.890]
$\sigma^i_{LT}(t-1)$	0.000		0.001	-0.009		-0.009
	[0.965]		[0.945]	[0.690]		[0.701]
$R^M(t-1)$	-0.002		-0.004	0.031		0.030
	[0.836]		[0.701]	[0.124]		[0.123]
$Contract\ Dummy$	-0.015		-0.014	0.003		0.004
	[0.742]		[0.744]	[0.956]		[0.938]
$\Delta Ind\ Production\ (Dev)$ *(t-4)*		-0.001	**0.010**		-0.003	0.006
		[0.892]	**[0.027]**		[0.634]	[0.491]
$\Delta Ind\ Production\ (Emerg)$*(t-4)*		0.000	0.000		-0.007	-0.006
		[0.977]	[0.988]		[0.188]	[0.230]
$\Delta Stock\ Index\ (Dev)$*(t-4)*		0.010	0.008		-0.003	0.000
		[0.346]	[0.261]		[0.850]	[1.000]
$\Delta Stock\ Index\ (Emerg)$ *(t-4)*		0.013	0.012		0.007	0.005
		[0.208]	[0.197]		[0.336]	[0.550]
Adj. R^2	0.081	0.000	0.082	0.000	0.025	0.026

Table 6 (continued)

PANEL B: Price Impact	**(1)**	**(2)**	**(3)**
Intercept	0.001	[0.000]	0.001
	[0.862]	[0.583]	[0.859]
$\Delta NetOI^i_{spec}(t)$	**0.354**		**0.354**
	[0.001]		**[0.001]**
$\Delta NetOI^i_{small}(t)$	**0.131**		**0.131**
	[0.013]		**[0.013]**
$\Delta NetOI^i_{spec}(t-1)$	**-0.085**		**-0.085**
	[0.009]		**[0.009]**
$\Delta NetOI^i_{small}(t-1)$	**-0.016**		**-0.016**
	[0.105]		**[0.104]**
$NetOI^i_{spec}(t-1)$	**0.045**		**0.045**
	[0.001]		**[0.001]**
$NetOI^i_{small}(t-1)$	**0.012**		**0.012**
	[0.058]		**[0.046]**
$R^i_{ST}(t-1)$	**-0.032**		**-0.033**
	[0.031]		**[0.028]**
$R^i_{LT}(t-1)$	0.005		0.005
	[0.538]		[0.468]
$\sigma^i_{ST}(t-1)$	0.014		0.014
	[0.467]		[0.468]
$\sigma^i_{LT}(t-1)$	-0.004		-0.004
	[0.788]		[0.781]
$R^M(t-1)$	**0.316**		**0.316**
	[0.017]		**[0.017]**
$Contract\ Dummy$	-0.003		-0.003
	[0.909]		[0.907]
$\Delta Ind\ Production\ (Dev)$		**0.022**	-0.001
		[0.064]	[0.920]
$\Delta Ind\ Production\ (Emerg)$		-0.002	0.001
		[0.788]	[0.894]
$\Delta Stock\ Index\ (Dev)$		0.008	0.000
		[0.738]	[0.994]
$\Delta Stock\ Index\ (Emerg)$		0.014	0.002
		[0.460]	[0.892]
Adj. R^2	0.296	0.001	0.296
PANEL C: Volatility	**(1)**	**(2)**	**(3)**
Intercept	0.007	0.000	0.007
	[0.004]	[0.284]	[0.003]
$\Delta NetOI^i_{spec}(t-1)$	0.012		0.013
	[0.535]		[0.522]
$\Delta NetOI^i_{small}(t-1)$	0.008		0.008
	[0.469]		[0.459]
$[\Delta NetOI^i_{spec}(t-1)]^2$	**-0.017**		**-0.017**
	[0.021]		**[0.021]**
$[\Delta NetOI^i_{small}(t-1)]^2$	-0.005		-0.005
	[0.164]		[0.160]
$\sigma^i_{ST}(t-1)$	**0.572**		**0.571**
	[0.001]		**[0.001]**
$\sigma^i_{LT}(t-1)$	**0.229**		**0.229**
	[0.001]		**[0.001]**
$Contract\ Dummy$	**-0.061**		**-0.061**
	[0.000]		**[0.000]**
$\Delta Ind\ Production\ (Dev)$		**-0.080**	-0.003
		[0.015]	[0.764]
$\Delta Ind\ Production\ (Emerg)$		-0.004	0.001
		[0.390]	[0.717]
$\Delta Stock\ Index\ (Dev)$		-0.044	-0.008
		[0.167]	[0.200]
$\Delta Stock\ Index\ (Emerg)$		0.018	-0.002
		[0.506]	[0.774]
Adj. R^2	0.530	0.009	0.530

Table 7: Traders' Positions, Pricing Effects and Market Conditions

The table reports estimates from regression models in equation (1), (2) and (3). $NetOI^{i}_{type}(t)$and$\Delta NetOI^{i}_{type}(t)$ are the weekly levels and changes in net long positions (i.e. the difference between the long and short positions) for each type of investor (speculators or non-commercial and small). $R^{i}_{ST}(t-1)$,$R^{i}_{LT}(t-1)$,$\sigma^{i}_{ST}(t-1)$ and $\sigma^{i}_{LT}(t-1)$ are the short term and long term returns and volatilities for commodity i, $R^{M}(t-1)$ is the lagged futures market return weighted by open-interest. The short term measures are defined over the previous week, and the long term measures are built over the last six months with one month non-overlapping windows relative to week t. Volatility is calculate as a weekly or a six months average of the daily log(P_{high}/P_{low}). Contract dummy is an indicator equal to 1 for the weeks in which the contracts are rolled over. The models are estimated using the observations corresponding to VIX, TED, SENTIM and CFNAI to be above their 90th percentile. VIX is the implied volatility index, TED is the spread between 3 month LIBOR and T-Bill rates, SENTIM is the Baker and Wurgler (2006) sentiment measure, and CFNAI is the Chicago Fed National Activity Index. The model is estimated as a pooled OLS regression. The table reports the slope coefficients and p-values computed using robust standard errors clustered at the level of the group. Both the dependent and the independent variables are demeaned and standardized using the entire time series means and standard deviations, respectively. The sample period is from 01-Jan-1986 to 30-Jun-2012.

	PANEL A: SPEC					**PANEL B: SMALL**				
PANEL A: Positions		**VIX**	**TED**	**SENT**	**CFNAI**		**VIX**	**TED**	**SENT**	**CFNAI**
Intercept	0.002	**-0.110**	-0.009	**-0.100**	-0.021	0.000	**-0.089**	**-0.059**	0.007	0.022
	[0.712]	**[0.003]**	[0.660]	**[0.034]**	[0.487]	[0.979]	**[0.099]**	**[0.036]**	[0.783]	[0.215]
$\Delta NetOI^{i}_{spec}(t-1)$	**0.118**	**0.143**	**0.109**	**0.104**	**0.107**	**0.049**	**0.106**	0.085	**0.058**	**0.043**
	[0.004]	**[0.013]**	**[0.008]**	**[0.050]**	**[0.009]**	**[0.043]**	**[0.023]**	[0.127]	**[0.074]**	**[0.094]**
$\Delta NetOI^{i}_{small}(t-1)$	**0.055**	**0.095**	**0.093**	**0.041**	0.030	-0.039	-0.043	-0.074	**-0.086**	0.020
	[0.011]	**[0.030]**	**[0.067]**	**[0.107]**	[0.166]	[0.266]	[0.317]	[0.180]	**[0.040]**	[0.258]
$NetOI^{i}_{spec}(t-1)$	**-0.123**	**-0.194**	**-0.157**	**-0.241**	**-0.163**	**-0.019**	**-0.052**	-0.031	-0.015	-0.026
	[0.000]	**[0.000]**	**[0.000]**	**[0.013]**	**[0.000]**	**[0.109]**	**[0.097]**	[0.344]	[0.740]	[0.354]
$NetOI^{i}_{small}(t-1)$	-0.013	0.032	**-0.017**	0.001	0.019	**-0.128**	**-0.162**	**-0.188**	**-0.116**	**-0.147**
	[0.464]	[0.131]	**[0.009]**	[0.956]	[0.392]	**[0.001]**	**[0.005]**	**[0.001]**	**[0.009]**	**[0.003]**
$R^{i}_{ST}(t-1)$	**0.170**	**0.141**	**0.083**	**0.149**	**0.173**	0.035	0.062	**0.071**	0.038	0.016
	[0.001]	**[0.024]**	**[0.058]**	**[0.021]**	**[0.003]**	[0.377]	[0.206]	**[0.093]**	[0.206]	[0.654]
$R^{i}_{LT}(t-1)$	**-0.039**	**-0.043**	**-0.017**	**-0.020**	**-0.035**	-0.025	-0.014	**-0.024**	**-0.033**	-0.041
	[0.002]	**[0.001]**	**[0.177]**	**[0.082]**	**[0.108]**	[0.170]	[0.427]	**[0.043]**	**[0.001]**	[0.252]
$\sigma^{i}_{ST}(t-1)$	-0.006	-0.001	**-0.023**	0.020	-0.020	0.002	0.032	0.001	0.001	0.013
	[0.594]	[0.954]	**[0.010]**	[0.270]	[0.289]	[0.915]	[0.255]	[0.958]	[0.964]	[0.823]
$\sigma^{i}_{LT}(t-1)$	0.000	0.039	0.012	-0.008	-0.018	-0.009	-0.010	-0.019	-0.015	-0.015
	[0.965]	[0.143]	[0.138]	[0.570]	[0.214]	[0.690]	[0.682]	[0.571]	[0.644]	[0.733]
$R^{M}(t-1)$	-0.002	**-0.026**	0.002	0.004	-0.027	0.031	-0.003	0.011	**0.035**	0.030
	[0.836]	**[0.087]**	[0.926]	[0.795]	[0.469]	[0.124]	[0.872]	[0.700]	**[0.065]**	[0.165]
$Contract\ Dummy$	-0.015	-0.076	**-0.093**	0.042	-0.038	0.003	-0.006	-0.006	0.031	-0.054
	[0.742]	[0.335]	**[0.082]**	[0.696]	[0.442]	[0.956]	[0.947]	[0.826]	[0.671]	[0.376]
Adj. R^2	0.081	0.120	0.068	0.080	0.082	0.025	0.044	0.050	0.025	0.023

Table 7 (continued)

PANEL B: Price Impact		**VIX**	**TED**	**SENT**	**CFNAI**
Intercept	0.001	-0.011	-0.009	0.023	0.025
	[0.862]	[0.755]	[0.681]	[0.078]	[0.277]
$\Delta NetOI^i_{spec}(t)$	**0.354**	**0.339**	**0.282**	**0.400**	**0.406**
	[0.001]	**[0.004]**	**[0.002]**	**[0.002]**	**[0.002]**
$\Delta NetOI^i_{small}(t)$	**0.131**	**0.165**	**0.109**	**0.143**	**0.089**
	[0.013]	**[0.006]**	**[0.005]**	**[0.084]**	**[0.051]**
$\Delta NetOI^i_{spec}(t-1)$	**-0.085**	**-0.078**	**-0.032**	**-0.091**	**-0.098**
	[0.009]	**[0.008]**	**[0.023]**	**[0.004]**	**[0.032]**
$\Delta NetOI^i_{small}(t-1)$	-0.016	-0.005	0.013	0.000	-0.008
	[0.105]	[0.612]	[0.385]	[0.999]	[0.513]
$NetOI^i_{spec}(t-1)$	**0.045**	**0.048**	0.042	**0.069**	**0.054**
	[0.001]	**[0.012]**	[0.207]	**[0.001]**	**[0.110]**
$NetOI^i_{small}(t-1)$	**0.012**	0.042	0.015	0.027	-0.031
	[0.058]	[0.132]	[0.465]	[0.180]	[0.186]
$R^i_{ST}(t-1)$	**-0.032**	**-0.029**	-0.023	-0.026	0.007
	[0.031]	**[0.079]**	[0.499]	[0.427]	[0.836]
$R^i_{LT}(t-1)$	0.005	-0.001	-0.013	0.025	0.005
	[0.538]	[0.976]	[0.667]	[0.223]	[0.831]
$\sigma^i_{ST}(t-1)$	0.014	-0.016	-0.020	**-0.053**	**0.050**
	[0.467]	[0.707]	[0.279]	**[0.009]**	**[0.007]**
$\sigma^i_{LT}(t-1)$	-0.004	0.050	**0.038**	**0.054**	**-0.052**
	[0.788]	[0.135]	**[0.093]**	**[0.102]**	**[0.023]**
$R^M(t-1)$	**0.316**	**0.349**	**0.404**	**0.240**	**0.304**
	[0.017]	**[0.014]**	**[0.008]**	**[0.073]**	**[0.025]**
$Contract\ Dummy$	-0.003	0.011	-0.019	-0.034	-0.054
	[0.909]	[0.286]	[0.158]	[0.377]	[0.461]
Adj. R^2	0.296	0.396	0.344	0.258	0.254

PANEL C: Volatility		**VIX**	**TED**	**SENT**	**CFNAI**
Intercept	**0.007**	**0.050**	**0.087**	0.015	-0.023
	[0.004]	**[0.032]**	**[0.057]**	[0.347]	[0.241]
$\Delta NetOI^i_{spec}(t-1)$	0.012	-0.017	0.045	-0.022	0.036
	[0.535]	[0.521]	[0.199]	[0.554]	[0.204]
$\Delta NetOI^i_{small}(t-1)$	0.008	0.000	0.005	0.006	**0.044**
	[0.469]	[0.976]	[0.804]	[0.801]	**[0.055]**
$[\Delta NetOI^i_{spec}(t-1)]^2$	**-0.017**	**-0.026**	0.009	**-0.025**	-0.024
	[0.021]	**[0.077]**	[0.168]	**[0.091]**	[0.247]
$[\Delta NetOI^i_{small}(t-1)]^2$	-0.005	-0.013	**-0.018**	-0.016	-0.027
	[0.164]	[0.384]	**[0.093]**	[0.263]	[0.174]
$\sigma^i_{ST}(t-1)$	**0.572**	**0.583**	**0.602**	**0.555**	**0.588**
	[0.000]	**[0.000]**	**[0.000]**	**[0.000]**	**[0.000]**
$\sigma^i_{LT}(t-1)$	**0.229**	**0.213**	**0.194**	**0.241**	**0.147**
	[0.001]	**[0.003]**	**[0.001]**	**[0.001]**	**[0.004]**
$Contract\ Dummy$	**-0.061**	-0.083	-0.108	0.072	-0.041
	[0.000]	[0.286]	[0.158]	[0.377]	[0.461]
Adj. R^2	0.530	0.542	0.521	0.451	0.436

Table 8: Traders' Positions, Pricing Effects and Industry Effects

The table reports estimates from regression models in equation (1), (2) and (3) for each commodity group. $NetOI^{i}_{type}(t)$and$\Delta NetOI^{i}_{type}(t)$ are the weekly levels and changes in net long positions (i.e. the difference between the long and short positions) for each type of investor (speculators or non-commercial and small). $R^{i}_{ST}(t-1)$,$R^{i}_{LT}(t-1)$,$\sigma^{i}_{ST}(t-1)$ and $\sigma^{i}_{LT}(t-1)$ are the short term and long term returns and volatilities for commodity i, $R^{M}(t-1)$ is the lagged futures market return weighted by open-interest. The short term measures are defined over the previous week, and the long term measures are built over the last six months with one month non-overlapping windows relative to week *t*. Volatility is calculate as a weekly or a six months average of the daily log(P_{high}/P_{low}). Contract dummy is an indicator equal to 1 for the weeks in which the contracts are rolled over. *Industrial Production and Stock Index* are computed as monthly equally weighted averages of log values corresponding to each group of Developed countries (U.S., Canada, France, Germany, UK, Japan) and Emerging countries (Brazil, China, India, Korea, Mexico, Philippines, Russia). The model is estimated as a pooled OLS regression. The table reports the slope coefficients and p-values computed using robust standard errors clustered at the level of the group. Both the dependent and the independent variables are demeaned and standardized using the entire time series means and standard deviations, respectively. The sample period is from 01-Jan-1986 to 30-Jun-2012.

	PANEL A: SPEC					**PANEL B: SMALL**				
PANEL A: Positions	**Energy**	**Food and Fiber**	**Grains**	**Livestock**	**Metals**	**Energy**	**Food and Fiber**	**Grains**	**Livestock**	**Metals**
Intercept	-0.022	-0.001	**0.011**	0.005	0.003	-0.028	0.006	**0.002**	-0.002	0.011
	[0.453]	[0.849]	**[0.037]**	[0.359]	[0.652]	[0.238]	[0.235]	**[0.638]**	[0.633]	[0.054]
$\Delta NetOI^{i}_{spec}(t-1)$	0.021	**0.135**	**0.118**	**0.237**	**0.104**	**0.138**	**0.054**	**0.030**	-0.011	**0.074**
	[0.200]	**[0.000]**	**[0.001]**	**[0.024]**	**[0.009]**	**[0.007]**	**[0.023]**	**[0.043]**	[0.818]	**[0.006]**
$\Delta NetOI^{i}_{small}(t-1)$	**0.096**	**0.076**	**0.056**	**0.102**	0.037	**-0.118**	**-0.104**	-0.012	-0.003	-0.076
	[0.012]	**[0.010]**	**[0.008]**	**[0.126]**	[0.227]	**[0.070]**	**[0.019]**	[0.565]	[0.866]	[0.008]
$NetOI^{i}_{spec}(t-1)$	**-0.117**	**-0.153**	**-0.117**	**-0.167**	**-0.130**	0.003	-0.037	**-0.028**	0.002	0.022
	[0.078]	**[0.000]**	**[0.000]**	**[0.018]**	**[0.005]**	[0.952]	[0.258]	**[0.045]**	[0.602]	[0.437]
$NetOI^{i}_{small}(t-1)$	-0.009	0.020	**-0.048**	**-0.063**	0.016	**-0.149**	**-0.132**	**-0.139**	**-0.094**	-0.131
	[0.867]	[0.316]	**[0.021]**	**[0.074]**	[0.516]	**[0.027]**	**[0.001]**	**[0.001]**	**[0.031]**	**[0.001]**
$R^{i}_{ST}(t-1)$	0.058	**0.205**	**0.182**	**0.222**	**0.122**	0.073	0.061	0.074	**-0.152**	**0.088**
	[0.321]	**[0.000]**	**[0.000]**	**[0.007]**	**[0.012]**	[0.119]	[0.223]	**[0.019]**	**[0.023]**	**[0.002]**
$R^{i}_{LT}(t-1)$	-0.037	**-0.038**	**-0.029**	-0.056	**-0.034**	**-0.049**	**-0.050**	-0.012	0.040	**-0.056**
	[0.118]	**[0.006]**	**[0.016]**	[0.160]	**[0.033]**	**[0.018]**	**[0.002]**	[0.275]	[0.152]	**[0.001]**
$\sigma^{i}_{ST}(t-1)$	-0.014	-0.008	0.015	-0.026	**-0.030**	0.007	**-0.040**	**0.031**	-0.001	0.007
	[0.825]	[0.379]	[0.153]	[0.173]	**[0.014]**	[0.890]	**[0.042]**	**[0.000]**	[0.964]	[0.499]
$\sigma^{i}_{LT}(t-1)$	0.002	0.021	**-0.027**	0.025	-0.008	-0.002	**0.032**	**-0.062**	**0.025**	0.016
	[0.944]	[0.300]	**[0.102]**	[0.274]	[0.775]	[0.913]	**[0.035]**	**[0.001]**	**[0.028]**	[0.196]
$R^{M}(t-1)$	0.034	0.017	-0.011	-0.010	**0.023**	0.043	**0.046**	-0.015	0.009	0.026
	[0.247]	[0.119]	[0.255]	[0.374]	**[0.016]**	[0.183]	**[0.013]**	[0.399]	[0.355]	[0.134]
$Contract\ Dummy$	0.094	0.011	**-0.105**	-0.048	-0.035	0.124	-0.063	-0.015	0.025	**-0.123**
	[0.456]	[0.808]	**[0.036]**	[0.348]	[0.643]	[0.238]	[0.232]	[0.714]	[0.683]	**[0.039]**
Adj. R^2	0.037	0.126	0.086	0.135	0.060	0.066	0.042	0.025	0.032	0.038

Table 8 (continued)

PANEL B: Price Impact	Energy	Food and Fiber	Grains	Livestock	Metals
Intercept	0.014	0.000	-0.001	-0.008	-0.004
	[0.195]	[0.899]	[0.563]	[0.161]	[0.425]
$\Delta NetOI^i_{spec}(t)$	0.155	**0.380**	**0.355**	**0.378**	**0.353**
	[0.143]	**[0.001]**	**[0.001]**	**[0.009]**	**[0.001]**
$\Delta NetOI^i_{small}(t)$	**0.063**	**0.218**	**0.143**	0.017	**0.144**
	[0.054]	**[0.001]**	**[0.000]**	[0.840]	**[0.013]**
$\Delta NetOI^i_{spec}(t-1)$	**-0.046**	**-0.128**	**-0.074**	**-0.142**	**-0.072**
	[0.041]	**[0.001]**	**[0.004]**	**[0.042]**	**[0.003]**
$\Delta NetOI^i_{small}(t-1)$	0.015	-0.023	-0.026	-0.054	-0.001
	[0.365]	[0.203]	[0.156]	[0.196]	[0.952]
$NetOI^i_{spec}(t-1)$	**0.031**	**0.043**	**0.060**	**0.063**	**0.067**
	[0.062]	**[0.046]**	**[0.008]**	**[0.026]**	**[0.018]**
$NetOI^i_{small}(t-1)$	0.003	0.027	0.001	0.027	-0.004
	[0.839]	[0.201]	[0.927]	[0.356]	[0.796]
$R^i_{ST}(t-1)$	-0.009	-0.013	**-0.058**	-0.055	-0.028
	[0.643]	[0.522]	**[0.005]**	[0.165]	[0.192]
$R^i_{LT}(t-1)$	0.004	**0.025**	-0.012	0.015	0.002
	[0.840]	**[0.092]**	[0.178]	[0.318]	[0.924]
$\sigma^i_{ST}(t-1)$	**-0.032**	0.015	0.003	**0.109**	-0.010
	[0.083]	[0.344]	[0.745]	**[0.005]**	[0.573]
$\sigma^i_{LT}(t-1)$	**0.044**	-0.018	**-0.021**	-0.021	0.032
	[0.053]	[0.103]	**[0.037]**	[0.193]	[0.247]
$R^M(t)$	**0.626**	**0.153**	**0.413**	0.079	**0.287**
	[0.001]	**[0.004]**	**[0.001]**	[0.143]	**[0.001]**
$Contract\ Dummy$	-0.054	0.013	0.018	**0.084**	0.027
	[0.237]	[0.734]	[0.480]	**[0.064]**	[0.590]
Adj. R^2	0.485	0.263	0.409	0.133	0.302

PANEL C: Volatility	Energy	Food and Fiber	Grains	Livestock	Metals
Intercept	0.013	0.006	0.007	0.007	0.004
	[0.164]	[0.285]	[0.055]	[0.296]	[0.483]
$\Delta NetOI^i_{spec}(t-1)$	-0.010	0.019	**0.060**	**-0.075**	-0.019
	[0.698]	[0.239]	**[0.001]**	**[0.037]**	[0.390]
$\Delta NetOI^i_{small}(t-1)$	-0.006	**0.028**	-0.013	**-0.042**	**0.037**
	[0.808]	**[0.053]**	[0.500]	**[0.009]**	**[0.001]**
$[\Delta NetOI^i_{spec}(t-1)]^2$	-0.013	-0.008	-0.012	**-0.025**	**-0.035**
	[0.270]	[0.245]	[0.153]	**[0.049]**	**[0.091]**
$[\Delta NetOI^i_{small}(t-1)]^2$	0.004	-0.006	-0.003	0.002	**-0.020**
	[0.773]	[0.520]	[0.848]	[0.898]	**[0.024]**
$\sigma^i_{ST}(t-1)$	**0.597**	**0.526**	**0.550**	**0.586**	**0.598**
	[0.000]	**[0.001]**	**[0.001]**	**[0.002]**	**[0.001]**
$\sigma^i_{LT}(t-1)$	**0.258**	**0.254**	**0.215**	**0.184**	**0.208**
	[0.002]	**[0.000]**	**[0.001]**	**[0.006]**	**[0.001]**
$Contract\ Dummy$	-0.064	-0.063	**-0.066**	-0.081	-0.040
	[0.101]	[0.257]	**[0.077]**	[0.319]	[0.402]
Adj. R^2	0.530	0.542	0.521	0.451	0.436