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Convective Risk Flows in Commodity Futures Markets*

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Abstract. We study the joint responses of commodity future prices and positions of various trader groups to changes of the CBOE Volatility Index (VIX) before and after the recent financial crisis. Financial traders reduced their net long positions during the crisis in response to market distress, whereas hedgers facilitated this by reducing their net short positions as prices fell. This "convective risk flow" induced by the greater distress of financial institutions led to a change in the allocation of risk with hedgers holding more risk than they did previously. The presence of such a risk flow confirms the market impact of financial traders conditional on trades they initiate.

JEL Classification: G12, G01, G20, G14

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1. Introduction

According to an estimate by a report of the Commodity Futures Trading Commission (CFTC) in 2008, over $160 billion of investment capital had accumulated into commodity futures markets in the USA through index investment. This large investment flow, together with episodes of large commodity price volatility, has led to a heated debate among the academic and policy circles regarding the impact of both index and non-index financial traders on commodity futures prices. This debate largely builds on the premise that if financial traders' trading impacts commodity futures prices, their positions should be correlated with and predict futures prices. So far, the literature has provided mixed results in testing this hypothesis.[1] On one hand, by using various data from the CFTC on futures positions of commodity index traders (CITs), a number of recent studies, such as Brunetti and Buyuksahin (2009), Irwin, Sanders, and Merrin (2009), Sanders, Irwin, and Merrin (2010), Stoll and Whaley (2010), Brunetti, Buyuksahin, and Harris (2011), Buyuksahin and Harris (2011), and Hamilton and Wu (2013), who argue that there is little evidence of CIT positions being either correlated with or predictive of futures prices. On the other hand, Singleton (2013) provides evidence of positive price impact of CITs on futures prices of crude oil based on CIT positions imputed from index weights of different commodities and CIT positions in agricultural commodities.

To resolve this controversy, it is important to fully account for the multiple roles played by financial traders in commodity futures markets. The long-standing hedging-pressure theory, which was initially proposed by Keynes (1923) and Hicks (1939) and formally developed by Hirshleifer (1988, 1990), emphasizes that commodity producers need to short commodity futures to hedge their commodity price risk. By taking the other side of commodity producers' trades, financial traders facilitate their hedging needs. On the other hand, financial traders may also have to trade for their own reasons such as portfolio diversification and risk management. For example, reduced risk appetite due to investment losses elsewhere may cause them to cut down their commodity futures positions.

These two motives for trading may mitigate the ability of empirical tests to pick up evidence of a relationship between position changes and futures prices. For example, for financial traders, an increase in their futures position which facilitates producers' hedging needs should be negatively correlated with futures prices, whereas an increase in their futures position for other trading purposes might positively impact prices. Empirical tests

[1] See Cheng and Xiong (2014) for a systematic review of this literature.

may pick up zero relationship between financial traders' positions and futures prices because they do not condition on the motive for trading.

To confront this challenge, we take advantage of the lower risk absorption capacity experienced by many financial institutions during the recent financial crisis to isolate the trades initiated by financial traders in commodity futures markets. Our analysis builds on a growing body of theoretical work examining the relationship between financial institutions and asset prices (e.g., Shleifer and Vishny, 1997; Kyle and Xiong, 2001; Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009; Danielsson, Shin, and Zigrand, 2010; He and Krishnamurthy, 2013). This intermediary pricing theory emphasizes that at times, especially during crises, reduced risk appetite and binding funding and risk constraints may cause financial traders to unwind positions.[2] This mechanism also implies that lower risk absorption capacities may cause financial traders to reduce their commodity futures positions during the recent crisis. Following the literature, we use changes in the Chicago Board Options Exchange Volatility Index (VIX) to proxy for shocks to financial traders' risk appetite and funding constraints during the crisis.[3]

Our approach relies on the basic idea that the group of traders driving the price at any given moment is the group with the most incentive to trade. If financial traders experience lower risk absorption capacities due to a larger exposure to changes in the VIX than hedgers during the crisis period, the amount of risk transferred from hedgers to financial traders may be reduced as financial traders' risk absorption capacity tightens. This is true even if the VIX also affects hedgers' incentives to hedge, so long as financial traders have a differentially larger exposure. As financial traders cut down their long positions due to their smaller risk absorption capacity, the equilibrium price falls and hedgers end up holding more risk than they did previously. Much as warm air flows toward cool air in a convective current, a portion of the risk that was previously held by financial traders will be taken back on by hedgers. We call this phenomenon a "convective risk flow".

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[2] Mitchell, Pedersen, and Pulvino (2007), Froot (2008), Adrian and Shin (2010), and He, Khang, and Krishnamurthy (2010) provide evidence for capital constraints to affect liquidity and risk premium in various asset markets such as convertible bond market, catastrophe reinsurance market, and mortgage-backed security market.

[3] Shocks to the VIX are widely used to analyze the risk absorption capacity of financial institutions on asset markets. For example, Brunnermeier, Nagel, and Pedersen (2009), Coffey, Hrung, and Sarkar (2009), and Longstaff et al. (2011) show that VIX shocks can explain price dynamics in several markets that are not directly related to equity during the crisis, such as currency crashes, violation of covered interest rate parity, and fluctuations of sovereign bond spreads.

Our empirical analysis identifies the existence and direction of a convective risk flow by exploiting the joint dynamics of futures price changes and position changes of different trader groups. Our analysis proceeds in two steps. First, we examine whether changes in futures prices are correlated with changes in the VIX during the crisis period. Second, using a comprehensive dataset of positions of market participants, we examine which trader groups' position changes are correlated with changes in the VIX in the same direction. For example, if prices tend to fall as the VIX rises in the crisis, we examine which trader groups are selling. This identifies which groups transmit the VIX movements into the futures prices and thus who the marginal price setters are during this period. If, as the prices fall, financial traders reduce their positions in response to increases in the VIX, there is a convective risk flow toward hedgers.

We obtain account-level data on each trader's daily positions in commodity futures markets by making use of the CFTC's Large Trader Reporting System (LTRS) database.[4] Based on each trader's registration with the CFTC and its positions in the LTRS database, we classify the trader as a hedger, hedge fund, or CIT. Hedge funds and CITs are the two major groups of financial traders.

We find that during the recent financial crisis, the aggregated positions of both CITs and hedge funds displayed significant and negative position responses to increases in the VIX in a large number of commodity futures markets. Hedgers took the other side and displayed a positive position response to increases in the VIX, meaning they tended to reduce their net short positions just as uncertainty was rising. Averaging the effect across agricultural commodities, a one standard deviation (SD) increase in the VIX is associated with a 0.20-SD decrease in CIT positions, 0.12-SD decrease in hedge fund positions, and 0.16-SD increase in hedger positions. The increases in the VIX were also accompanied by significant price drops in almost all commodity futures. In contrast, prior to the financial crisis, neither financial traders nor hedgers exhibited significant responses to the VIX. This contrast in the traders' responses before and during the crisis is consistent with an implication of the intermediary pricing theory that financial traders' exposures to financial shocks are non-linear and are particularly large after they suffer large losses during a crisis.

[4] By regulation, when a trader's position in a commodity futures contract becomes larger than a certain threshold, clearing members are obligated to report the trader's end-of-day positions in the commodity to the CFTC. The reportable traders in the LTRS account for 70–90% of open interest in any given commodity.

The main alternative hypothesis for our results is that the observed price and position correlations are driven by changes to hedgers' hedging demand rather than the fluctuating risk absorption capacities of financial traders. To more directly associate the observed position responses to the VIX with the risk absorption of financial traders, we exploit the detailed cross-section of traders within different trader groups. First, by taking advantage of the availability of CDS spreads of many CITs, we find more sensitive position responses to the VIX by more distressed CITs (i.e., those with larger CDS spreads). Second, we find that, within hedgers, net short hedgers reduced their short positions in response to increases in the VIX, whereas net long hedgers did not reduce their long positions or even increased their long positions. This absence of a response by long hedgers suggests that changes in the VIX were less related to hedging demand and more related to the capacity of financial traders to bear risk.

Our results are robust to including macroeconomic controls and other indicators of risk in commodities, and do not rely on a particular definition of the financial crisis. To show our results do not rely on our use of the CFTC's proprietary LTRS data, we also re-confirm similar convective flows in positions of different trader groups covered by the CFTC's public Commitment of Trader (COT) reports, although the public COT reports do not allow for as fine of a disaggregation of groups of traders as our analysis. We also check our results using other measures of financial traders' risk appetite and arbitrage capital, including the implied volatility of financial sector ETFs, the average CDS spread of primary dealers, and the measure of Treasury market illiquidity developed by Hu, Pan, and Wang (2013). Overall, these alternative measures yield consistent, although statistically weaker, results than the VIX. As we will discuss later, each of these alternative measures picks up some aspects of the time-varying risk appetite of either CITs or hedge funds, none of them is perfect in capturing the overall variation of both CITs and hedge funds.

Taken together, our empirical evidence suggests that, during the recent crisis, in response to distress in the financial markets, financial traders reduced their commodity futures positions instead of facilitating the hedging needs of hedgers. Our results link the changing face of market participants in commodity futures markets over the past 10 years to changes in commodity futures price dynamics. In this sense, our results echo those of Etula (2013), which emphasizes the balance sheet strength of securities brokers and dealers as an important determinant of risk premia and return volatility in commodity markets, and Acharya, Lochstoer, and Ramadorai (2013), which shows that decreases in hedgers' hedging cost appear to fluctuate with the strength of the financial sector. However, our study is distinct in that it focuses on the recent dramatic changes in market participation and thus helps identify the effect of these changes, notably the growth of CITs, on commodity futures price dynamics.[5] Furthermore, while distressed sales are a phenomenon shown to exist in other asset classes (e.g., as in Coval and Stafford, 2007), our article emphasizes the interaction between different trader groups and highlights which traders provide liquidity during sales and purchases related to fluctuations in risk absorption capacity.

Our results also help resolve some specific controversies in the aforementioned debate of CITs on commodity markets. First, our results motivate the need to expand the debate about the impact of speculators' trading on commodity prices to one that studies which trader groups have the greatest incentive to trade during different time periods. For example, our results help reconcile the views of Singleton (2013) and Hamilton and Wu (2013), the latter of which argues that the findings of the former are specific to the crisis. Other studies in the aforementioned debate do not condition on how shocks affect different traders during specific periods in their analyses.

Second, our results help directly resolve the controversy over the lack of a contemporaneous relationship between futures price changes and CIT position changes, which is often used as key evidence against any effect of CIT trading on prices. The final section of the article shows that conditioning on changes in the VIX to isolate trades due to the fluctuation of risk absorption capacity of CITs in the crisis reveals consistently positive and significant correlations between CIT position changes and price changes across almost all commodities in our sample, although our point estimates only provide upper bounds of price impacts. Our analysis thus echoes another recent study of Henderson, Pearson, and Wang (2012), who identify price impacts of CITs by conditioning on the startup of a set of commodity-linked notes (CLNs, a type of instruments used by CITs) to isolate trades initiated by CITs. They find that such trading by CITs has a positive impact on commodity prices over a 2-day window following the launch of CLNs. Our analysis complements theirs by studying the reaction of all market participants and expanding the scope of their study to whether such effects related to market microstructure can lead to persistent re-allocations of risk over long horizons.

The article is organized as follows. Section 2 introduces a theoretical framework and discusses our empirical design. Section 3 describes the data and provides summary information on participation of different trader

5 Tang and Xiong (2012) argue that the increasing presence of index traders in commodity futures markets improves risk sharing at the expense of having volatility spillover from outside markets, but do not directly measure positions of market participants.

groups. Section 4 examines the joint responses of futures prices and traders' positions to VIX changes. Section 5 concludes the article. We also provide Supplementary material, available online, to report additional data description and empirical results.

2. Theory and Empirical Design

2.1 A THEORETICAL FRAMEWORK

To develop the notion of a convective risk flow, we adopt a setting broadly consistent with the hedging pressure theory formulated by Hirshleifer (1988, 1990). Specifically, we consider a futures market with two groups of participants, hedgers, and financial traders. The hedgers represent commodity producers and need to short futures to hedge the commodity price risk in their commercial business.[6] The financial traders take the other side of the hedgers' trade, but also face their own shocks that motivate them to change their position.

We consider only one period (possibly out of many periods in a more general model), during which random shocks cause the two groups of traders to change their positions. For simplicity, we specify the following demand curves for the two groups:

$$dx_h = -\beta_h dF - \gamma_h z - u_h,$$

$$dx_f = -\beta_f dF - \gamma_f z,$$

where dx_h and dx_f are changes in the futures position of the hedgers and financial traders across the period. dF is the futures price change. The coefficients $\beta_h \geq 0$ and $\beta_f \geq 0$ are the slopes of the two groups' demand curves with respect to the price change dF. These slopes also represent the two groups' capacities to absorb each other's trades.

Note that financial traders' slope β_f reflects the number of financial traders who choose to participate in this market in the presence of a fixed setup cost (a la Hirshleifer, 1988). A larger β_f implies that for the same futures price drop, financial traders are able to absorb a larger position sold by hedgers. Similarly, β_h measures how price sensitive the hedgers are. Hedgers will choose a smaller hedging position when the futures price drops.

[6] Our setting takes as given several conditions highlighted by Hirshleifer (1990) for the existence of hedging pressure. First, different from concentrated commodity price risk faced by producers, consumers face dispersed risk across a variety of commodities and do not hedge due to fixed setup costs in participating in each futures market. Second, producers face inelastic commodity demand and need to short futures to hedge their risk.

We build in two types of random shocks in the hedgers' and financial traders' position changes. u_h is an idiosyncratic shock that causes hedgers to increase their short position in the futures contract. We also introduce another shock, z, which motivates financial traders to reduce their positions. One can think of the z shock as a shock to the VIX during the financial crisis, which increased the overall risk of financial traders' investment portfolios and thus caused them to cut down their positions in commodity futures. $\gamma_f > 0$ measures financial traders' exposure to the shock. For generality, we also allow the z shock to affect hedgers although with a different degree, γ_h. In the case that $\gamma_f > \gamma_h$, financial traders have a greater exposure than hedgers to the z shock.

Market clearing imposes an add-up constraint on dx_h and dx_f:

$$dx_h + dx_f = 0.$$

The equilibrium price acts as the key channel to balance the two groups' net demand. Simple algebra gives that the futures price has to change by:

$$dF = -\frac{1}{\beta_h + \beta_f}\left[u_h + \left(\gamma_h + \gamma_f\right)z\right], \tag{1}$$

which is accompanied by the following position changes:

$$dx_h = -\frac{\beta_f}{\beta_h + \beta_f}u_h + \frac{\beta_h\gamma_f - \beta_f\gamma_h}{\beta_h + \beta_f}z, \tag{2}$$

and

$$dx_f = -dx_h = \frac{\beta_f}{\beta_h + \beta_f}u_h - \frac{\beta_h\gamma_f - \beta_f\gamma_h}{\beta_h + \beta_f}z. \tag{3}$$

Equation (1) nests the hedging pressure theory in the sense that the presence of financial traders dampens the price impact of the hedgers' idiosyncratic shock u_h. That is, a higher value of β_f leads to a smaller exposure of the futures price to u_h due to the financial traders' greater capacity to share the hedgers' shock [e.g., Equations (2) and (3)].

Equations (2) and (3) also highlight the convective risk flow induced by the z shock from the financial traders to the hedgers. For illustration, consider the simple case with $\gamma_h = 0$ (i.e., the z shock does not affect the hedgers). In this case, the z shock nevertheless causes the hedgers to increase their futures position by $\frac{\beta_h\gamma_f}{\beta_h+\beta_f}z$. This is because the shock causes the futures price to drop by $\frac{\gamma_f}{\beta_h+\beta_f}z$, which in turn induces the hedgers to buy back their short position. In other words, the price drops so much that the hedgers find it desirable to take some risks back.

More generally, as long as $\beta_h\gamma_f - \beta_f\gamma_h > 0$, which is equivalent to $\frac{\gamma_f}{\beta_f} > \frac{\gamma_h}{\beta_h}$ (i.e., the financial traders' exposure to the z shock after adjusting for their capacity is greater than the hedgers'), the hedgers buy back some of their futures position in response to the shock. As a result, a convective risk flow, or a change in how much risk is held by different trader groups, emerges. The premise of this convective risk flow is that one group of participants (financial traders) has a greater exposure to the shock than the other group (hedgers) and that both groups are price sensitive (i.e., both groups have elastic demand curves). This convective flow reduces risk sharing by financial traders even though they may nevertheless still hold a net long position and share some of hedgers' risks. Our empirical analysis anchors on documenting such a convective flow in the commodity futures markets during the recent financial crisis.

This simple framework also shows a subtle relationship between the futures price change and traders' position changes. In the ongoing debate regarding whether the large inflows of investment capital into commodity futures markets affect commodity prices, a commonly used test of the price impact of CITs is to examine whether their position changes are correlated with futures price changes. The premise of the test is that, if CITs' trading affects futures prices, there must be a positive correlation between their position changes and price changes. Despite its intuitive appeal, this test ignores that CITs might trade for different reasons.

It is convenient to interpret the financial traders in our model as CITs and/or hedge funds. Equations (1) and (3) show that the hedgers' shock u_h and financial traders' shock z induce opposite correlations between the futures price change dF and financial traders' position change dx_f. When financial traders trade to accommodate hedgers' shock u_h, they share hedgers' risk and their position change is negatively correlated with the price change. On the other hand, when they trade in response to their own shock, they demand risk sharing from hedgers and their position change is positively correlated with the price change. The unconditional correlation of their position change and the price change nets out these two offsetting effects:

$$Corr\left(dx_f, dF\right) = \frac{1}{\sqrt{Var\left(dx_f\right)Var(dF)}} \times \left[-\frac{\beta_f}{\left(\beta_h+\beta_f\right)^2}Var(u_h) + \frac{\left(\beta_h\gamma_f - \beta_f\gamma_h\right)\left(\gamma_h+\gamma_f\right)}{\left(\beta_h+\beta_f\right)^2}Var(z)\right].$$

The sign of this unconditional correlation is ambiguous and depends on the relative magnitudes of the two terms in brackets. The ambiguous sign helps explain the lack of consistent findings in the extant literature of significant correlations between the changes of CITs' positions and futures prices.[7] At the same time, it also motivates more systematic tests of price impacts of CITs and other financial traders after conditioning on trades initiated by them or accommodated by them. Our analysis of convective risk flows exactly serves as such a conditional test.

2.2 EMPIRICAL DESIGN

Our empirical analysis focuses on using the change in the VIX as a proxy for the z shock. An increased VIX implies greater volatility in financial markets. This may particularly affect financial traders as they face both more stringent risk controls as well as potential funding constraints (e.g., Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009). In response, they may have to reduce their risk exposures. A common implication of these models (e.g., Kyle and Xiong, 2001; He and Krishnamurthy, 2013) is that this effect is non-linear and is particularly strong during a crisis after financial institutions suffer large losses and are vulnerable to any additional shock to their risk appetite and funding constraints. As a result, during the recent crisis, they could have responded to increases in the VIX by reducing their commodity exposures, even though they may not have responded in the same way before the crisis.[8]

The VIX may also affect hedgers' incentives to hedge, although the existing literature does not provide a clear-cut implication on the effect. To the extent that an increase in the VIX implies greater economic uncertainty in the economy, the greater economic uncertainty may motivate hedgers to hedge more, either due to increased wedge between costs of external and internal sources of funding (e.g., Froot, Scharfstein, and Stein, 1993) or greater default risk faced by leveraged firms (e.g., Smith and Stulz, 1985). Hirshleifer (1991) provides a two-good model to analyze how a farmer's optimal hedging policy depends on various factors such as demand elasticity and sensitivity of his output to weather. He shows that the farmer's optimal hedging position can be time-varying and even reverse in

[7] Although our analysis focuses on the contemporaneous relationship between position changes and price changes, the same concern also applies to lead–lag relationship between them.

[8] One caveat, however, is that the VIX may affect both financial institutions' funding constraints as well as the risk appetites of clients (who themselves may be financial institutions), and our analysis does not explicitly differentiate between these mechanisms.

direction during the crop year. On the other hand, Rampini, Sufi, and Viswanathan (2014) show that commercial hedgers may wish to reduce hedges in times of distress due to collateral constraints. To be clear, our framework allows for the VIX to induce distress at commercial hedgers. Our analysis is designed to tease out which trader groups are more incentivized to trade as a result of VIX fluctuations during the crisis, by identifying whether $\frac{\gamma_f}{\beta_f} > \frac{\gamma_h}{\beta_h}$.

We examine how price changes and position changes are correlated with changes in the VIX, conditional on a set of controls. We focus on the following set of weekly time-series regressions estimated before and after the financial crisis:

$$\text{Price correlation}: dF_t = \tilde{a} + \tilde{b}_1 z_t + \tilde{b}_2 z_{t-1} + \tilde{c}\, dF_{t-1} + \tilde{d}\, Controls_t + u_t, \quad (4)$$

$$\text{Position change}: dx_t = a + b_1 z_t + b_2 z_{t-1} + c\, dF_{t-1} + d\, Controls_t + v_t, \quad (5)$$

where z_t is the change in the VIX, dF_t is the fully collateralized return to a rolling position in the currently indexed futures contract, and dx_t is the position change for a group of traders (e.g., CITs, hedge funds, or hedgers). We control for lagged changes in the VIX due to its persistence, and also control for one lag of commodity returns to allow for persistence in commodity price movements.[9] Our other control variables are a series of macroeconomic forecasting variables plus commodity-specific fundamental indicators and are designed to control for fundamental factors that may affect prices discussed in Section 3. We focus on the weekly frequency to abstract away from daily microstructure-related effects.

By establishing a price correlation $\tilde{b}_1$ of the VIX shock and then examining b_1 for different trader groups during different sample periods, we identify which traders are trading in the same direction as the price correlation with the VIX shock, and thus which way risk is flowing during that time period. Notice that $\tilde{b}_1$ will have the same sign as $\frac{dF}{dz}$ from Equation (1), b_1 for hedgers will have the same sign as $\frac{dx_h}{dz}$ from Equation (2), and b_1 for financial traders will have the same sign as $\frac{dx_f}{dz}$ from Equation (3). Maintaining the assumption that $\beta_h, \beta_f \geq 0$, if we observe $\tilde{b}_1 < 0$, then $\gamma_h + \gamma_f > 0$, so at least one group of traders has exposure to the VIX. If, at the same time, $b_1 < 0$ for financial traders and $b_1 > 0$ for hedgers,

[9] We focus on changes in the VIX orthogonal to lagged changes in the VIX instead of imputed innovations to the VIX, as estimating such innovations requires using the full sample of the VIX.

then $\frac{\gamma_f}{\beta_f} > \frac{\gamma_h}{\beta_h}$. In words, a rising VIX induces financial traders to sell and hedgers to accommodate the trade, while the equilibrium price falls. Alternatively, if $b_1 > 0$ for financial traders and $b_1 < 0$ for hedgers, a rising VIX induces hedgers to short more, with financial traders buying as the equilibrium price falls. Note that, by the market clearing condition, b_1 for financial traders cannot have the same sign as b_1 for hedgers.

Observing $\tilde{b}_1 < 0$, along with $b_1 < 0$ for financial traders and $b_1 > 0$ for hedgers, establishes that the VIX-induced fluctuations in the risk absorption capacity of financial institutions during the crisis to a greater degree than commercial hedgers, which in turn affected prices. An alternative hypothesis is that hedgers were intentionally reducing short hedges (i.e., buying) in response to rises in the VIX, which would generate the same pattern of b_1 coefficients. This may arise, for example, if commercial hedgers experienced greater distress than financial traders from rises in the VIX so that $\frac{\gamma_f}{\beta_f} < \frac{\gamma_h}{\beta_h}$. However, this hypothesis is actually not consistent with $\tilde{b}_1 < 0$ if Equations (4) and (5) are well-specified, because prices should rise if hedgers were the marginal price setters and were buying in response to rises in the VIX; instead, prices fell during the crisis. One could go on to tell a story where $\tilde{b}_1 < 0$ due to an omitted variable negatively correlated with the VIX, where the omitted variable is positively correlated with prices, so that the counterfactual price would have been even lower had hedgers not been buying. An example of such a variable might be expected demand, which presumably fell during the crisis as the VIX rose, and drove prices down. Or, hedgers might have certain beliefs that prices would mean revert.

To address these concerns, we exploit the cross-section of traders in more detail to directly establish the role of financial institutions. First, we take advantage of the availability of CDS spreads for CIT traders (spreads are not available for hedge funds) to examine whether CITs with higher CDS spreads displayed a higher sensitivity of positions to the VIX than those with lower CDS spreads. If so, this would provide direct evidence that it was financial institutions under distress which were responding to the VIX.

Second, we also directly examine hedgers. As discussed above, the existing theories do not provide a sharp prediction on how the VIX affects hedgers' incentives to hedge commodity price risk. Without taking a strong stand on a particular mechanism, we examine whether the VIX increased hedging demand by examining whether the hedging demand of both long and short hedgers increased in response to the VIX. If the relationship between the VIX and prices is driven by hedging behavior, one might expect that it should motivate both long hedgers and short hedgers to reduce their hedges.

In contrast, the effect coming from financial institutions would be more consistent with either a muted response from long hedgers or even long hedgers buying in response to rises in the VIX.

Note that the VIX is not a perfect measure of financial traders' risk appetite and arbitrage capital. In our analysis, we also explore several alternative measures, including the implied volatility of financial sector ETFs, the average CDS spread of primary dealers, and the measure of Treasury market illiquidity developed by Hu, Pan, and Wang (2013).

3. The Data and Market Participants

Our analysis uses the CFTC's proprietary Large Trader Reporting System (LTRS) database. The LTRS data includes disaggregated end-of-day positions for each large trader in all commodity futures and options markets subject to the jurisdiction of the CFTC. The LTRS data underlies the weekly reports published by the CFTC on aggregate long and short positions of trader groups: the Commitments of Traders (COT) report and the Supplemental Report on Commodity Index Traders.

Our data spans January 1 2000 to June 1 2011. We focus on large traders with positions in the nineteen US commodity futures included in the Standard & Poor's-Goldman Sachs Commodity Index (SP-GSCI Index) and the Dow Jones-UBS Commodity Index (DJ-UBSCI). These commodities include Chicago wheat, corn, Kansas City wheat, soybeans, and soybean oil in grain; feeder cattle, lean hogs, and live cattle in livestock; cocoa, coffee, cotton, and sugar in softs; crude oil, heating oil, natural gas, and gasoline in energy; and copper, gold, and silver in metals.

The LTRS compiles daily account-level data of traders' long and short end-of-day positions in individual commodity futures contracts, for example, a Chicago Board of Trade (CBOT) corn futures contract expiring in December 2001. Based on the LTRS data, we construct a weekly time series from 2000 to 2011 aggregated across contracts but within commodities that matches the timing of the Tuesday-to-Tuesday COT reports to best facilitate comparison with public data. We provide more details of our data construction in the Supplementary Material.

3.1 TRADER CLASSIFICATION

We use specific attributes that identify each trader's registration, designation, or reporting status, as well as the previous year's position patterns, to classify the trader in any given year into several trader groups, including hedgers, hedge funds, and CITs, for the 2000–11 period. We give a rough outline of our classification below; full details are in the Supplementary Material. Relative to the COT reports, our classification is conservative in the sense that we aim to minimize the effect of traders with ambiguous purposes by moving any trader with ambiguous registration into a fourth unclassified group called others. This conservative classification gives a more accurate measure of the covariance of each group's position change with shocks and prices, at the expense of under-estimating its net size.[10]

We classify hedgers as traders in the LTRS system with registration, reporting and designation codes that clearly indicate commercial use in all the commodities in which they trade. They represent farmers, producers, and consumers, who regularly trade commodity futures to hedge commodity price risk inherent in their commercial activities.

We group Commodity Pool Operators (CPOs), Commodity Trading Advisors (CTAs), and traders otherwise labeled by the CFTC as "Managed Money" together as hedge funds. These funds invest others' money on a discretionary basis in commodities, commodity futures, and options on futures, and make extensive use of leverage. The use of leverage makes funding risk an important part of their business, as illustrated in other crisis episodes such as the LTCM crisis in 1998.

CITs represent portfolio investors who seek index exposure to commodities.[11] At a practical level, investors often establish commodity

[10] The existing literature on the role of CITs and financial traders has primarily drawn on three data sources in addition to the LTRS. The first two are public data sources: the weekly Disaggregated Commitment of Traders report (DCOT), and the weekly Supplemental CIT report, and the third is the CFTC's special call report on CIT positions. The Supplemental CIT report contains data specifically measuring CIT positions; however, the only other market participant categories are broad commercial and non-commercial categories, rather than more precise categories for hedge funds and commercial hedgers. Although the DCOT report contains detailed data on hedge fund and commercial hedger positions, it does not contain data specifically measuring CIT positions. It does contain aggregated positions for general swap dealers—i.e., physical and financial swap dealers together—and many studies have proxied for CIT positions using these swap dealer positions. However, this swap dealer classification is likely a noisy the measure of CIT positions due to the presence of physical swap dealers. The CFTC's special call report on CITs is not ideal for our analysis, both because of its low-frequency and unavailability before December 2007. In the Supplementary Material, we provide a more detailed review of our classification as well as how it compares with the literature.

[11] A commodity index functions like an equity index, such as the S&P 500, in that its value is derived from the total value of a specified basket of commodity futures contracts with specified weights. These contracts are typically nearby contracts with delivery times longer than one month. When a first-month contract matures and the second-month contract becomes the first-month contract, a commodity index specifies the so-called "roll" (i.e., replacing the current contract in the index with a following contract). In this way,

index positions by acquiring index swap contracts from financial swap dealers, rather than directly taking long positions in individual commodity futures. These financial swap dealers then hedge themselves by taking long positions in individual commodity futures and report their futures positions to the CFTC. For this reason, many CITs classified in our analysis are swap dealers, even though many swap dealers—in particular, physical swap dealers—are not CITs. Unlike CPOs and CTAs, CITs are not a registered category with the CFTC. We identify CITs based on the CIT classification of the CFTC's Supplemental CIT report and two additional criteria motivated by the trading patterns of broad-based portfolio investors in commodity indices: (1) they should be invested in many commodities (have exposure to at least eight commodities on average over a year); and (2) they should be mostly net long in those commodities over the previous year (the daily average over the previous year of the equal-weight commodity average percentage of total contracts held which were long must be >70%). We refresh our classification each year based on the previous year's data.

3.2 THE NETTING PROBLEM

Although CITs should be theoretically 100% long, this is not true in the data due to a netting problem. CITs are large financial institutions which may hold positions both on behalf of clients as well as proprietary non-client positions. However, client positions are not broken out from non-client positions in the LTRS data—the data are "netted" together. Furthermore, the LTRS does not cover commodity swaps, as until recently, the CFTC lacked jurisdiction over the swap market. The data thus includes only a subset of positions of market participants in the universe of commodity derivatives. As a result of these two issues, certain commodities, particularly those where derivatives other than futures are very common, are particularly ill-suited for measuring CIT positions using the LTRS data. As noted by the CFTC (in the accompanying note to its initial Supplemental COT report), this problem is severe in energy and metals, where proprietary and client positions might be more mixed due to the size of markets such as

commodity indices provide returns comparable to passive long positions in listed commodity futures contracts. By far the largest two indices by market share are the SP-GSCI and the Dow-Jones UBS Commodity Index (DJ-UBS). These indices differ in terms of index composition, commodity selection criteria, rolling mechanism, rebalancing strategy, and weighting scheme. Instead of entering positions on individual futures contracts, CITs typically purchase financial instruments that give them exposures to returns of a commodity index. There are three types of such instruments: commodity index swaps, exchange-traded funds, and exchange-traded notes.

gold and oil and where over-the-counter derivatives other than futures are common, but less so in agricultural commodities, where derivatives other than futures are rarer.

The netting problem also manifests itself in that some traders may carry multiple designations; for example, a trader may be both a CIT and hedge fund according to the above criteria. For the bulk of our analysis, we exclude traders with multiple designations in order to best capture the covariance properties of their position changes with prices. We discuss the netting problem in more detail in the Supplementary Material.

3.3 MARKET PARTICIPATION OF DIFFERENT TRADER GROUPS

Table I reports summary statistics by trader types and year. Each summary statistic is a cross-sectional statistic (over traders) of a measure that is a daily average over a year. There are relatively few CITs, yet their net positions are typically very large, and, by construction, they are invested in many commodities.[12] Since 2004, both the number of CIT traders and their median net notional position have grown significantly, reflecting the rapid rise in index investing. Hedge funds tend to have slightly net long exposure. Despite the diversity of hedgers, the average hedger tends to be net short in commodity futures. Hedgers are also mostly invested in one or two commodities, consistent with the nature of their specific hedging needs.[13] The number of hedge funds and commercial hedgers has also grown markedly throughout our sample.

Our annual categorization is persistent. Table I shows that the probability of a given account having the same categorization in the following year is almost 1 for a hedger, hedge fund, or otherwise unclassified trader. For a CIT trader, the probability is 93%.

Figure 1 plots the aggregate net notional position of each trader category, where positions have been aggregated across all nineteen commodities, once

[12] The number of traders is low compared with those reported in the public COT reports. In this sense, our classification scheme is conservative and likely an underestimate of the size of the CIT sector. For our purposes, we are more interested in the time series properties of changes in true CIT behavior.

[13] As indicated in Table II, there are a number of other unclassified traders. Although most of these traders are small, some of them have a significant net short exposure. These traders might be hedgers who were not registered with, reported to or designated by the CFTC as such, or traders who are registered as hedgers in one but not all commodities in which they trade. There are also a few traders with both CIT and HF designations. The behavior of these traders, however, appears to be fairly similar to CITs. There are very few traders who have designations as both a hedger and a hedge fund. To preserve confidentiality, statistics for CIT-HFs and Hedger-HFs are omitted.

Table I. Trader characteristics

We report the number of traders and trader characteristics by year and trader category. Each summary statistic is a cross-sectional statistic of a measure that is an average over a year for each trader. Panel A reports the number of traders, Panel B reports the cross-sectional median total dollar notional net position for each category, Panel C reports the average of the number of commodities to which a trader has exposure, while Panel D reports the average percentage of contracts long. Panel E reports the persistence in our annual categorization. For confidentiality reasons, the number of traders for CIT-HF and Hedger-HFs are concealed as they are very small.

Ranking year	Population	CIT	C. hedger	Hedge fund	Others
Panel A: Number of traders					
2000	4,822	4	810	324	3,672
2001	4,576	4	857	334	3,369
2002	4,729	6	953	391	3,363
2003	4,990	6	1,075	466	3,424
2004	5,376	9	1,169	567	3,610
2005	5,197	9	1,208	688	3,267
2006	5,664	12	1,453	874	3,293
2007	5,629	12	1,483	974	3,123
2008	5,667	15	1,503	1,089	3,027
2009	5,148	20	1,332	1,082	2,686
2010	5,699	18	1,465	1,116	3,072
Panel B: Median notional net position, December 15 2006 indexed contract prices $M					
2000	0.026	549.758	−2.434	0.806	0.070
2001	0.014	527.124	−1.056	−0.039	0.055
2002	0.005	315.939	−2.970	1.712	0.046
2003	0.023	482.972	−2.482	2.394	0.056
2004	−0.008	352.938	−3.265	0.720	0.000
2005	−0.181	1893.471	−3.626	0.110	−0.041
2006	−0.103	1737.572	−4.760	0.192	0.000
2007	−0.191	2678.250	−5.569	0.368	−0.024
2008	−0.291	2335.372	−5.301	0.200	−0.014
2009	−0.261	1746.668	−5.084	0.438	−0.054
2010	−0.242	2332.411	−7.128	1.362	−0.013
Panel C: Average number of commodities with any exposure					
2000	1.257	14.925	1.246	2.364	1.147
2001	1.268	15.070	1.215	2.427	1.148
2002	1.263	15.629	1.210	2.442	1.113
2003	1.289	16.383	1.210	2.387	1.131
2004	1.328	16.345	1.204	2.543	1.128
2005	1.373	16.795	1.194	2.593	1.113
2006	1.415	17.626	1.200	2.571	1.101
2007	1.480	18.493	1.243	2.634	1.111
2008	1.502	17.627	1.239	2.410	1.174
2009	1.549	16.227	1.208	2.506	1.161
2010	1.574	16.713	1.242	2.594	1.216

(continued)

Table I. (Continued)

Ranking year	Population	CIT	C. hedger	Hedge fund	Others
Panel D: Average percentage of contracts long					
2000	0.522	0.860	0.394	0.599	0.545
2001	0.528	0.858	0.449	0.512	0.550
2002	0.521	0.842	0.400	0.609	0.546
2003	0.520	0.863	0.392	0.646	0.542
2004	0.495	0.894	0.367	0.587	0.522
2005	0.465	0.873	0.352	0.545	0.489
2006	0.469	0.887	0.323	0.563	0.506
2007	0.452	0.893	0.295	0.581	0.484
2008	0.448	0.873	0.299	0.549	0.483
2009	0.452	0.880	0.301	0.575	0.473
2010	0.445	0.872	0.250	0.604	0.477
Panel E: Persistence in annual categorization, 2000–09					
Pr[Category(t+1)=X | Category(t)=X]		0.91	0.86	0.85	0.66
Pr[Category(t+1)=X | Category(t)=X, Alive(t+1)=True]		0.93	1.00	1.00	1.00

where we have aggregated using contemporaneous prices and once where we have aggregated using fixed prices as of December 15 2006.[14] Although our categorizations are meant to conservatively capture the trading pattern of different groups rather than the pure level of positions, the plots are useful in describing the pattern of investing through time. Evidently, the long side of commodities futures markets has become increasingly dominated by CITs and hedge funds, with hedgers and other unclassified traders forming the bulk of the short side.

Figure 2 plots the aggregate net notional positions (using fixed prices) for each of the five sectors of commodities, and these observations seem to hold within each sector. It is evident that the netting problem is severe in energy and metals, with CITs “appearing” to take even a net short position in metals, consistent with our earlier discussion. Metals face the additional

[14] Figures 1 and 2 may exhibit jumps in positions on January 1 of each year, as positions are re-shuffled due to the re-categorization of traders on an annual basis. In this sense, the change in the aggregate level here is not the same as the flow on the first trading day of each year (or any week/time unit that spans multiple years). In subsequent calculations involving flows, flows are always computed using a constant sample composition. For example, the flow on the first trading day of the year for the CIT grouping is the change in position for the new group.

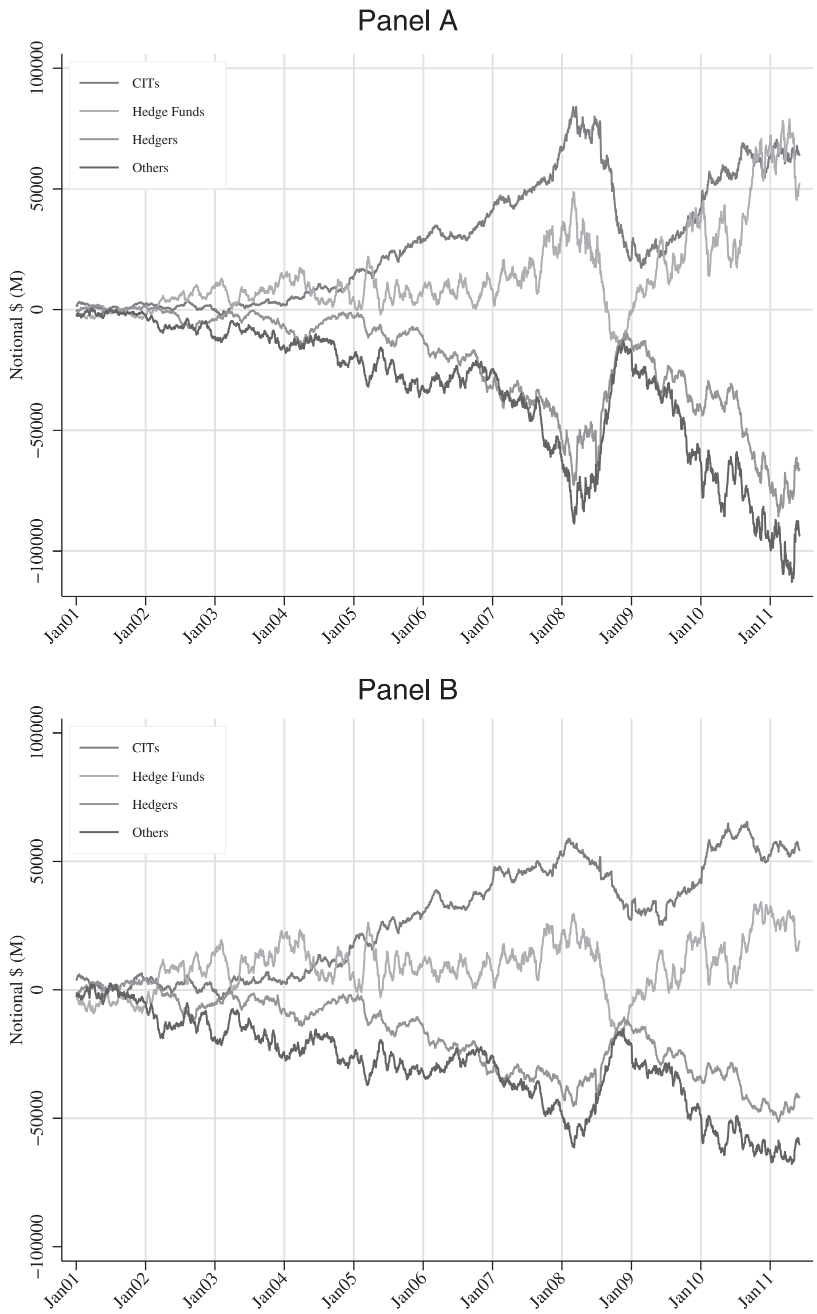

Figure 1. Net commodity exposures. This figure plots the daily net notional value of positions held by the different trader groups. Panel A computes notional values using contemporaneous nearby prices adjusted for inflation (CPI All-Items, Urban Consumers, non-seasonally adjusted) to real December 2006 prices. Panel B computes notional values using fixed nearby prices as of December 15 2006.

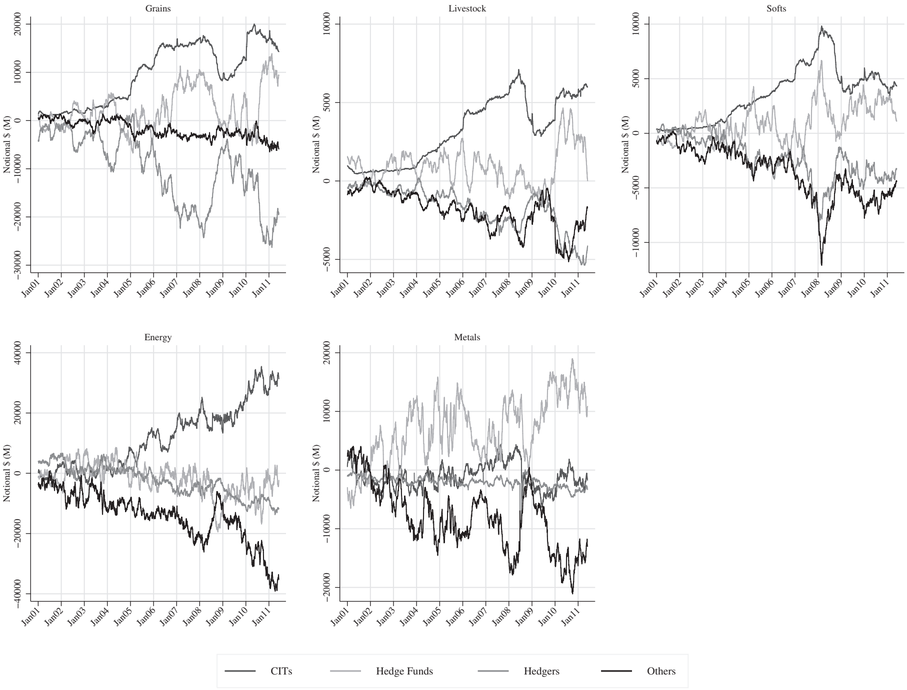

Figure 2. Net commodity exposure by sector. This figure plots the daily net notional value of positions held by the different trader groups across each commodity sector. Notional values were computed using fixed nearby prices as of December 15 2006.

issue that many positions are taken in the London Metals Exchange, for which there is no position data available.

Relative to other trader groups, CITs should be passive traders, and this is borne out in the data. Table II shows that the volatility of flows for CITs is substantially lower than other groups in nearly every commodity. Averaged across the twelve agricultural commodities, the volatility of hedge fund flows is 2.6 times the volatility of CIT flows. However, although CITs are passive, their positions are not constant, as Figures 1 and 2 show sharp decreases in CIT positions during the financial crisis. Additionally, contrary to the common perception that hedgers establish hedges and then do not trade, hedgers have a high volatility of flows, which is twice as large as that of CITs and 70% as large as that of hedge funds. The large amount of trading by each of the trader groups suggests that each group is price sensitive and would accommodate trades initiated by another group.

Table II. Time series summary statistics for flows and returns

We report summary statistics for 19 indexed commodities at a weekly frequency. Indexed contract returns are expressed in basis points, whereas flows are expressed as notional dollar values ($M) normalized using indexed contract prices on December 15 2006. Panel A reports summary statistics for the period September 15 2008 onwards. Panel B reports the ratio of trader flow volatilities from September 15 2008 onwards, as well as for the periods January 1 2006 to September 15 2008 and January 1 2001 to January 1 2006.

Panel A: Summary statistics, September 15 2008 to June 1 2011

Sector	Commodity	Mean Indexed contract return	SD Indexed contract return	SD Flow: CIT	SD Flow: HF	SD Flow: C. hedger	SD Flow: other unclassified	*T*
Grains	Chicago wheat	−14.5	547.3	103.7	194.6	141.7	132.4	142
	Corn	13.5	566.7	177.6	457.1	391.1	204.3	142
	Kansas City wheat	4.8	509.3	28.8	78.7	92.8	44.3	142
	Soybeans	23.9	422.3	121.6	429.7	386.7	254.9	142
	Soybean oil	10.1	441.3	49.2	150.6	139.7	104.9	142
Livestock	Feeder cattle	−1.3	222.4	16.8	55.5	28.4	35.5	142
	Lean hogs	−28.2	370.8	50.2	105.7	52.6	113.2	142
	Live cattle	−14.1	209.9	81.9	194.0	118.3	141.5	142
Softs	Cocoa	12.6	447.2	17.3	53.1	38.8	41.5	142
	Coffee	40.3	454.9	68.8	204.5	171.7	108.5	142
	Cotton #2	68.4	532.2	62.9	125.4	67.3	145.6	142
	Sugar #11	50.6	615.4	98.0	136.5	160.3	158.2	142
Energy	Crude oil	−27.7	619.5	851.8	1173.7	388.5	755.3	142
	Heating oil	−6.4	566.1	288.1	567.0	264.2	526.9	142
	Natural gas	−99.3	655.3	512.5	834.1	244.8	637.2	142
	RBOB gasoline	16.7	616.7	156.8	519.3	279.4	479.9	142
Metals	Copper	29.0	486.0	121.7	267.8	78.8	253.0	142
	Silver	98.0	573.4	123.7	216.6	63.1	143.4	142
	Gold	49.4	295.9	493.4	741.5	182.9	627.0	142

Panel B: Ratio of flow volatilities, grain/livestock/softs average

Period:	HF/CIT	C. hedger/CIT	Other/CIT	HF/C. hedger
September 15 2008 to June 1 2011	2.6	2.0	1.8	1.4
January 1 2006 to September 15 2008	3.5	2.6	2.4	1.5
January 1 2001 to January 1 2006	6.3	4.2	4.2	1.6

3.4 PRICE AND OTHER DATA

We define excess returns in a commodity as the returns to a position that is always invested in the currently indexed contract.[15] It accounts for a roll

[15] The currently indexed contract is often, but not necessarily, the front month contract. In particular, the index rolls out of the front month contract in the month before expiration, so that after the roll date in that month, the second month contract is typically held by the

return where the position in the currently indexed contract is liquidated and reinvested in the next indexed contract on a pre-specified schedule. We follow the S&P GSCI roll schedule to roll contracts on the fifth business day of each contract month.[16] Tracking the indexed contract ensures that our generic contract is always liquid.

Our baseline analysis controls for the one-week percentage change in the Baltic Dry Index (BDI), change in break-even inflation compensation (Gürkaynak, Sack, and Wright 2010), and change in the Baa credit spread. The BDI tracks worldwide international dry cargo shipping rates and is a measure of global demand for commodities (Kilian, 2009); higher values represent higher shipping rates and greater expected demand. Higher Baa credit spreads indicate worsening credit conditions in the economy, and higher inflation compensation generally indicates higher inflation expectations. We also include the 12-month percentage change in expected world demand, US production, and US stocks for the harvest year for wheat, corn, soybeans, soybean oil, and cotton, hand-collected from the monthly US Department of Agriculture (USDA) "World Agricultural Supply and Demand Estimates".

4. Empirical Results

4.1 COMMODITY RETURNS AND THE VIX

Table III reports the estimated $\tilde{b}_1$ coefficients from Equation (4), a linear regression where the left-hand side variable is the weekly commodity futures

index. Additionally, the index may choose to skip certain contract months due to liquidity reasons. For example, in some commodities, the CME introduces contracts for certain expiration months after contracts for other expiration months. An example is October gold, which is introduced 24 months before expiration, whereas December gold is introduced 72 months before expiration. This results in certain front-month contracts having lower liquidity than others.

[16] The S&P GSCI rolls smoothly over the fifth through ninth business days; for simplicity we switch contracts on the fifth day. The monthly roll schedule for the GSCI is provided in the Supplementary Material. We define the fifth business day as the fifth trading day of the month, where a trading day is a day in which all nineteen commodities have positions. We use the S&P GSCI schedule for most commodities, except for soybean oil and copper we use the DJ-UBSCI roll schedule. This is because, S&P GSCI does not include soybean oil and tracks copper contracts traded in London (for which we have no data) rather than the CME. Mou (2011) finds price pressure associated with CITs rolling during the GSCI roll period. Our results are similar under alternative rolling schedules, such as one which rolls later during the month closer to when contracts expire. Singleton (2013) finds that rolling according to later schedules increases noise significantly due to the lower liquidity of those contracts.

Table III. Commodity returns and the VIX

We report coefficients from a weekly regression of commodity returns as the left-hand side variable on contemporaneous and one lag of changes in the VIX as right-hand side variables, controlling for lagged commodity returns, percentage changes in the BDI index, changes in the Baa credit spread, and changes in inflation compensation. For wheat, corn, soybeans, soybean oil, and cotton, we also include the 12-month percentage change in projected world demand, US stocks, and US production. Each row reports coefficients for a different commodity and each set of columns reports coefficients for different sample periods. For brevity, only the coefficient on the contemporaneous change in VIX is reported. Coefficients are reported where returns are in percentage points and the change in VIX is standardized to one standard deviation. We use the Newey and West (1987) construction for standard errors with four lags.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Chi W, Chicago wheat; KC W, Kansas City wheat; Soyb oil, soybean oil; F cattle, feeder cattle; L hogs, lean hogs; L cattle, live cattle.

		Coefficient on contemporaneous ΔVIX (1 σ)							
		Post-crisis				Pre-crisis			
		September 15 2008 to June 1 2011		January 1 2010 to June 1 2011		January 1 2006 to September 15 2008		January 1 2001 to January 1 2006	
		$T=142$ Weeks		$T=74$ Weeks		$T=141$ Weeks		$T=262$ Weeks	
Returns (%)		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
Grains	Chi W	−2.700	[−7.37]***	−2.416	[−3.70]***	−0.105	[−0.20]	0.190	[0.83]
	Corn	−1.991	[−3.83]***	−1.968	[−4.71]***	−0.298	[−0.71]	−0.042	[−0.19]
	KC W	−2.457	[−6.94]***	−2.395	[−3.96]***	−0.086	[−0.15]	0.287	[1.24]
	Soybeans	−1.569	[−4.26]***	−1.350	[−3.35]***	−0.050	[−0.14]	0.052	[0.23]
	Soyb oil	−1.792	[−4.99]***	−1.341	[−3.97]***	−0.082	[−0.24]	−0.149	[−0.66]
Livestock	F cattle	−0.973	[−3.91]***	0.018	[0.11]	0.128	[0.52]	0.121	[0.93]
	L hogs	−0.397	[−1.17]	−0.997	[−2.39]**	0.035	[0.12]	−0.340	[−1.33]

(continued)

Table III. (Continued)

Returns (%)		Coefficient on contemporaneous ΔVIX (1 σ)							
		Post-crisis				Pre-crisis			
		September 15 2008 to June 1 2011		January 1 2010 to June 1 2011		January 1 2006 to September 15 2008		January 1 2001 to January 1 2006	
		$T = 142$ Weeks		$T = 74$ Weeks		$T = 141$ Weeks		$T = 262$ Weeks	
		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
	L cattle	−0.848	[−4.94]***	−0.214	[−1.14]	−0.103	[−0.40]	0.169	[1.30]
Softs	Cocoa	−0.922	[−2.35]**	−0.339	[−0.77]	−0.847	[−1.71]*	−0.176	[−0.50]
	Coffee	−1.259	[−4.07]***	−1.177	[−2.27]**	−0.574	[−1.76]*	0.085	[0.26]
	Cotton	−1.596	[−5.98]***	−1.112	[−1.85]*	−0.219	[−0.62]	−0.262	[−0.89]
	Sugar	−1.167	[−2.10]**	−1.652	[−2.19]**	−0.141	[−0.34]	0.583	[1.80]*
Energy	Oil	−2.020	[−3.77]***	−1.364	[−2.65]***	0.050	[0.14]	−0.193	[−0.61]
	Heat oil	−1.786	[−3.78]***	−1.004	[−2.58]***	0.176	[0.46]	−0.385	[−1.13]
	Natural gas	−1.554	[−2.53]**	−0.891	[−1.16]	−0.140	[−0.25]	−0.678	[−1.59]
	Gas	−1.526	[−2.49]**	−1.225	[−2.92]***	0.244	[0.58]		
Metals	Copper	−1.576	[−3.95]***	−1.763	[−5.11]***	−1.060	[−1.83]*	−0.493	[−2.82]***
	Gold	−0.518	[−1.17]	−0.253	[−0.79]	−0.294	[−0.63]	−0.045	[−0.30]
	Silver	−1.434	[−2.39]**	−1.190	[−1.52]	−1.025	[−1.51]	−0.217	[−0.98]
Average R^2		22.67%		25.41%		10.22%		3.99%	

return and the right-hand side variables are weekly VIX changes (contemporaneous and lagged), the lagged futures return, plus our baseline control variables. Unless otherwise noted, we use the Newey and West (1987) construction for the covariance matrix with four lags throughout.

The results indicate a strong correlation of VIX changes with commodity futures returns in the 142 weeks of what we define as the post-crisis period (September 15 2008 to June 1 2011). The first column reports the coefficient of a 1-SD contemporaneous change in the VIX during this period. With the exception of lean hogs and gold, all commodities display a negative price relationship with the VIX, with almost all coefficients statistically significant at the 5% level. On average, a 1-SD change in the VIX during this period (432 basis points) was associated with a 1.5% drop in commodity prices. The second column shows that this negative correlation persisted over the period January 1 2010 to June 1 2011, more than a year after the collapse of Lehman Brothers, although the magnitudes are smaller.

This relationship does not hold during the pre-crisis period. The third column of Table III reports the estimated $\tilde{b}_1$ for the period January 1 2006 to September 15 2008, a pre-crisis period of nearly equal length with our post-crisis period. The coefficients during this period are mostly insignificant with the exception of cocoa, coffee, and copper having negative coefficients statistically significant at the 10% level. The fourth column goes back even further and analyzes the period January 1 2001 to January 1 2006 and similarly finds little systematic relationship between VIX changes and commodity returns.[17]

4.2 TRADER POSITIONS AND THE VIX

We estimate the effect of changes in the VIX on the changes of aggregate positions of different groups of traders in Equation (5). We focus on the aggregate positions of different trader groups as we are interested in identifying which groups have been driving the price, and do not want small

[17] For brevity, we report coefficients for our control variables in the Supplementary Material. The contemporaneous percent-change in the BDI index generally shows a positive relationship to commodity returns, with statistical significance in five commodities. Contemporaneous increases in breakeven inflation are generally positively related to commodity returns, with statistical significance in four commodities. The change in the Baa spread is negatively related to futures price change in most commodities (statistically significant in three commodities). For wheat, corn, soybeans, soybean oil, and cotton, we also include the 12-month percentage change in expected world demand, US production, and US stocks, which do not show consistent patterns with price changes, likely due to these variables being equilibrium quantities that are correlated.

individual traders who may behave in a nonsystematic way to change our analysis.

As discussed above, the netting problem in the LTRS position data is particularly severe for commodities in energy and metals. Below, we focus on the twelve agricultural commodities (grains, livestock, and softs) when discussing the behavior of CITs and hedge funds. For commercial hedgers and other traders, we report results for all nineteen commodities including energy and metals, on the notion that the netting problem is less severe for these traders.

Table IV reports the estimated b_1 coefficients from Equation (5). Panel A reports the estimated b_1 coefficients during the post-crisis September 15 2008 to June 1 2011 period, whereas Panel B reports the estimated b_1 coefficients during the period immediately before the crisis, January 1 2006 to September 15 2008. The results in Panel A strongly indicate asymmetric responses of market participants to VIX changes in the post-crisis period. When the VIX increases, both CITs and hedge funds tend to reduce their net long exposures, while hedgers and other unclassified traders tend to buy, in virtually all commodities. For CITs, the association between position changes and contemporaneous VIX changes is negative and statistically significant at the 10% level or better in eight of the twelve agricultural commodities, with an average economic significance of −0.20-SD. Hedge funds display a negative and statistically significant relationship (at the 10% level or better) between position changes and contemporaneous VIX changes in seven of the twelve commodities, with an average economic significance of −0.12-SD; only one commodity has a positive point estimate.

In contrast, hedgers tend to display a positive relationship between VIX changes and position changes. The relationship is positive and statistically significant for thirteen of the nineteen broader commodities, with only one negative point estimate. The average economic significance among all nineteen commodities is +0.15-SD. The other unclassified traders are similar to hedgers: the relationship is negative and statistically significant for eleven of the nineteen commodities, with an average economic significance of +0.14-SD.[18]

Panel B of Table IV shows little evidence of traders' positions correlating with the VIX during the pre-crisis period from January 1 2006 to September 15 2008, a period nearly equal in length to our post-crisis period, consistent

[18] Our baseline control variables show mixed relationships with changes in positions for the various trader groups. For example, the percentage change in the BDI exhibits only weak statistical correlation with the position changes of each group, as does the change in break-even inflation and Baa credit spread.

Table IV. Positions changes and the VIX

We report coefficients from a weekly regression of position changes as the left-hand side variable on contemporaneous and one lag of changes in the VIX as right hand side variables, controlling for lagged commodity returns, percentage changes in the BDI index, changes in the Baa credit spread, and changes in inflation compensation. For wheat, corn, soybeans, soybean oil, and cotton, we also include the 12-month percentage change in projected world demand, US stocks, and US production. Each row reports coefficients for a different commodity, and each column reports coefficients for different trader groups. The sample period in Panel A is September 15 2008 through June 1 2011. Panel B reports results for January 1 2006 through September 15 2008, whereas Panel C reports results for January 1 2001 through January 1 2006. Coefficients are standardized to standard deviations in flows per one standard deviation of VIX changes. For brevity, only the term on the contemporaneous change in VIX is reported. We use the Newey and West (1987) construction for standard errors with four lags.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		CITs		Hedge funds		C. Hedgers		Other unclassified	
Flows (σ)		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
Panel A: Post-crisis, September 15 2008 to June 1 2011 ($T=142$ weeks) Coefficient on contemporaneous ΔVIX (1 σ)									
Grains	Chi W	−0.177	[−2.50]**	−0.219	[−2.73]***	0.295	[3.92]***	0.183	[1.64]
	Corn	−0.161	[−1.82]*	−0.166	[−1.78]*	0.134	[1.61]	0.190	[2.65]***
	KC W	−0.191	[−2.34]**	−0.133	[−1.67]*	0.222	[2.70]***	0.004	[0.06]
	Soybeans	−0.206	[−2.12]**	−0.169	[−1.82]*	0.176	[2.24]**	0.211	[2.54]**
	Soyb oil	−0.093	[−0.96]	−0.145	[−1.70]*	0.179	[1.81]*	0.151	[2.19]**
Livestock	F cattle	−0.087	[−1.39]	−0.069	[−0.84]	0.181	[2.31]**	−0.037	[−0.55]
	L hogs	−0.179	[−1.08]	−0.059	[−1.02]	−0.003	[−0.04]	0.208	[2.30]**
	L cattle	−0.372	[−2.71]***	−0.058	[−0.67]	0.175	[2.41]**	0.158	[2.36]**
Softs	Cocoa	−0.112	[−1.08]	0.003	[0.04]	0.040	[0.75]	0.063	[0.55]
	Coffee	−0.383	[−3.69]***	−0.137	[−1.63]	0.210	[2.73]***	0.202	[2.46]**
	Cotton	−0.203	[−2.07]**	−0.192	[−2.39]**	0.222	[2.69]***	0.250	[2.64]***
	Sugar	−0.284	[−2.35]**	−0.151	[−1.77]*	0.144	[2.28]**	0.243	[2.75]***
Energy	Oil					0.200	[1.94]*	0.041	[0.43]
	Heat oil					0.018	[0.29]	0.251	[3.81]***
	Nat gas					0.151	[2.04]**	0.057	[0.92]
	Gas					0.100	[1.16]	0.196	[2.65]***
Metals	Copper					0.248	[2.22]**	0.188	[2.26]**
	Gold					0.127	[1.16]	0.051	[0.57]
	Silver					0.076	[0.88]	0.097	[1.13]
Average R^2		12.68%		15.75%		12.75%		9.55%	

(*continued*)

Table IV. (Continued)

Flows (σ)		CITs Coef.	CITs *t*-statistic	Hedge funds Coef.	Hedge funds *t*-statistic	C. Hedgers Coef.	C. Hedgers *t*-statistic	Other unclassified Coef.	Other unclassified *t*-statistic
Panel B: Pre-crisis, January 1 2006 to September 15 2008 (T = 141 weeks) Coefficient on contemporaneous ΔVIX (1 σ)									
Grains	Chi W	0.133	[1.25]	0.215	[2.17]**	−0.161	[−1.34]	−0.246	[−2.49]**
	Corn	0.024	[0.22]	−0.038	[−0.41]	0.086	[1.05]	−0.087	[−0.89]
	KC W	0.117	[1.62]	0.086	[0.65]	−0.126	[−0.86]	0.007	[0.06]
	Soybeans	0.116	[1.02]	0.026	[0.26]	−0.038	[−0.39]	−0.160	[−1.41]
	Soyb oil	0.102	[1.11]	−0.048	[−0.50]	0.061	[0.80]	−0.044	[−0.36]
Livestock	F cattle	0.171	[1.12]	−0.118	[−1.69]*	0.010	[0.13]	0.077	[0.74]
	L hogs	−0.195	[−1.71]*	−0.116	[−1.48]	−0.115	[−1.01]	0.269	[2.30]**
	L cattle	−0.014	[−0.16]	−0.007	[−0.06]	0.111	[1.23]	−0.052	[−0.40]
Softs	Cocoa	0.078	[0.70]	−0.181	[−2.07]**	0.163	[1.33]	0.108	[1.31]
	Coffee	−0.062	[−0.64]	0.001	[0.01]	0.032	[0.35]	0.012	[0.11]
	Cotton	−0.007	[−0.05]	0.018	[0.20]	−0.058	[−0.68]	0.041	[0.35]
	Sugar	−0.209	[−1.78]*	−0.069	[−0.63]	0.071	[0.53]	0.096	[0.77]
Energy	Oil					0.092	[0.77]	0.026	[0.28]
	Heat oil					0.042	[0.47]	−0.059	[−0.64]
	Natural gas					−0.020	[−0.21]	0.136	[1.27]
	Gas					0.006	[0.05]	0.032	[0.36]
Metals	Copper					0.032	[0.25]	0.354	[3.08]***
	Gold					−0.169	[−1.17]	0.033	[0.27]
	Silver					−0.125	[−0.95]	0.025	[0.31]
Average R^2		9.02%		16.77%		12.41%		9.92%	

(continued)

Table IV. (Continued)

Flows (σ)		CITs		Hedge funds		C. Hedgers		Other unclassified	
		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
Panel C: January 1 2001 to January 1 2006 ($T=262$ weeks) Coefficient on contemporaneous ΔVIX (1 σ)									
Grains	Chi W	0.001	[0.02]	−0.001	[−0.02]	−0.028	[−0.46]	0.039	[0.78]
	Corn	0.096	[1.71]*	−0.013	[−0.22]	0.001	[0.02]	0.005	[0.09]
	KC W	−0.099	[−1.54]	0.111	[1.77]*	−0.103	[−1.80]*	−0.023	[−0.31]
	Soybeans	0.152	[2.80]***	−0.011	[−0.21]	−0.017	[−0.25]	−0.004	[−0.06]
	Soyb oil	0.017	[0.39]	−0.028	[−0.50]	0.035	[0.57]	0.044	[0.74]
Livestock	F cattle	0.028	[0.75]	0.085	[1.11]	−0.018	[−0.27]	−0.069	[−0.99]
	L hogs	0.027	[0.55]	−0.010	[−0.17]	−0.043	[−0.84]	0.031	[0.47]
	L cattle	−0.029	[−0.61]	0.067	[1.13]	−0.126	[−2.43]**	0.082	[1.36]
Softs	Cocoa	0.023	[0.69]	−0.113	[−1.87]*	0.070	[1.04]	0.108	[1.57]
	Coffee	−0.014	[−0.26]	0.002	[0.04]	−0.023	[−0.42]	0.022	[0.37]
	Cotton	0.057	[1.32]	0.048	[0.83]	−0.022	[−0.33]	−0.052	[−0.98]
	Sugar	−0.033	[−0.65]	0.145	[1.87]*	−0.160	[−2.17]**	−0.081	[−1.26]
Energy	Oil					0.005	[0.09]	0.064	[0.71]
	Heat oil					0.068	[0.81]	0.081	[1.19]
	Natural gas					−0.098	[−1.28]	0.205	[2.94]***
	Gas								
Metals	Copper					0.081	[0.77]	0.162	[2.44]**
	Gold					−0.052	[−0.68]	0.035	[0.58]
	Silver					0.054	[0.78]	−0.006	[−0.10]
Average R^2		2.52%		12.84%		7.43%		7.77%	

with the lack of price correlation before the crisis. In sharp contrast to the post-crisis period, across all of the trader groups and all commodities, the coefficients of the contemporaneous VIX changes in the pre-crisis period are virtually insignificant with the exception of one or two commodities for each group. R^2 values during this period are relatively low for the CIT group during this pre-crisis period relative to other groups, both because funding constraints had yet to tightly bind and because of their general passiveness in trading before the crisis. Panel C of Table IV reports results for January 1 2001 through January 1 2006 and similarly finds little relationship.

4.3 CROSS-SECTIONAL EVIDENCE

In this subsection, we exploit individual traders within each group to provide additional evidence supporting the presence of convective risk flows during the crisis.

4.3.a *Evidence on distressed financials*

We test whether distressed financials are driving the negative sensitivity of CIT positions to the VIX by identifying CIT traders with high CDS spreads and examining whether they are more negatively sensitive to the VIX than CIT traders with lower CDS spreads. The theory implies that CIT traders with high CDS spreads should have a higher position change-sensitivity to the VIX changes through two possible channels. First, the CITs (large financial institutions) may need to sell their own proprietary positions when volatility rises in order to control risk exposures. Second, investors who entered into swap contracts with a CIT may potentially withdraw their investment when the institution is distressed.

We manually match large traders identified as CITs to the names of their respective firms and collected their CDS spreads from Bloomberg. For each week, we split the group of CIT accounts into accounts with high CDS spreads (above the median) and low CDS spreads (below the median). We regress the account-level position change as the left-hand side variable on the change in the VIX, an indicator for whether the trader has a high CDS spread, and the interaction of these two terms, including our baseline controls and the lagged logarithm of absolute notional position size in the commodity. This regression exploits the relative ranking of firms with high and low CDS spreads.

Table V reports the results from this regression. The point estimates for the base effect of CDS spreads on position changes are negative for almost all commodities, with four statistically significant at the 5% level.

Table V. Financial distress and CIT position changes

We report coefficients from a weekly account-level panel regression of CIT position changes as the left-hand side variable on changes in the VIX, an indicator for whether the trader has a CDS spread above the median for the week, and an interaction between the two, controlling for the lagged log of absolute notional position size in the commodity, lagged commodity returns, percentage changes in the BDI index, changes in the Baa credit spread, and changes in inflation compensation. For wheat, corn, soybeans, soybean oil, and cotton, we also include the 12-month percentage change in projected world demand, US stocks, and US production. Each row reports coefficients for a different commodity. The sample period is September 15 2008 through June 1 2011. Coefficients are standardized to standard deviations in flows per one standard deviation of VIX changes. Standard are clustered at the week level ($T = 142$).

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		CDS Hi/Lo		Change in VIX (1 σ)		Interaction		
Flows (σ)		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	R^2
Grains	Chi W	−0.116	[−2.52]**	−0.006	[−0.31]	−0.085	[−2.19]**	0.020
	Corn	−0.001	[−0.01]	0.005	[0.21]	−0.110	[−2.35]**	0.025
	KC W	0.083	[1.44]	−0.040	[−0.94]	−0.060	[−1.34]	0.012
	Soybeans	−0.037	[−0.66]	−0.055	[−1.62]	0.017	[0.28]	0.017
	Soyb oil	−0.053	[−0.88]	−0.026	[−1.02]	0.015	[0.27]	0.008
Livestock	F cattle	−0.041	[−0.65]	0.007	[0.1]	−0.051	[−0.83]	0.006
	L hogs	−0.118	[−2.23]**	−0.033	[−1.2]	−0.018	[−0.3]	0.019
	L cattle	−0.096	[−2.02]**	−0.091	[−2.50]**	−0.029	[−0.42]	0.020
Softs	Cocoa	−0.050	[−0.81]	0.006	[0.09]	−0.050	[−0.46]	0.003
	Coffee	−0.116	[−2.37]**	−0.028	[−0.75]	−0.159	[−2.98]***	0.037
	Cotton	−0.068	[−1.38]	0.019	[0.59]	−0.120	[−1.87]*	0.026
	Sugar	−0.080	[−1.53]	0.000	[0.02]	−0.124	[−1.99]**	0.018

Furthermore, high CDS spread traders are more sensitive to changes in the VIX in five of the twelve commodities.[19] These results are consistent with CIT traders reducing their positions and becoming more sensitive to fluctuations in risk when their risk appetite is low or when they are in distress.

4.3.b *Evidence on long vs short hedgers*

To further isolate the intermediary pricing channel, we address the possibility that observed reactions of traders to the VIX is driven by hedgers'

[19] We cluster standard errors at the weekly level because position changes across traders may be correlated within a week given aggregate shocks. Clustering standard errors at the account-level generates nearly identical results, which are available from the authors. Including our extended set of controls also yields nearly identical results.

hedging demand by exploiting the fact that some hedgers are long and some hedgers are short. While hedgers' positions are typically net short, there is a subset of hedgers taking net long positions. These net long hedgers are clustered in the lower right corner of each plot. If the position responses to the VIX observed during the crisis were driven by increased hedging demand, we should expect long hedgers to increase their long positions and short hedgers to increase their short positions during this period.

To explore this consideration, we classify a hedger as a "long hedger" in a commodity if the hedger maintained an average net long position in the previous calendar year. Specifically, for each day, we compute the fraction of long contracts in which a hedger is invested (first within commodities, and then as an equal-weight average over commodities in which there is a position), and compute the time average over the year. If the average fraction is $>50\%$, we classify the hedger as long, whereas a fraction $<50\%$ corresponds to short. We then separately regress the aggregate position change of long hedgers on changes in the VIX, including both contemporaneous and lagged changes, together with our baseline controls.

Table VI reports the results and shows that, consistent with Table IV, short hedgers drive the positive relationship between hedgers' position changes and changes in the VIX. However, there is no clear pattern of long hedgers reducing positions. For example, it appears that although long hedgers were selling in cotton, sugar, and heating oil, they were buying in Chicago wheat, coffee, and copper. These long hedgers in Chicago wheat, coffee, and copper were trading in the same direction as short hedgers, which is inconsistent with the hypothesis that traders' reactions to the VIX during the crisis were driven by changes in hedging demand.

4.4 ROBUSTNESS

In this subsection, we conduct a series of tests to ensure the robustness of our main result.

4.4.a *Public Commitment of Traders report*

We first check whether our results can be replicated using the public Commitment of Traders reports. Table VII reports estimated b_1 coefficients for Equation (5) with position changes calculated for the trader groups from the public Disaggregated Commitment of Traders (DCOT) reports, as well as the Supplemental CIT report. The results from the DCOT classification are consistent with those in Table IV, and show that producers' positions react positively to the VIX and that managed money traders react negatively

Table VI. Commercial hedger sub-groups

We report coefficients from a weekly regression of position changes as the left-hand side variable on contemporaneous and one lag of changes in the VIX as right-hand side variables, controlling for lagged commodity returns, percentage changes in the BDI index, changes in the Baa credit spread, and changes in inflation compensation, for trader sub-groups. For wheat, corn, soybeans, soybean oil, and cotton, we also include the 12-month percentage change in projected world demand, US stocks, and US production. Each row reports coefficients for a different commodity, and each column reports coefficients for different trader groups. The sample period is September 15 2008 through June 1 2011 (T = 142 weeks). Coefficients are standardized to standard deviations in flows per one standard deviation of VIX changes. For brevity, only the term on the contemporaneous change in VIX is reported. We use the Newey and West (1987) construction for standard errors with four lags.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Coefficient on ΔVIX (1 σ)					
		C. hedgers, long		C. hedgers, short	
Flows (σ)		Coef.	*t*-statistic	Coef.	*t*-statistic
Grains	Chi W	0.150	[1.96]**	0.285	[3.87]***
	Corn	0.000	[0.00]	0.141	[1.71]*
	KC W	0.008	[0.11]	0.280	[3.21]***
	Soybeans	0.003	[0.04]	0.177	[2.07]**
	Soyb oil	0.138	[1.58]	0.148	[1.62]
Livestock	F cattle	0.060	[1.04]	0.159	[2.04]**
	L hogs	0.124	[1.37]	0.011	[0.17]
	L cattle	−0.097	[−1.41]	0.230	[3.04]***
Softs	Cocoa	0.015	[0.24]	0.047	[0.70]
	Coffee	0.130	[1.71]*	0.246	[2.71]***
	Cotton	−0.125	[−1.75]*	0.237	[2.74]***
	Sugar	−0.153	[−2.25]**	0.164	[2.45]**
Energy	Oil	0.072	[0.79]	0.162	[1.33]
	Heat oil	−0.117	[−1.80]*	0.099	[1.36]
	Natural gas	0.122	[1.55]	0.110	[1.45]
	Gas	−0.101	[−0.77]	0.229	[2.74]***
Metals	Copper	0.220	[1.96]*	0.185	[1.80]*
	Gold	−0.082	[−0.68]	0.151	[1.55]
	Silver	0.155	[1.58]	0.069	[0.90]
Average R^2		7.30%		11.94%	

to the VIX. Although CITs are not separately classified within the DCOT reports, much of the CIT business is conducted through swaps. Consistent with this, swap dealers in the DCOT reports react qualitatively negatively to the VIX. However, the statistical significance is limited. This suggests that

Table VII. Analysis of commitment of traders data

We report coefficients from a weekly regression of position changes as the left-hand side variable on contemporaneous and one lag of changes in the VIX as right-hand side variables, controlling for lagged commodity returns, percentage changes in the BDI index, changes in the Baa credit spread, and changes in inflation compensation. For wheat, corn, soybeans, soybean oil, and cotton, we also include the 12-month percentage change in projected world demand, US stocks, and US production. Each row reports coefficients for a different commodity, and each column reports coefficients for different trader groups from the Commitment of Traders reports. The sample period is September 15 2008 through June 1 2011 ($T = 142$ weeks). Coefficients are standardized to standard deviations in flows per one standard deviation of VIX changes. For brevity, only the term on the contemporaneous change in VIX is reported. We use the Newey and West (1987) construction for standard errors with four lags.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		Coefficient on contemporaneous ΔVIX (1 σ)									
		Disaggregated COT report								CIT supplemental	
		Producers		Swap dealers		Managed money		Other non-comm.		CITs	
Flows (σ)		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
Grains	Chi W	0.270	[3.41]***	−0.078	[−1.20]	−0.176	[−2.10]**	−0.115	[−1.89]*	−0.106	[−1.79]*
	Corn	0.179	[2.18]**	−0.075	[−1.13]	−0.166	[−1.83]*	−0.088	[−1.07]	−0.233	[−3.55]***
	KC W	0.221	[3.04]***	−0.111	[−1.44]	−0.119	[−1.44]	−0.142	[−1.95]*	−0.197	[−2.49]**
	Soybeans	0.216	[2.55]**	−0.117	[−1.33]	−0.178	[−2.07]**	0.025	[0.33]	−0.236	[−2.70]***
	Soyb oil	0.168	[2.09]**	−0.058	[−0.89]	−0.156	[−1.80]*	0.123	[1.40]	−0.134	[−1.69]*
Livestock	F cattle	0.167	[2.35]**	−0.066	[−1.00]	−0.089	[−1.20]	−0.083	[−1.38]	−0.055	[−0.75]
	L hogs	0.063	[0.88]	−0.063	[−0.47]	−0.087	[−1.50]	0.167	[1.86]*	−0.073	[−0.56]
	L cattle	0.177	[2.42]**	−0.216	[−2.47]**	−0.093	[−1.15]	−0.014	[−0.19]	−0.296	[−3.03]***

(continued)

Table VII. (Continued)

		Coefficient on contemporaneous ΔVIX (1 σ)									
		Disaggregated COT report								CIT supplemental	
		Producers		Swap dealers		Managed money		Other non-comm.		CITs	
Flows (σ)		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
Softs	Cocoa	0.066	[0.90]	−0.045	[−0.51]	0.041	[0.49]	−0.166	[−3.42]***	−0.007	[-0.07]
	Coffee	0.209	[2.60]***	−0.235	[−2.53]**	−0.151	[−1.81]*	−0.008	[−0.11]	−0.266	[−2.85]***
	Cotton	0.257	[3.28]***	−0.140	[−1.39]	−0.158	[−1.88]*	−0.064	[−0.88]	−0.067	[−0.73]
	Sugar	0.222	[3.31]***	−0.153	[−1.75]*	−0.140	[−1.69]*	0.140	[2.00]**	−0.211	[−1.91]*
Energy	Oil	0.211	[2.62]***	0.122	[1.27]	−0.213	[−1.90]*	0.020	[0.18]		
	Heat oil	0.163	[2.97]***	0.283	[3.85]***	−0.207	[−3.34]***	0.044	[0.57]		
	Natural gas	0.032	[0.42]	0.059	[0.85]	−0.041	[−0.66]	0.049	[0.88]		
	Gas	0.170	[2.55]**	−0.013	[−0.15]	−0.151	[−2.25]**	0.057	[0.59]		
Metals	Copper	0.117	[1.29]	0.107	[1.59]	−0.124	[−1.83]*	−0.017	[−0.29]		
	Gold	0.040	[0.36]	0.154	[2.19]**	−0.080	[−0.82]	−0.017	[−0.23]		
	Silver	0.048	[0.86]	0.080	[0.94]	−0.074	[−0.95]	0.059	[0.65]		
Average R^2		14.32%		8.59%		13.21%		7.08%		13.86%	

swap dealer positions in the DCOT are a noisy signal of CIT positions, because although many CITs are swap dealers, many swap dealers such as physical swap dealers are not CITs.

Table VII also examines how position changes of CITs from the Supplemental CIT report respond to changes in the VIX, and confirm our earlier result that CITs react negatively. Overall, the analysis of the public data echoes the results from our proprietary LTRS data. However, the nature of the aggregation implies that our groups are not jointly represented in any single public report.

4.4.b *Alternative measures of risk appetite*

Next, we estimate Equation (5) using several alternative proxies for the risk appetite of financial traders other than the VIX. The first alternative measure is the implied volatility of at-the-money options on the Financial Select Sector SPDR exchange-traded fund (ETF). This ETF (ticker: XLF) tracks the S&P Financial Select Sector Index, which itself tracks S&P 500 finance stocks as defined using their GICS sector code. We obtain at-the-money-forward, constant 91-days-to-expiration implied volatilities from the volatility surface provided by OptionMetrics and average over puts and calls. The results, reported in Table VIII, Panel A, are largely consistent with results using the VIX, although the relationship with the ETF implied volatility is much stronger for CITs than hedge funds.[20]

Table VIII, Panel B uses the illiquidity measure developed by Hu, Pan, and Wang (2013), which captures the non-smoothness of the Treasury yield curve resulted from market illiquidity. The panel shows that CIT position changes load negatively on increases in the Treasury market illiquidity (statistically significant at the 10% level or better in five commodities), while hedge funds position changes are not sensitive to Treasury market illiquidity. This contrast highlights the role of CITs as multi-asset class investors whose demand may be affected by shocks outside the commodity sector.

Table VIII, Panel C uses the average CDS spread of primary dealers as our last alternative measure.[21] The panel shows that hedge fund positions

[20] One might argue that the difference between the XLF-implied volatility and the VIX might capture shocks specific to the financial sector. We have also tested our results using this variable, which yields consistent results, albeit somewhat weaker than those from only using the XLF-implied volatility or VIX. This is not surprising as the financial sector was the key driver of market-wide fluctuations in the post-crisis period.

[21] We average the CDS spreads collected from Bloomberg for all primary dealers, not just CITs, and account for the changing composition of the primary dealer group using the historical list of primary dealers available from the Federal Reserve Bank of New York website.

Table VIII. Positions changes and alternative measures

We report coefficients from a weekly regression of position changes as the left-hand side variable on contemporaneous and one lag of changes in: (1) the implied volatility of options on the Financial Select Sector XLF SPDR ETF (Panel A); (2) the Hu, Pan, and Wang (2013) measure of Treasury market illiquidity (Panel B); and (3) the average primary dealer CDS spread (Panel C), as right-hand side variables. We control for lagged commodity returns, percentage changes in the BDI index, changes in the Baa credit spread, and changes in inflation compensation. For wheat, corn, soybeans, soybean oil, and cotton, we also include the 12-month percentage change in projected world demand, US stocks, and US production. Each row reports coefficients for a different commodity, and each column reports coefficients for different trader groups. The sample period is September 15 2008 through June 1 2011. Coefficients are standardized to standard deviations in flows per one standard deviation of changes the right-hand side variable. For brevity, only the term on the contemporaneous change in the alternative measure is reported. We use the Newey and West (1987) construction for standard errors with four lags.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		CITs		Hedge funds		C. hedgers		Other unclassified	
Flows (σ)		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
Panel A: Coefficient on contemporaneous ΔXLF implied vol. (1 σ)									
Grains	Chi W	−0.150	[−1.89]*	−0.215	[−3.51]***	0.253	[4.11]***	0.237	[2.59]***
	Corn	−0.202	[−2.25]**	−0.038	[−0.43]	0.066	[0.92]	0.143	[1.86]*
	KC W	−0.139	[−1.56]	−0.100	[−1.58]	0.175	[2.32]**	−0.030	[−0.44]
	Soybeans	−0.278	[−4.11]***	−0.104	[−1.16]	0.134	[1.69]*	0.191	[2.46]**
	Soyb oil	−0.186	[−2.35]**	−0.141	[−1.36]	0.134	[1.15]	0.202	[3.26]***
Livestock	F cattle	−0.018	[−0.29]	−0.069	[−0.82]	0.132	[2.15]**	0.008	[0.15]
	L hogs	−0.207	[−1.11]	−0.081	[−1.25]	0.044	[0.64]	0.179	[2.28]**
	L cattle	−0.376	[−2.65]***	−0.030	[−0.30]	0.194	[2.91]***	0.121	[1.99]**
Softs	Cocoa	−0.218	[−1.66]*	0.024	[0.33]	0.036	[0.77]	0.070	[0.83]
	Coffee	−0.411	[−5.35]***	−0.070	[−0.86]	0.198	[1.91]*	0.101	[1.54]
	Cotton	−0.177	[−1.75]*	−0.216	[−2.24]**	0.109	[1.10]	0.256	[3.21]***
	Sugar	−0.300	[−2.55]**	−0.147	[−1.23]	0.135	[1.94]*	0.275	[2.69]***
Energy	Oil					0.041	[0.46]	−0.022	[−0.28]
	Heat oil					0.085	[1.36]	0.267	[4.32]***
	Natural gas					0.162	[2.52]**	0.115	[2.14]**
	Gas					0.081	[1.02]	0.213	[2.83]***
Metals	Copper					0.175	[1.99]**	0.208	[3.22]***
	Gold					0.140	[1.59]	0.013	[0.15]
	Silver					0.108	[1.40]	0.120	[1.54]
Average R^2		12.62%		15.24%		11.93%		9.67%	

(continued)

Table VIII. (Continued)

Flows (σ)		CITs		Hedge funds		C. hedgers		Other unclassified	
		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
Panel B: Coefficient on contemporaneous ΔIlliquidity measure (1 σ)									
Grains	Chi W	−0.101	[−1.07]	0.050	[0.60]	0.023	[0.34]	−0.027	[−0.27]
	Corn	−0.230	[−3.63]***	0.011	[0.17]	0.102	[1.54]	0.013	[0.15]
	KC W	−0.036	[−0.44]	0.054	[0.92]	−0.028	[−0.58]	0.031	[0.41]
	Soybeans	−0.094	[−1.09]	0.055	[0.68]	−0.021	[−0.27]	−0.012	[−0.19]
	Soyb oil	−0.217	[−3.09]***	0.053	[0.90]	−0.005	[−0.09]	0.037	[0.45]
Livestock	F cattle	0.077	[1.08]	0.001	[0.01]	0.023	[0.31]	0.118	[1.73]*
	L hogs	−0.121	[−0.84]	0.075	[1.55]	−0.048	[−0.66]	−0.013	[−0.16]
	L cattle	−0.239	[−2.28]**	0.021	[0.31]	0.015	[0.19]	0.148	[2.43]**
Softs	Cocoa	0.134	[0.96]	0.033	[0.45]	−0.103	[−1.53]	−0.008	[−0.10]
	Coffee	−0.215	[−1.95]*	−0.039	[−0.46]	0.072	[0.68]	0.100	[1.29]
	Cotton	−0.136	[−1.29]	−0.018	[−0.27]	0.018	[0.26]	0.090	[1.03]
	Sugar	−0.296	[−3.11]***	−0.066	[−0.72]	0.039	[0.57]	0.187	[1.60]
Energy	Oil					0.027	[0.33]	−0.002	[−0.03]
	Heat oil					0.002	[0.03]	0.016	[0.18]
	Natural gas					0.012	[0.22]	0.020	[0.28]
	Gas					−0.077	[−1.10]	0.098	[1.09]
Metals	Copper					−0.053	[−0.92]	0.026	[0.31]
	Gold					0.129	[1.77]*	0.012	[0.15]
	Silver					−0.026	[−0.35]	−0.076	[−0.99]
Average R^2		10.92%		13.92%		10.50%		7.74%	

(continued)

Table VIII. (Continued)

Flows (σ)		CITs		Hedge funds		C. hedgers		Other unclassified	
		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
Panel C: Coefficient on contemporaneous ΔCDS index (1 σ)									
Grains	Chi W	−0.022	[−0.28]	−0.170	[−2.74]***	0.214	[2.76]***	0.103	[1.42]
	Corn	−0.065	[−0.83]	−0.113	[−1.27]	0.143	[1.35]	0.041	[0.36]
	KC W	0.069	[0.68]	−0.171	[−2.16]**	0.198	[2.62]***	−0.044	[−0.71]
	Soybeans	−0.036	[−0.49]	−0.046	[−0.67]	0.091	[1.22]	0.028	[0.45]
	Soyb oil	0.079	[0.93]	−0.071	[−0.85]	0.053	[0.66]	0.035	[0.46]
Livestock	F cattle	0.162	[1.82]*	−0.101	[−1.97]**	0.054	[0.83]	0.087	[1.12]
	L hogs	−0.008	[−0.04]	0.002	[0.03]	0.038	[0.62]	−0.014	[−0.19]
	L cattle	−0.055	[−0.33]	−0.023	[−0.39]	0.061	[0.82]	0.028	[0.41]
Softs	Cocoa	−0.018	[−0.27]	0.032	[0.70]	0.017	[0.30]	0.017	[0.27]
	Coffee	−0.108	[−0.82]	−0.100	[−1.40]	0.151	[1.71]*	0.077	[0.77]
	Cotton	−0.009	[−0.06]	−0.163	[−2.16]**	0.155	[1.86]*	0.109	[1.06]
	Sugar	0.050	[0.37]	−0.121	[−1.19]	0.038	[0.36]	0.153	[1.89]*
Energy	Oil					0.006	[0.07]	−0.019	[−0.16]
	Heat oil					0.072	[1.09]	0.084	[0.84]
	Natural gas					0.119	[2.14]**	0.085	[1.40]
	Gas					−0.043	[−0.60]	0.176	[2.08]**
Metals	Copper					0.237	[2.56]**	0.119	[1.44]
	Gold					0.281	[3.44]***	0.028	[0.39]
	Silver					0.166	[1.59]	0.043	[0.54]
Average R^2		8.42%		14.65%		11.48%		7.69%	

load negatively on increases in average primary dealer CDS spread, which suggest that distressed dealers may lead hedge funds to reduce positions due to tighter funding constraints. CIT positions do not load significantly on this spread, partly because many primary dealers are not involved with commodity index trading.

Overall, these alternative measures yield consistent, although statistically weaker, results than the VIX.[22] Although each of these alternative measures picks up some aspects of the time-varying risk appetite of either CITs or hedge funds, none of them is perfect in capturing the overall variation of both CITs and hedge funds. Nevertheless, these results together confirm that time-varying risk appetite played a role during the post-crisis period in inducing financial traders to change their positions in commodity futures markets.

4.4.c *Alternative classification of traders*

We have also adopted an alternative classification scheme by using a cutoff of 80% and tweleve commodities in classifying CITs. Doing so reduces the number of CIT traders over our baseline sample by roughly 20%, and we obtain very similar results. To save space, we report the results from using this alternative classification, as well as the subsequent robustness checks, in our Supplementary Material.

4.4.d *Additional controls*

We now further examine whether our results are robust to alternative factors that may have been influencing commodity prices during the crisis period. We add an extended series of controls to Equations (4) and (5): the 1-week return to the Shanghai A-share stock index (to capture the effect of demand from China on commodity prices), the lagged commodity basis (to further capture any other time-varying risk premia, storage costs, and convenience yields), a set of month dummies (to control for seasonality), the change in the 1-year minus 3-month term spread, the change in the 3-month interest rate (to capture other information about changes in the macroeconomy), as well as 3- and 6-month futures return to further control for changes in investment opportunities. We obtain these data from Bloomberg and the Federal Reserve Board website.

[22] We also considered the LIBOR-OIS and TED spreads as measures of financial sector distress. These measures show considerable variation at the peak of the crisis but very little afterwards. For this reason, they are less suitable for our analysis because our results capture not only the sharp spike in the distress of the financial sector at the peak of the crisis but also the continuing fluctuations in risk appetite during the post-crisis period.

In estimating Equation (4), the return to the Shanghai A-share stock index is positively related to futures price changes for many commodities across all sectors. The lagged basis, changes in interest rates and term spread, as well as monthly dummies add some explanatory power for futures price changes, but the signs are different across commodities. Overall, adding these controls increases the average R^2 from 22.7% to 35.4%, yet does not change our conclusion that $\tilde{b}_1 < 0$ across many commodities in the post-crisis period.

In estimating Equation (5), the 1-week lagged basis tends to be positively associated with changes in CIT positions. Hedge fund position changes load positively on returns to the Shanghai A-share stock index, while hedger position changes load negatively. Overall, including our extended controls raises the average R^2 for CITs, hedge funds, hedgers, and unclassified traders from 12.7% (averaged across commodities and groups) to 27.2% but does not change our overall results.

4.4.e *Alternative time periods*

We also show that our results are not dependent on a specific time window for the financial crisis. In the above analysis, we take the collapse of Lehman Brothers as a convenient starting point, but our results are very similar if we take either the starting point as mid-March 2008, immediately prior to the collapse of Bear Stearns, or August 2007, the period in which serious signs of strain began showing in the broader financial sector with significant increases in the rates of asset-backed commercial paper, or even June 2007. We also show that our results are driven more by the immediate post-crisis period of September 15 2008 through January 1 2010, rather than the 2010 period onward, although the sample size is significantly smaller.

4.4.f *Persistence of position changes*

We further test whether changes in risk allocation were persistent or transitory. This relates to an alternative hypothesis that financial traders were exploiting an informational advantage over hedgers by reacting more quickly to information about deteriorating fundamentals contained in a rising VIX during the crisis. We compute impulse response functions from a vector auto-regression of positions on lagged position changes and changes in the VIX, and we find that position changes of CITs in response to the VIX are largely persistent over a 13-week horizon. We also examine the trading patterns of sophisticated hedgers who trade actively and find that if anything they were reducing short positions in response to VIX changes, inconsistent with the informational advantage hypothesis.

4.4.g *Hedgers as middlemen*

Finally, we address a concern that the long hedgers examined in Section 4.3.b may not be sensitive to the VIX because of a potential mis-classification. One possibility is that these traders are middlemen, whose demand curves are insensitive to price and outside shocks ($\beta_h = \gamma_h = 0$ in the framework of Section 3). For four of the agricultural commodities, we have access through the CFTC to data on both futures positions and cash positions of so-called bona fide hedgers, who are often middlemen. By jointly analyzing their cash and futures positions, we find that these hedgers do reduce their net short positions in commodity futures in response to changes in the VIX as well as their long positions in cash commodities. This finding further suggests that changes in the risk appetite of financial traders led the ultimate producers of these commodities to hold more risk than otherwise.

4.5 CONDITIONING ON THE VIX TO INFER PRICE AND POSITION CORRELATIONS

As noted in Section 1, the ongoing debate on the effects of CITs on commodity markets is concerned by the lack of a contemporaneous relationship between commodity futures returns and CIT position changes (Stoll and Whaley, 2010). This finding is often used as evidence against any effect of CITs on commodity markets. In this subsection, we re-examine this relationship by conditioning on the VIX during the crisis period.

Table IX reproduces contemporaneous correlations between commodity futures returns and position changes of different trader groups. We estimate the following equation using OLS:

$$dF_t = \overline{a} + \overline{b}\, Flows_t + \overline{c}\, dF_{t-1} + \overline{d}\, Controls_t + e_t, \qquad (6)$$

where $Flows_t$ is the position change of a given trader group for that commodity, and the controls are the same as in Tables III and IV. We report the estimated $\overline{b}$ coefficients for various trader groups. Consistent with Stoll and Whaley (2010), there are only weak correlations between CIT position changes and contemporaneous commodity futures returns. Hedge funds display a strong positive correlation, whereas commercial hedgers display a negative correlation, which is consistent with the finding of Buyuksahin and Robe (2014) linking hedge fund trading to commodity futures returns.

For commodities in energy and metals, CIT position changes are even negatively correlated with returns. As we discussed before, this might be due to the netting problem in the measurement of CIT positions. Singleton (2013) and Hamilton and Wu (2013) use CIT positions in

Table IX. Returns and position changes

We report coefficients from a weekly regression of returns as the left-hand side variable on contemporaneous position changes as the right-hand side variable, controlling for lagged commodity returns, percentage changes in the BDI index, changes in the Baa credit spread, and changes in inflation compensation. For wheat, corn, soybeans, soybean oil, and cotton, we also include the 12-month percentage change in projected world demand, US stocks, and US production. Each row reports coefficients for a different commodity, and each column reports coefficients for different trader groups. The right-most column measures position changes as the aggregated position change across all agricultural commodities, where contracts are converted into a dollar quantity using fixed prices as of December 15 2006. The sample period is September 15 2008 through June 1 2011. Coefficients are standardized to percentage points in returns per one standard deviation in position changes. For brevity, only the term on the contemporaneous position change is reported. We use the Newey and West (1987) construction for standard errors with four lags.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		Coefficient on contemporaneous position changes (1 σ)									
		CITs		Hedge funds		C. hedgers		Other unclassified		CITs (agr. positions)	
Returns (%)		Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic	Coef.	*t*-statistic
Grains	Chi W	0.262	[0.54]	3.261	[8.96]***	−3.850	[−10.17]***	−1.555	[−2.66]***	0.780	[1.17]
	Corn	−0.298	[−0.53]	3.335	[9.18]***	−3.186	[−9.65]***	−1.341	[−3.51]***	−0.447	[−0.68]
	KC W	1.222	[2.83]***	2.692	[9.09]***	−3.058	[−8.86]***	−0.699	[−1.19]	0.337	[0.58]
	Soybeans	0.017	[0.04]	2.445	[7.14]***	−2.468	[−10.58]***	−1.361	[−3.94]***	0.009	[0.03]
	Soyb oil	−0.186	[−0.53]	2.043	[7.04]***	−2.120	[−10.13]***	−1.245	[−2.82]***	0.384	[0.75]
Livestock	F cattle	0.317	[1.83]*	0.970	[5.44]***	−0.824	[−4.90]***	−0.268	[−1.63]	0.536	[2.70]***
	L hogs	0.454	[1.58]	1.422	[3.61]***	0.083	[0.19]	−2.113	[−8.56]***	0.508	[1.80]*
	L cattle	0.291	[1.19]	0.824	[4.49]***	−1.114	[−7.06]***	−0.160	[−0.76]	0.507	[2.46]**
Softs	Cocoa	1.302	[2.43]**	2.179	[5.67]***	−2.456	[−7.16]***	−2.569	[−6.97]***	0.252	[0.81]
	Coffee	1.073	[2.27]**	3.244	[9.74]***	−3.205	[−10.14]***	−2.450	[−8.26]***	0.558	[1.76]*
	Cotton	0.035	[0.07]	1.658	[4.39]***	−1.665	[−3.37]***	−1.582	[−3.46]***	0.389	[1.10]
	Sugar	−0.918	[−2.04]**	2.910	[4.87]***	−1.521	[−3.16]***	−2.165	[−5.23]***	−0.420	[−0.82]
Energy	Oil	−1.613	[−3.73]***	2.070	[6.03]***	−0.352	[−1.07]	−0.521	[−0.83]	1.564	[1.85]*
	Heat oil	−0.876	[−2.30]**	2.566	[6.50]***	−1.001	[−2.98]***	−2.613	[−4.61]***	1.149	[1.66]*
	Natural gas	0.063	[0.12]	2.470	[5.12]***	−2.730	[−4.77]***	−3.313	[−8.37]***	0.421	[0.58]
	Gas	−1.002	[−2.32]**	2.219	[5.22]***	−0.622	[−1.48]	−2.442	[−5.47]***	1.177	[2.44]**
Metals	Copper	0.346	[1.14]	2.308	[7.88]***	−2.191	[−4.88]***	−2.367	[−7.99]***	1.130	[3.16]***
	Gold	−0.760	[−2.96]***	1.820	[6.17]***	−1.516	[−4.57]***	−1.560	[−5.25]***	−0.106	[−0.34]
	Silver	−0.041	[−0.07]	1.638	[3.25]***	−2.180	[−6.00]***	−1.924	[−4.15]***	0.077	[0.15]
Average R^2		14.83%		32.70%		30.65%		25.97%		14.34%	

agricultural commodities as an alternative to infer CIT positions in crude oil, as CIT positions in individual commodities should all reflect investors' portfolio allocations to the commodity class. This approach is appealing because, as we discussed before, the twelve agricultural commodities are less exposed to the netting problem. Motivated by this consideration, we use the aggregated CIT position changes in the twelve agricultural commodities as a measure of CIT flows in all commodities including those in energy and metals. To the extent that aggregation averages out noise, aggregate CIT flows may contain more information about CIT flows than flows measured for individual commodities.[23]

Table IX (the last major column) re-produces estimates of $\overline{b}$ by substituting aggregated CIT position changes in the twelve agricultural commodities, $Flows_{AG,t}$, in place of own-commodity CIT flows $Flows_t$. Based on this aggregate measure of CIT flows, the negative CIT position correlations with prices in energy and metals disappear with several of the correlations turning positive. This contrast confirms the appeal of using aggregated CIT flows in agricultural commodities to measure CIT position changes in individual commodities. Nevertheless, across the board, the correlations between the aggregated CIT flows and individual commodity returns are still weak, with only seven out of the nineteen commodities displaying marginally significant and positive correlations.

Our theoretical framework in Section 2 highlights the need to differentiate whether financial traders initiate the trades or trade to accommodate other traders in order to properly identify any relationship between their position changes and price changes. Failing to differentiate these two cases introduces a simultaneity bias as position changes stemming from trades initiated by financial traders should be positively correlated with price changes, whereas those stemming from accommodating other traders should be negatively correlated with price changes. In other words, Equation (6) is an endogenous regression.

Motivated by our previous analysis, we condition on VIX changes to analyze the correlations between CIT position changes and price changes. Table X reports results from a two-stage analysis. First, we extract the

[23] Singleton (2013) uses the Masters (2008) imputation method, which draws on information from agricultural commodities that are only in one of the GSCI or DJ-UBS indices, to impute CIT oil positions. Hamilton and Wu (2013) expand this to use a linear combination of all twelve agricultural commodities with a weighting determined by maximizing the in-sample fit of observed CIT positions from the Supplemental CIT report. We follow the spirit of this exercise but choose a simple weighting based on market prices determined as of December 2006, which avoids contaminating our exercise with information from the sample.

Table X. Returns and VIX-predicted flows

We report coefficients from a two-stage least squares regression of returns as the left-hand side variable on contemporaneous aggregate flows into grains, livestock, and softs as the right-hand side variable, where trader flows have been predicted in a first-stage using the contemporaneous change in VIX. We control for lagged commodity returns, percentage changes in the BDI index, changes in the Baa credit spread, changes in inflation compensation, and the lagged change in VIX in both stages. For wheat, corn, soybeans, soybean oil, and cotton, we also include the 12-month percentage change in projected world demand, US stocks, and US production as controls. The sample period is September 15 2008 through June 1 2011. Coefficients are reported where returns are in percentage points and trader flows are standardized to one standard deviation during the post-crisis period. Standard errors are calculated using a two-stage least-squares standard error with a Newey–West four-lag correction for serial correlation and are reported below the coefficient in brackets. First-stage *F*-tests and *p*-values of the null hypothesis that the VIX does not affect trader flows are reported as well, with *p*-values in parentheses.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		CITs		Total Financial Positions	
Returns (%)		Second-stage Coefficient	First-stage *F*- and *p*-values	Second-stage coefficient	First-stage *F*- and *p*-values
Grains	Chi W	7.830	10.30	8.263	25.50
		[2.94]***	(0.002)***	[4.66]***	(0.000)***
	Corn	6.147	8.05	5.771	26.70
		[2.12]**	(0.005)***	[3.31]***	(0.000)***
	KC W	7.147	6.19	7.111	24.40
		[2.25]**	(0.014)**	[4.34]***	(0.000)***
	Soybeans	4.917	5.79	4.469	23.70
		[1.83]*	(0.018)**	[3.40]***	(0.000)***
	Soyb oil	5.264	6.06	4.502	29.80
		[1.96]**	(0.015)**	[4.02]***	(0.000)***
Livestock	F cattle	2.531	8.57	2.427	28.20
		[2.23]**	(0.004)***	[2.93]***	(0.000)***
	L hogs	1.176	6.49	1.038	25.50
		[1.14]	(0.012)**	[1.32]	(0.000)***
	L cattle	2.128	11.00	2.024	29.70
		[2.83]***	(0.001)***	[3.70]***	(0.000)***
Softs	Cocoa	2.719	6.17	2.402	25.10
		[1.66]*	(0.014)**	[2.02]**	(0.000)***
	Coffee	3.703	6.30	3.223	27.40
		[2.19]**	(0.013)**	[3.82]***	(0.000)***
	Cotton	4.679	6.39	4.084	24.90
		[2.34]**	(0.013)**	[3.58]***	(0.000)***
	Sugar	3.424	6.29	3.033	27.10
		[1.42]	(0.013)**	[2.00]**	(0.000)***
Energy	Oil	5.863	6.78	5.186	30.80
		[2.32]**	(0.010)**	[3.49]***	(0.000)***
	Heat oil	5.019	7.21	4.368	34.20
		[2.30]**	(0.008)***	[3.37]***	(0.000)***
	Natural gas	4.563	6.20	4.032	27.70
		[2.08]**	(0.014)**	[2.45]**	(0.000)***
	Gas	4.445	6.50	3.852	30.10
		[1.57]	(0.012)**	[2.39]**	(0.000)***
Metals	Copper	4.621	6.29	4.076	26.90
		[2.10]**	(0.013)**	[3.72]***	(0.000)***
	Gold	1.549	6.32	1.323	27.20
		[0.92]	(0.013)**	[1.11]	(0.000)***
	Silver	4.239	6.53	3.718	27.00
		[1.44]	(0.012)**	[2.03]**	(0.000)***

component of the aggregate CIT flows in agricultural commodities predicted by changes in the VIX, $\widehat{Flows}_{AG,t}$, using a first-stage regression analogous to Equation (5):

$$Flows_{AG,t} = a + b\,\Delta VIX_t + c\,dF_{t-1} + d\,Controls_t + \epsilon_t. \tag{7}$$

Then, we estimate $\overline{b}$ for CITs by substituting $Flows_{AG,t}$ in Equation (6) with its component predicted by the VIX changes $\widehat{Flows}_{AG,t}$ and by excluding ΔVIX_t from Equation (6).[24] Econometrically, this is a classic two-stage least squares regression where Equation (7) is the first stage regression, Equation (6) is the endogenous second-stage regression, $Flows_{AG,t}$ is the endogenous regressor, and ΔVIX_t is the excluded instrument. We compute two-stage least squares standard errors with an adjustment for serial correlation applying the Newey–West (1987) construction of the covariance matrix with four lags. Economically, this procedure looks for a correlation between price changes and the portion of CIT position changes related to the VIX-induced fluctuations in risk tolerance of CIT traders during the crisis.

Table X reports the estimated $\overline{b}$ from the second stage as well as tests of the null hypothesis that $b = 0$ from the first stage. The first column reports results for CIT position changes measured by the aggregate CIT flows in the twelve agricultural commodities. Conditioning on the VIX yields economically and statistically significant correlations between CIT position changes and price changes in the second stage across fifteen out of all nineteen commodities. Even for the remaining four commodities, the correlations are also positive albeit not significant. Across all commodities, the magnitude of the estimated $\overline{b}$ is also much larger relative to the corresponding value reported in the last column of Table IX without conditioning on the VIX.

Econometrically, note that the correlation between the VIX changes and CIT position changes in the first stage is modest, with the F-statistics reported in Table X varying between 6 and 10 and a partial R^2 (unreported) across all commodities averaging to 0.1. An insufficiently strong correlation in the first stage may lead to significant size distortions in second stage hypothesis tests (Stock, Wright, and Yogo, 2002) as well as to inconsistent and significantly more finite-sample biased estimates of $\overline{b}$ (Bound, Jaeger and Baker, 1995). To alleviate this weak instrument problem in the first stage, we further aggregate position changes of both CITs and hedge funds in the twelve agricultural commodities to obtain a measure of aggregate flows of all financial traders. As shown earlier, hedge fund positions

[24] We subsume the lagged VIX change, ΔVIX_{t-1}, in the controls for both stages.

also moved significantly with the VIX during the crisis. The second column of Table IX shows that the aggregate flows of financial traders display much stronger correlations with the VIX in the first stage with the F-statistics in the 25–30 range. Importantly, the magnitudes of the correlations between aggregate flows of financial traders and price changes remain largely unchanged relative to the correlations of the CIT flows and price changes. This pattern suggests that the positive correlations between CIT flows and price changes are not spuriously induced by the weak instrument problem.

Economically, we should not over-interpret these correlations as price impacts of CITs. Changes in the VIX might have affected not only CITs but also hedgers, violating the exclusion restriction that would be necessary to interpret these as true estimates of price impacts. Nevertheless, one can view these correlations as upper bounds. At a minimum, Table X cautions against using unconditional correlations between CIT position changes and price changes to infer market impacts of CIT trading, as conditioning on the VIX reveals much greater correlations than previously documented.

5. Conclusion

Financial traders sold positions in response to rises in the VIX as prices fell during the recent financial crisis, with hedgers taking the other side. This evidence suggests that there was a flow of risk away from financial traders back toward hedgers. Much as warm air flows toward cool air, this convective risk flow reallocates risk from the groups less able to bear the risk to the groups more able to bear risk. Analyzing such a risk flow confirms the market impact of CIT traders conditional on trades initiated by them, and motivates future research in extending the long-standing hedging pressure theory of commodity futures markets to incorporate time-varying risk capacities of financial traders.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

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