Speculation and informational efficiency in commodity futures markets

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Abstract

We use recent data of the CFTC to re-assess the effects of financial traders on informational efficiency in commodity futures markets. To do so, we focus on excessive volatility as a means to reflect noise in the price discovery process. We show that the role of financial traders on volatility is more complex than often assumed in the literature. Researchers should distinguish between the trading motives of market actors, as well as between increases and decreases in open interest. Several findings stand out. In particular, we find that short-term fluctuations in open interest might primarily be driven by speculators' demand for liquidity, and that traditional speculators, as identified by the MM category of the CFTC, may be responsible for increasing volatility in several markets.

Keywords: Commodity markets; Informational efficiency; Speculation; Financialization.

JEL Classification: G14; G20; G01; Q02.

1 Introduction

In recent years, the role of speculation in commodity markets has largely been studied through the prism of financialization. This phenomenon refers to the large inflows of capital from index investors into commodity markets during the 2000's. Traditionally, market participants are separated into two broad categories: commercial and non-commercial traders. On the one hand, commercial traders, such as farmers, producers, or industrials, trade commodity futures to hedge the price risk of their physical activity. On the other hand, non-commercial traders, such as hedge funds and other managed-money vehicles, take positions in commodity futures, or options on commodity futures, on behalf of their clients on a discretionary basis. Since the early 2000's, however, another class of investors channelled large inflows of capital towards commodity markets: commodity index traders (CIT). According to a 2008 staff report of the CFTC, index investors increased their purchases of commodity index-related instruments from \$15 billion in 2003 to at least \$200 billion in mid-2008. CIT use commodities as an asset class to diversify their portfolio and often seek exposure through broad-based commodity indices such as the S&P GSCI or the Bloomberg Commodity Index (BCOM). In practice, they rarely take direct positions in commodity futures markets. They purchase exchange-traded funds and exchange-traded notes from fund companies, or enter into swap contracts with financial swap dealers (Cheng and Xiong, 2014). Fund companies and swap dealers then hedge their exposure in individual futures contracts. These capital inflows led to a surge of open interest as well as an increase in net exposure of CIT, commercial hedgers, and hedge funds to commodity futures prices.

At the same time, commodity futures prices experienced a boom and bust cycle. The prices of many commodities surged and peaked around mid-2008 before collapsing later in the year. Financialization has logically been suspected to participate to this bubble-like episode, and it revived the debate on the price impact of financial investors (see, among others, Tang and Xiong, 2012; Singleton, 2014; Cheng and Xiong, 2014; and Basak and Pavlova, 2016). In this paper, we propose a new and recent assessment of the effect of financialization, and financial traders in general, on two of the main functions of commodity futures markets:

risk sharing and price discovery. To do so, we adopt a methodology inspired by Cheng et al. (2015), who rely on a rapidly growing literature that analyses the links between financial institutions and asset prices to assess the effect of financialization on risk sharing. Specifically, Cheng et al. (2015) study the joint responses of traders' positions and commodity futures prices to changes in the VIX, where the VIX is a proxy for shocks to financial institutions' risk appetite during the crisis. Their approach is justified by the fact that assessing the effect of a category of traders on prices requires to isolate the trades these operators make for their own account. The underlying idea is that, during periods when financial institutions face important capital constraints, shocks to their risk absorption capacity may force them to liquidate their positions in risky financial assets such as commodity derivatives.

We first expand Cheng et al.'s (2015) analysis of risk sharing on more recent data to figure out whether this mechanism recovered the same properties as before the crisis. Then, for our main contribution, we adopt a similar methodology to study the effect of financial traders on the informational efficiency of commodity futures markets. To do so, we adopt the widespread view that excessive volatility in comparison to fundamentals reflects noise in the price discovery process, and is a sign of less efficient price informativeness. Furthermore, we also rely on an analysis of the risk premium as an alternative means to identify who motivates trading (see Kang et al., 2020). Even though the bulk of the literature assesses the impact of financial traders on returns, several papers focus on the volatility (see, for instance, Sanders and Irwin, 2011a; Bosch and Pradkhan, 2015; Brunetti et al., 2016). The originality of our paper in comparison to this literature is twofold. First, we distinguish between the effect of negative and positive changes in positions. As a matter of fact, we show how considering that the relation between changes in positions and volatility is monotonic on negative and positive values can be misleading. Second, as mentioned above, our methodology explicitly accounts for the simultaneity bias that prevents the proper identification of financial traders' impact on prices (Cheng and Xiong, 2014).

Several important findings stand out. First, it would seem that the shift in risk sharing from financial traders to hedgers may have persisted long after the crisis. This result seems consistent with Kang et al.'s (2020) recent finding that short-term fluctuations in open interest might primarily be driven by non-commercial traders demand for liquidity. Second, by contrast with most of the literature, and even though the evidence is not as strong as for other categories of traders, we find changes in CIT positions to be contemporaneously positively correlated with commodity returns in recent data. Third, the impact of speculators on the volatility is more complex than often assumed in the first studies of financialization. While there is a considerable level of heterogeneity between commodities, there is reasonable evidence to doubt the ever stabilizing role of financial traders. In particular, they might have altered the price discovery process for several commodities. We present a short literature review and our data in Section 2 and Section 3, respectively. Section 4 displays our methodology and results. Section 5 presents several robustness tests, and Section 6 concludes.

2 Literature review

Financialization is an all the more important issue that there are important linkages between futures and spot markets, and that several countries during the years 2007 and 2008 experienced critical episodes of food insecurity. Given the gravity of these suspected consequences, it is not surprising that it fuelled a large literature. Probably one of its most fruitful path has been its emphasis on how financialization affected the dependence structure across commodities, and between commodities and other asset classes (Tang and Xiong, 2012; Charlot et al., 2016; Ma et al., 2021). While there are evidence of significant changes in the dependence structure of financial assets, it is not obvious as to whether these changes pertain to CIT.

Besides the fact that they can be attributable to other financial traders such as hedge funds, several other explanations, such as macroeconomic fluctuations (Alquist et al., 2020) or sentiment (Ma et al., 2021), have been put forth to explain these co-movements. In fact, rising demand from emerging countries, and from China in particular, remains one of the main explanation for the boom and burst in Crude oil prices (Hamilton, 2009). Moreover, Hamilton (2009) points to the lack of inventory response to the rise in futures prices as a reason to doubt the responsibility of speculators. According to the theory of storage (Kaldor, 1939; Working, 1949), the basis serves as an incentive to stock a commodity. If the basis is higher than the cost of storing the commodity, there is an arbitrage to be made by shorting the futures and carrying the commodity. Therefore, if speculation were to drive futures prices upward, the theory of storage would predict an increase in inventories, which would then drive up spot prices as less commodity is available for current consumption.

Another strand of the empirical literature relies on this prediction and use inventories in structural vector autoregressive (SVAR) models as a means to identify speculation shocks (Kilian and Murphy, 2014; Juvenal and Petrella, 2015). By doing so, they make abstraction of other possible transmission channels, i.e. the risk sharing and information-discovery channels (Cheng and Xiong, 2014). Sockin and Xiong (2015), for instance, develop a theoretical model that integrates centralized commodity market in a context of asymmetric information, that shows how non-fundamental shocks can spread from the futures market to the spot market without a noticeable change in inventories. In a more recent example of SVAR model applied to Cotton, Janzen et al. (2018) rely on the correlation between Cotton and an external market (net of any comovement with real economic activity) to identify the effect of financial speculation. They find a limited impact of financial speculators. While interesting, this study also has potential shortcomings as it does not account for the diversity of speculative strategies of financial traders. There is no reason for speculative activity unrelated to index investing to be captured by correlations with commodity indices.

This paper falls within a last strand of the empirical literature that relies directly on financial traders' positions from the Commodity Futures Trading Commission (CFTC) to investigate their impact on prices and volatility. Several papers (Büyüksahin and Harris, 2011; Sanders and Irwin, 2011a, 2011b; Singleton, 2014; Bosch and Pradkhan, 2015; Brunetti et al., 2016) test whether speculative positions are contemporaneously correlated or Granger-cause changes in commodity prices and volatility. They find limited evidence of an impact of CIT on prices, while hedge funds seem to have a rather stabilizing effect.[1] However, Cheng and Xiong (2014) and Cheng et al. (2015) raise a crucial shortcoming to these analyses.

[1]Singleton (2014) is a notable exception who finds that longer-term growth rates of index traders' positions have a significant effect on Crude oil futures prices.

Contrary to the clear distinction between hedgers and speculators in economic theory, the role of every market operator is not as plainly defined. Accordingly, the distinction between physical hedgers and speculators in reality is not quite as clear as the CFTC's categories would suggest. As a matter of fact, operators that have a direct activity in physical commodities sometimes take speculative positions, and speculators sometimes assume the role of market makers as they take opposite positions to producers and manufacturers and bring liquidity to the market. Hence, Cheng et al. (2015) highlight the need to differentiate between situations when financial traders trade for their own reasons such as portfolio diversification and risk management, from situations when they trade to accommodate other traders. The underlying idea is that, as there are both sides to each trade, it is the counterparty that motivates the trade that drives prices. Failing to differentiate between these situations introduces a simultaneity bias as changes in the positions of speculators stemming from trades initiated for their own needs should be positively correlated with price changes, while those stemming from trades to accommodate other traders should be negatively correlated with price changes.

This need for a differentiation between trades is part of a broader recommendation of Cheng and Xiong (2014) that researchers should depart from the simplistic dichotomous view of financialization as either a bubble-like or "business as usual" phenomenon. Instead, they argue that researchers should focus on how financialization affect the three main functions of commodity markets: incentive for storage, risk sharing, and information discovery. In this paper, we mostly focus on the effect of financial traders on information discovery. We are not the first to do so. Henderson et al. (2015) study the impact of financialization on informational efficiency through over-the-counter (OTC) commodity-linked notes (CLNs). Issuances of CLNs can have an impact on futures prices through the trades issuers make to hedge their exposure to commodity price risk. CLN issuers usually hedge their risk by taking a long position in the commodity futures market - or, alternatively, in commodity swaps that are then rehedged in the futures market - on the CLN pricing date, and then unwind their position on the determination date. Henderson et al. (2015) use this mechanism and analyse the impact of hedge trades around the pricing and determination dates. They find that the underlying futures price increases on pricing dates and diminishes on determination dates. They also show that the price impacts where larger during the crisis when many market participants were financially constrained. Bohl et al. (2020) investigate whether measures of speculative and hedging activity can explain variations in informational efficiency based on Choi's (1999) automatic variance ratio. They find no evidence that speculators participated to a deterioration of market efficiency.[2]

These papers, that, to the best of our knowledge, are the only ones to directly address the effect of financialization on informational efficiency, find contradictory results. Thereupon, the debate remains open. Our methodology is notably inspired by the work of Cheng et al. (2015) who address the effect of financialization on risk sharing during the crisis. To do so, they rely on a growing literature that analyses the links between financial institutions and asset prices. This literature documents evidence that intermediary institutions and, more generally, arbitrageurs, face a number of constraints that impact asset prices, and that ultimately make the standard arbitrage theory unrealistic (see, among many others, Xiong, 2001; Kyle and Xiong, 2001; Mitchell et al., 2007; Adrian and Shin, 2010). During financial crises, when risk appetite is limited and when financial traders are the more likely to face important funding constraints, they should be more reluctant to endorse the risk of hedgers, and may reduce their commodity positions. Cheng et al. (2015) exploit this idea to identify trades institutional investors make for their own account. Specifically, they study the joint responses of traders' positions and commodity futures prices to changes in the VIX using the CFTC's LTRS database, where the VIX is a proxy for shocks to financial institutions' risk appetite during the crisis (see, for instance, Brunnermeier et al., 2009; Coffey et al., 2009). They find that, during the crisis, aggregate positions of hedge funds and CIT fell in response to an increase in the VIX in a large number of commodity futures markets. On the opposite, hedgers seem to take the other side of those trades as their net positions display

[2]Bohl et al.'s (2020) paper may be the closest in spirit to the early literature on informational efficiency (Samuelson, 1965; Fama, 1970) as variance-ratio tests rest on the random walk hypothesis. This approach has the merit to consider a clear and well-defined asset pricing model, i.e. a clear model of equilibrium expected returns. It seems to us, however, that the risk-neutrality assumption that underlies the random walk model is too strong an hypothesis in the light of the current state of the asset pricing literature (Cochrane, 2005; Szymanowska et al., 2014).

a positive response to changes in the VIX. It means that, during the crisis, hedgers reduced their net short hedging positions just as uncertainty was rising. Changes in the VIX were also accompanied by significant price drops in almost all commodity futures, which is consistent with the theory that the trades of CIT and hedge funds drove price changes during the crisis while hedgers accommodated them. It is paradoxical in the sense that it was when risk sharing was needed the most by hedgers that it failed to function. In contrast, prior to the financial crisis, neither financial traders, nor hedgers exhibited significant response to the VIX. The allocation of risk somewhat shifted from financial traders to hedgers during financial turmoil, a phenomenon Cheng et al. (2015) call the “convective risk flow” hypothesis.

In the last section of their article, Cheng et al. (2015) design an interesting framework to analyse the effects of CIT on prices and bypass the simultaneity bias. Specifically, they take advantage of the lower risk absorption capacity of financial institutions documented during the crisis to isolate the trades initiated by CIT. In practice, they use the VIX to proxy for shocks to financial traders' willingness to endorse risk during the crisis, and find that financial traders' positions conditional on the VIX were correlated with changes in futures prices. In this paper, our goal is to expand this analysis in two ways. First, we adopt a similar methodology to a more recent time period in order to figure out whether responses from traders' positions to the VIX returned to its pre-crisis relationship, or whether financial traders more permanently react to changes in the VIX by adjusting their holdings of commodities for fear of future financial distress. Second, we adapt the methodology to address the effect of financial traders on another function of futures markets: information discovery. Specifically, we wonder whether those changes in positions introduce noise in the price discovery process and alter informational efficiency.

To do so, we focus on the volatility. The traditional position that speculation plays a stabilizing role on prices originated long ago. It is well illustrated, for instance, in Friedman's (1953) famous defence of a flexible exchange rate system. Rational arbitrageurs prevent prices to move away from their fundamental value by taking advantage of any mispricing caused by irrational traders. By doing so, speculators mitigate movements resulting from noise and hasten convergence towards fundamentals, i.e. they have a smoothing effect on prices. This might not be true, however, when financial traders face important risk absorption constraints. In such periods, their behaviour - unwinding risky positions - may make prices more volatile, and speculation could be destabilizing.[3] Therefore, in this context, it seems appropriate to use excess volatility in comparison to fundamentals as an argument for less efficient price informativeness; where fundamentals are defined as information directly relevant to the physical supply and demand for commodities.[4] We control for fundamentals using both macroeconomic and commodity-specific variables. They are discussed in details in Section 3.4.

From a more technical point of view, the possibility of large and sudden unwinding of positions from financial traders points to another shortcoming of the literature. Since both increase and decrease in traders' positions can have a positive effect on volatility, these fund flows should not be studied as monotonic on negative and positive values as is generally the case in the literature (Sanders and Irwin, 2011a; Bosch and Pradkhan, 2015). It incurs to important misinterpretations of the impact of financial traders' behaviour on prices.

3 Data

We consider a total of 18 commodities: 12 agricultural commodities (Chicago wheat, Corn, Kansas City wheat, Soybeans, Soybean oil, Feeder cattle, Lean hogs, Live cattle, Cocoa, Coffee, Cotton, Sugar), 3 energy commodities (WTI crude oil, Heating oil, Natural gas), and 3 metals (Copper, Silver, Gold). Because our analysis relies on open intesrest data from the CFTC's reports - which are released on Fridays for closing positions of the preceding Tuesdays -, we focus on the weekly frequency. It should be pointed out that weekly open

[3] Focusing on the volatility also allows to test empirically a crucial implication of Basak and Pavlova's (2016) theoretical model of financialization, according to which a market with index investors undergoes higher levels of volatility.

[4] It should be pointed out here that our approach to informational efficiency is concerned much more with its "prices are right" interpretation than to its "there is no free lunch" interpretation (see Barberis and Thaler, 2003). It is related in spirit to the work of Shiller (1981, 1984) who argue that the excessive volatility of stock returns compared to dividends may be a sign that investors overreact to new information, and hence points to informational inefficiencies.

interest can hide traded volume several times higher than the resulting positions, and, in that regard, data availability is a considerable limit to our analysis.

Our dataset starts on June 20^{th} 2006, when CIT positions first become available, and ends on September 24^{th} 2019 (685 points). In addition to the entire sample, we consider several subsamples: a pre-crisis sample from June 27^{th} 2006 to July 31^{st} 2007 (57 points), a first crisis sample, from August 7^{th} 2007 to June 30^{th} 2009 (98 points), a post-crisis sample from July 7^{th} 2009 to September 24^{th} 2019 (529 points), and a second extended crisis sample that starts on August 7^{th} 2007 but ends on May 31^{st} 2011 (198 points).[5] Selected descriptive statistics for commodity returns and volatility are displayed in Table 1 of the Appendix.[6]

3.1 Weekly commodity returns

Since our main focus is on financialization and the impact of index investors on prices, we choose our futures price series to follow the rolling strategy of the S&P GSCI (see Singleton, 2014; Mou, 2011). The S&P GSCI is the most popular composite commodity index that index investors tried to replicate during our sample. Hence, price series based on this rolling specification are more susceptible to reflect the price impact of index traders. In practice, we follow Singleton (2014) and choose to roll our series on the 10^{th} calendar day of the month. This choice represents a reasonable compromise as the S&P GSCI typically rolls between the 5^{th} and the 9^{th} business day of the month. We follow as closely as possible Appendix A to the S&P GSCI Index Methodology of July 2019 to identify the designated contracts used for each period of the year.[7] For Chicago wheat, for instance, this methodology indicates that the contracts included in the index are the March contract from December to February, the May contract in March and April, the July contract in May and June, the September contract in July and August, and the December contract from September to November. Table

[5]For that second crisis sample, May 31^{st} 2011 corresponds the end date of the post-crisis sample in Cheng et al. (2015). For the sake of space, results for this second crisis sample are only provided in the *Supplementary material* file.

[6]Complementary descriptive statistics for all variables described in this section can be found in the *Supplementary material* file.

[7]The S&P GSCI Index Methodology can be found on the following website: https://www.spglobal.com/spdji/en/indices/commodities/sp-gsci.

2 summarizes our contract schedule for each commodity.

We build our price series by hand. That is, we download the historical prices of all futures contracts and implement the roll procedure ourselves. Given that there is a gap between the level of two contracts with different maturity, we adjust the return during the roll procedure. Specifically, we calculate returns as follows:

$$\begin{cases} y_t = \ln(F^1_{s,T_1}/F^1_{t,T_1}), & \text{if } s < r, \\ y_t = \ln(F^1_{s,T_2}F^1_{r-1,T_1}/F^2_{r-1,T_2}) - \ln(F^1_{t,T_1}), & \text{if } t < r \leq s, \end{cases} \tag{1}$$

where F^j_{s,T_i} denotes the price of the futures contract at time s with expiration date T_i. j denotes the position of the contract in the index schedule, meaning that F^1_{s,T_i} is the price of the contract currently used in the index, and r is the date of the first roll after time t. We compute returns with the top equation in weeks when the designated contract does not change, and with the bottom equation in weeks when it does change. In the latter case, returns are adjusted by the ratio between the prices of the former and new designated contracts at time $r-1$. Since the Commodity Futures Trading Commission (CFTC) reports weekly Tuesday closing positions of commodity traders, we compute Tuesday-to-Tuesday returns.

3.2 Weekly commodity volatility

Our main contribution is to analyse the effects of institutional investors on price discovery. To do so, we focus on the volatility as high levels of volatility in comparison to fundamentals are associated with lower informational efficiency. In the same vein as Sanders and Irwin (2011a), we construct a weekly measure of realized volatility based on the intraday range of Parkinson (1980):

$$\sigma_t = \sqrt{\frac{Z}{n4\ln(2)}\sum_{i=1}^{n}\left(\ln\frac{H_i}{L_i}\right)^2}, \tag{2}$$

where H_i and L_i are the daily high and low prices, n is the number of days in week t, and Z is equal to 52 and serves to annualize the volatility. The underlying futures contracts to high and low prices are the same as for returns, and, similarly as for returns, we compute the volatility from Tuesday to Tuesday.[8]

3.3 Commitment of traders

In order to detect and prevent futures and options market manipulation, the Commodity Futures Trading Commission (CTFC) collects information on daily positions of traders that exceed some reporting levels. For a long time, they have been publishing a weekly aggregate summary of these information on their website: the Commitment of Traders (COT) report. The COT report divides traders' positions into two broad categories: commercial and non-commercial traders. Quite recently, to respond to demands for more transparency, the CFTC began publishing two additional weekly reports: the Supplemental CIT report, since 2007, and the Disaggregated Commitment Of Traders report (DCOT), since 2009.[9] These reports are released on Fridays for closing positions of the preceding Tuesdays. At first glance, these reports can be difficult to apprehend. We detail their main features in the following paragraphs.

The weekly Supplemental CIT report breaks down the reported traders' positions into three categories: Non-Commercial, Commercial, and CIT. In comparison to the traditional COT report, the CFTC isolates CIT. This category regroups the positions of: (1) managed funds and pension funds who seek exposure to an index of commodity prices, and who would have previously been classified into the Non-Commercial category; and of (2) swap dealers who hedge OTC transactions involving commodity indices in the futures markets, and who would have previously been classified as Commercial traders. A first shortcoming of the CIT report is that it does not allow to jointly analyse the positions of CIT with the positions of other specific non-commercial traders, such as hedge funds (Cheng et al., 2015). A second, and even more manifest, shortcoming is that Supplemental CIT reports contain information solely for 12 agricultural commodities. Soon after the publication of the first Supplemental

[8]In Section 5.1, we consider an alternative measure of the volatility based on the estimation of an ARMA-GARCH model. Our results are overall robust to this different specification.

[9]They also provided historical data back to 2006.

CIT report, concerns that it did not extend to other markets motivated the CFTC to publish the DCOT report.

The DCOT report breaks down traders' positions into four categories: Processors and Merchants, Swap Dealers, Managed Money, and Other Reportables. Processors and Merchants are traditional commercial actors who use the futures markets to hedge their physical, real-world positions. Swap Dealers provide swaps to their customers and hedge their positions in the futures markets. Managed Money encompasses the positions of operators who invest in commodity futures markets on behalf of clients. They are either hedge funds, commodity trading advisors (CTAs), or commodity pool operators (CPOs). And, finally, Other Reportables designate non-commercial traders who did not belong in any other category. Several papers assess the effect of index traders on prices using the Swap Dealers category. Index investments in commodity futures markets is indeed primarily made through swaps (Sanders and Irwin, 2011a), but not exclusively, and the remaining index positions are reported either in the Managed Money or the Other Reportables categories. Moreover, an arguably more important issue that hinders the Swap Dealers category from being a reliable proxy for CIT positions stems from the fact that it includes non-indexed over-the-counter (OTC) positions. That is, Swap Dealers data mingle positions related to index investing with positions related to physical commercial activity. Therefore, Swap Dealers positions are only a noisy proxy for CIT positions. While it is a relatively minor issue for commodities for which there is very little OTC or swap trading unrelated to index investing, like Wheat, it becomes a major issue for other commodities for which swap trading is used for other purposes than index investing, like Crude oil (Sanders and Irwin, 2011a).[10]

In these reports, data is divided into long, short, and spread positions.[11] In this paper, we estimate the impact of financial traders using net positions, which are simply constructed as the difference between long and short positions. We do not consider the spread positions in our calculations as their impact on the market is usually considered to be neutral (Sanders

[10]It should also be noted that the positions of swap dealers in the futures market reflect a low bound of index investments. This is because swap dealers will net their positions internally, and only cover their residual risk in the futures markets. This issue concerns both the Swap Dealers and CIT categories.

[11]A spread position is a combination of a short and a long position in the same market, but with different maturities.

and Irwin, 2011a). Additionally, we focus on three categories of traders: CIT from the Supplemental CIT report, and Processors and Merchants (henceforth, PM) and Managed Money (henceforth, MM) from the DCOT report. We let aside aside the Non-commercial and Commercial categories of the Supplemental CIT report as they are very general and encompass various types of traders. Similarly, we do not use the Swap Dealers and Other Reportables categories of the DCOT report. The former is a less accurate proxy of CIT, while the latter regroups traders that did not belong in any other category. Although data in the three retained categories may sometimes overlap, they overall represent positions taken by index traders, physical hedgers, and speculators who actively manage positions in commodity futures markets, respectively.

As noted earlier, the Supplemental CIT report only concerns twelve agricultural commodities, and there is no consensus in the literature on how to measure CIT positions for non-agricultural commodities (Cheng and Xiong, 2014). In this paper, we use aggregated changes in CIT positions of agricultural commodities as a proxy for index exposure in energy commodities and metals.[12]

For our econometric analysis, we measure change in the net long positions of a group of trader j with:

$$pos_t^{i,j} = NPOS_t^{i,j} - NPOS_{t-1}^{i,j}, \tag{3}$$

where $NPOS_t^{i,j}$ is the net position of group of trader j (either CIT, PM, or MM) in commodity i. It is computed as follows: $NPOS_t^{i,j} = LPOS_t^{i,j} - SPOS_t^{i,j}$, with $LPOS_t^{i,j}$ and $SPOS_t^{i,j}$ being the long and short positions of group of trader j in commodity i, respectively.[13]

[12]Originally, we tried to bypass this issue using the same method as Verleger (2007), Masters (2008), and Singleton (2014). It relies on the composition of the two most popular commodity indices (the S&P GSCI and the Bloomberg Commodity Index) and CIT data for agricultural commodities to infer exposure from index investors into non-agricultural commodities. However, we found this approach to be very sensitive to small changes in the index composition, and we eventually decided to adopt a simpler but more transparent method that is notably use by Cheng et al. (2015).

[13]For non-agricultural commodities, our proxy for changes in positions related to index investing is therefore: $pos_t^{agg,CIT} = \sum_{i=1}^{12} pos_t^{i,CIT}$.

3.4 VIX and control variables

Following the literature, we use changes in the VIX to proxy for shocks to the risk appetite of financial traders (Brunnermeier et al., 2009; Coffey et al., 2009; Cheng et al., 2015). We retrieve the VIX from Bloomberg, and compute its Tuesday-to-Tuesday change.

We use several variables to control for changes in prices and volatility that relate to fundamentals.[14] The latter are defined as factors reflecting information relevant to the physical supply and demand for commodities; information that is incorporated into futures prices through the mechanism of price discovery. (i) *The weekly percent change in the Baltic Dry Index (BDI).* Economic activity is recognized as a key driver of commodity demand, and the BDI is particularly well suited to capture its changes. Indeed, commodities are majoritarily transported by sea, and the BDI is a composite index that takes into account the freight rates of 26 different shipping routes. Contrary to many other indices of global economic activity, it accounts for the fact that, in many countries, the weight of the service sector has grown considerably. Since the service sector is far less commodity consuming than the industrial sector, the correlation between indices that include the service sector, such as GDP, and commodity prices tend to change over time. We download the BDI from Bloomberg.

(ii) *The weekly percent change in the basis (i.e., the difference between the futures and the spot price).* The standard formulation of the theory of storage (ToS) predicts a monotonic negative correlation between inventory and volatility. When supplies are scarce, both short-term prices and volatility are expected to rise (Fama and French, 1988; Ng and Pirrong, 1994; Geman and Ohana, 2009; Geman and Smith, 2013; Gorton et al., 2013). This prediction is often tested using the basis, or some equivalent measure such as the slope of the futures curve or the futures spread (Fama and French, 1987; Geman and Ohana, 2009; Geman and Smith, 2013; Nikitopoulos et al., 2017). Indeed, according to the ToS, the basis is composed of a convenience yield net of storage costs and an opportunity cost of forgone interest (Fama and French, 1987; Gospodinov and Ng, 2013). It thus often serves as a measure of scarcity.

[14] We also compute weekly change from Tuesday to Tuesday for our control variables. Whenever the Tuesday value is missing, we compute our weekly change by using the Monday value. Whenever both Monday and Tuesday values are missing, we used the value on the day closest to Tuesday. This procedure to handle missing values was necessary only for a handful of data points.

We compute the basis as the difference between futures and spot prices, divided by the spot price. To be consistent with the return series constructed in Section 3.1, we adopt the same roll schedule as for returns. That is, for most commodities, we use the designated contract and the following designated contract as defined in the S&P GSCI methodology for the spot price and the futures price, respectively.

(iii) *The weekly change in the Baa credit spread.* Changes in the Baa credit spead reflects evolving credit conditions in the economy. It is computed as the difference between Moody's seasoned Baa corporate bond yield and the yield on 10-year Treasury with constant maturity. The lower the spread, the more favourable credit conditions are, and the higher expected future demand for commodities. We retrieve the Baa credit spread from the Fred database.

For Chicago wheat, Kansas City wheat, Corn, Soybeans, Soybean oil, Cotton, and Sugar, we adopt three additional control variables available at a monthly frequency in the U.S. Department of Agriculture's (USDA) *World Agricultural Supply and Demand Estimates* reports. For all these commodities but Sugar, we use the 12-month percent change in (iv) expected world supply, (v) expected world demand, and (vi) expected end-of-harvest world stocks. For Sugar, only U.S. data is available, and we use 12-month percent change in expected U.S. supply, demand, and stocks instead. We download the reports from the USDA's website, and compute the series by hand.[15]

4 Methodology and results

4.1 Shocks to the VIX, risk absorption capacity, and the direction of price changes

We first seek to identify the groups of traders that drive prices in response to shocks to the VIX, where the the VIX serves as proxy for the risk-absorption capacity of financial traders. On the one hand, we could find that shocks to the VIX, during the crisis, were simulta-

[15] We often find non-stationarity not to be rejected for these variables. As it can lead to spurious regressions, we also estimated all models without these variables. We find our results to be very robust to this alternative specification.

neously associated with low returns and decreasing positions of financial traders. A logical interpretation would then be, that, in periods when financial intermediaries face important capital constraints and limited risk appetite, shocks to their risk absorption capacity may force financial traders to unwind positions to reduce commodity exposure. On the other hand, we could alternatively find that shocks to the VIX affect hedgers' willingness to hedge. In markets where hedgers are net short, they may have incentives to take even larger short positions when the VIX increases. In such case, shocks to the VIX may be simultaneously associated with low returns and shorter positions of hedgers. Hedgers would still require other traders to act as counterparty, but they would be in fact driving prices.

Failure to distinguish between these two cases would be critical for the follow-up analysis as we seek to investigate the price impact of financial traders when they motivate the trades. Only if speculators diminish their positions in response to an increase in the VIX, can we condition their position changes on shocks to the VIX and ascribe the price impact to the actions of speculators. In the alternative where it is in fact hedgers that diminish their positions when the VIX rises, this interpretation would be flawed.

Our econometric framework is similar to Cheng et al. (2015) and rest on simple linear equations:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \zeta_0 \Delta VIX_t + \zeta_1 \Delta VIX_{t-1} + \sum_{s=1}^{S} \beta_s x_{s,t} + \epsilon_t, \tag{4}$$

$$pos_t^i = \alpha_0 + \alpha_1 y_{t-1} + \zeta_0 \Delta VIX_t + \zeta_1 \Delta VIX_{t-1} + \sum_{s=1}^{S} \beta_s x_{s,t} + \epsilon_t, \tag{5}$$

where $x_{s,t}$ are control variables. Specifically, $x_{s,t}$ are macroeconomic and commodity-specific variables that are meant to capture changes in economic fundamentals that may affect commodity prices. They are described in Section 3.4, and include weekly percentage change in the BDI and in the basis, and weekly change in the Baa credit spread. For several agricultural commodities, we add 12-month percentage change in expected world (or U.S.) demand, supply, and end-of-harvest stocks at a monthly frequency. We also control for lagged commodity returns and lagged changes in the VIX to account for the persistence of these variables. We estimate Eqs. (4) and (5) independently by OLS, and use Newey and West's (1987) standard errors which are robust to heteroskedasticity and serial correlation. Table 3 displays our summarized results with a focus on contemporaneous shocks to the VIX.[16]

Several important findings stand out. (i) Except for Lean hogs and Gold, contemporaneous commodity returns fall consecutively to shocks to the VIX in several samples.[17] (ii) Still for Eq. (4), there is clear evidence that returns respond differently to shocks to the VIX before and during the crisis. ζ_0 is significantly negative in the pre-crisis sample only for Cocoa, while it is strongly significantly negative in crisis samples for virtually all commodities. Evidence for the post-crisis sample suggests that this new regime persisted long after the end of the recession as returns for all commodities, but Leans hogs, Natural gas, and Gold, fell contemporaneously to an increase in the VIX during this period. (iii) Results for Eq. (5) show overwhelming evidence that CIT and MM drive prices in response to shocks to the VIX. Coefficients on the VIX for these group of traders are strongly negatively significant in most samples but the pre-crisis sample, while, conversely, coefficients on PM are often strongly positively significant.[18]

Overall, these results seem relatively consistent with the convective risk flow hypothesis introduced by Cheng et al. (2015). During the crisis, there was a shift in risk bearing from financial traders (CIT and MM) toward physical hedgers (PM), and the risk sharing role of commodity futures markets somehow malfunctioned. New evidence suggests, however, that this situation did not go back to normal in recent years as financial traders positions seem still sensitive to fluctuations in the VIX. This result is in line with recent findings of Kang et al. (2020), that short-term fluctuations in open interest might in fact be mostly driven by speculators' demand for liquidity, whether in crisis or not.

[16]For the sake of space, detailed results of Section 4 are reported in an *Supplementary material* file.

[17]The fact that Gold is an exception is no surprise in regard to its role as a safe haven. In fact, we might have expected Gold returns to increase contemporaneously to a rise in the VIX. It is not the case either, which suggests that the two opposing effects (index investing and safe haven) might be at hand and cancel each other.

[18]An alternative interpretation would be that, during the crisis, PM increased their long positions in response to shocks to the VIX. However, PM are net short in most of these markets, and hedging against price increases during the crisis does not seem to be the most rational behaviour. More straightforwardly, this hypothesis is inconsistent with data on PM positions.

4.2 Trader positions and commodity prices

In this section, we focus on the effect of market participants on returns. We estimate two models. The first one is:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \zeta_0 pos_t^i + \zeta_1 \Delta VIX_{t-1} + \sum_{s=1}^{S} \beta_s x_{s,t} + \epsilon_t. \tag{6}$$

As explained earlier, the identification of the impact of traders on prices with Eq. (6) suffers from a simultaneity bias. Results can therefore be misleading, and we should try to identify the trades market participants make for their own account. Cheng et al. (2015) propose an ingenious way to do so. They assess the effect of changes in CIT positions on prices conditional on shocks to their risk appetite, as proxied by innovations in the VIX. We follow their methodology. In Section 4.1, we found that, during the crisis, both CIT and MM reduced their exposure to commodities when the VIX rose. Hence, both these categories of traders are suspected to drive prices in response to shocks to the VIX. In practice, we proceed in two steps. First, we extract the component of fund flows explained by changes in the VIX, $\widehat{pos}_t^i$, with the regression:

$$pos_t^i = \alpha_0 + \alpha_1 y_{t-1} + \zeta_0 \Delta VIX_t + \zeta_1 \Delta VIX_{t-1} + \sum_{s=1}^{S} \beta_s x_{s,t} + \epsilon_t, \tag{7}$$

where i denotes either CIT or MM. Then, we re-estimate Eq. (6) but substitute pos_t^i with $\widehat{pos}_t^i$:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \zeta_0 \widehat{pos}_t^i + \zeta_1 \Delta VIX_{t-1} + \sum_{s=1}^{S} \beta_s x_{s,t} + \epsilon_t, \tag{8}$$

where $\widehat{pos}_t^i$ denotes fitted changes in traders positions using Eq. (7). Since the theoretical justification for this model is based on the limited risk appetite of financial traders during the crisis, we only estimate this model for our two crisis subsamples. We estimate all equations independently by OLS, and use Newey and West's (1987) standard errors which are robust to heteroskedasticity and serial correlation. We report ζ_0 and its t-stat for Eqs. (6) and (8) in Tables 4 and 5, respectively.

Our results show that while they are discrepancies between commodities, some patterns emerge for almost all of them. (i) Positions of PM and MM are very strongly significant in all samples. In absolute value, their t-stats are often of similar magnitude, and regularly above 10. However, they are of opposite signs, as changes in PM and MM positions are contemporaneously negatively and positively correlated with returns, respectively. (ii) Contrary to most of the literature, we find changes in CIT positions to be strongly significant in several samples. This is most likely due to our more recent data. In particular, changes in CIT positions are only significant for three commodities in the pre-crisis sample (Soybean oil, Cotton, and Gold), but they become positively significant during or after the crisis for all commodities. While coefficients for CIT are not as significant as for PM and MM, their t-stats often exceed 5% and 1% critical values. (iii) Results of Eq. (8) are mixed. Among the commodities for which CIT clearly diminished their open interest when the VIX rose (see Section 4.1), conditioning on the VIX strengthens the evidence of an impact of CIT on prices only for Kansas City wheat, Coffee, and Live cattle.[19] Evidence is unclear for Corn, Soybeans, Soybean oil, Sugar, Feeder cattle, Crude oil, Heating oil, and Silver. For Cocoa and Copper, conditioning on the VIX results in lower t-stats, even though they remain significant. (iv) Conditioning MM positions on the VIX results in a significant loss of information. Still, changes in MM positions remain in general very strongly significant with Eq. (8).

Our analysis for recent data shows rather clearly that changes in CIT positions are positively associated with commodity returns. We insisted that a category of trader, or even a single trader for that matter, can trade for different reasons, and that, consequently, we should isolate the trades they make for their own account to have a proper assessment of their effect on prices. CIT could be providing liquidity to other traders. In this particular case, however, the argument does not seem to hold. Remember that hedgers in commodity futures markets are net short, and that the strategy of CIT entails taking long passive positions in the market. Let us assume that the signal we get from our results are blurred by positions taken by CIT to accommodate hedgers. Theory says that, if CIT were to respond to hedgers

[19]The t-stats of CIT positions also go up for Chicago wheat and Cotton, but, although CIT responded to a rise in the VIX by diminishing their positions, the coefficient did not reach critical values.

taking shorter positions, hedgers would be driving prices, meaning that prices should fall and that the positions taken by CIT should be negatively correlated with prices. The same conclusion ensues from CIT accommodating for long hedging needs. In any case, the fact that CIT could be providing liquidity to other traders means that results of Eq. (6) must be an underestimation of the effect of CIT activity on prices.

4.3 Trader positions and commodity volatility

In this section, we propose our main contribution to the literature. We depart from risk sharing to focus on price discovery during the crisis. Specifically, we are interested in studying whether prices exhibit noise (as measured by the volatility), that can be traced back to position changes of financial traders. In comparison to other studies that analyse the effects of institutional investors on volatility (Sanders and Irwin, 2011a; Bosch and Pradkhan, 2015; Brunetti et al., 2016), we retain the underlying idea of Cheng et al. (2015) that distinct trading motives can have different effects on prices. We proceed in a similar fashion as in Section 4.2. Analogously to Eq. (6), an intuitive first model is:

$$\sigma_t = \alpha_0 + \alpha_1 \sigma_{t-1} + \zeta_0 pos_t^i + \zeta_1 \Delta VIX_{t-1} + \sum_{s=1}^{S} \beta_s x_{s,t} + \epsilon_t, \tag{9}$$

where σ_t is a measure of realized volatility computed with Eq. (2). According to traditional finance theory (Friedman, 1953), we should expect financial traders to have a stabilizing effect, smooth the price discovery process, and hence, have a negative effect on volatility. However, we know that a same category of market participants can trade for different motives, and we highlighted in the introduction how capital constraints and liquidity requirements can alter the proper functioning of financial markets and affect prices. When it is the case that changes in the positions of financial traders are driven by shocks to their risk appetite, the behaviour of financial traders could be destabilizing, spread panic, and increase volatility.

Hence, we might find that the impact of financial traders on the volatility turns from negative to positive during periods of constrained capital. Yet, there might be an important level of heterogeneity between traders of a same category, and Eq. (9) could also be subject to a simultaneity bias. We therefore conduct a similar two-step analysis as in the previous section. We first extract the component of the fund flows of financial traders explained by changes in the VIX with Eq. (7), and then estimate:

$$\sigma_t = \alpha_0 + \alpha_1 \sigma_{t-1} + \zeta_0 \widehat{pos}_t^i + \zeta_1 \Delta VIX_{t-1} + \sum_{s=1}^{S} \beta_s x_{s,t} + \epsilon_t. \tag{10}$$

Eq. (9) very much looks like the way the literature first assessed the effect of traders on commodity futures volatility. Besides the heterogeneity of reasons to trade, we feel like there is another important shortcoming to this model. Contrary to returns, it seems that the relation between position changes and volatility should not be modelled as monotonic on positive and negative values. Let us say short hedging demand from producers increases while positions of other traders remain constant, theory says that commodity futures prices should fall as hedging pressure rises. Conversely, if short hedging demand from producers decreases, prices are expected to rise. For the volatility the effect is not so clear as both increasing and decreasing positions can potentially have a destabilizing effect on volatility. In particular, financial traders can have a destabilizing effect when liquidating large positions in the context of limited risk absorption capacity. It then seems problematic to simply study the effect of position changes on volatility without distinguishing between negative and positive values. If changes in both directions increase volatility, effects can cancel each other out and not be detected in a framework similar to Eq. (9), as ζ_0 should come as negative for position decreases and as positive for position increases. Worse still, if the effect of position decreases dominates, as may be the case when financial traders liquidate large positions in response to shocks to their risk absorption capacity, a negative coefficient could be interpreted as stabilizing when the behaviour of financial traders is clearly destabilizing. This issue is overlooked in the literature (for instance, Sanders and Irwin, 2011a; or Bosch and Pradkhan, 2015). We fill this gap here, and split position changes into two variables, position increases and position decreases. Contrary to Brunetti et al. (2016), we choose this solution instead of the absolute value as it also allows to cater for asymmetric effects between negative and positive changes.

We still process in two steps. In the first one, we simply replace position changes by two variables in Eq. (9):

$$\sigma_t = \alpha_0 + \alpha_1\sigma_{t-1} + \zeta_0^- pos_t^{i,-} + \zeta_0^+ pos_t^{i,+} + \zeta_1 \Delta VIX_{t-1} + \sum_{s=1}^{S} \beta_s x_{s,t} + \epsilon_t. \qquad (11)$$

where $pos_t^{i,-} = \mathbb{1}_{\{pos_t^i<0\}} pos_t^i$ and $pos_t^{i,+} = \mathbb{1}_{\{pos_t^i\geq 0\}} pos_t^i$.[20] For the second step, we focus on our two crisis samples, and try to isolate the effects due to trades financial traders make for their own account. We first extract the component of fund flows explained by changes in the VIX using Eq. (7). We then split this variable into negative and positive position changes, and estimate:

$$\sigma_t = \alpha_0 + \alpha_1\sigma_{t-1} + \zeta_0^- \widehat{pos}_t^{i,-} + \zeta_0^+ \widehat{pos}_t^{i,+} + \zeta_1 \Delta VIX_{t-1} + \sum_{s=1}^{S} \beta_s x_{s,t} + \epsilon_t. \qquad (12)$$

where $\widehat{pos}_t^{i,-} = \mathbb{1}_{\{\widehat{pos}_t^i<0\}} \widehat{pos}_t^i$ and $\widehat{pos}_t^{i,+} = \mathbb{1}_{\{\widehat{pos}_t^i\geq 0\}} \widehat{pos}_t^i$.[21] The hypothesis that the behaviour of financial traders, during periods of limited risk absorption capacity, participates to an increase in volatility and to lower price informativeness should manifest in Eq. (12) by a negative ζ_0^-. It would mean that, when financial traders respond to shocks to the VIX by unwinding positions, volatility increases.[22]

As a means of comparison, and to justify the need to distinguish between positive and negative position changes when studying volatility, we report the results of Eqs. (9) in Tables 6. Tables

[20] Increases and decreases in positions tend to be very balanced for all commodities, all groups of traders, and all samples. For instance, for the whole sample, the most important imbalance concerns Coffee and MM, for which 46.3% of all positions are increases, while 53.2% are decreases. It should also be pointed out that, for a particular category of traders, the percentages of observations with increases and decreases in positions are not very representative of its change in open interest. In particular, for most commodities, there is a pronounced fall in net open interest of CIT during the crisis that is not reflected in the balance between increases and decreases in positions.

[21] There are generally larger imbalances between increases and decreases in positions for Eq. (12) than for Eq. (11). Still, there are few examples of increases or decreases in positions that go below 40% of observations. The most extreme example is for Kansas City wheat and MM, in the first crisis sample, where decreases in positions represent only 33.7% of all positions.

[22] It is not so clear what we should expect for ζ_0^+. In theory, it might be negative, since, when financial traders increase their positions in futures markets consecutively to a fall in the VIX, they bring liquidity to the market. However, it is not obvious at all that, in trouble times, financial traders would react to a fall in the VIX by immediately reinvesting in commodity futures markets.

7 and 8 display our summarized results for Eqs. (11) and (12), respectively.[23]

Several interesting findings emerge. We should be cautious, however, as the share of insignificant coefficients for the volatility is far more important than for returns. The following comments necessarily focus on significant results. (i) Overall, our results question the stabilizing role of speculators. More often than not, the estimation of ζ_0 in Eq. (9) gives a negative coefficient for CIT, while results are mixed for MM. Similar evidence of negative coefficients in the literature served as a claim to assert that financial traders had a smoothing effect on prices. However, results of Eq. (11) show that, in a vast majority of cases, it is due to the coefficient on $pos_t^{i,-}$ being significantly negative, while the coefficient on $pos_t^{i,+}$ is, simultaneously, either insignificant or significantly positive but at a lower magnitude.[24] This distinction is important as it does not necessarily comfort the traditional theory that a larger involvement of speculators fosters stabilization. The latter would have implied ζ_0^+ to be negative. A negative ζ_0^+ would have been a clear sign that an increase in financial traders' open interest brings liquidity and information to the market, and stabilizes prices. Yet, ζ_0^+ is much more often significantly positive than significantly negative.[25]

A negative ζ_0^- is harder to interpret. On the one hand, it could be seen as consistent with the stabilizing theory, in the sense that, when financial traders diminish their open interest, they reduce liquidity in the market, and volatility increases. On the other hand, in conjunction with the fact that ζ_0^+ is more often positive than negative, a negative ζ_0^- adds to the destabilizing role of financial traders. We would have expected this effect to be stronger during the crisis, since financial traders may be forced to liquidate positions. It doesn't seem

[23]Given our findings for Eqs. (9) and (11), we find results of Eq. (10) to be superfluous. Still, they are available upon request.

[24]Specifically, this is the case for Corn, Kansas City wheat, Soybeans, Soybean oil, Feeder cattle, Live cattle (except for MM in the post-crisis sample), Crude oil, Copper, Gold, and Silver. Counter examples only include Chicago wheat for which both ζ_0^- and ζ_0^+ are negatively significant in the pre-crisis sample for CIT; Cocoa for which only ζ_0^+ is negatively significant in the whole sample, and for which both ζ_0^- and ζ_0^+ are negatively significant in the pre-crisis sample for MM; and Sugar, for which CIT seem to have a stabilizing effect in the whole sample and both crisis samples. Evidence goes in both directions for Coffee and Heating oil depending on the sample and the category of traders.

[25]If we consider the whole sample, for CIT, ζ_0^+ is significantly positive for 5 commodities (Corn, Kansas Ciy wheat, Cotton, Live cattle, and Copper) and significantly negative only for Sugar. Similarly, for MM, ζ_0^+ is significantly positive for 6 commodities (Chicago wheat, Corn, Kansas City wheat, Soybean oil, Coffee, and Cotton), and significantly negative only for 2 (Cocoa and Silver).

to be the case, however. Furthermore, it should be noted that there is a considerable level of heterogeneity between commodities.

(ii) Large increases and decreases in PM positions are also associated with high levels of volatility.[26] Moreover, it is often the case that when ζ_0^- is negatively significant for PM, ζ_0^+ is positively significant either for MM or for CIT. And, conversely.[27] This is still quite coherent as futures markets are a zero sum game. If one group of traders takes a short or long position in a market, it means that another group of traders - or several other groups of traders - takes the opposite position. The implication is then similar as for returns: assessing the impact of a particular group of traders on the volatility necessarily requires to identify who drive the trades (with the additional constraint that increases and decreases in positions should be studied separately).

Consider a situation where short hedging demand increases, and financial traders act as counterparties. If the volatility were to increase because of those trades, it wouldn't be imputable to financial hedgers. Besides, it is the role of commodity futures markets to serve as a place where physical actors can hedge their price risk. On the opposite, it would seem more problematic if trades between purely financial actors, or if sudden large unexpected liquidations from a group of traders, were to significantly increase the volatility.[28] Do our results provide evidence of such situations? It is hard to say without identifying who motivates the trades. In a preliminary analysis reported in the *Supplementary material* file, we computed the correlation between Working's (1960) speculative T index - an index meant to measure the level of speculation relative to hedging needs - and realized volatility. This analysis can help us make a few hypotheses. For most commodities, we found the correlations to be negative,

[26] For PM, ζ_0^- is negatively significant at the 5% level in at least two samples for Chicago wheat, Corn, Kansas City wheat, Soybean oil, Coffee, Cotton, Sugar, Lean hogs, Crude oil, and Gold, while it is positively significant at the 10% level in more than one sample only for Cocoa. Likewise, ζ_0^+ is positively significant at the 5% level in at least two samples for Corn, Kansas City wheat, Soybeans, Soybean oil, Cotton, Sugar, Feeder Cattle, Lean hogs, Live cattle, Heating oil, and Gold, and never negatively significant in more than one sample.

[27] There are many such instances. Let us consider two of them. First, for Chicago wheat, in the post-crisis sample, the t-stat for negative change in PM positions is -3.7, while the t-stat for positive change in MM positions is 3.8. Second, for Soybean oil, the t-stat of positive change in PM positions is 4.7 in the first crisis sample, while the t-stats of negative change in CIT and PM positions are respectively -2.2 and -2.0.

[28] It should be noted here that, while the focus of this paper is on purely financial traders, the speculative activity of traders categorized as PM could obviously also be detrimental.

but it sometimes turned significantly positive during the crisis. It is the case for Cotton, for instance. If we focus on the latter, we find negative changes in PM positions to be strongly negatively significant, in the post-crisis sample, while positive changes in CIT and MM positions are positively significant at the 10% and 1% level, respectively. Combined to the fact that Working's speculative T index is negatively correlated with realized volatility, it may be that, in this case, financial traders respond to hedging needs. In both crisis samples, however, negative changes in CIT positions are negatively significant, while positive changes in PM positions are positively significant. At the same time, the correlation between Working T and volatility is positive. In this situation, the behaviour of CIT can be suspected to be the cause of higher volatility. Similar examples during the crisis notably include Soybeans, Soybean oil, and Coffee. Yet, these are only conjectures as long as we haven't identified who motivates the trades.

(iii) The purpose of conditioning the positions of financial traders on shocks to the VIX is precisely to try to isolate the positions they take for their own needs when they face important capital constraints. Unfortunately, our results are not convincing. Assuming the method is adequate, evidence in favour of the hypothesis that liquidations from financial traders participated to higher volatility, would be for ζ_0^- to turn negatively significant (or to become more negatively significant) in Eq. (12). To be coherent with our results in Section 4.1, we only examine the commodities and samples in which financial traders responded to shocks to the VIX by diminishing their positions. For CIT, conditioning positions on the VIX makes ζ_0^- become negatively significant only for Chicago wheat (in both samples) and Corn (in the second crisis sample). On the opposite, significance diminishes for Soybeans and Silver, and disappears, at least in one sample, for Coffee, Live cattle, Natural gas, and Copper. For MM, negative positions conditional on shocks to the VIX become significant for Corn (in the second crisis sample), Feeder cattle (in the first crisis sample), and Live cattle (in both samples). Significance falls for Soybeans and Soybean oil, and disappears for Sugar.

4.4 Trader positions, risk premium, and volatility

We found the method that consists in conditioning positions on the VIX to identify who motivates the trades to be hardly convincing. In a recent paper, Kang et al. (2020) demonstrate how a "speculative" premium coexists with the traditional hedging premium (Keynes, 1930; Hirshleifer, 1990). Specifically, they rely on return predictability to identify who provides and who consumes liquidity, and find commercial traders to be liquidity providers in the short-term. In this section, we rely on a similar approach to determine which of the hedging or speculative premium dominates, and identify who is at the initiative of the trades. We estimate:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \zeta_0 pos^i_{t-j} + \zeta_1 \Delta VIX_{t-1} + \sum_{s=1}^{S} \beta_s x_{s,t} + \epsilon_t, \tag{13}$$

with $j \in (1, 2)$. A significantly positive ζ_0 signals that category of trader i receives a premium for the trades it carried out in prior weeks, that is, it provided liquidity. Conversely, a significantly negative ζ_0 indicates that it consumed liquidity.[29]

We should first point out that the significance of ζ_0 in Eq. (13) is generally much lower than in Eq. (6), as the majority of changes in positions are not significant predictors of returns in $t+1$ or $t+2$. That being said, the results still shed light on some of our earlier findings. (i) In Section 4.2, we found PM to act as contrarians in an overwhelming majority of cases. Results of Eq. (13) show that they may provide liquidity to MM for a number of commodities. Evidence is generally concentrated in the whole and post-crisis samples. In particular, the most conclusive results include Cocoa, Coffee, Live cattle, and Heating oil.[30] We also find similar but weaker evidence for KC wheat and Soybean oil. If we refer to the volatility results of Eq. (11), it suggests that MM have a destabilizing impact on prices for Coffee, Heating oil, Kansas City wheat, and Soybean oil, and a stabilizing impact on Cocoa.[31] (ii) ζ_0 is almost never negative for PM, suggesting that they are very rarely

[29] For the sake of space, summarized results of Eq. (13) are reported in the *Supplementary material* file.

[30] For instance, for Cocoa, ζ_0 appears significantly positive for PM at the 1% level in the whole and post-crisis samples, both for $j = 1$ and $j = 2$, while it appears significantly negative at least at the 10% level in those same samples for MM.

[31] Results are mixed for Live cattle as MM seems to have a destabilizing impact on prices in the whole and pre-crisis samples, while the effect is unclear in the post-crisis sample.

short-term liquidity consumers. Moreover, only for Lean hogs do we find a situation where the risk premium indicates that PM may be liquidity consumers, while their positions are, at the same time, associated with higher volatility. (iii) Surprisingly, ζ_0 also appear positively significant for CIT for an important number of commodities. In contrast with PM, however, it concerns almost exclusively the crisis samples (especially the first one).[32] Chances are that it is a byproduct of the crisis, and not a consequence of CIT being liquidity providers. As a matter of fact, commodity prices plummeted in a short time frame, while, simultaneously, CIT reduced importantly their exposure. (iv) We also find limited evidence that CIT are liquidity consumers in the short term. Furthermore, only for Kansas City wheat and Gold do we find evidence that CIT position is simultaneously a significant predictor of returns and associated with higher volatility. Even then, evidence is rather weak and only concerns the pre-crisis sample. (v) We already mentioned that PM seem to provide liquidity to MM, and that these trades are in majority associated with higher volatility. There are other instances where ζ_0 is negatively significant for MM, but evidence is rather limited. Similarly, ζ_0 is significantly positive in a few cases suggesting that MM may, at times, be liquidity providers. For these occurences, we find coincident evidence that PM may be liquidity consumers for three commodities: Lean hogs (whole and post-crisis samples), Corn (first crisis sample), and Cotton (pre-crisis sample). According to Eq. (11), only for Lean hogs do we find these changes in open interest to be associated with higher volatility.

4.5 Results summary

In accordance with Cheng et al. (2015), we find financial traders to respond to a rise in the VIX by diminishing their positions. It seems however that this behaviour persisted long after the crisis, so that there are continuous rebalancing of who bears risk in commodity markets. It aligns with the explanation of Kang et al. (2020) that hedgers also speculate as they willingly choose to provide liquidity to speculators in exchange of a risk premium.

[32]Specifically, for CIT, ζ_0 is positively significant in at least one sample for Soybean oil, Cocoa, Cotton, Lean hogs, Crude oil, Natural gas, Heating oil, Copper, Gold, and Silver for $j = 1$, and Cocoa, Live cattle, Crude oil, Heating oil, and Copper for $j = 2$. If we exclude crisis samples, however, ζ_0 only turns out to be positively significant for Cocoa in the pre-crisis sample, and for Copper in the whole sample.

Section 4.2 shows that both MM and CIT take positions that are contemporaneously significantly correlated with returns, while hedgers act as contrarians. Even though significance proves to be of a lower degree for CIT than for other groups of traders, this result conflicts with most of the literature. We attribute this outcome to our more recent data.

For our main contribution, we reassess the effect of these different groups of traders on the volatility, and demonstrate why it is necessary to distinguish between the effect of increases and decreases in positions. Similarly as for returns, we often find the link between the variations in a group of traders' open interest and volatility to mirror that of another group of traders. It therefore requires to identify which counterparty motivates the trade. In an effort to reveal the role of speculators during the crisis, we study the effect of conditioning changes in positions to a shock to their risk appetite (as proxied by the VIX), but find overall disappointing results. Instead, we rely on an analysis of the risk premium that reveals how hedgers may in fact provide liquidity to MM. It confirms the assumption that short-term movements in open interest must be largely related to speculative activity. In combinaison with Eq. (11), it provides evidence that MM may introduce noise in the price discovery mechanism of several commodity futures markets. Finally, it should be pointed out that this analysis still lets some questions unanswered as it does not help identify who initiates the trade for every commodity for which we observe excessive volatility.

5 Robustness tests

5.1 Alternative measure for the volatility

In our baseline analysis, we used a measure of volatility based on Parkinson's (1980) intraday range, because some of our samples were too short for the consistent estimation of GARCH type models with covariates. As a first robustness test, we propose to retrieve the conditional volatility from the estimation of a GARCH model on daily returns, and use it as an alternative measure of volatility in Eqs. (9) to (12). Specifically, we proceed as follows: (i) we fit an ARMA(p,q) model on daily returns (3345 points) and retrieve the residuals; (ii) we fit a GARCH(P,Q) model on these residuals; and (iii) we extract the estimated conditional volatility, and keep only Tuesday values as our alternative measure.[33]

Despite variations in the amplitude and significance of the coefficients for some individual commodities, all the general comments in Section 4.3 remain valid. We focus here on the main results. (i) For Eq. (11), there are even less examples for which an increase in the positions of CIT or MM have a significantly negative coefficient. In particular, in the whole sample, there is simply no commodity for which we find a negative and significant coefficient for positive change in CIT and MM positions, while, at the same time, these coefficients are more often positive and significant than in the baseline specification. (ii) Increases and decreases in PM positions are still associated with higher volatility. It is also still the case that, when negative changes in positions are significant for a particular category of traders, then positive changes in positions are often significant for one or several other categories. (iii) Similarly as for the baseline specification, results for Eq. (12) are not conclusive. (iv) That being said, we find results to sometimes differ when we look more closely at individual commodities. For instance, for Cotton, we do not find coefficients on positive changes in PM positions and negative changes in CIT positions to be simultaneously significant during the crisis, as was the case in the baseline specification. It is still the case, however, for Soybeans, Soybean oil, and Coffee (although to a lower extent for Soybean oil and Coffee). We also find more evidence that this result may concern Corn and Live cattle, in particular.

5.2 Alternative measures of risk appetite

In our main analysis, we followed the literature and used the VIX to proxy for shocks to financial traders' risk absorption capacity during the crisis. As explained in Cheng et al. (2015), several papers (Brunnermeier et al., 2009; Coffey et al., 2009; Longstaff et al., 2011) show that shocks to the VIX explain price dynamics in markets not directly related to equity during the crisis, such as currency crashes, violation of covered interest rate parity, and

[33] We select the ARMA and GARCH parameters to minimize the BIC with a maximum of 5 lags for p, q, P, and Q.

fluctuations in sovereign bond spreads. In this section, we replicate our analysis of Section 4 with two other proxies for funding constraints: the capital ratio introduced by He et al. (2017) and Hu et al.'s (2013) noise measure.[34]

5.2.1 Capital ratio

With the aim of testing intermediary asset pricing theories, He et al. (2017) build an aggregate capital ratio for the intermediary sector based on the primary dealers of the Federal Reserve Bank of New York. These large and active institutions serve as counterparties to the Federal Reserve in its implementation of monetary policy, and are likely to be marginal investors in almost all financial markets. The intermediary capital ratio is constructed as follows:

$$\eta_t = \frac{\sum_i MarketEquity_{i,t}}{\sum_i (MarketEquity_{i,t} + BookDebt_{i,t})}, \tag{14}$$

where firm i is a NY Fed primary dealer designee during quarter t. We retrieve the daily capital ratio from Zhiguo He's website, and compute its Tuesday-to-Tuesday change:[35]

$$\Delta\eta_t = \eta_t - \eta_{t-1}.^{36} \tag{15}$$

If we replace the VIX by the capital ratio in Eq. (5), and if the capital ratio of primary dealers is linked to the marginal value of wealth of our different categories of financial traders, then we should expect ζ_0 to be positive. A negative shock to intermediaries' equity capital impairs their risk bearing capacity, which results in liquidating positions, and negative commodity returns. Hence, we should also expect ζ_0 to be positive in Eq. (4) if we substitute the VIX with η_t.

Our results indeed show that $\Delta\eta_t$ is significantly positive to explain returns for most commodities in the whole sample (Chicago wheat, Corn, Kansas City wheat, Soybeans,

[34]For the sake of space, we do not report the results of our robustness tests. They are available upon request.

[35]We would also like to thank Zhiguo He for providing us updated data.

[36]In their analysis, He et al. (2017) use the capital ratio growth rate as the innovation to an AR(1) process divided by the lagged capital ratio. For simplicity, we chose to take the first difference.

Soybean oil, Cocoa, Coffee, Cotton, Live cattle, Crude oil, Natural gas, Heating oil, Copper, and Silver). Interestingly, only MM significantly increase their positions in response to a rise in intermediaries' capital ratio. In the whole sample, it is the case for Chicago wheat, Soybeans, Soybean oil, Coffee, Cotton, Feeder cattle, Crude oil, Heating oil, and Copper. These findings mostly stem from the post-crisis and the second crisis-samples.

In the samples where $\Delta\eta_t$ is significant both to explain returns and changes in MM positions, we find MM positions to be positively associated with returns and volatility. However, we should note that these correlations with returns and volatility are not specific to those samples. In particular, for the volatility, these results are not systematic in the samples where MM positions trade in the same direction as shocks to intermediaries' capital ratio, nor are not limited to them. Furthermore, conditioning positions on changes in the capital ratio of intermediary institutions (Eqs. (8) and (12)) does not help identify stronger effects.

5.2.2 Market illiquidity

Hu et al.'s (2013) noise measure aims to capture illiquidity in overall financial markets using deviations from fundamental value in U.S. Treasury bonds. It relies on the idea that, while, in normal times, institutional investors have abundant capital to exploit arbitrage opportunities, it is no longer the case during market crises. In such periods, arbitrage capital is scarce and deviations are more likely to persist. In practice, Hu et al. (2013) fit a yield curve using the function-based model of Svensson (1994) on daily bonds data between 1 month and 10 years, and they create their noise measure by calculating the root mean squared distance between the observed yields and the model-implied yields for bonds with maturity between 1 year and 10 years. The noise measure is available on Jun Pan's homepage.[37] We compute its Tuesday-to-Tuesday change.

We find aggregated CIT positions and CIT positions in some individual commodities (Corn, Soybeans, Soybean oil, Coffee, Sugar, and Lean hogs) to fall when illiquidity rises, during the crisis. Yet, illiquidity is never significant to explain contemporaneous returns.

[37]http://en.saif.sjtu.edu.cn/junpan/

It may explain why the positions of financial traders, that are often positively significant in crisis samples (Eq. (6)), become insignificant when considered conditional on shocks to illiquidity (Eq. (8)). Surprisingly, however, conditioning negative CIT positions on illiquidity makes a few of them become negatively significant for volatility (Eq. (12)) - or exacerbates the effect if they already were. It is the case, in particular, of Corn, Soybean oil, Lean hogs, Crude oil, Heating oil, and Copper.

6 Conclusion

In this paper, we reassessed the effects of financial traders on two of the main functions of commodity prices: risk sharing and price discovery. Our analysis shows that the shift in risk sharing identified by Cheng et al. (2015) may have persisted well after the global crisis. It suggests, in accordance with recent results of Kang et al. (2020), that short-term fluctuations in open interest may be mostly driven by non-commercial traders' demand for liquidity. In addition, the combination of the facts that changes in CIT positions are often positively correlated with contemporaneous returns since the financial crisis, and that CIT seem to drive prices in response to shocks to the VIX, indicates that CIT may have an impact on prices that is not explained by fundamentals.

In a related analysis of price discovery based on the volatility, we find the role of financial traders to be more complex than often assumed in the literature. We show how the effects of increases and decreases in traders' open interest should be distinguished. In particular, we often find that negative changes in positions increase the volatility, while positive changes have a small positive impact, or no impact at all. In these situations, assuming that the relation between changes in traders' positions and volatility is monotonic on both negative and positive values can be strongly misleading.

Similarly as for returns, to recognize that the behaviour of a category of traders is responsible for high levels of volatility requires to identify who initiates the trades. The combination of our analyses on the risk premium and on the effects of financial traders' positions on the volatility indicates that traditional speculators, as represented by the Managed Money category of the CFTC, may have altered the price discovery process for several commodities.

Our results to the methodology (borrowed to Cheng et al., 2015) that consists in conditioning financial traders' positions on shocks to the VIX are overall mitigated. The method might give different results if it were applied to a more accurate dataset such as the LTRS. Data availability, and the fact that the CFTC necessarily classifies traders by industry affiliation, while economists refer to different trading strategies or behaviours, remain important impediments to the identification of traders' impact on prices.

Financialization has already attracted considerable attention. Yet, given how dynamics in futures markets can spread to spot prices (Sockin and Xiong, 2015; Henderson et al., 2015) and along global commodity chains (Staritz, Newman, Tröster, and Plank, 2018), we feel like measuring how speculation impact commodity prices is still a crucial topic on the research agenda. For this purpose, data availability is still an important issue. As pointed out by Berg (2011): "*Open interest does not move markets*". That is, open interest largely underscores traded volumes. In that regard, we reiterate the need for enhanced transparency from regulatory authorities to foster new research directly based on order flows and transactions.

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Appendix

Table 1: Descriptive statistics

In this table, we report the mean, standard deviation, and p-value of the ADF test, for the returns and volatility of our commodities. Complementary descriptive statistics can be found in the supplementary material to this paper. *, **, and ***, in the ADF column, mean that non-stationarity is rejected at the 10%, 5%, and 1% level, respectively.

Commodity	Returns (y)			Volatility (σ)		
	Mean	SD	ADF	Mean	SD	ADF
Chicago wheat	-0,184	4,521	$< 0,01$***	0,133	0,053	$< 0,01$***
Corn	-0,058	4,100	$< 0,01$***	0,114	0,048	$< 0,01$***
KC wheat	-0,194	4,305	$< 0,01$***	0,120	0,047	$< 0,01$***
Soybeans	0,125	3,281	$< 0,01$***	0,093	0,039	$< 0,01$***
Soybean oil	-0,090	3,257	$< 0,01$***	0,094	0,037	0,036**
Cocoa	0,072	3,913	$< 0,01$***	0,104	0,048	$< 0,01$***
Coffee	-0,179	4,274	$< 0,01$***	0,117	0,042	$< 0,01$***
Cotton	-0,058	3,806	$< 0,01$***	0,105	0,041	$< 0,01$***
Sugar	-0,207	4,541	$< 0,01$***	0,131	0,050	0,034**
Feeder cattle	-0,023	2,269	$< 0,01$***	0,064	0,024	$< 0,01$***
Lean hogs	-0,112	3,593	$< 0,01$***	0,093	0,034	$< 0,01$***
Live cattle	0,006	2,158	$< 0,01$***	0,061	0,019	$< 0,01$***
Crude oil	-0,281	4,842	$< 0,01$***	0,141	0,069	0,042**
Natural gas	-0,688	5,567	$< 0,01$***	0,175	0,068	$< 0,01$***
Heating oil	-0,134	4,195	$< 0,01$***	0,122	0,054	0,238
Copper	-0,041	3,508	$< 0,01$***	0,098	0,049	$< 0,01$***
Gold	0,106	2,442	$< 0,01$***	0,075	0,037	$< 0,01$***
Silver	0,048	4,333	0,010**	0,129	0,066	0,010**

Table 2: Roll schedule

This table details the rolling specifications of our price series. We use conventional letter codes used in tickers to specify delivery month: January (F), February (G), March (H), April (J), May (K), June (M), July (N), August (Q), September (U), October (V), November (X), and December (Z). For instance, for Chicago wheat, "H" in column "1" means that we use the price of the contract that expires in March during January.

Commodity	Ticker	Designated contracts per month											
		1	2	3	4	5	6	7	8	9	10	11	12
Agriculture													
Chi. wheat	W	H	H	K	K	N	N	U	U	Z	Z	Z	H
Corn	C	H	H	K	K	N	N	U	U	Z	Z	Z	H
KC wheat	KW	H	H	K	K	N	N	U	U	Z	Z	Z	H
Soybeans	S	H	H	K	K	N	N	X	X	X	X	F	F
Soybean oil	BO	H	H	K	K	N	N	Z	Z	Z	Z	F	F
Cocoa	CC	H	H	K	K	N	N	U	U	Z	Z	Z	H
Coffee	KC	H	H	K	K	N	N	U	U	Z	Z	Z	H
Cotton	CT	H	K	K	N	N	Z	Z	Z	Z	Z	H	H
Sugar	SB	H	K	K	N	N	V	V	V	H	H	H	H
Feeder cattle	FC	H	H	J	K	Q	Q	Q	U	V	X	F	F
Lean hogs	LH	G	J	J	M	M	N	Q	V	V	Z	Z	G
Live cattle	LC	G	J	J	M	M	Q	Q	V	V	Z	Z	G
Energy													
Crude oil	CL	H	J	K	M	N	Q	U	V	X	Z	F	G
Natural gas	NG	H	J	K	M	N	Q	U	V	X	Z	F	G
Heating oil	HO	H	J	K	M	N	Q	U	V	X	Z	F	G
Metals													
Copper	HG	G	H	J	K	M	N	Q	U	V	X	Z	F
Gold	GC	G	J	J	M	M	Q	Q	Z	Z	Z	Z	G
Silver	SI	H	H	K	K	N	N	U	U	Z	Z	Z	H

Table 3: Shocks to the VIX, returns, and position changes

We report in this table the coefficients and t-stats for contemporaneous change in the VIX in Eqs. (6) and (7). For each commodity, the first line correspond to the results of Eq. (6), while line 2 to 4 correspond to the results of Eq. (7) for CIT, Processors and Merchants, and Managed Money. *, **, and ***, mean that change in the VIX is significant at the 10%, 5%, and 1% levels, respectively.

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Chicago wheat								
Returns	-2,58E-01	-3,62***	2,26E-01	1,41	-4,78E-01	-4,50***	-1,83E-01	-2,27**
CIT	-4,55E+01	-1,01	1,02E+02	0,66	-3,15E+01	-0,45	-9,96E+01	-1,66*
PM	1,04E+02	0,77	-2,07E+03	-5,27***	4,57E+02	3,64***	7,74E+01	0,39
MM	1,06E+01	0,07	2,20E+03	5,58***	-3,48E+02	-2,88***	4,87E+01	0,24
Corn								
Returns	-1,92E-01	-3,04***	4,88E-01	2,22**	-2,54E-01	-2,16**	-1,40E-01	-2,09**
CIT	-3,27E+02	-2,37**	5,08E+02	0,98	-2,17E+02	-1,90*	-3,59E+02	-1,67*
PM	5,07E+02	1,26	-4,18E+03	-1,97**	1,27E+03	1,70*	3,15E+02	0,56
MM	8,55E+01	0,22	3,56E+03	1,96*	-4,90E+02	-0,86	2,83E+01	0,05

(continued)

Table 3 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Kansas City wheat								
Returns	-2,57E-01	-3,95***	6,27E-02	0,35	-3,92E-01	-4,41***	-1,99E-01	-2,58***
CIT	-3,07E+01	-1,74*	-3,39E+01	-0,51	-3,92E+01	-1,66*	-3,80E+01	-1,51
PM	-4,26E+00	-0,06	2,05E+02	0,63	1,34E+02	2,57**	-4,20E+01	-0,40
MM	3,61E+01	0,56	9,13E+01	0,39	-5,66E+01	-1,56	4,50E+01	0,48
Soybeans								
Returns	-2,27E-01	-4,40***	1,38E-01	1,02	-3,32E-01	-2,83***	-1,96E-01	-3,85***
CIT	-1,51E+02	-2,48**	5,38E+01	0,39	-1,45E+02	-1,66*	-1,92E+02	-2,16**
PM	8,98E+02	3,49***	-1,47E+03	-2,53**	5,09E+02	2,73***	1,25E+03	3,27***
MM	-5,55E+02	-2,45**	1,38E+03	2,11**	-2,34E+02	-1,75*	-8,53E+02	-2,48**
Soybean oil								
Returns	-2,70E-01	-4,46***	-2,95E-02	-0,15	-3,33E-01	-2,50**	-2,50E-01	-4,71***
CIT	-4,99E+01	-1,22	2,78E+00	0,05	2,00E+00	0,05	-9,15E+01	-1,55
PM	5,13E+02	2,61***	7,44E+01	0,08	5,82E+01	0,26	7,98E+02	2,62***
MM	-3,12E+02	-2,03**	7,24E+00	0,01	-2,82E+01	-0,26	-4,91E+02	-1,99**

(continued)

Table 3 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Cocoa								
Returns	-1,60E-01	-2,91***	-6,89E-01	-2,22**	-1,21E-01	-1,30	-1,55E-01	-2,48**
CIT	-2,19E+01	-0,85	-4,05E+01	-1,02	1,70E+00	0,05	-4,98E+01	-1,51
PM	9,71E+01	1,45	2,88E+02	1,19	3,37E+01	0,47	1,74E+02	1,95*
MM	-1,65E+01	-0,26	-4,12E+02	-1,24	-1,38E+00	-0,03	-3,58E+01	-0,40
Coffee								
Returns	-2,34E-01	-3,60***	7,19E-02	0,39	-3,20E-01	-4,80***	-1,98E-01	-2,05**
CIT	-5,48E+01	-3,13***	-5,74E+01	-1,75*	-9,48E+01	-3,25***	-3,13E+01	-1,53
PM	1,92E+02	2,57**	-5,39E+02	-2,78***	2,69E+02	2,82***	1,74E+02	1,59
MM	-1,38E+02	-1,61	4,59E+02	2,49**	-1,51E+02	-1,78*	-1,53E+02	-1,21
Cotton								
Returns	-3,12E-01	-7,68***	2,43E-01	1,93*	-3,72E-01	-5,85***	-2,97E-01	-5,42***
CIT	-4,21E+01	-1,61	-1,05E+01	-0,19	-4,54E+01	-0,58	-5,15E+01	-1,69*
PM	3,77E+02	3,49***	-5,74E+02	-1,12	3,74E+02	1,95*	4,57E+02	3,01***
MM	-2,54E+02	-3,16***	2,14E+02	0,11	-2,21E+02	-1,79*	-3,24E+02	-2,82***

(continued)

Table 3 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Sugar								
Returns	-1,67E-01	-2,27**	-1,29E-01	-0,55	-2,32E-01	-1,88*	-1,65E-01	-1,89*
CIT	-2,63E+02	-3,37***	-6,16E+01	-0,38	-2,07E+02	-1,55	-2,65E+02	-2,82***
PM	7,69E+02	3,00***	-7,33E+02	-0,68	1,32E+03	3,39***	6,00E+02	1,87*
MM	-3,07E+02	-1,48	7,43E+02	0,73	-7,85E+02	-2,60***	-1,96E+02	-0,71
Feeder cattle								
Returns	-1,62E-01	-4,04***	-4,51E-02	-0,30	-2,50E-01	-3,80***	-1,30E-01	-3,25***
CIT	2,72E+00	0,52	2,61E+01	1,88*	-2,65E+00	-0,31	5,84E+00	0,93
PM	3,34E+01	1,99**	-2,45E+00	-0,05	4,24E+01	3,52***	2,95E+01	1,11
MM	-2,58E+01	-1,51	-5,34E+01	-0,97	-3,34E+01	-2,05**	-1,36E+01	-0,55
Lean hogs								
Returns	3,21E-02	0,76	1,58E-01	1,01	5,39E-02	0,86	1,09E-02	0,19
CIT	4,62E+01	1,31	-1,93E+01	-0,29	-1,35E+01	-0,62	7,39E+01	1,38
PM	4,44E+01	0,72	2,88E+01	0,10	1,06E+02	1,24	3,15E+01	0,38
MM	-6,38E+00	-0,11	-2,41E+02	-0,68	-1,17E+02	-2,13**	5,23E+01	0,63

(continued)

Table 3 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Live cattle								
Returns	-1,56E-01	-4,95***	-9,63E-02	-0,47	-2,18E-01	-4,15***	-1,36E-01	-3,98***
CIT	-4,58E+01	-1,44	1,08E+01	0,18	-1,67E+02	-3,86***	4,45E+00	0,15
PM	1,74E+02	2,03**	-1,33E+02	-0,39	3,03E+02	3,23***	1,23E+02	1,08
MM	-1,34E+02	-1,63	2,30E+02	0,59	-2,35E+02	-2,33**	-9,27E+01	-0,90
Crude oil								
Returns	-5,04E-01	-5,81***	3,00E-03	0,01	-4,72E-01	-2,32**	-5,59E-01	-6,13***
CIT	-1,01E+03	-3,30***	1,03E+03	1,88*	-1,38E+03	-2,52**	-1,08E+03	-2,92***
PM	3,72E+02	3,13***	-1,27E+03	-1,12	5,42E+02	3,03***	3,21E+02	2,20**
MM	-1,07E+03	-3,49***	-1,19E+02	-0,09	-6,10E+02	-2,05**	-1,40E+03	-3,28***
Natural gas								
Returns	-1,88E-01	-1,94*	-4,01E-01	-1,15	-2,77E-01	-1,61	-1,31E-01	-1,25
CIT	-9,94E+02	-3,58***	6,83E+02	0,42	-1,40E+03	-2,61***	-1,02E+03	-2,99***
PM	6,98E+01	1,03	4,21E+02	1,08	6,09E+01	0,93	5,40E+01	0,54
MM	2,69E+02	1,17	9,59E+02	1,37	7,56E+02	2,33**	5,01E+01	0,17

(continued)

Table 3 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Heating oil								
Returns	-4,15E-01	-5,63***	6,24E-02	0,20	-3,91E-01	-2,12**	-4,39E-01	-7,36***
CIT	-1,03E+03	-3,46***	8,06E+02	0,60	-1,41E+03	-2,51**	-1,08E+03	-3,01***
PM	2,87E+02	3,79***	9,13E+01	0,23	1,55E+02	2,35**	3,42E+02	3,13***
MM	-2,82E+02	-3,90***	4,38E+01	0,08	-1,27E+02	-2,86***	-3,48E+02	-3,37***
Copper								
Returns	-3,00E-01	-4,94***	-1,55E-02	-0,04	-2,69E-01	-2,07**	-3,35E-01	-4,64***
CIT	-1,01E+03	-3,55***	5,61E+02	0,99	-1,27E+03	-2,44**	-1,06E+03	-2,97***
PM	2,56E+02	2,87***	1,12E+01	0,10	5,21E+01	1,07	3,73E+02	3,21***
MM	-3,26E+02	-2,90***	1,27E+02	1,00	-6,32E+01	-1,40	-4,88E+02	-2,83***
Gold								
Returns	-3,33E-02	-0,87	1,36E-01	0,66	-4,37E-02	-0,520	-3,57E-02	-0,89
CIT	-1,00E+03	-3,37***	9,77E+02	1,12	-1,34E+03	-2,09**	-1,06E+03	-2,87***
PM	7,58E+00	0,05	-3,48E+02	-0,52	-1,09E+02	-0,47	5,99E+01	0,28
MM	1,03E+02	0,41	9,73E+02	0,78	1,03E+01	0,05	1,33E+02	0,38

(continued)

Table 3 *(continued)*

	Whole sample		Pre-crisis sample		1^{st} crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Silver								
Returns	-2,91E-01	-4,64***	-1,81E-01	-0,41	-3,16E-01	-2,31**	-3,02E-01	-3,59***
CIT	-1,04E+03	-3,43***	7,95E+02	1,48	-1,30E+03	-1,99**	-1,10E+03	-3,04***
PM	7,80E+01	1,77*	-4,99E+02	-1,15	6,79E+00	0,22	1,40E+02	2,23**
MM	-1,92E+02	-2,14**	4,70E+02	0,86	-4,00E+01	-0,99	-2,98E+02	-2,29**

Table 4: Trader positions and returns

We report in this table the coefficients and t-stats for the change in trader positions in Eq. (8). *, **, and *** mean that a variable is significant at the 10%, 5%, and 1% levels, respectively.

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Chicago wheat								
CIT	1,31E-04	2,57**	-1,22E-04	-0,78	2,70E-04	1,41	1,16E-04	2,18**
PM	-2,45E-04	-14,79***	-3,02E-04	-7,73***	-5,17E-04	-8,08***	-2,27E-04	-15,39***
MM	2,15E-04	14,77***	3,18E-04	6,35***	5,22E-04	5,71***	2,04E-04	15,34***
Corn								
CIT	5,64E-05	2,67***	2,50E-05	0,26	1,98E-04	1,88*	3,39E-05	1,75*
PM	-7,61E-05	-11,90***	-1,26E-04	-9,51***	-1,29E-04	-8,26***	-6,48E-05	-11,92***
MM	6,99E-05	10,76***	1,36E-04	5,28***	1,46E-04	6,39***	6,34E-05	10,78***
Kansas City wheat								
CIT	6,60E-04	6,35***	2,27E-04	0,68	7,06E-04	1,56	6,82E-04	6,23***
PM	-4,57E-04	-11,54***	-5,06E-04	-6,11***	-1,30E-03	-6,47***	-4,45E-04	-11,98***
MM	4,57E-04	11,60***	6,60E-04	6,14***	1,44E-03	7,43***	4,44E-04	11,91***

(continued)

Table 4 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Soybeans								
CIT	1,78E-04	4,92***	5,62E-05	0,31	6,83E-04	6,16***	1,25E-04	3,78***
PM	-1,07E-04	-13,77***	-1,60E-04	-11,43***	-2,96E-04	-11,56***	-9,67E-05	-15,27***
MM	1,10E-04	11,71***	1,91E-04	10,51***	3,29E-04	9,05***	1,03E-04	12,31***
Soybean oil								
CIT	1,74E-04	3,20***	4,12E-04	2,09**	3,67E-04	1,32	1,40E-04	2,78***
PM	-1,50E-04	-20,14***	-1,89E-04	-16,24***	-3,44E-04	-5,89***	-1,39E-04	-25,74***
MM	1,75E-04	18,57***	2,55E-04	14,09***	4,20E-04	4,97***	1,69E-04	19,93***
Cocoa								
CIT	3,71E-04	3,82***	-5,91E-04	-0,84	1,23E-03	3,64***	3,11E-04	3,24***
PM	-3,85E-04	-15,43***	-4,45E-04	-8,56***	-7,32E-04	-7,21***	-3,71E-04	-15,35***
MM	3,87E-04	13,35***	3,69E-04	7,28***	6,47E-04	4,44***	3,97E-04	12,32***
Coffee								
CIT	4,54E-04	2,87***	-5,37E-04	-1,06	8,21E-04	3,45***	4,05E-04	2,18**
PM	-5,57E-04	-22,22***	-5,96E-04	-16,42***	-5,99E-04	-8,93***	-5,46E-04	-18,98***
MM	5,38E-04	16,35***	5,55E-04	13,02***	6,80E-04	7,49***	5,20E-04	14,45***

(continued)

Table 4 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Cotton								
CIT	1,71E-04	2,13**	3,98E-04	1,87*	4,41E-04	1,90*	8,17E-05	0,88
PM	-2,30E-04	-15,19***	-2,62E-04	-6,46***	-2,93E-04	-5,73***	-2,21E-04	-14,85***
MM	2,88E-04	16,12***	3,48E-04	6,40***	4,17E-04	7,55***	2,77E-04	15,65***
Sugar								
CIT	-2,23E-05	-0,84	-1,98E-06	-0,03	1,08E-04	3,02***	-6,36E-05	-1,91*
PM	-1,10E-04	-12,70***	-1,55E-04	-3,38***	-1,44E-04	-5,87***	-1,00E-04	-12,27***
MM	1,32E-04	11,22***	2,23E-04	3,20***	2,03E-04	7,71***	1,21E-04	11,26***
Feeder cattle								
CIT	5,63E-04	2,48**	3,97E-05	0,04	-1,84E-04	-0,49	7,24E-04	2,71***
PM	-1,01E-03	-9,52***	-1,86E-03	-5,20***	-1,24E-03	-4,54***	-9,68E-04	-7,89***
MM	8,09E-04	12,83***	9,49E-04	3,70***	7,51E-04	3,18***	8,22E-04	11,89***
Lean hogs								
CIT	1,40E-04	1,99**	-2,07E-04	-0,89	1,38E-05	0,09	1,59E-04	2,07**
PM	-3,04E-04	-12,81***	-4,86E-04	-6,02***	-4,07E-04	-7,14***	-2,90E-04	-10,94***
MM	3,13E-04	10,93***	3,77E-04	7,19***	5,99E-04	7,80***	2,96E-04	9,28***

(continued)

Table 4 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Live cattle								
CIT	2,19E-04	4,69***	-1,89E-05	-0,15	2,39E-04	2,20**	2,21E-04	4,29***
PM	-1,49E-04	-11,89***	-2,75E-04	-3,10***	-2,49E-04	-6,29***	-1,34E-04	-11,11***
MM	1,42E-04	11,52***	2,94E-04	5,60***	2,29E-04	6,29***	1,30E-04	10,13***
Crude oil								
CIT	4,52E-05	3,17***	5,81E-05	1,61	1,39E-04	4,04***	2,45E-05	1,92*
PM	-5,50E-05	-2,87***	-1,42E-04	-6,85***	-5,33E-05	-1,13	-3,88E-05	-1,58
MM	1,13E-04	13,30***	9,85E-05	2,98***	1,52E-04	4,21***	1,12E-04	13,01***
Natural gas								
CIT	1,17E-05	1,13	-5,22E-06	-0,09	9,15E-05	2,76***	-4,67E-06	-0,51
PM	-2,33E-04	-6,00***	-6,54E-04	-6,55***	-6,18E-04	-4,55***	-1,74E-04	-4,89***
MM	9,41E-05	7,99***	6,63E-05	0,74	-2,39E-04	-7,95***	1,19E-04	14,10***
Heating oil								
CIT	3,21E-05	2,77***	4,75E-05	1,29	1,24E-04	4,69***	9,40E-06	0,97
PM	-3,02E-04	-13,42***	-3,99E-04	-10,44***	-4,66E-04	-3,86***	-2,81E-04	-11,77***
MM	3,17E-04	12,29***	4,50E-04	10,47***	4,90E-04	3,09***	3,01E-04	11,10***

(continued)

Table 4 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Copper								
CIT	4,08E-05	4,05***	9,41E-05	1,58	8,98E-05	5,23***	2,53E-05	2,69***
PM	-3,15E-04	-10,57***	-1,43E-03	-5,05***	-8,76E-04	-4,13***	-3,11E-04	-12,24***
MM	1,98E-04	11,29***	1,93E-03	9,20***	9,62E-04	4,56***	1,93E-04	13,80***
Gold								
CIT	1,96E-05	4,26***	7,90E-05	2,73***	3,23E-05	1,99**	1,31E-05	2,79***
PM	-1,40E-04	-15,32***	-1,64E-04	-6,07***	-2,16E-04	-10,20***	-1,17E-04	-16,01***
MM	7,89E-05	10,89***	1,10E-04	3,91***	2,04E-04	7,74***	6,69E-05	11,74***
Silver								
CIT	3,73E-05	3,83***	7,30E-05	1,53	6,89E-05	3,14***	2,80E-05	2,54**
PM	-6,48E-04	-10,49***	-9,27E-04	-5,51***	-1,13E-03	-9,91***	-5,69E-04	-9,08***
MM	2,83E-04	7,79***	7,70E-04	5,73***	9,65E-04	7,84***	2,40E-04	8,30***

Table 5: Trader positions conditional on shocks to the VIX and returns

We report in this table the coefficients and t-stats for the change in trader positions conditional on shocks to the VIX in Eq. (10). *, **, *** Mean that a variable is significant at the 10%, 5%, and 1% levels, respectively.

	1^{st} crisis sample		2^{nd} crisis sample		1^{st} crisis sample		2^{nd} crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
	Chicago wheat				*Soybean oil*			
CIT	1,52E-02	4,68***	8,27E-03	6,82***	-1,66E-01	-2,76***	5,73E-03	3,86***
MM	1,38E-03	5,38***	1,20E-03	6,49***	1,18E-02	2,61***	1,01E-03	4,27***
	Corn				*Cocoa*			
CIT	1,17E-03	2,52**	1,09E-03	4,86***	-7,09E-02	-1,30	1,57E-01	2,47**
MM	5,18E-04	2,37**	4,17E-04	4,20***	8,77E-02	1,37	1,68E-02	2,54**
	Kansas City wheat				*Coffee*			
CIT	1,00E-02	4,55***	1,23E-02	6,13***	3,37E-03	5,36***	4,67E-03	4,58***
MM	6,93E-03	4,91***	4,84E-03	6,19***	2,11E-03	5,28***	1,55E-03	4,58***
	Soybeans				*Cotton*			
CIT	2,30E-03	3,03***	2,11E-03	3,78***	8,21E-03	5,56***	9,91E-03	7,27***
MM	1,42E-03	2,82***	4,83E-04	3,89***	1,68E-03	5,85***	1,66E-03	7,31***

(continued)

Table 5 *(continued)*

	1^{st} crisis sample		2^{nd} crisis sample		1^{st} crisis sample		2^{nd} crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
	Sugar				*Natural gas*			
CIT	1,12E-03	2,02**	8,34E-04	2,15**	1,98E-04	2,03**	2,32E-04	2,40**
MM	2,95E-04	2,02**	3,26E-04	1,96**	-3,66E-04	-2,01**	-5,21E-04	-2,29**
	Feeder cattle				*Heating oil*			
CIT	9,46E-02	3,80***	-7,25E-02	-3,43***	2,77E-04	2,70***	3,26E-04	4,27***
MM	7,49E-03	3,74***	8,08E-03	3,68***	3,08E-03	2,15**	1,51E-03	3,68***
	Lean hogs				*Copper*			
CIT	-3,98E-03	-0,84	-5,07E-03	-0,18	2,11E-04	2,06**	2,86E-04	4,18***
MM	-4,61E-04	-0,90	1,44E-04	0,18	4,25E-03	2,71***	2,87E-03	3,96***
	Live cattle				*Gold*			
CIT	1,31E-03	4,18***	1,61E-03	4,61***	3,26E-05	0,51	6,42E-05	1,402
MM	9,29E-04	4,19***	7,81E-04	4,59***	-4,26E-03	-0,47	5,40E-04	1,25
	Crude oil				*Silver*			
CIT	3,43E-04	2,27**	4,00E-04	4,73***	2,42E-04	2,44**	2,88E-04	4,04***
MM	7,74E-04	2,32**	4,07E-04	5,44***	7,91E-03	2,64***	4,11E-03	3,97***

Table 6: Trader positions and volatility

We report in this table the coefficients and t-stats for the change in trader positions in Eq. (11). *, **, and *** mean that a variable is significant at the 10%, 5%, and 1% levels, respectively.

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Chicago wheat								
CIT	-2,55E-07	-0,61	-5,29E-06	-4,13***	-3,54E-06	-1,26	1,56E-07	0,43
PM	-3,22E-07	-2,70***	6,90E-07	2,58***	-4,18E-07	-0,48	-3,56E-07	-2,91***
MM	3,60E-07	3,24***	-2,97E-07	-1,15	6,76E-07	0,88	3,80E-07	3,27***
Corn								
CIT	1,26E-07	0,84	-1,65E-06	-3,49***	-1,35E-06	-2,10**	3,87E-07	2,87***
PM	1,22E-08	0,31	-9,99E-08	-0,70	1,73E-07	1,79*	-5,77E-09	-0,13
MM	9,88E-09	0,26	2,20E-07	1,13	-4,44E-08	-0,33	1,21E-08	0,28
Kansas City wheat								
CIT	1,22E-06	1,46	-6,59E-06	-3,49***	1,02E-06	0,22	1,54E-06	1,69*
PM	-3,57E-07	-1,53	4,78E-07	0,45	-9,23E-07	-0,52	-4,95E-07	-1,96*
MM	6,70E-07	2,33**	-9,55E-07	-0,51	3,11E-06	1,34	7,48E-07	2,38**

(continued)

Table 6 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Soybeans								
CIT	-3,02E-08	-0,13	2,44E-06	1,79*	-3,13E-06	-2,84***	1,86E-07	0,89
PM	7,76E-08	1,44	-3,55E-07	-1,19	1,12E-06	4,01***	3,99E-08	0,79
MM	-8,12E-08	-1,46	3,69E-07	1,00	-1,38E-06	-2,92***	-5,41E-08	-1,02
Soybean oil								
CIT	-2,33E-07	-0,59	-8,36E-08	-0,05	-4,31E-06	-2,50**	2,71E-07	0,79
PM	1,30E-07	1,72*	-4,57E-07	-1,74*	5,66E-07	1,89*	7,67E-08	1,07
MM	-1,01E-07	-1,16	9,13E-07	2,30**	-3,18E-07	-0,51	-7,88E-08	-0,94
Cocoa								
CIT	-7,25E-07	-1,05	2,06E-06	0,41	-3,78E-06	-1,13	-6,01E-07	-0,89
PM	7,46E-07	2,90***	1,73E-06	2,76***	8,48E-07	0,40	7,52E-07	3,28***
MM	-6,51E-07	-2,47**	-1,64E-06	-3,12***	2,06E-07	0,11	-6,85E-07	-2,50**
Coffee								
CIT	-2,18E-06	-2,09**	-1,23E-05	-3,94***	-6,20E-06	-2,33**	-1,18E-06	-1,02
PM	-7,55E-07	-2,36**	-2,81E-06	-4,38***	1,06E-06	1,13	-8,67E-07	-2,57**
MM	8,77E-07	2,93***	3,09E-06	5,33***	-9,49E-07	-0,87	9,11E-07	2,91***

(continued)

Table 6 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Cotton								
CIT	-1,67E-07	-0,33	2,72E-06	1,22	-1,73E-06	-1,16	4,66E-07	0,95
PM	-1,29E-07	-1,09	-8,24E-08	-0,29	1,53E-07	0,58	-2,09E-07	-1,51
MM	1,78E-07	1,13	4,69E-08	0,12	-1,58E-07	-0,39	2,26E-07	1,33
Sugar								
CIT	-4,69E-07	-2,63***	-8,30E-07	-1,17	-1,07E-06	-3,27***	-3,31E-07	-1,34
PM	6,83E-08	1,00	-3,73E-07	-1,16	4,77E-07	1,70*	3,46E-08	0,52
MM	-2,83E-08	-0,42	7,28E-07	2,12**	-5,48E-07	-1,38	-1,65E-08	-0,26
Feeder cattle								
CIT	6,65E-09	0,00	-9,53E-07	-0,13	2,26E-06	1,00	-3,23E-07	-0,15
PM	2,01E-06	3,20***	1,64E-06	0,59	3,77E-06	2,27**	1,82E-06	2,61***
MM	-1,88E-06	-3,82***	2,70E-06	1,51	-1,57E-06	-1,16	-2,16E-06	-3,85***
Lean hogs								
CIT	-3,11E-07	-0,81	3,54E-07	0,27	-1,76E-07	-0,09	-3,75E-07	-0,93
PM	-2,42E-08	-0,13	-2,17E-06	-3,92***	-2,09E-07	-0,40	9,18E-08	0,48
MM	4,31E-08	0,25	1,95E-06	4,68***	-4,02E-07	-0,56	-6,38E-08	-0,38

(continued)

Table 6 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Live cattle								
CIT	-6,17E-07	-1,78*	2,00E-06	1,48	-1,31E-06	-2,04**	-5,44E-07	-1,41
PM	3,38E-07	3,92***	-1,31E-06	-2,22**	1,03E-07	0,33	3,95E-07	4,31***
MM	-3,21E-07	-4,17***	1,35E-06	2,44**	-8,04E-08	-0,28	-3,92E-07	-4,84***
Crude oil								
CIT	-2,80E-08	-0,33	-1,04E-07	-0,36	-5,15E-10	-0,00	-2,88E-08	-0,33
PM	-1,46E-07	-0,97	-5,73E-07	-1,68*	6,17E-08	0,23	-1,66E-07	-0,88
MM	-1,04E-07	-1,67*	-3,18E-08	-0,20	7,69E-08	0,34	-7,03E-08	-0,99
Natural gas								
CIT	1,11E-08	0,11	1,86E-06	2,83***	8,44E-08	0,24	-1,06E-07	-1,17
PM	-1,70E-07	-0,72	-5,06E-07	-0,47	-6,93E-07	-0,51	-1,13E-07	-0,53
MM	7,63E-08	0,93	-3,10E-07	-0,40	4,43E-07	0,94	7,76E-08	0,96
Heating oil								
CIT	4,94E-08	0,77	-5,52E-08	-0,32	4,70E-08	0,22	5,11E-08	0,72
PM	3,28E-07	2,17**	1,41E-07	0,44	5,32E-07	0,82	2,73E-07	1,62
MM	-4,15E-07	-2,46**	-5,31E-08	-0,15	-1,09E-06	-1,41	-3,19E-07	-1,69*

(continued)

Table 6 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Copper								
CIT	-9,21E-08	-1,05	-1,05E-06	-1,81*	-4,09E-07	-1,80*	3,06E-08	0,43
PM	-4,65E-08	-0,27	4,66E-06	2,17**	-3,00E-06	-1,33	6,23E-08	0,34
MM	1,87E-07	1,62	-1,42E-06	-0,47	1,49E-06	0,68	1,55E-07	1,33
Gold								
CIT	-8,28E-08	-1,11	-4,21E-07	-1,96**	-5,00E-07	-1,76*	-8,81E-09	-0,20
PM	3,76E-08	0,27	5,45E-07	1,74*	-4,94E-07	-0,87	1,25E-07	1,23
MM	-4,94E-08	-1,02	-3,30E-07	-1,67*	2,55E-07	0,58	-5,49E-08	-1,23
Silver								
CIT	-2,10E-07	-1,49	-1,00E-06	-2,74***	-7,62E-07	-1,97**	-8,05E-08	-0,64
PM	1,25E-06	1,44	2,78E-06	1,55	1,00E-06	0,48	1,24E-06	1,26
MM	-3,32E-07	-1,39	-2,92E-06	-2,49**	-3,55E-06	-2,34**	-1,41E-07	-0,62

Table 7: Trader positions, asymmetry, and volatility

We report in this table the coefficients and t-stats for the change in trader positions in Eq. (13). *, **, and *** mean that a variable is significant at the 10%, 5%, and 1% levels, respectively.

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Chicago wheat								
CIT pos_t^-	-1,02E-06	-1,56	-3,98E-06	-2,01**	-6,44E-06	-1,50	-6,38E-07	-1,35
CIT pos_t^+	6,43E-07	0,95	-7,37E-06	-2,41**	2,86E-07	0,14	1,05E-06	1,48
PM pos_t^-	-7,47E-07	-3,27***	-5,72E-07	-1,10	-1,43E-06	-1,17	-8,81E-07	-3,69***
PM pos_t^+	1,89E-07	0,85	1,89E-06	2,76***	5,75E-07	0,25	2,88E-07	1,18
MM pos_t^-	4,86E-08	0,24	-2,07E-06	-2,24**	2,20E-06	1,49	-1,68E-07	-0,84
MM pos_t^+	6,05E-07	2,62***	1,22E-06	2,62***	-8,31E-07	-0,54	8,09E-07	3,82***

(continued)

Table 7 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Corn								
CIT pos_t^-	-4,30E-07	-1,72*	-2,36E-06	-3,34***	-1,19E-06	-1,50	-6,90E-08	-0,34
CIT pos_t^+	6,79E-07	2,86***	2,09E-07	0,23	-1,53E-06	-1,12	7,97E-07	3,33***
PM pos_t^-	-2,01E-07	-3,15***	-1,06E-06	-3,57***	4,47E-07	1,68*	-2,44E-07	-3,91***
PM pos_t^+	2,42E-07	2,86***	5,93E-07	3,29***	-7,05E-08	-0,45	2,68E-07	2,83***
MM pos_t^-	-1,18E-07	-1,43	-5,89E-07	-2,58**	1,67E-07	0,50	-1,74E-07	-2,09**
MM pos_t^+	1,19E-07	2,01**	1,08E-06	3,08***	-2,44E-07	-0,67	1,67E-07	2,86***
Kansas City wheat								
CIT pos_t^-	-2,43E-07	-0,15	-2,97E-05	-11,05***	-1,37E-06	-0,19	-9,48E-07	-0,54
CIT pos_t^+	2,46E-06	2,07**	4,95E-06	2,71***	3,26E-06	0,56	3,67E-06	2,89***
PM pos_t^-	-1,56E-06	-3,89***	-4,49E-06	-3,83***	-4,13E-06	-1,14	-2,05E-06	-4,94***
PM pos_t^+	9,61E-07	2,30**	5,25E-06	2,87***	1,77E-06	0,60	1,20E-06	2,53**
MM pos_t^-	-2,93E-07	-0,58	-6,85E-06	-5,24***	3,00E-06	0,59	-7,90E-07	-1,57
MM pos_t^+	1,50E-06	2,87***	5,45E-06	3,62***	3,23E-06	0,85	2,07E-06	4,04***

(continued)

Table 7 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Soybeans								
CIT pos_t^-	-3,33E-07	-0,72	-4,94E-06	-1,54	-4,59E-06	-3,20***	9,47E-08	0,23
CIT pos_t^+	3,03E-07	0,90	6,30E-06	2,51**	-1,27E-06	-0,71	2,83E-07	0,92
PM pos_t^-	-1,35E-07	-1,52	-5,90E-07	-1,21	3,17E-07	0,47	-2,03E-07	-2,33**
PM pos_t^+	3,01E-07	3,02***	2,94E-08	0,06	1,74E-06	3,03***	2,98E-07	3,10***
MM pos_t^-	-2,53E-07	-2,48**	-2,88E-07	-0,60	-2,62E-06	-3,21***	-2,54E-07	-2,48**
MM pos_t^+	7,32E-08	0,74	8,03E-07	1,35	4,04E-08	0,04	1,24E-07	1,28
Soybean oil								
CIT pos_t^-	-9,62E-07	-1,07	-6,98E-06	-2,70***	-8,32E-06	-2,85***	2,47E-07	0,33
CIT pos_t^+	3,30E-07	0,66	5,28E-06	2,39**	1,79E-06	0,58	2,88E-07	0,60
PM pos_t^-	-4,80E-07	-4,12***	-1,12E-06	-3,94***	-1,31E-06	-1,82*	-4,73E-07	-4,34***
PM pos_t^+	7,48E-07	5,42***	3,98E-07	1,03	1,96E-06	4,05***	6,39E-07	5,26***
MM pos_t^-	-6,40E-07	-3,63***	-7,37E-07	-1,50	-8,71E-07	-0,83	-7,00E-07	-4,19***
MM pos_t^+	3,89E-07	2,69***	2,22E-06	5,39***	4,60E-07	0,49	4,81E-07	3,63***

(continued)

Table 7 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Cocoa								
CIT pos_t^-	-2,76E-06	-2,43**	-7,87E-06	-0,61	-8,11E-06	-1,65*	-2,68E-06	-2,47**
CIT pos_t^+	1,00E-06	0,91	6,42E-06	1,53	5,01E-07	0,09	1,17E-06	1,04
PM pos_t^-	7,47E-07	1,76*	1,92E-06	2,93***	-2,90E-06	-0,98	8,11E-07	1,79*
PM pos_t^+	7,44E-07	1,50	1,44E-06	1,51	4,23E-06	0,92	7,03E-07	1,61
MM pos_t^-	-5,76E-07	-1,10	-1,68E-06	-1,83*	-1,50E-06	-0,29	-7,42E-07	-1,48
MM pos_t^+	-7,29E-07	-2,07**	-1,61E-06	-3,03***	2,07E-06	0,89	-6,22E-07	-1,45
Coffee								
CIT pos_t^-	-4,28E-06	-2,58***	-1,92E-05	-2,33**	-1,75E-05	-2,87***	-2,44E-06	-1,61
CIT pos_t^+	2,88E-08	0,02	-9,46E-06	-3,11***	1,28E-06	0,36	3,24E-07	0,14
PM pos_t^-	-2,00E-06	-3,49***	-4,53E-06	-4,83***	-1,84E-06	-1,26	-1,71E-06	-2,66***
PM pos_t^+	5,74E-07	1,06	-3,56E-07	-0,38	3,73E-06	2,10**	5,26E-08	0,10
MM pos_t^-	1,94E-07	0,36	1,85E-06	1,75*	-3,76E-06	-1,47	5,13E-07	0,97
MM pos_t^+	1,46E-06	2,87***	3,88E-06	4,64***	1,38E-06	1,02	1,25E-06	2,18**

(continued)

Table 7 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Cotton								
CIT pos_t^-	-1,95E-06	-2,33**	1,64E-06	0,91	-4,63E-06	-3,58***	-4,34E-07	-0,55
CIT pos_t^+	1,67E-06	2,06**	3,48E-06	0,99	9,58E-07	0,57	1,43E-06	1,70*
PM pos_t^-	-8,11E-07	-4,28***	1,91E-07	0,34	-6,26E-07	-1,42	-8,11E-07	-3,54***
PM pos_t^+	6,14E-07	2,87***	-4,59E-07	-0,79	1,03E-06	1,96*	4,44E-07	1,93*
MM pos_t^-	-4,63E-07	-1,70*	3,76E-07	0,43	-7,44E-07	-0,85	-4,04E-07	-1,53
MM pos_t^+	8,02E-07	3,16***	-1,91E-07	-0,30	4,68E-07	0,60	8,44E-07	2,96***
Sugar								
CIT pos_t^-	-3,93E-07	-1,18	-2,27E-06	-0,71	-1,00E-06	-1,91*	-3,19E-07	-0,73
CIT pos_t^+	-5,28E-07	-1,80*	-4,93E-07	-0,65	-1,13E-06	-1,86*	-3,41E-07	-0,85
PM pos_t^-	-2,36E-07	-2,64***	-9,88E-07	-2,94***	-1,06E-07	-0,40	-1,69E-07	-1,76*
PM pos_t^+	3,95E-07	2,62***	3,71E-07	0,58	1,15E-06	2,63***	2,45E-07	1,88*
MM pos_t^-	-2,13E-07	-1,80*	-4,54E-07	-0,53	-1,86E-06	-3,76***	-8,74E-08	-0,88
MM pos_t^+	1,53E-07	1,36	1,61E-06	4,16***	6,51E-07	1,27	5,40E-08	0,46

(continued)

Table 7 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Feeder cattle								
CIT pos_t^-	-4,58E-06	-1,68*	9,69E-08	0,01	-1,76E-06	-0,41	-5,83E-06	-1,90*
CIT pos_t^+	5,34E-06	1,61	-1,77E-06	-0,26	1,30E-05	1,18	5,33E-06	1,44
PM pos_t^-	-9,33E-07	-0,69	2,98E-06	0,77	4,79E-06	1,24	-1,89E-06	-1,41
PM pos_t^+	4,60E-06	3,72***	5,99E-08	0,01	2,92E-06	0,74	5,09E-06	3,87***
MM pos_t^-	-3,98E-06	-4,81***	3,07E-06	1,08	-2,27E-06	-0,79	-4,61E-06	-5,01***
MM pos_t^+	3,82E-07	0,47	2,33E-06	0,91	-6,78E-07	-0,26	4,02E-07	0,43
Lean hogs								
CIT pos_t^-	-1,69E-06	-2,25**	-4,49E-07	-0,19	-1,22E-06	-0,28	-1,65E-06	-2,15**
CIT pos_t^+	9,14E-07	1,50	1,54E-06	0,43	9,41E-07	0,35	7,27E-07	1,18
PM pos_t^-	-6,13E-07	-2,31**	-3,52E-06	-3,34***	-1,21E-07	-0,12	-5,28E-07	-1,82*
PM pos_t^+	7,13E-07	2,36**	-6,96E-07	-1,03	-2,99E-07	-0,39	8,84E-07	2,64***
MM pos_t^-	-2,95E-07	-0,97	6,03E-07	0,63	-2,71E-06	-2,10**	-2,13E-07	-0,66
MM pos_t^+	3,52E-07	1,20	2,82E-06	4,19***	1,92E-06	1,20	7,60E-08	0,25

(continued)

Table 7 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Live cattle								
CIT pos_t^-	-2,30E-06	-4,15***	-2,43E-06	-2,00**	-3,13E-06	-3,29***	-1,83E-06	-2,72***
CIT pos_t^+	1,26E-06	2,45**	3,69E-06	2,41**	1,77E-06	2,21**	8,04E-07	1,34
PM pos_t^-	1,29E-07	0,89	-2,03E-06	-1,71*	7,19E-08	0,15	2,03E-07	1,37
PM pos_t^+	5,37E-07	3,00***	-3,93E-07	-0,30	1,33E-07	0,20	5,77E-07	3,08***
MM pos_t^-	-4,28E-07	-2,86***	-1,34E-06	-2,04**	3,07E-07	0,52	-4,88E-07	-2,95***
MM pos_t^+	-2,02E-07	-1,49	3,98E-06	4,61***	-5,15E-07	-0,90	-2,84E-07	-2,03**
Crude oil								
CIT pos_t^-	-1,34E-07	-0,87	-7,70E-08	-0,16	7,56E-07	2,09**	-2,77E-07	-1,70*
CIT pos_t^+	8,21E-08	0,59	-1,33E-07	-0,29	-9,31E-07	-2,38**	2,17E-07	1,63
PM pos_t^-	-5,72E-07	-2,03**	-1,20E-06	-2,62***	1,61E-07	0,22	-7,62E-07	-2,12**
PM pos_t^+	2,58E-07	1,09	2,99E-07	0,86	-3,26E-08	-0,06	3,32E-07	1,15
MM pos_t^-	-3,45E-07	-2,98***	5,45E-07	1,36	9,63E-07	1,42	-4,65E-07	-3,69***
MM pos_t^+	1,36E-07	1,22	-4,16E-07	-1,55	-9,18E-07	-1,32	3,26E-07	2,85***

(continued)

Table 7 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Natural gas								
CIT pos_t^-	-2,27E-07	-1,57	8,12E-07	1,00	-6,79E-07	-1,60	-2,48E-07	-1,60
CIT pos_t^+	2,64E-07	1,29	2,90E-06	2,30**	1,05E-06	1,10	3,48E-08	0,24
PM pos_t^-	3,94E-07	1,19	-1,67E-06	-0,70	-4,72E-07	-0,14	3,46E-07	1,17
PM pos_t^+	-8,04E-07	-2,04**	2,96E-07	0,20	-9,25E-07	-0,41	-6,51E-07	-1,62
MM pos_t^-	2,83E-07	1,47	2,00E-06	2,37**	1,38E-07	0,18	1,63E-07	0,82
MM pos_t^+	-1,03E-07	-0,93	-3,81E-06	-3,39***	7,15E-07	1,41	3,31E-09	0,03
Heating oil								
CIT pos_t^-	-4,41E-08	-0,38	3,26E-07	1,02	4,64E-07	1,48	-1,31E-07	-1,07
CIT pos_t^+	1,47E-07	1,14	-4,53E-07	-1,16	-4,56E-07	-1,60	2,31E-07	1,72*
PM pos_t^-	-1,15E-07	-0,42	9,71E-07	1,49	2,07E-07	0,16	-4,13E-07	-1,34
PM pos_t^+	7,31E-07	2,86***	-8,69E-07	-2,02**	8,43E-07	0,97	8,84E-07	3,28***
MM pos_t^-	-4,49E-07	-1,61	4,89E-07	0,80	-7,47E-07	-0,73	-5,93E-07	-1,94*
MM pos_t^+	-3,75E-07	-1,46	-5,22E-07	-0,91	-1,48E-06	-1,12	9,04E-09	0,03

(continued)

Table 7 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Copper								
CIT pos_t^-	-3,54E-07	-2,35**	-1,54E-06	-1,29	-6,74E-07	-1,66*	-1,56E-07	-1,19
CIT pos_t^+	1,86E-07	1,96*	-5,15E-07	-0,60	-7,11E-08	-0,25	2,13E-07	2,05**
PM pos_t^-	5,48E-07	1,90*	2,17E-06	0,54	5,60E-07	0,17	1,73E-07	0,63
PM pos_t^+	-6,58E-07	-1,77*	7,99E-06	2,31**	-7,66E-06	-1,58	-5,14E-08	-0,14
MM pos_t^-	5,79E-07	2,70***	-1,22E-05	-2,17**	9,39E-08	0,02	3,32E-07	1,62
MM pos_t^+	-2,00E-07	-0,99	6,65E-06	1,64	2,86E-06	0,73	-1,99E-08	-0,11
Gold								
CIT pos_t^-	-2,53E-07	-1,55	-1,27E-06	-3,11***	-1,26E-06	-3,34***	4,96E-08	0,52
CIT pos_t^+	9,56E-08	1,17	4,85E-07	1,71*	4,62E-07	1,83*	-6,69E-08	-1,13
PM pos_t^-	-7,69E-07	-2,60***	-1,37E-07	-0,43	-2,11E-06	-2,14**	-3,93E-07	-2,72***
PM pos_t^+	7,90E-07	4,05***	1,12E-06	1,61	1,18E-06	2,61***	6,05E-07	3,05***
MM pos_t^-	-2,27E-07	-2,36**	-9,05E-07	-2,17**	-8,24E-07	-2,47**	-1,76E-07	-1,66*
MM pos_t^+	1,30E-07	1,41	1,87E-07	1,21	1,21E-06	1,28	6,60E-08	0,98

(continued)

Table 7 *(continued)*

	Whole sample		Pre-crisis sample		Crisis sample		Post-crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Silver								
CIT pos_t^-	-6,24E-07	-2,03**	-1,97E-06	-3,28***	-1,85E-06	-3,37***	-2,01E-07	-0,76
CIT pos_t^+	2,24E-07	1,57	3,23E-08	0,05	5,36E-07	1,22	3,88E-08	0,30
PM pos_t^-	-2,88E-07	-0,30	-4,00E-07	-0,12	2,60E-06	0,74	-3,64E-07	-0,34
PM pos_t^+	2,64E-06	1,33	5,55E-06	1,63	-6,21E-07	-0,11	2,70E-06	1,16
MM pos_t^-	-8,00E-08	-0,20	-4,91E-06	-3,04***	-6,33E-06	-2,15**	2,83E-07	0,79
MM pos_t^+	-6,07E-07	-1,87*	1,14E-06	0,51	-4,97E-07	-0,27	-5,89E-07	-1,83*

Table 8: Trader positions conditional on shocks to the VIX, asymmetry, and volatility

We report in this table the coefficients and t-stats for the change in trader positions conditional on shocks to the VIX in Eq. (14). *, **, and *** mean that a variable is significant at the 10%, 5%, and 1% levels, respectively.

	1^{st} crisis sample		2^{nd} crisis sample		1^{st} crisis sample		2^{nd} crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
	Chicago wheat				*Kansas City wheat*			
CIT pos_t^-	-4,46E-05	-1,66*	-2,33E-05	-1,74*	1,98E-05	0,68	1,35E-05	0,61
CIT pos_t^+	-3,46E-05	-1,40	-1,20E-05	-1,35	-1,77E-05	-0,39	3,08E-06	0,11
MM pos_t^-	3,61E-06	0,62	-1,80E-06	-0,60	2,05E-05	1,37	-6,43E-07	-0,09
MM pos_t^+	1,25E-06	0,34	7,57E-06	2,04**	1,89E-05	0,68	2,00E-05	1,80*
	Corn				*Soybeans*			
CIT pos_t^-	-1,88E-06	-1,04	-3,96E-06	-2,70***	-1,02E-05	-3,10***	-1,19E-05	-3,36***
CIT pos_t^+	-6,08E-06	-2,28**	-1,79E-06	-0,86	-5,25E-06	-0,87	-2,50E-06	-0,53
MM pos_t^-	-1,84E-06	-1,44	-1,50E-06	-2,16**	-9,88E-06	-2,39**	-3,67E-06	-3,10***
MM pos_t^+	-1,22E-06	-0,65	-9,64E-07	-1,08	-1,03E-05	-3,17***	-5,33E-07	-0,39

(continued)

Table 8 *(continued)*

	1st crisis sample		2nd crisis sample		1st crisis sample		2nd crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
	Soybean oil				*Cotton*			
CIT pos_t^-	-1,77E-05	-0,56	-2,82E-05	-2,33**	-1,46E-05	-1,25	-1,01E-05	-0,70
CIT pos_t^+	-1,69E-05	-0,51	-1,28E-05	-1,11	9,14E-06	0,53	3,16E-05	1,48
MM pos_t^-	-2,61E-06	-0,56	-3,78E-06	-2,23**	-4,93E-06	-0,96	2,47E-07	0,06
MM pos_t^+	-2,12E-06	-0,67	-1,52E-07	-0,10	8,93E-07	0,18	-2,89E-06	-0,95
	Cocoa				*Sugar*			
CIT pos_t^-	-2,87E-05	-0,51	-3,59E-05	-0,97	-3,88E-07	-0,09	-3,65E-06	-1,16
CIT pos_t^+	-7,97E-06	-0,18	2,11E-06	0,06	2,56E-07	0,05	-5,01E-06	-1,12
MM pos_t^-	-5,31E-06	-1,22	-1,32E-06	-0,34	-4,50E-07	-0,42	-2,31E-06	-1,08
MM pos_t^+	7,21E-07	0,12	2,70E-07	0,06	4,11E-07	0,32	3,21E-06	1,98**
	Coffee				*Feeder cattle*			
CIT pos_t^-	-1,38E-05	-1,32	-6,45E-06	-0,63	-8,87E-05	-1,36	-5,52E-05	-1,40
CIT pos_t^+	9,76E-06	0,69	1,52E-05	0,97	1,76E-04	2,61***	2,63E-05	0,83
MM pos_t^-	-3,66E-06	-1,14	-2,11E-06	-0,97	-1,73E-05	-3,28***	-6,77E-06	-1,46
MM pos_t^+	2,99E-06	1,36	2,34E-06	1,20	5,26E-06	1,20	2,76E-07	0,06

(continued)

Table 8 *(continued)*

	1^{st} crisis sample		2^{nd} crisis sample		1^{st} crisis sample		2^{nd} crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
	Lean hogs				*Natural gas*			
CIT pos_t^-	-3,73E-05	-1,79*	-3,69E-05	-2,25**	6,97E-07	1,02	1,34E-07	0,17
CIT pos_t^+	-4,96E-05	-1,51	-4,15E-05	-2,35**	3,07E-06	3,49***	1,95E-06	1,88*
MM pos_t^-	-1,01E-05	-2,81***	-3,93E-06	-1,70*	-6,11E-06	-3,06***	-5,34E-06	-1,68*
MM pos_t^+	3,35E-06	0,61	-2,55E-06	-1,22	2,09E-07	0,14	5,32E-07	0,29
	Live cattle				*Heating oil*			
CIT pos_t^-	-5,28E-06	-1,63	-8,51E-06	-2,78***	6,36E-07	1,07	-8,77E-08	-0,14
CIT pos_t^+	9,12E-06	2,30**	4,15E-06	1,14	7,33E-07	0,84	2,40E-07	0,26
MM pos_t^-	-2,17E-06	-1,46	-2,36E-06	-2,05**	2,08E-06	0,27	3,49E-06	1,18
MM pos_t^+	3,75E-07	0,11	2,85E-07	0,18	1,19E-05	0,83	-1,40E-05	-3,26***
	Crude oil				*Copper*			
CIT pos_t^-	9,79E-07	1,56	7,04E-08	0,10	-1,06E-06	-0,89	-1,60E-06	-1,59
CIT pos_t^+	2,25E-07	0,15	-2,11E-07	-0,19	1,90E-06	0,95	7,64E-07	0,62
MM pos_t^-	2,64E-06	1,43	-8,21E-07	-0,78	-1,82E-05	-0,69	-1,27E-05	-1,28
MM pos_t^+	8,95E-06	2,94***	1,61E-06	1,08	3,49E-05	0,74	2,05E-06	0,20

(continued)

Table 8 *(continued)*

	1^{st} crisis sample		2^{nd} crisis sample		1^{st} crisis sample		2^{nd} crisis sample	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
	Gold				*Silver*			
CIT pos_t^-	-2,05E-06	-2,656***	-2,23E-06	-3,062***	-3,91E-06	-2,473**	-3,53E-06	-2,539**
CIT pos_t^+	1,12E-06	2,154**	5,90E-07	1,407	2,82E-06	2,260**	9,53E-07	0,796
MM pos_t^-	-1,40E-06	-0,770	-2,21E-06	-1,276	-4,02E-05	-1,379	-2,99E-05	-1,715*
MM pos_t^+	1,32E-06	0,693	9,47E-07	0,640	3,34E-05	2,529**	1,54E-05	1,156