

THE INTERACTION OF SPECULATORS AND INDEX INVESTORS IN AGRICULTURAL DERIVATIVES MARKETS

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ABSTRACT

Through the analysis of the weekly CFTC reports on 12 US traded agricultural commodities, we revisit the heated debate on the impact of index flows on commodities prices. After introducing a novel stock-to-use proxy that may be used to represent inventory variations at the intra-month level, we show that speculators, contrary to index investors, are sensitive to commodity-specific fundamental information. Their endogeneity to commodities markets hinders the estimation of their market impact. Regarding the market impact of index flows, the endogeneity problem is alleviated in two ways: first, we restrict the scope to agricultural commodities, for which index flows are more exogenous to market prices; second, we introduce two novel instrumental variables that are computed from index flows outside the market under analysis. We find that index investment flows are offset by commercial players, not speculators. The serial correlation of index flows may explain the tendency of speculators to synchronize with index investors. There is strong evidence of an index flows' impact in those commodities markets where speculative and index positions are the most correlated. The market impact of index flows is located in periods of liquidity stress, as is the correlation between speculative and index positions. Overall, our results demonstrate an impact of index investors on some agricultural prices and suggest that the synchronicity between speculative and index positions is an important determinant of this impact.

INTRODUCTION

The question of the impact of the commodity investors on commodities prices has garnered a lot of interest from academic and political circles since the ascent of commodity index investing and the well-synchronized booms and busts experienced by commodities markets from 2004 onwards. However, in spite of the numerous academic studies, policy papers and news articles written on the subject, this issue still remains fiercely debated due to the difficulty of properly disentangling “speculative” and “fundamental” effects in commodities prices. The objective of this paper is to revisit this question by introducing a new methodology to assess the impact of index speculators on the prices.

It is common to encounter the claims that commodity investors provide liquidity to hedgers and are beneficial or at worst innocuous for price discovery. For example, Krugman, in his New York Times columns and blog, argues that the positioning of speculators on commodity derivatives markets cannot interfere with the spot price determination in the physical market, which is necessarily set according to level of supply and demand. For example, on June 23, 2008, he wrote in a post entitled “Speculative nonsense, once again”: *“Well, a futures contract is a bet about the future price. It has no, zero, nada direct effect on the spot price.”* For Krugman, an impact is possible only if *“someone who actually has oil”* sells oil to a long speculator through a forward contract and *“holds oil off the market so he can honor that contract when it comes due”*. The inventory data showed no evidence of this happening at the time the post was written. On top of that, the forward curves were backwardated, which made it unprofitable to hoard inventories anyway. The conclusion for Krugman is that oil prices were set according to supply and demand fundamentals at that time.

Krugman’s views have been challenged by Babusiaux and Pierru (2010) and Babusiaux et al. (2011), who provide canals through which speculation in the paper market may lead to price “overshooting” without stockpiling as a signature. Their reasoning is as follows. If a stream of uninformed investors flows into the paper market, it has to be balanced out by equivalent short positions from hedgers (e.g. producers), which will happen only if prices increase sufficiently to attract new sellers in the paper market. Spot prices necessarily converge towards the prices set in the paper market because the futures market, due to its liquidity, serves as price reference for the physical market. Stockpiling is not even required for this convergence to happen. Subsequently, the spot price may remain higher than justified by “current fundamentals” for a sustained period because of the price inelasticity of supply and demand in the short term. Time is indeed necessary for users to change their consumption habits and for producers to ramp up production in the face of a price spike. It may take weeks, even months, before negative feedback effects develop in the real world, provoking a return of the price back to its “fundamental value”. Unwarranted speculative activity in the paper market is therefore enough to drive commodities prices away from fundamentals, without involving stockpiling as a signature.

The empirical literature on the estimation of the “impact of index funds on commodities prices” has started with the seminal paper of Masters (2008), uncovering the striking link between commodities index flows and commodities prices during the boom and bust of 2006-2008. Since then, a number of papers have tried to identify whether these correlated patterns were due to an “abnormal impact of index funds” on prices or were the result of alternative phenomena

compatible with a positive view of index speculation (inverse causality running from the prices to the flows, omitted fundamental variables driving both prices and flows).

Some studies (see in particular Irwin and Sanders, 2011; Büyüksahin and Harris, 2011; Capelle-Blancard and Coulibaly, 2011) have tried to identify the direction of the causality between prices and flows by performing a Granger causality test between investment flows and prices or alternatively by analyzing the relationship between flows and subsequent price returns at the cross-sectional level (see Irwin and Sanders 2010-2012). Most studies in this strand of literature reach the conclusion that flows do not “Granger cause” price changes. More recently, Gilbert et al. (2012) have found that index flows *do* Granger cause price variations for less liquid markets (soybeans oil, live cattle and lean hogs). They conclude that the causality is probably present in more liquid markets such as grains but is undetectable with the available statistical techniques. However, temporal precedence is not equivalent to causation. A forecasting power of index flows on price returns may come indeed from a third omitted variable driving both flows and prices (such as market liquidity). Conversely, an absence of Granger causality from flows to prices returns does not necessarily imply absence of causation, as the causal relation between flows and prices could be nonlinear or contemporaneous. Singleton (2011) illustrates the importance of allowing for a nonlinear impact of index flows, observing that the 13-weeks rolling cumulative index flows predict the subsequent oil prices weekly returns after controlling for fundamental financial and non-financial variables (convenience yield, equities prices returns, financing conditions offered by large investment banks...). However, an ad-hoc choice of the horizon defining the “lagged cumulative flows” gives rise to a “data snooping” objection, as the test becomes biased if this choice is at the discretion of the author of the test. The documented instability of the precedence relation between flows and prices is an additional concern. For example, Robles et al. (2009), who carry out Granger causality tests on sliding 30-months windows, show that the hypothesis that flows “Granger cause” prices is sometimes rejected, sometimes validated depending on the period of the test.

Some studies (see Frankel and Rose, 2010; Morana, 2012; Juvenaly and Petrella, 2012; Lombardi and Robays, 2011), departing from the traditional Granger causality analysis, explore the relation between *contemporaneous* flows and price changes. To infer an estimation of the abnormal speculative impact, these studies employ structural models whose goal is to estimate the way prices overshoot with respect to the “fundamental” supply/demand and liquidity variables governing commodity price fluctuations. Most studies lead to the conclusion that prices are mainly driven by fundamentals but provide evidence of “bandwagon effect” of 10 to 20% compared to what is justified by market fundamentals. The abovementioned study by Singleton (2011) is positioned at the exact crossroads between the structural models and the price/flow causality literature as it introduces as well the 13-weeks cumulative index investment flows in the model explaining the price dynamics.

A related stream of literature attempts to test for the presence of “speculative bubbles” in commodities markets. The studies lead to diverging conclusions, following mainly from a lack of consensus on the definition of bubbles. While Sornette (2009) identifies a bubble on oil prices in 2008, and Guttierrez (2012) and Emketer et al. (2012) identify bubbles on grains prices, Gilbert (2012) and Liu et al. (2012), with other definitions of bubbles, reach opposite conclusions.

Mou (2009), focusing on the impact of index investors on calendar spreads instead of price levels, showed that a strategy front-running the GSCI investors just a few days before the

monthly rolling of the positions yields abnormal returns. The abnormal return disappears if the strategy is executed on contracts which are not included in the Goldman Sachs Commodity Index. This shows that GSCI investors cause the spread between first-nearby and second-nearby contracts to widen (the first-nearby contract, which is sold by the GSCI investor, depreciates with respect to the second-nearby, which is bought by GSCI investors) at the time of the rolling. This represents a direct proof of a market impact of index investors on the term structure of futures prices during the rolling period.

Bringing a different perspective to the literature on the financialization of commodity markets, Tang and Xiong (2012) have uncovered a marked increase of short-term correlations, inside the commodities complex. This increase in correlations concerns on-index rather than off-index commodities, suggesting that the observed rise in commodities integration is closely linked to the behavior of index investors. As shown by Bicchetti and Maystre (2012), the increase in correlations is also found at the intra-day level between commodities and other asset classes, which indicates that high-frequency arbitrage strategies probably play a role in the integration trend observed since the mid-2000s.

In this paper, we revisit the question of the causality between index flows and commodities prices through the analysis of the *contemporaneous* relation between flows and prices. Our analysis exploits the 352 weekly “Supplemental Reports” released by the CFTC from January 2006 to end of September 2012 on twelve US agricultural contracts.

Gilbert (2010) finds a significant positive association between contemporaneous weekly index flows and prices variations for a set of energy, metal and agricultural commodities after controlling for equities price returns. From here, the author evaluates that the maximum price impact of index flows may have been to raise prices by the order of 15% in 2008. The issue of “inverse causation” is addressed in this paper by the use of a Two Stage Least Squares specification, where index flows are regressed on lagged flows and price returns.

We build on this study, employing alternative techniques to mitigate endogeneity issues. The omitted variables problem is addressed by introducing relevant fundamental and financial control variables. In particular, we define a novel stock-to-use proxy that may be used to represent inventory variations at the infra-month level. As for the reverse causality problem, it is alleviated in two ways: first, we restrict the scope to agricultural commodities, for which index flows are more exogenous to the prices⁴; second, we introduce two novel instrumental variables that are computed from index flows outside the market under analysis⁵. But our main contribution lies in the analysis of the interaction of “traditional speculators” and index investors in agricultural derivatives markets. More specifically, we show that the synchronicity of “speculative” and index positions may be an important determinant of index investors’ market impact.

⁴ The focus on agricultural commodities also avoids employing the questionable Masters’ methodology to reconstruct energy and metals index flows from agricultural flows data or using the imprecise “Swap Dealers” field in the CFTC Disaggregated Report (see Irwin and Sanders 2012).

⁵ Hendersen et al. (2012) use Commodity-Linked-Notes (CLN) issues as a plausibly exogenous index flows variable. Through an event-study analysis, they observe the existence of an impact of CLN issues on commodities prices.

Our findings can be summarized as follows.

First, contrary to speculators, index investors hardly respond to specific supply and demand information; they are however somewhat related to dollar fluctuations and to revisions in the global macroeconomic outlook.

Second, index investment flows are offset by commercial players, not by speculators, in agricultural derivatives markets. The impact of index flows on commodities prices varies across commodities: it is the strongest for those markets where speculators trade in sync with index investors.

The impact is significantly increased when global market liquidity is disrupted. Liquidity disruption periods are also the ones where speculators align their positions with the ones of index investors. Again, the excess sensitivity of commodities prices to index flows relates (across different commodities markets) to the excess synchronicity of speculative flows to index flows in stressed periods.

Overall, our results suggest that the correlation between index and speculative positions may be an important determinant of index investors' impact on agricultural prices. The soybeans complex displays the most important synchronicity and price impact, and this effect is reinforced in stressed periods. Meat markets, where speculators trade independently of index investors, are remarkably insulated from the impact of index investing and global market stresses.

The remainder of this paper is organized as follows. The first part analyzes the motives and intervention modes of index and speculators in agricultural derivatives markets. The second part estimates the impact of index flows on agricultural markets. The third part contains concluding comments.

I) THE BEHAVIOR OF INDEX INVESTORS AND SPECULATORS IN AGRICULTURAL DERIVATIVES MARKETS

1) Global investors' positioning and volatility of investment flows

Of the three reports released every week by the CFTC, we use the most precise Supplemental Data report providing the weekly positions (in number of lots) held by three well-defined categories of traders: Commodity Index Traders (henceforth CIT), Non Commercial Non CIT (henceforth NonCom), and Commercial Non CIT (henceforth Com for Commercial). A last category, which will not be used in the sequel, is called "Non reportable positions". This report is only available for 12 agricultural commodities traded in the U.S. (wheat, bean oil, corn, soybeans at the CBOT, Kansas Wheat at the KCBT, feeder cattle, lean hogs and live cattle at the CME, and cocoa, coffee, cotton and sugar at the ICE Futures US). We use the aggregate data combining options and futures positions.

Figure 1 represents the average Open Interests (in thousands of lots) on the twelve agricultural contracts. CBOT grains and ICE sugar largely stand out in terms of size, while the feeder cattle contract lags behind other agricultural commodities.

[insert Figure 1 here]

The first category of traders identified by the CFTC corresponds to index speculators, tracking a given commodity index (such as the broad GSCI and DJ UBS or indices written on specific commodities or commodities sectors...). They may either invest through Exchange-Traded-Funds (ETFs) or through OTC derivatives instruments directly marketed by investment banks. These investors may take long or short exposures to the index and the CFTC therefore separately provides the Long and Short index positions in each commodity.

The second category of investors corresponds to speculators that do not track a specific commodity index but instead engage in active trading strategies (trend-following, statistical arbitrage, carry strategies, mean-reversion...). For convenience, we will refer to these investors as "speculators". Three fields are available for each commodity: Long/Short/Spreading positions, as some active strategies involve the trading of calendar spreads on one specific commodity.

The last category of participants represents "hedgers", i.e. buyers, processors, physical traders and producers that mostly use derivatives markets for the purpose of hedging commodity price risk. Like in the case of speculators, three fields are available for each commodity: Long/Short/Spreading positions.

In what follows, we will use only the global net position defined by the difference between Long and Short positions for each category of traders.

This starting date of the report is beginning of January 2006. The data used for this study covers the 352 reports released by the CFTC from January 3rd 2006 to Sept 25th 2012.

From Tables 1 and 2, it emerges that: i) index investors remain net long in all circumstances and have weekly flows that rarely exceed 4% of lagged Open Interest; ii) the global net positioning of speculators may change sign in time and display more than twice as big weekly volatility as the one of CITs.

[insert Tables 1a to 2b here]

Another important difference relates to their temporal persistence, reflected in their autocorrelation function (Figure 2). As shown in figure 2, index flows exhibit serial correlation up to four months ahead, contrary to speculators' flows, whose memory is lost after one week. This reveals that index flows come in waves, with long-lasting investment booms followed by sequences of withdrawals. This pattern is also illustrated by Figure A.2.3 in appendix 2.

[insert Figures 2 and A.2.3 in appendix 2 here]

2) The economic and financial determinants of index and speculative flows

In this section, we investigate the economic and financial determinants of index and speculators investments into agricultural derivatives markets. Our objective is to characterize in particular the sensitivities of index and speculators to global funding conditions in financial markets, to dollar currency effects and to specific supply and demand fundamental information.

2.1 Global liquidity conditions

The *global liquidity conditions* are captured through a risk aversion index, which is a daily-refreshed stress signal aggregating the instantaneous market prices of risk in all liquid assets⁶. To allow the comparison of the stress levels across different asset classes, all market prices of risk are normalized by means of z-scores computed over different time horizons (from 3 months to 2 years). More details on the construction of the aversion index are provided in the first supplemental document attached to this paper.

An increase in the risk aversion index reflects a rise in the funding stress with respect to the recent past. The zero threshold can be interpreted as the tipping point between stability and

⁶ The considered risk premiums belong to the following list: emerging and corporate credit spreads, spread between LIBOR and three-months government yield (TED spread) in euro zone/US/Japan, CDS of main European/US/Japanese banks and insurance companies, CDS of key sovereign states, implied volatilities of equities/carry trades/crude oil

instability. As shown in Figure 3, an increase of the risk aversion above the threshold of 1 generally signals an impending large scale liquidity crisis.

[insert Figure 3 here]

2.2. Dollar effect

The *dollar effect* is captured by means of the Dollar Index, representing the trade-weighted average of the US Dollar against a basket of currencies (euro, yen, sterling...). The Dollar index has been strongly connected to the liquidity variable in the past decade, as a depreciation of the dollar is traditionally associated to a “risk-on” attitude among investors: in the risk-on mode, investors fund risky investments (high-yield currencies, corporate credit bonds, equities, commodities...) by borrowing low-yield US dollars. Conversely, in the “risk-off” mode, investors brutally unwind these trades, boosting the dollar currency and driving all risky asset classes downward.

2.3. Inventory revisions

Here, we define a novel variable serving as a proxy for inventory revisions in agricultural markets. From the theory of storage, we know that forward calendar spreads have strong positive correlation to inventories (Kaldor 1939, Working 1949, Fama & French 1987, Gorton et al. 2007, Geman & Ohana 2009). However, the strong seasonality of agricultural forward curves precludes directly using the forward calendar spread (for example the one-year-out to prompt futures price ratio) as a proxy for the inventory level as this would lead to artificial jumps after each rolling date. We therefore create a smooth inventory proxy from the performance of a strategy shorting the first maturity after the closest harvest (denoted F1), while buying the first maturity after the second closest harvest (F2)⁷:

$$W_t = \prod_{\tau \leq t - \Delta t} \left(1 + \frac{\Delta F_{2\tau}}{F_{2\tau}} - \frac{\Delta F_{1\tau}}{F_{1\tau}}\right) \quad (1)$$

where $\Delta F_\tau = F_{\tau + \Delta t} - F_\tau$ stands for the daily futures price variation between τ and $\tau + \Delta t$. The inventory shock proxy between dates t1 and t2 is then defined by:

$$Inv\ shock\ proxy_{[t1:t2]} = \ln\left(\frac{W_{t2}}{W_{t1}}\right) \quad (2)$$

In the appendix 1, we explain why this variable may be used as a proxy for infra-month stock-to-use revisions. In the sequel, we use a weekly inventory shock proxy.

⁷ For example, in the case of corn (resp. wheat) futures at the CBOT, the strategy shorts the prompt December (resp. July) month and longs the subsequent December (resp. July) month. When reaching the last trading day of the prompt December contract, the strategy moves to the next two December contracts available. For soybeans, we use the November contract instead of the December contract.

The inventory proxy is only available for storable commodities as, for non-storables, the spread should not be interpreted anymore as a proxy for the perceived “inventory”, but rather as a measure of the one-year-ahead expected spot price variation (see e.g. Fama and French, 1987). Therefore, the inventory index is only computed for the nine agricultural commodities outside meat products.

For four commodities (bean oil, cocoa, coffee, sugar), there were not enough maturities available to perform the calculation. We therefore defined instead F1 as the prompt-month contract and F2 as the contract whose delivery is precisely one year after F1⁸.

2.4. Manufacturing cycle

The market perception of the *global manufacturing cycle* is captured through the forward curves of 9 highly liquid cyclical commodities: five energy (NYMEX WTI Crude Oil, NYMEX Heating Oil, NYMEX Gasoline, NYMEX natural gas, ICE Brent crude, and four base metal contracts (copper, nickel, zinc and aluminum at the LME).

For each commodity, the daily curve is computed as:

$$Curve_t^i = \frac{F13_t}{F1_t} - 1 \quad (3)$$

where F1 and F13 respectively stand for the one-month and thirteen-months-out futures prices at date t. The one year distance between the maturities of the two contracts is meant to filter the seasonal effects in some commodities forward curves (heating oil, gasoline, natural gas)⁹. We then compute the average of the 9 forward curves to obtain a proxy for the perceived inventory of cyclical commodities:

$$Cyclical\ Commodities\ Inv\ Proxy_t = \frac{1}{9} \cdot \sum_{i=1}^9 Curve_t^i \quad (4)$$

In Figure 4, we note that the average curve has never returned to backwardation since the summer 2008, indicating well-supplied energy and base metal commodities and lackluster global industrial activity.

[insert Figure 4 here]

[insert Table 3 here]

⁸ We have compared the results obtained from the two different calculations for the five commodities where they can both be performed (wheat CBOT, wheat KCBT, corn CBOT, soybeans CBOT and cotton ICE US). The correlation between the weekly shocks obtained with the two different methods is around 99% for these five commodities.

⁹ The seasonality of these three energy commodities is not an issue here, contrary to the case of grains at the CBOT, as the effect of the jumps at the rolling dates is smoothed out by the averaging of the forward curves across the 9 commodities

2.5. Rolled futures price series

In what follows, we will use, for each commodity, a “rolled futures price series”, representing the performance of a strategy that invests an initial amount of \$1 in the first-nearby contract and rolls over this long position (i.e. sells the first-nearby and buys the second-nearby contract) the day before the last trading day of the first-nearby contract. At day t , the number of contracts held is such that the notional of the position at time t is equal to the wealth accumulated up to date t . As a result, the rolled futures price series is defined by:

$$\varphi_t = \prod_{\tau \leq t - \Delta t} \left(1 + \frac{\Delta F_{1\tau}}{F_{1\tau}}\right) \quad (5)$$

where $\Delta F_{1\tau} = F_{1\tau + \Delta t} - F_{1\tau}$ stands for the daily price variation of the futures contract that was held at time τ (the first or second-nearby contract according to the case).

In the sequel, “price returns” will always be defined as the returns of strategy φ_t between two consecutive weekly observations.

2.6. Analysis of the relation of index and speculative flows to the financial and fundamental variables

Table 3 displays the correlation between flows, prices returns and control variables for the twelve agricultural markets.

[insert Table 3 here]

We observe the expected positive correlation between the risk aversion and dollar index. Interestingly, the agricultural inventory proxy has a strong negative correlation to the prices (as should be expected) but, contrary to agricultural prices, it presents only a mild correlation to the risk aversion and dollar indices. Hence, agricultural prices are driven by a combination of purely fundamental (medium-term inventory projection) and financial factors (liquidity, dollar effects). Also, index and speculative flows both exhibit a positive correlation to market liquidity but only speculative flows correlate to projected inventories (with the expected sign). Global index flows towards agricultural products are only sensitive to the broad manufacturing cycle, as shown by the mild negative correlation to the cyclical commodities inventory proxy. We find here a first indirect evidence of the fact that index investors, contrary to speculators, are generalist rather than specialized investors. Both types of investors have a pro-cyclical activity with respect to the prices (as revealed by the positive correlation between flows and prices), but the pro-cyclicality of speculators is markedly higher than the one of index investors. The trend-following strategy is one of the oldest and most popular styles of active strategies employed by speculators. We know from Moskowitz et al. (2012) that speculators benefit from momentum at the expense of hedgers in futures markets. This makes it very difficult to estimate the impact of speculators on commodities markets, as the causality for sure runs both ways between

speculative flows and commodities prices. The question of the direction of causality between index flows and prices will be addressed later in this paper.

Tables 4a and 4b display, for each commodity, the OLS regressions of weekly index and speculative flows on inventory shock proxy, cyclical commodities inventory shock proxy, dollar index returns and changes in the risk aversion signal,:

$$\frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i} = \alpha + \gamma_1 Inv Shock Proxy_t^i + \gamma_2 Cycl Inv Shock Proxy_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \varepsilon_t^i \quad (6)$$

$$\frac{NonCom_t^i - NonCom_{t-1}^i}{OI_{t-1}^i} = \alpha + \gamma_1 Inv Shock Proxy_t^i + \gamma_2 Cycl Inv Shock Proxy_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \varepsilon_t^i \quad (7)$$

In equations (6) and (7), CIT_t^i and $NonCom_t^i$ respectively stand for index and speculative net positions (in number of lots) in commodity i in week t and OI_{t-1}^i the lagged Open Interests (in number of lots) in commodity i in week $t-1$. ΔRA_t stands for the variation of the risk aversion signal between weeks $t-1$ and t and $\frac{\Delta Dollar_t}{Dollar_{t-1}}$ denotes the relative variation of the dollar index between $t-1$ and t . $Inv Shock Proxy_t^i$ is the commodity-specific inventory shock proxy between weeks $t-1$ and t defined in section 2.3. $Cyclical Commodities Inv Shock Proxy_t$ is the weekly variation of the cyclical commodities inventory proxy defined in 2.4

[insert Tables 4a and 4b here]

Several important conclusions can be drawn. First, the dollar effect is present for both index and speculators. Other “risk aversion” effects are much more present for speculators than for index investors: for five commodities out of twelve, speculators invest in (resp. divest from) agricultural commodities when liquidity improves (resp. contracts). The effect is the strongest for the soybeans complex, sugar and coffee. Importantly, index investors are much more sensitive to the manufacturing cycle than speculators. This confirms that most index investors are in fact tracking broad commodity indices with a high loading on cyclical commodities. Finally, soybeans, coffee and sugar are the only products where index investors’ flows display a significant sensitivity to inventory news (index investors increase their exposure when the inventory proxy declines). This suggests that index flows may be slightly more endogenous to these three specific markets than to the rest of the agricultural constellation. Nevertheless, this effect has to be put in perspective as the impact is two to three times smaller than in the case of speculators.

II) THE IMPACT OF INDEX INVESTORS ON AGRICULTURAL COMMODITIES MARKETS

In this section, we intend to evaluate the impact of index investors on agricultural commodities markets. After assessing their impact on speculative flows, we turn to the assessment of their impact on agricultural prices.

1) Discussion of the endogeneity of index flows in agricultural markets

We begin with a discussion of the endogeneity problem in the estimation of the index flows impacts on commodity markets.

Index investor's positions in individual agricultural markets can be broken down into three distinct components, ranked by decreasing level of exogeneity to individual agricultural markets:

1. Index investors' investment into generalist commodity indices (consisting of baskets of agriculture, energy and metal contracts)
2. Index investors' investment into general agricultural commodity indices (consisting of baskets of agricultural contracts only)
3. Idiosyncratic index investors' investment into single-commodity indices

It should be noted also that a fourth part of index positions changes does not come from investment flows *per se* but corresponds instead to periodic rebalancings designed to maintain the weights of each commodity constant in the basket (cases 1 and 2 above). The rebalancing is done by divesting from (resp. investing in) the assets which have outperformed (resp. underperformed) with respect to the global index. This mechanical counter-cyclical effect running from the prices to the flows may confound the analysis of the impact of the flows on the prices, as the observed index flows are in fact the combination of outright investment inflows and mechanical rebalancings that are negatively correlated to price returns and whose price impact is probably modest due to their high degree of predictability.

Generalist index investment in commodities indices such as the GSCI or the DJ UBS probably carries a high level of exogeneity to individual agricultural markets. Indeed, agricultural commodities weigh just more than 30% in the most popular commodity indices, most of the remaining 70% being cyclical components with a strong correlation to industrial activity (energy products represent 45% of the index and metals with a direct relation to manufacturing industries 20%). This explains the quasi-absence of relation of index flows to our inventory proxy and the significant negative relation found between index flows and the cyclical commodities inventory proxy (Table 4a). In addition, the correlation of grains prices to a global commodity index computed as the equal-weighted average of the GSCI and DJ UBS indices has been around 50% since 2006, the correlation falling to less than 40% for meat and other soft

products¹⁰. This pales in comparison to the over 90% correlation observed between the brent crude price and the average commodity index¹¹. Therefore, index flows towards broad commodity indices such as the GSCI or the DJ UBS could follow the trend set in the energy markets but probably not specific agricultural price dynamics.

Unfortunately, the CFTC does not provide a finer decomposition of index flows into generalist and specialized index investors. A standard OLS regression of prices on index flows may lead to a biased estimate of their market impact: the trend-following behavior of specialized index investors (or their ability to predict future prices) could lead to an overestimation of the impact whereas the rebalancing problem may result in an undervalued estimate.

For this reason, we propose two different instrumental variables (henceforth denoted IV_t) to alleviate the endogeneity concern:

1. The first instrument used in the sequel to assess the impact of index flows in market i is constructed as the aggregate agricultural index flows (inferred from the CFTC Supplemental Report) outside market i . This instrument spans the liquid and illiquid forms of index investment but has the inconvenient of including index flows towards global agricultural indices which are more endogenous to individual agricultural markets.
2. The second instrument is computed from the weekly net flows into the three main commodity indices ETF (appendix 2). Projecting the individual index flows on this variable makes it possible to filter out the agriculture-centric index flows (components 2 and 3 above). However, the limitation of this approach is that ETF investment represents only a minor part of global commodity index investment (appendix 2). More illiquid forms of index investment (total return swaps, structured products, Medium-Term Notes...) in fact get the lion's share of global index flows.

In the appendix 2, we analyze the relations between these two instruments.

2) Who balances out changes in index positions?

The objective here is to estimate the way index flows are mitigated in derivatives markets. More precisely, we want to determine what kind of players (speculators or commercial players) take the other side of the trade when there is a flow of index investors into agricultural derivatives markets.

The response of speculators to a change in index positions in commodity i can be represented by the following simple linear model (model denoted M1 Flows):

$$\Delta NonCom_t^i = NonCom_t^i - NonCom_{t-1}^i = \alpha_1 + \beta_1 \Delta CIT_t^i + \varepsilon_t^i \quad (8)$$

where we have posed: $\Delta CIT_t^i = CIT_t^i - CIT_{t-1}^i$

¹⁰ These two correlations were respectively 25% and 10% between 2000 and 2005, a period where commodity markets were less integrated.

¹¹ The correlation was still high at 85% between 2000 and 2005.

This model is first estimated by running OLS regressions of speculative flows on index flows at the weekly horizon. This should lead to an unbiased estimate of the impact coefficient β_1 if the hypothesis of exogeneity (ΔCIT_t^i is uncorrelated to the residuals ε_t^i) is valid.

We then proceed by running 2SLS regressions using the two previously introduced instrumental variables.

The first instrument is obtained from the index flows into the 11 contracts outside commodity i : $IV_t^i = \sum_{j \neq i} \Delta CIT_t^j$. The second instrumental variable is calculated from the inflows to three generalist ETFs (see appendix 2).

As confirmed by Table 5, these two instrumental variables have a strong positive correlation to ΔCIT_t^i for all twelve commodities. However, as could be expected, there is a stronger correlation to the first instrument than to the second.

[insert Table 5 here]

In the first stage regression, we estimate the following model:

$$\Delta CIT_t^i = \tilde{\alpha} + \tilde{\beta}_1 IV_t + \tilde{\varepsilon}_t^i \quad (9)$$

In the second stage, we estimate the following regression:

$$\Delta NonCom_t^i = \alpha + \widehat{\beta}_1 \widehat{\Delta CIT}_t^i + \varepsilon_t^i \quad (10)$$

where $\widehat{\Delta CIT}_t^i$ are the fitted values of ΔCIT_t^i obtained from the first stage linear regression.

The Hausman test examines the null hypothesis of exogeneity, i.e. the hypothesis that $\beta_1 = \widehat{\beta}_1$ ($\widehat{\beta}_1$ is estimated from the 2SLS ETF specification).

The conclusions from Table 6 are very clear-cut: for five commodities (CBOT corn, CBOT soybeans, CBOT bean oil, ICE US coffee, ICE US cotton), the three methods agree that speculators' trades are positively correlated with the ones of index investors, and for two other commodities (ICE US cocoa, CME live cattle), there is some disagreement between the three tests. Overall, the OLS coefficients are lower than the 2SLS ones. This may be due to the effect of the counter-cyclical index positions rebalancings, which run counter to the pro-cyclical speculators' interventions. However, cocoa is the only commodity where the Hausman test leads to reject the null of exogeneity (the OLS coefficient being largely lower than the 2SLS estimates).

[insert Table 6 here]

Overall, we may conclude that speculators tend to align their positioning with the one of index investors, as the lean hogs market is the only one to present some (weak) evidence of antithetic speculators' and index investors' positions.

However, the sensitivity of speculators' flows to index flows varies quite importantly across different commodities: it is less than 0.8 for meat, corn, wheat and sugar markets, reaching a low

of -0.1 for lean hogs, and more than 1 for the soybeans complex, coffee, cocoa and cotton, reaching a high of 1.8 for bean oil.

The synchronicity of speculative and index positions may appear surprising as speculators are generally expected to trade against unspecialized investors, hereby smoothing out their impact on market prices. Trading along index investors may however be tempting for a speculator if the observation of a sequence of positive (negative) index flows makes it more likely that a significant amount of money will be poured into (withdrawn from) commodity indices in the near future. Our preliminary observations from the first section of this paper show that this is largely the case today: even if index flows are of lower magnitude than speculators' flows at the weekly level, they tend to come in predictable large waves that speculators, insofar as they behave like trend followers in aggregate, may attempt to ride.

Because speculators do not perform the task of balancing out index investors' changes of positions, commercial players are required to do the job instead. This simple observation directly challenges the often-encountered claim that index investors "bring liquidity to hedgers". In fact, what is observed is the opposite: commercial players, not speculators, take the other side of the trade when index investors are willing to adjust their commodities exposure.

3) The price impact of index flows: linear and nonlinear models

In this section, we present different specifications describing the impact of index flows on agricultural prices and explain the estimation methodology.

In a first representation (model denoted M1 Prices in the sequel), we assume a linear impact independent of liquidity conditions between the index flows and price changes in commodity i:

$$\frac{P_t^i - P_{t-1}^i}{P_{t-1}^i} = \alpha + \beta_1 \frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i} + \gamma_1 Inv Proxy_t^i + \gamma_2 Cycl Inv Proxy_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \varepsilon_t^i \quad (11)$$

where $\frac{P_t^i - P_{t-1}^i}{P_{t-1}^i}$ represents the return of the rolled futures price series between weeks t-1 and t.

The dollar, risk aversion, commodity-specific inventory proxy and cyclical commodities inventory proxy are included as control variables as the previous section has shown that index flows may be correlated to them for a certain number of agricultural commodities.

Again, we first estimate M1 by a standard OLS regression and second, we compare the OLS estimate to the one obtained with a 2SLS regression using our two instruments.

As we here regress price returns on the ratio of index flows to lagged Open Interests, we use a slightly modified version of the first instrument for commodity i: $IV_t^i = \frac{\sum_{j \neq i} \Delta CIT_t^j}{\sum_{j \neq i} OI_{t-1}^j}$.

At the end of this section, we will address an additional endogeneity concern coming from the connection of index flows and agricultural markets to the oil prices.

We then refine the models (M1 Flows) and (M1 Prices) to incorporate non-stationary effects. Our intuition is that the market impact of index flows is not the same under “calm” and “stressed” conditions. When liquidity is ample, index investors’ flows may be more easily absorbed whereas during degraded liquidity periods, index investors may have more trouble finding a counterpart to adjust their commodities exposure at a convenient price. The delimitation between these two kinds of liquidity conditions is done through the sign of our risk aversion indicator.

The models, defined as follows, are respectively denoted M2 flows and M2 prices in the sequel:

$$\Delta NonCom_t^i = \alpha_1 + \beta_1(CIT_t^i - CIT_{t-1}^i) + \beta_2(CIT_t^i - CIT_{t-1}^i) * 1(RA_{t-1} > 0) + \varepsilon_t^i \quad (12)$$

$$\begin{aligned} \frac{P_t^i - P_{t-1}^i}{P_{t-1}^i} = & \alpha_1 + \beta_1 \frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i} + \beta_2 \frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i} * 1(RA_{t-1} > 0) \\ & + \gamma_1 Inv Proxy_t^i + \gamma_2 Cycl Inv Proxy_t + \gamma_3 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \gamma_4 \Delta RA_t + \varepsilon_t^i \end{aligned} \quad (13)$$

MZ flows and M2 Prices are estimated through OLS regressions, using the most exogenous (ETF) index flows variable as a dependent variable to alleviate endogeneity issues. The economic significance of the index flows variable is assessed by rescaling independent and independent variables so that they have unitary variance.

4) Presentation and discussion of the results

The results of the M1 Prices regression are presented in Table 7.

[insert Table 7 here]

The three tests point to a positive impact of index investors for the soybeans complex, cocoa and cotton. There is disagreement in the test conclusions for wheat, live cattle, coffee and sugar. The case of sugar is interesting since the coefficients have the higher absolute value but also the higher variance, making the significance tests inconclusive in two cases out of three. Finally, the existence of an impact is unequivocally rejected for corn, feeder cattle and lean hogs.

Again, the OLS coefficients are lower, overall, than the ones obtained via the 2SLS regressions. This indicates that counter-cyclical index positions rebalancings have a bigger impact than specialized pro-cyclical index investing in the OLS regressions. However, the Hausman test does not reject the null of exogeneity in any of the thirteen situations.

The OLS regressions of agricultural prices on ETF flows are reported in Table 8 and the OLS regressions of speculative flows on ETF flows displayed in Table 9 (regressions 1). The price responses are then plotted against the speculative flows responses in Figure 5.

[insert Tables 8 and 9 here]

[insert Figure 5 here]

We observe that the impact of index flows on commodities prices is strongly associated with the propensity of speculators to trade along index investors. The heavier the burden placed on commercials to balance out correlated speculative and index positions changes, the stronger the index flows' impact on the prices. On one side, we find the soybeans complex, cocoa and cotton, for which the correlation of index and speculative flows and the market impact of index flows are the strongest. On the opposite side, we find lean hogs (and to a lesser extent feeder cattle, live cattle and sugar), for which speculators trade independently of index investors and the price impact of index flows is negative or insignificant.

The results of the M2 Prices regressions, presented in Table 8, show that the impact of index flows is increased in stressed periods. Cocoa is the only market where the impact of index investors is truly linear, as for all other (non-meat) commodities, the index flows' impact is entirely driven by stressed periods. CBOT and KCBT wheat, cocoa, sugar and coffee globally present a weaker differentiation between calm and stressed periods than the group of commodities composed of soybeans, bean oil, corn, and cotton (Figure 6). The cases of corn and sugar are particularly interesting as, while no impact was found in the linear model, a very significant impact is uncovered in stressed periods. This is the result of opposite types of responses in calm and stressed periods: for example, the index flows coefficient is 0.31 (-0.15 + 0.46) in stressed periods and -0.15 in calm periods in the corn market.

Overall, the results are not only statistically but also economically significant: while the index flows impact is much lower than the one of the inventory shock, it is comparable in magnitude to the one of the dollar index. For example, the index flows coefficient is -0.31 (in stressed periods) against -0.29 for the dollar index coefficient in the aggregate regression (the rescaling of the variables allow for a direct comparison between the two coefficients). The dollar impacts systematically decline in absolute value when the flows and dollar variables are simultaneously introduced. The effect is particularly strong for coffee, sugar, bean oil, cotton and corn where the dollar coefficient declines by more than 30% in absolute value. This suggests that a significant part of the relation between commodities prices and the dollar index may be attributed to the "anti-dollar" behavior of index investors. Similarly, around 30% of the correlation of agricultural prices to index flows may be attributed to an omitted liquidity variable, as shown by the significant decrease in the index flows regression coefficient when the dollar and risk aversion effects are introduced (the statistical significance of the index flows' coefficient is even lost in the case of CBOT wheat and coffee). Again, meat products stand out from other agricultural markets by their mild sensitivity to the dollar and liquidity factors (lean hogs are even positively correlated to the dollar index), revealing their unique "haven" status in the commodities galaxy.

As reported in Table 9, the correlation between index investors and speculative behaviors is also driven overall by periods of financial turbulence. Cocoa- and to a lesser extent coffee- are exceptions to the rule, with a quasi linear relation between index and speculative flows.

Figure 6, which plots excess index investors' impact against excess speculators' synchronicity in stressed periods, shows that the liquidity effect is the strongest for corn, soybeans, bean oil, cotton and sugar.

[insert Figure 6 here]

Wheat, cocoa and coffee form a second group of commodities, where the correlation between index and speculative positions increases modestly with the level of market stress. The case of meat products is again specific, and particularly the one of lean hogs. We have already noted that there is a very weak statistical association between speculative and index positions changes in the three meat markets. However, in the case of lean hogs, an exactly opposite relation is found between calm and stressed periods, with significant coefficients of 0.13 (-0.12) in calm (stressed) periods (see Table 9). The same phenomenon is observed for feeder cattle, though with a lack of statistical significance. This points to a unique “anti-index” behavior of lean hogs speculators in periods of turmoil. Without surprise, this commodity is also the only one with a negative price impact of index flows in stressed periods (-0.07). The cases of corn, sugar and cocoa deserve a particular attention since, as pointed out before, they correspond to two opposite extreme situations: corn and sugar display the most strongly nonlinear relation between index flows and price returns, with a negative (positive) sign in calm (stressed) markets, while cocoa is the only commodity where this relation is both significant and linear. The relations between index and speculative flows are coherent with these observations: the relation is again almost perfectly linear for cocoa and similarly changes direction for corn and sugar according to the level of turbulence in the market.

Overall, the behavior of prices and index/speculative flows in calm and stressed periods supports the hypothesis that the correlation between speculative and index positions is associated to index investors’ market impact. Speculators trading in the soybeans, bean oil, corn, cotton and sugar markets exhibit a highly pro-cyclical attitude with respect to index investors in periods of turmoil. This corresponds to strong price response to index flows in this type of periods. Cocoa, coffee, and KCBT and CBOT wheat are intermediate commodities, with similar responses of prices and speculative flows to index flows in calm and stressed periods. Meat products again distinguish themselves by the fact that speculators trade against index investors and index investors’ impact is negligible in turbulent markets.

5) Additional tests

In this section, our aim is to investigate three additional issues: the reason for increased speculators' synchronicity in periods of turmoil, a potential endogeneity issue linked to the "oil effect", the issue of the direction of causality between speculators' synchronicity and index investors' impact.

5.1. Explaining the increased speculators' synchronicity in stressed periods

How to explain the fact, first, that speculators synchronize further with index investors in periods of turmoil? A first possibility is that this behavior is due to an increased sensitivity of index investors and speculators to liquidity conditions in stressed periods. Table 10 reports further regressions that tend to invalidate this hypothesis. A second possibility might be that speculators are more tempted to trade like index investors when liquidity is disrupted because index flows are more serially correlated in this type of periods. The last regression in Table 10, showing an increase in the serial correlation by more than 40% in stressed periods, runs in support of this second hypothesis.

[insert Table 10 here]

5.2. Endogeneity issue related to the oil price

An "oil price effect" could confound the evaluation of the index investors' impact on agricultural prices. The reasoning behind this concern goes as follows: index investors are probably influenced by the oil prices (trend following behavior), but, as oil and agricultural prices are themselves correlated due to fundamental reasons (e.g. energy commodities serve as inputs in the production of fertilizers and some food products may be converted into energy), we may have a correlation between index flows and agricultural prices that is not due to an impact of index flows on agricultural prices *per se* but instead to a common relation of index flows and agricultural products to the oil prices. We have addressed this concern by including the brent control variable into the regressions of Table 8. The index flows' impact estimated through this method therefore excludes any indirect impact transiting through the oil price as well as any simultaneous impact jointly affecting oil and agricultural prices. Only the impact on the *relative* pricing to the brent is assessed. The results are displayed in Table 11.

[insert Table 11 here]

The comparison with the regressions 4 of Table 8 reveals that we may attribute around 30% of the index flows coefficient to diverse "oil market effects" (correlation to an "exogenous" oil factor, indirect impact through the oil price, joint impacts on oil and agricultural markets...) and the remaining 70% to an impact on the relative pricing to the brent. The index flows' coefficient in stressed periods loses its significance for KCBT wheat and cocoa, two markets where the index flows' impact before controlling for the brent effect was already very mild. However, the

index flows' coefficient remains significant for those five commodity markets where it was already the strongest in the uncontrolled regressions: corn, soybeans, bean oil, cotton and, to a lesser extent, sugar. This indicates that, for these five commodities, index flows significantly impact the relative pricing to oil in periods of market turmoil. This may be due to the lower depth of agricultural markets relative to the oil market, translating into a stronger market impact of index flows in the former in stressed periods.

5.3. What drives the relation between speculators' synchronicity and index investors' impact?

We end this section by analyzing further the association between index flows/price correlation and index/speculative flows synchronicity. This relation may indeed be interpreted in several ways.

The first hypothesis is that the index flows/price correlation drives speculators' synchronicity: speculators synchronize more with index investors in those markets where the correlation between index flows and the prices is the strongest. But this interpretation raises the question of which factors drive the widely contrasted CIT's impacts across different markets. A first natural guess is to relate the impact of index investors to the level of market depth as, everything else equal, a lack of market depth should make index flows more difficult to absorb hence more impactful. This hypothesis predicts that the index investors' price impact (hence speculators' synchronicity) should be stronger in illiquid commodity markets. There is little support for this hypothesis, given the fact that the impact of index investors is very strong in the relatively liquid soybeans market and is null in the relatively illiquid lean hogs market. A second possibility could be that the correlation to the brent or the dollar index is in fact the driver of the relation. The mechanism would be as follows: the commodities which are the most fundamentally connected to the oil and dollar effects (bean oil, soybeans, wheat, corn and coffee have the strongest correlation to the brent and to the dollar at the weekly level, as indicated by figure 7) should also present the strongest correlation to index flows (since index investors follow the brent and the dollar) as well as the strongest synchronicity between speculative and index investors (speculators may want to follow index investors more closely in the oil/dollar driven markets, as suggested by Figure 7 also).

[insert Figure 7 here]

To test this hypothesis, we have recomputed the relation between CIT's impact and speculators' synchronicity after controlling for oil and dollar effects in the price impact regression. Figure 6 reveals that the relation continues to hold (see the bottom graph). Hence, the more speculators synchronize with index investors, the more index investors affect the commodity's pricing *relative* to oil and the dollar. We therefore conclude that the relation between speculators' synchronicity and CIT's impact is not driven by the correlation to the oil and currency markets.

An alternative interpretation is therefore supported: speculators absorb (resp. amplify) the impact of index flows in agricultural derivatives markets by trading opposite (resp. along) them. However, it remains to explain the different behaviors of speculators across different markets. A tentative hypothesis is that there is a two-way relationship between speculators' synchronicity

and correlation to major cyclical financial assets (high-yield currencies against dollar, oil, equities...). Speculators appear more tempted to synchronize with index investors in those markets which are the most strongly connected to risky assets (see Figure 7). This behavior, which plausibly aggravates the CIT's impact, could reinforce in turn the connection of these "cyclical agricultural commodities" to other risky financial assets. Wheat markets appear as a noteworthy exception, with a relatively high level of cyclicity yet low speculators' synchronicity.

CONCLUSION

The financialization of commodity markets has triggered a fierce debate in academic and political circles about the impacts of “financial speculators” on commodities prices and market integrity. There has been a vast literature since the commodities’ boom and bust of 2008 attempting to assess whether financial speculation has had an abnormal impact on commodities prices. In spite of this, the question remains debated due to the difficulty to disentangle fundamental and speculative effects in commodities prices.

In this paper, we contribute to this debate in three ways. First, by introducing a novel intra-month inventory proxy, we document a high (low) sensitivity of speculative (index) flows to fundamental information. Second, we estimate the impact of index flows on commodity markets by introducing two novel instrumental variables. These instruments have the property to be calculated from index flows outside the market under analysis. Third, we bring several new insights on speculative behavior and index investors’ price impact: i) commercials, not speculators, offset index flows in agricultural markets; speculators even trade in sync with index investors for a number of commodities (corn, soybeans, bean oil, coffee and cotton display the clearest evidence of such behavior); the propensity of speculators to trade in the same direction as index investors is aggravated in periods of global market stress; ii) index flows *do* have an impact on several agricultural prices at the weekly level; the impact varies across commodities, increasing with the correlation between index and speculative positions; iii) finally, index investors’ impact significantly increases in periods where global liquidity conditions are degraded; again, this effect is cross-sectionally related to the excess synchronicity of speculative and index positions in periods of turmoil.

These observations add to the rising evidence that commodities prices are influenced by non-fundamental trading behaviors in derivatives markets. The tendency of speculators to imitate index investors appears as an important determinant of index investors’ impact on commodities prices. This result holds both cross-sectionally (across the set of twelve agricultural commodities) and temporally (across time periods characterized by different levels of risk aversion). The soybeans complex presents the most strongly synchronized speculative and index behaviors and the strongest index investors’ impact. Both effects are entirely driven by stressed periods. Meat markets, where speculators trade counter-cyclically to index investors in stressed periods, are remarkably insulated from the impact of index investing and global liquidity crises.

The serial correlation of index flows may provide an explanation for the alignment of speculative positions with the ones of index investors. Speculators, which, as shown by recent literature, are trend followers in aggregate, may attempt to exploit predictable index investment/divestment waves by trading along index investors. This interpretation is supported by the fact that stress periods experience more strongly correlated index and speculative positions as well as more serially correlated index flows.

Beyond their relevance to the debate on the regulation of commodities derivatives markets, our findings suggest more generally that the interaction between unspecialized and trend-chasing traders may create unwarranted volatility and correlations in financial securities prices.

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FIGURES AND TABLES

Figure 1: Average Open Interests of the different contracts (in thousands of lots)

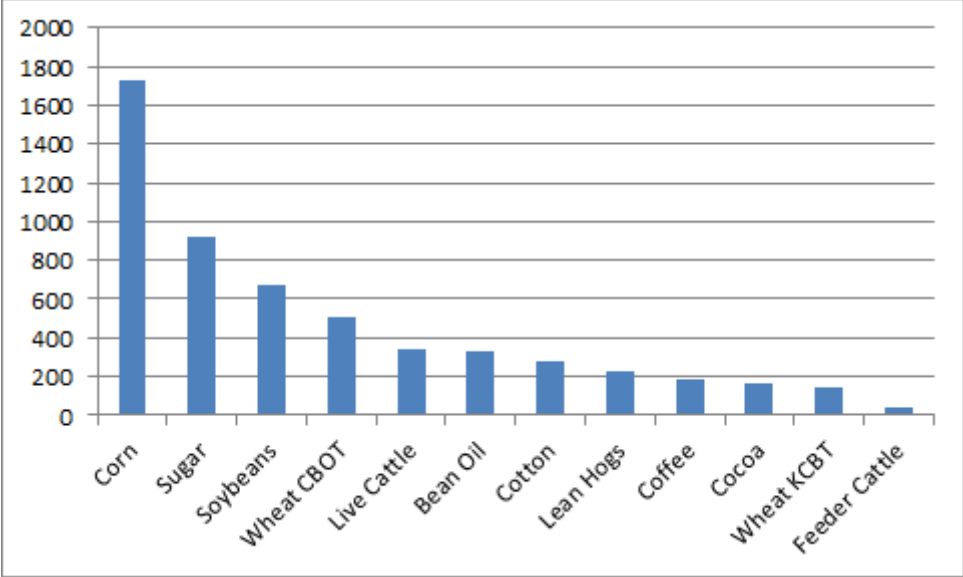


Table 1a: Mean net investing position of CIT and HF in % of the Open Interests; the second column reports the standard deviation of the net investing positions across the 352 different weekly CFTC reports

	CIT		HF	
	Mean	Std	Mean	Std
Wheat (CBOT)	38%	4%	-6%	6%
Bean Oil (CBOT)	24%	4%	5%	10%
Corn (CBOT)	22%	4%	7%	5%
Soybeans (CBOT)	24%	3%	7%	8%
Feeder Cattle (CME)	23%	5%	10%	13%
Lean Hogs (CME)	39%	5%	1%	9%
Live Cattle (CME)	36%	5%	8%	8%
Kansas Wheat (KCBT)	23%	5%	13%	11%
Cocoa (ICE US)	14%	4%	8%	12%
Coffee (ICE US)	25%	5%	5%	9%
Cotton (ICE US)	28%	7%	6%	10%
Sugar (ICE US)	22%	5%	7%	5%
Average	26%	5%	6%	9%

Table 1b: Minimum and maximum net investing position of CIT and HF in % of the Open Interests across the 352 different weekly CFTC reports

	CIT		HF	
	Min	Max	Min	Max
Wheat (CBOT)	29%	51%	-20%	5%
Bean Oil (CBOT)	14%	37%	-15%	23%
Corn (CBOT)	13%	33%	-6%	18%
Soybeans (CBOT)	15%	32%	-15%	20%
Feeder Cattle (CME)	14%	35%	-21%	33%
Lean Hogs (CME)	28%	51%	-18%	18%
Live Cattle (CME)	27%	47%	-7%	27%
Kansas Wheat (KCBT)	12%	34%	-9%	35%
Cocoa (ICE US)	3%	22%	-16%	29%
Coffee (ICE US)	18%	42%	-13%	22%
Cotton (ICE US)	11%	43%	-21%	23%
Sugar (ICE US)	10%	32%	-7%	15%
Average	16%	38%	-14%	22%

Table 2a: Standard deviation of weekly changes in net investing positions (in % of lagged Open Interest) across the 352 reports.

	CIT	HF
Wheat (CBOT)	0.7%	1.5%
Bean Oil (CBOT)	0.8%	3.0%
Corn (CBOT)	0.5%	1.5%
Soybeans (CBOT)	0.6%	2.4%
Feeder Cattle (CME)	1.1%	3.3%
Lean Hogs (CME)	1.0%	2.3%
Live Cattle (CME)	0.6%	1.8%
Kansas Wheat (KCBT)	0.8%	2.3%
Cocoa (ICE US)	0.8%	2.9%
Coffee (ICE US)	0.7%	2.7%
Cotton (ICE US)	0.8%	2.2%
Sugar (ICE US)	0.7%	1.4%
Average	0.8%	2.3%

Table 2b: Minimum and maximum weekly changes in net investing positions (in % of lagged Open Interest) across the 352 reports.

	CIT		HF	
	Min	Max	Min	Max
Wheat (CBOT)	-2.0%	3.4%	-4.6%	5.8%
BeanOil (CBOT)	-3.3%	4.7%	-9.2%	14.4%
Corn (CBOT)	-1.9%	3.3%	-6.8%	7.8%
Soybeans (CBOT)	-2.6%	2.2%	-7.0%	10.3%
Feeder Cattle (CME)	-6.9%	3.8%	-11.9%	10.7%
Lean Hogs (CME)	-5.8%	6.2%	-8.2%	8.0%
Live Cattle (CME)	-4.3%	2.9%	-6.0%	6.0%
Kansas Wheat (KCBT)	-4.2%	5.4%	-6.8%	9.2%
Cocoa (ICE US)	-5.4%	4.0%	-12.6%	18.1%
Coffee (ICE US)	-3.3%	3.1%	-7.7%	9.7%
Cotton (ICE US)	-2.6%	3.6%	-9.0%	7.0%
Sugar (ICE US)	-2.3%	3.4%	-4.6%	6.5%
Average	-3.7%	3.8%	-7.9%	9.4%

Figure 2: **Autocorrelation function of index (upper graph) and speculators' (lower graph) weekly flows.** In each case, the flows are the net aggregate weekly flows divided by lagged aggregate open interests in the twelve agricultural contracts.

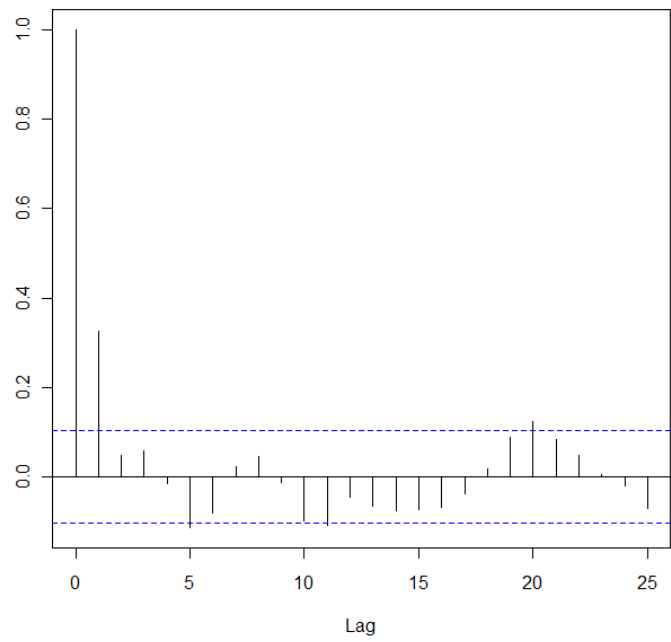
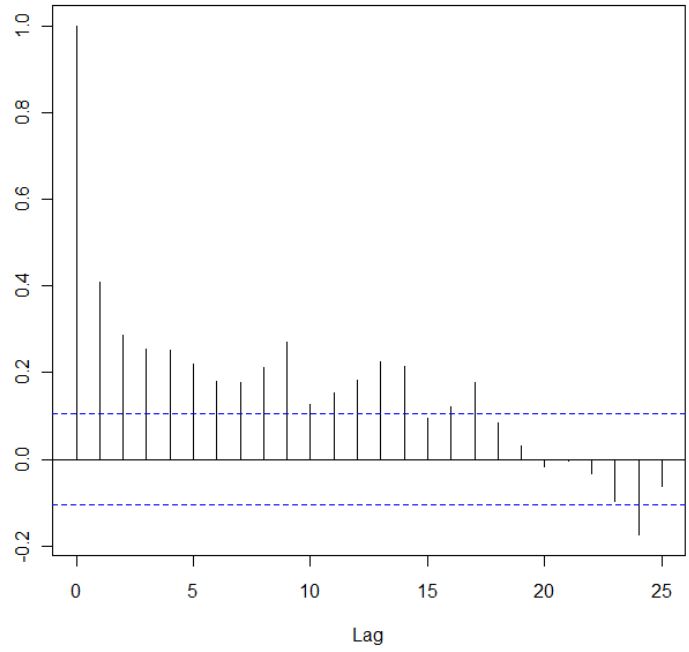


Figure 3: Weekly Risk aversion index since 1997. The zero line represents the frontier between stability and instability. The breakouts of the 1 threshold (in red) often signal an impending large scale liquidity crisis.



Figure 4: Average curve of 9 cyclical commodities, representing a proxy of perceived industrial activity. We note that the average curve has never returned in backwardation since the summer 2008, indicating well-supplied energy and base metal commodities and lackluster world industrial activity

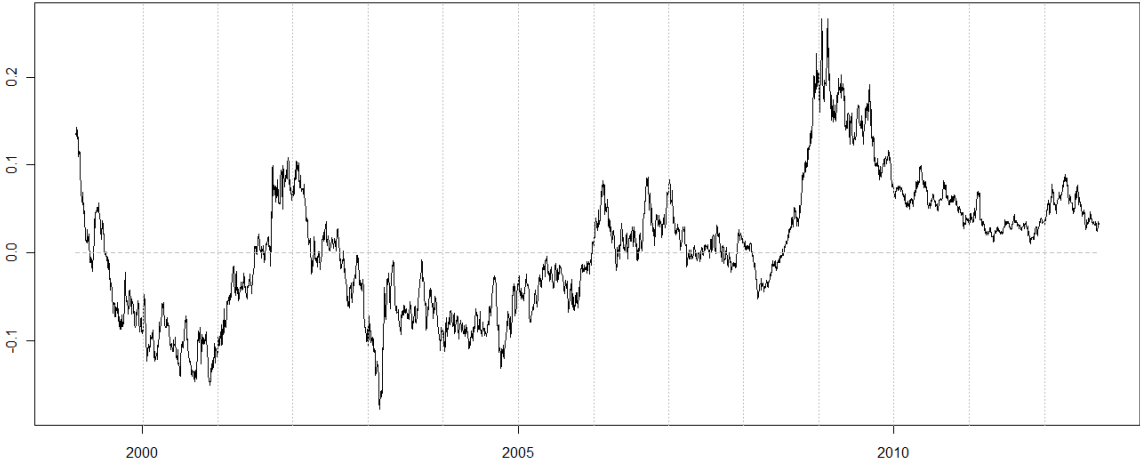


Table 3: Correlation between flows, prices returns, dollar index, risk aversion and inventory proxies at weekly time intervals

“Index” (resp. Spec) flows” stand for the net aggregate index (resp. speculative) weekly flows into the twelve agricultural markets expressed in % of lagged (aggregate) Open Interests.

“Agri Prices” stands for the average weekly return of the twelve first-nearby agricultural futures prices.

RA stands for the weekly change in risk aversion , Dollar_t refers to the dollar index weekly return.

For each commodity (outside the three meat markets), we construct an inventory shock proxy as the weekly return of a strategy longing the one-year-ahead and shorting the prompt-month futures contracts. We then average the eleven inventory shocks into a variable called “Agri Inv Proxy”.

Cycl Inv Proxy_t stands for the average change in the one-year forward curve of nine cyclical energy and metal commodities from week t-1 to week t.

To the right of the correlation coefficient is reported its significance (***) significant at 1%, ** significant at 5%, * significant at 10%). There are 351 weekly observations in each case.

	RA	Dollar	Cycl Inv Proxy	Agri Inv Proxy	Agri Prices	Index flows	Spec flows
RA	1	0.32***	0.03	0.08	-0.34***	-0.13**	-0.27***
Dollar		1	0.22***	0.12**	-0.44***	-0.29***	-0.26***
Cycl Inv Proxy			1	0.16***	-0.3***	-0.16***	-0.12**
Agri Inv Proxy				1	-0.61***	-0.11**	-0.42***
Agri Prices					1	0.33***	0.63***
Index flows						1	0.20***
Spec flows							1

Table 4a: OLS regressions of weekly net index flows on changes in risk aversion, dollar index returns and inventory shock proxies

The model specification is as follows:

$$\frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i} = \alpha + \gamma_1 \text{Inv Shock Proxy}_t + \gamma_2 \text{Cycl Inv Shock Proxy}_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta \text{Dollar}_t}{\text{Dollar}_{t-1}} + \varepsilon_t$$

$\frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i}$ is the net weekly index flow into commodity i in week t to the lagged Open Interests. ΔRA_t stands for the change in risk aversion in week t , $\frac{\Delta \text{Dollar}_t}{\text{Dollar}_{t-1}}$ refers to the dollar index weekly return. Inv Proxy_t^i represents the inventory shock proxy for commodity i in week t , calculated from the return of a strategy longing the one-year-ahead and shorting the prompt-month futures contracts. It is available for all agricultural commodities except the three meat markets. Cycl Inv Proxy_t stands for the change in the inventory of cyclical commodities from week $t-1$ to week t .

The aggregate regression uses the ratio of aggregate index flows to aggregate lagged Open Interest as dependent variable and average inventory news proxy as independent variable.

All the variables are rescaled so that they have zero mean and unitary variance.

Below the regression coefficient is reported the standard error in parentheses and to the right of the regression coefficient its significance (***) significant at 1%, ** significant at 5%, * significant at 10%). There are 351 weekly observations in each case.

		Inv Proxy	Cycl Inv Proxy	RA	Dollar	Adj. R ²
Corn	Coeff	-0.07	-0.04	0.00	-0.23***	0.05
	Std	(0.05)	(0.05)	(0.06)	(0.06)	
Wheat CBOT	Coeff	-0.04	0.03	-0.10*	-0.11*	0.02
	Std	(0.05)	(0.05)	(0.06)	(0.06)	
Wheat KCBT	Coeff	-0.08	-0.03	-0.05	-0.11*	0.02
	Std	(0.05)	(0.05)	(0.05)	(0.06)	
Soybeans	Coeff	-0.18***	-0.03	-0.07	-0.21***	0.08
	Std	(0.05)	(0.05)	(0.05)	(0.06)	
Bean Oil	Coeff	-0.03	0.00	0.01	-0.09	0.00
	Std	(0.06)	(0.06)	(0.06)	(0.06)	
Feeder Cattle	Coeff	-	-0.03	0.04	-0.05	0.00
	Std	-	(0.06)	(0.06)	(0.06)	
Lean Hogs	Coeff	-	-0.05	0.05	-0.10*	0.01
	Std	-	(0.05)	(0.06)	(0.06)	
Live Cattle	Coeff	-	-0.16***	0.07	-0.19***	0.06
	Std	-	(0.05)	(0.05)	(0.06)	
Cocoa	Coeff	-0.09*	-0.02	0.03	-0.20***	0.04
	Std	(0.05)	(0.05)	(0.06)	(0.06)	
Coffee	Coeff	-0.13**	-0.11**	-0.07	-0.06	0.04
	Std	(0.05)	(0.05)	(0.06)	(0.06)	
Cotton	Coeff	-0.07	-0.06	-0.01	-0.01	0.00
	Std	(0.05)	(0.06)	(0.06)	(0.06)	

Table 4a (continued)		Inv Proxy	Cycl Inv Proxy	RA	Dollar	Adj. R ²
Sugar	Coeff	0.13**	-0.13**	-0.05	-0.10*	0.04
	Std	(0.05)	(0.05)	(0.06)	(0.06)	
Aggregate	Coeff	-0.06	-0.09*	-0.04	-0.25***	0.09
	Std	(0.05)	(0.05)	(0.05)	(0.06)	

Table 4b: OLS regressions of weekly net speculative flows on changes in risk aversion, dollar index returns and inventory shock proxies

The model specification is as follows:

$$\frac{NonCom_t^i - NonCom_{t-1}^i}{OI_{t-1}^i} = \alpha + \gamma_1 Inv\ Shock\ Proxy_t + \gamma_2 Cycl\ Inv\ Shock\ Proxy_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \varepsilon_t$$

$\frac{NonCom_t^i - NonCom_{t-1}^i}{OI_{t-1}^i}$ is the net weekly speculative flow into commodity i in week t to the lagged Open Interests.

ΔRA_t stands for the change in risk aversion index in week t , $\frac{\Delta Dollar_t}{Dollar_{t-1}}$ refers to the dollar index weekly return.

$Inv\ Proxy_t^i$ represents the inventory shock proxy for commodity i in week t , calculated from the return of a strategy longing the one-year-ahead and shorting the prompt-month futures contracts. It is available for all agricultural commodities except the three meat markets. $Cycl\ Inv\ Proxy_t$ stands for the change in the inventory of cyclical commodities from week $t-1$ to week t .

The aggregate regression uses the ratio of aggregate speculative flows to aggregate lagged Open Interest as dependent variable and average inventory news proxy as independent variable.

All the variables are rescaled so that they have zero mean and unitary variance.

Below the regression coefficient is reported the standard error in parentheses and to the right of the regression coefficient its significance (***) significant at 1%, ** significant at 5%, * significant at 10%). There are 351 weekly observations in each case.

		Inv Proxy	Cycl Inv Proxy	RA	Dollar	Adj. R ²
Corn	Coeff	-0.39***	-0.07	-0.05	-0.09	0.18
	Std	(0.05)	(0.05)	(0.05)	(0.05)	
Wheat CBOT	Coeff	-0.34***	-0.02	-0.09*	-0.12**	0.14
	Std	(0.05)	(0.05)	(0.05)	(0.05)	
Wheat KCBT	Coeff	-0.31***	0.04	-0.03	-0.14***	0.11
	Std	(0.05)	(0.05)	(0.05)	(0.06)	
Soybeans	Coeff	-0.35***	0.01	-0.24***	-0.11**	0.2
	Std	(0.05)	(0.05)	(0.05)	(0.05)	
Bean Oil	Coeff	-0.36***	-0.06	-0.14***	-0.10*	0.18
	Std	(0.05)	(0.05)	(0.05)	(0.05)	
Feeder Cattle	Coeff	-	-0.02	-0.08	0.03	0.00
	Std	-	(0.06)	(0.06)	(0.06)	
Lean Hogs	Coeff	-	0.07	0.00	-0.05	0.00
	Std	-	(0.06)	(0.06)	(0.06)	
Live Cattle	Coeff	-	0.04	-0.11*	-0.03	0.01
	Std	-	(0.05)	(0.06)	(0.06)	
Cocoa	Coeff	-0.22***	0.09*	-0.04	-0.10*	0.06
	Std	(0.05)	(0.05)	(0.06)	(0.06)	
Coffee	Coeff	-0.39***	0.04	-0.13**	-0.05	0.18
	Std	(0.05)	(0.05)	(0.05)	(0.05)	
Cotton	Coeff	-0.24***	0.05	-0.04	-0.12**	0.07
	Std	(0.05)	(0.05)	(0.05)	(0.06)	

Table 4b continued		Inv Proxy	Cycl Inv Proxy	RA	Dollar	Adj. R ²
Sugar	Coeff	-0.41***	-0.04	-0.13***	-0.06	0.19
	Std	(0.05)	(0.05)	(0.05)	(0.05)	
Aggregate	Coeff	-0.39***	-0.01	-0.20***	-0.15***	0.25
	Std	(0.05)	(0.05)	(0.05)	(0.05)	

Table 5: First stage OLS regression of commodity-specific index flows on “exogenous” index flows

The model specification is as follows:

$$\Delta CIT_t^i = \tilde{\alpha} + \tilde{\beta}_1 IV_t + \tilde{\varepsilon}_t^i$$

where $\Delta CIT_t^i = CIT_t^i - CIT_{t-1}^i$ represents the net weekly index flows to commodity i in week t and IV_t stands for an instrumental variable representing “exogenous” index flows. We successively use two instruments: the first (Agri Flows) is constructed from the aggregate index flows towards the 11 agricultural contracts outside the market under consideration and the second (ETF Flows) is computed from the weekly index flows towards the three main global commodity index ETFs presented in the appendix 2.

All the variables are rescaled so that they have zero mean and unitary variance.

		Agri Flows (351 obs.)	ETF Flows (322 obs.)
Corn	Coeff	0.48***	0.27***
	Std	(0.05)	(0.05)
	Adj. R ²	0.23	0.07
Wheat CBOT	Coeff	0.41***	0.30***
	Std	(0.05)	(0.05)
	Adj. R ²	0.16	0.09
Wheat KCBT	Coeff	0.23***	0.13**
	Std	(0.05)	(0.06)
	Adj. R ²	0.05	0.01
Soybeans	Coeff	0.44***	0.24***
	Std	(0.05)	(0.06)
	Adj. R ²	0.19	0.05
Bean Oil	Coeff	0.32***	0.17***
	Std	(0.05)	(0.06)
	Adj. R ²	0.1	0.02
Feeder Cattle	Coeff	0.21***	0.16***
	Std	(0.05)	(0.06)
	Adj. R ²	0.04	0.02
Lean Hogs	Coeff	0.39***	0.16***
	Std	(0.05)	(0.06)
	Adj. R ²	0.15	0.02
Live Cattle	Coeff	0.53***	0.31***
	Std	(0.05)	(0.05)
	Adj. R ²	0.28	0.09
Cocoa	Coeff	0.27***	0.30***
	Std	(0.05)	(0.06)
	Adj. R ²	0.07	0.08
Coffee	Coeff	0.51***	0.24***
	Std	(0.05)	(0.06)
	Adj. R ²	0.26	0.05

Table 5 (continued)		Agri Flows (351 obs.)	ETF Flows (322 obs.)
Cotton	Coeff	0.38***	0.16***
	Std	(0.05)	(0.06)
	Adj. R ²	0.14	0.02
Sugar	Coeff	0.17***	0.21***
	Std	(0.05)	(0.06)
	Adj. R ²	0.02	0.04
Aggregate	Coeff	-	0.42***
	Std	-	(0.05)
	Adj. R ²	-	0.17

Table 6: OLS and 2SLS estimates of the impact of index flows on speculative flows for the twelve agricultural contracts

The OLS estimate corresponds to a simple OLS regression of speculative flows on index flows:

$$\Delta NonCom_t^i = NonCom_t^i - NonCom_{t-1}^i = \alpha + \beta_1 \Delta CIT_t^i + \varepsilon_t^i$$

where we have posed: $\Delta CIT_t^i = CIT_t^i - CIT_{t-1}^i$. $\Delta NonCom_t^i (CIT_t^i - CIT_{t-1}^i)$ stand for the net speculative (index) flows to commodity i in week t .

The 2SLS estimates correspond to second stage regressions of the impact of index flows on speculative flows:

$$\Delta NonCom_t^i = \alpha + \widehat{\beta}_1 \widehat{\Delta CIT}_t^i + \varepsilon_t^i$$

where $\widehat{\Delta CIT}_t^i$ are the fitted values of ΔCIT_t^i obtained from the first stage linear regression (of index flows on the two possible instrumental variables). We successively use as instruments the index flows towards the 11 agricultural contracts outside the commodity under consideration (2SLS Agri) and the index flows towards the three main generalist commodity ETFs (2SLS ETF).

In the aggregate regression, we use the aggregate flows towards the twelve agricultural contracts, hence only the ETF instrumental variable may be used.

The Hausman test tests the null hypothesis that $\beta_1 = \widehat{\beta}_1$ ($\widehat{\beta}_1$ is estimated from the 2SLS ETF specification). The statistics and p-value of the test are provided in each case.

		OLS (351 obs.)	2SLS Agri (351 obs.)	2SLS ETF (322 obs.)	Hausman test	
Corn	Coeff	0.37**	0.90***	1.07*	stat	1.76
	Std	(0.16)	(0.34)	(0.62)	pval	0.42
	Adj. R ²	0.01	-0.02	-0.08		
Wheat CBOT	Coeff	-0.23*	0.29	0.51	stat	3.12
	Std	(0.12)	(0.31)	(0.45)	pval	0.21
	Adj. R ²	0.01	-0.05	-0.11		
Wheat KCBT	Coeff	0.06	1.14*	0.90	stat	0.57
	Std	(0.15)	(0.69)	(1.27)	pval	0.75
	Adj. R ²	0.00	-0.15	-0.12		
Soybeans	Coeff	0.93***	0.90**	1.85**	stat	1.92
	Std	(0.20)	(0.46)	(0.90)	pval	0.38
	Adj. R ²	0.05	0.05	0.02		
Bean Oil	Coeff	0.39*	1.52**	3.42**	stat	3.84
	Std	(0.20)	(0.66)	(1.61)	pval	0.15
	Adj. R ²	0.01	-0.08	-0.71		
Feeder Cattle	Coeff	0.24	0.27	1.04	stat	0.57
	Std	(0.16)	(0.80)	(1.14)	pval	0.75
	Adj. R ²	0.00	0.00	-0.06		
Lean Hogs	Coeff	-0.22*	-0.11	0.07	stat	0.12
	Std	(0.13)	(0.33)	(0.85)	pval	0.94
	Adj. R ²	0.01	0.00	-0.01		

Table 6 (continued)		OLS (351 obs.)	2SLS Agri (351 obs.)	2SLS ETF (322 obs.)	Hausman test	
Live Cattle	Coeff	0.31*	0.52*	0.75	stat	1.36
	Std	(0.16)	(0.30)	(0.55)	pval	0.51
	Adj. R ²	0.01	0.00	0.00		
Cocoa	Coeff	-0.12	2.20**	1.64**	stat	7.07**
	Std	(0.20)	(0.87)	(0.69)	pval	0.03
	Adj. R ²	0.00	-0.40	-0.25		
Coffee	Coeff	0.52**	1.23***	2.21**	stat	2.96
	Std	(0.22)	(0.43)	(1.04)	pval	0.23
	Adj. R ²	0.01	-0.02	-0.16		
Cotton	Coeff	0.63***	1.02**	1.76*	stat	1.76
	Std	(0.15)	(0.40)	(1.03)	pval	0.42
	Adj. R ²	0.05	0.03	-0.07		
Sugar	Coeff	-0.07	1.93**	0.63	stat	1.4
	Std	(0.11)	(0.93)	(0.61)	pval	0.5
	Adj. R ²	0,00	-0.91	-0.12		
Aggregate	Coeff	0.63***	-	1.15***	stat	2.3
	Std	(0.15)	-	(0.38)	pval	0.32
	Adj. R ²	0.05	-	0.01		

Table 7: **OLS and 2SLS estimates of the impact of index flows on the twelve agricultural price returns**

The OLS estimate corresponds to an OLS regression of price returns on index flows:

$$\frac{P_t^i - P_{t-1}^i}{P_{t-1}^i} = \alpha + \beta_1 \frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i} + \gamma_1 Inv Proxy_t^i + \gamma_2 Cycl Inv Proxy_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \varepsilon_t^i$$

where $\frac{P_t^i - P_{t-1}^i}{P_{t-1}^i}$ represents the return of the rolled futures price series between in week t and $\frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i}$ refers to net index flows to commodity i in week t divided by lagged Open Interests.

ΔRA_t stands for the change in risk aversion in week t, $\frac{\Delta Dollar_t}{Dollar_{t-1}}$ refers to the dollar index return. $Inv Proxy_t^i$ represents the inventory shock proxy for commodity i in week t while $Cycl Inv Proxy_t$ stands for the change in the inventory of cyclical commodities from week t-1 to week t.

The 2SLS estimates correspond to second stage regressions of the impact of index flows on agricultural prices:

$$\frac{P_t^i - P_{t-1}^i}{P_{t-1}^i} = \alpha + \widehat{\beta}_1 \widehat{\Delta CIT}_t^i + \gamma_1 Inv Proxy_t^i + \gamma_2 Cycl Inv Proxy_t + \gamma_3 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \gamma_4 \Delta RA_t + \varepsilon_t^i$$

where $\widehat{\Delta CIT}_t^i$ are the fitted values of $\frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i}$ obtained from the first stage linear regression (of $\frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i}$ on the different instruments). We successively use as instruments the index flows towards the 11 agricultural contracts outside the commodity under consideration (2SLS Agri) and the index flows towards the three main generalist commodity ETFs (2SLS ETF).

In the aggregate regression, the index flows correspond to the ratio of aggregate index flows to the lagged aggregate Open Interests in the twelve agricultural contracts, hence, only the ETF instrumental variable may be used. The inventory variable is calculated as the mean inventory shock across the nine contracts where the measure is available and the price returns is calculated as the mean price return across the twelve agricultural contracts.

The Hausman test tests the null hypothesis that $\beta_1 = \widehat{\beta}_1$ ($\widehat{\beta}_1$ is estimated from the 2SLS ETF specification). The statistics and p-value of the test are provided in each case.

		OLS (351 obs.)	2SLS Agri (351 obs.)	2SLS ETF (322 obs.)	Hausman test	
Corn	Coeff	0.21	0.87	0.37	stat	2.51
	Std	(0.36)	(0.75)	(1.59)	pval	0.87
	Adj. R ²	0.52	0.52	0.51		
Wheat CBOT	Coeff	0.26	1.72***	1.16	stat	4.1
	Std	(0.25)	(0.61)	(0.96)	pval	0.66
	Adj. R ²	0.53	0.49	0.52		
Wheat KCBT	Coeff	0.38*	2.54***	1.76	stat	2.48
	Std	(0.23)	(0.97)	(1.57)	pval	0.87
	Adj. R ²	0.44	0.29	0.36		
Soybeans	Coeff	0.95***	1.34**	3.21**	stat	3.95
	Std	(0.28)	(0.57)	(1.40)	pval	0.68
	Adj. R ²	0.44	0.44	0.37		
Bean Oil	Coeff	0.40**	2.24***	5.17**	stat	4.82
	Std	(0.19)	(0.63)	(2.23)	pval	0.57
	Adj. R ²	0.39	0.23	-0.67		

Table 7 (continued)		OLS (351 obs.)	2SLS Agri (351 obs.)	2SLS ETF (322 obs.)	Hausman test	
Feeder Cattle	Coeff	0.11	0.32	0.27	stat	2.71
	Std	(0.09)	(0.45)	(0.71)	pval	0.75
	Adj. R ²	0.01	0.00	0.01		
Lean Hogs	Coeff	0.14	0.04	-2.01	stat	1.85
	Std	(0.17)	(0.41)	(1.65)	pval	0.87
	Adj. R ²	0.00	0.00	-0.47		
Live Cattle	Coeff	0.50***	0.39	0.46	stat	-17.48
	Std	(0.17)	(0.31)	(0.67)	pval	1.00
	Adj. R ²	0.03	0.03	0.04		
Cocoa	Coeff	1.14***	1.90*	2.68***	stat	4.55
	Std	(0.22)	(1.02)	(0.92)	pval	0.6
	Adj. R ²	0.52	0.51	0.47		
Coffee	Coeff	0.70***	1.13**	1.32	stat	3.36
	Std	(0.25)	(0.51)	(1.23)	pval	0.76
	Adj. R ²	0.55	0.54	0.55		
Cotton	Coeff	0.40*	1.69***	3.66**	stat	3.65
	Std	(0.21)	(0.52)	(1.76)	pval	0.72
	Adj. R ²	0.61	0.57	0.39		
Sugar	Coeff	0.32	2.89	3.91**	stat	4.17
	Std	(0.26)	(1.96)	(1.88)	pval	0.65
	Adj. R ²	0.62	0.51	0.44		
Aggregate	Coeff	0.98***	-	1.91***	stat	3.85
	Std	(0.22)	-	(0.65)	pval	0.70
	Adj. R ²	0.58	-	0.57		

Table 8: OLS estimate of the impact of index flows on agricultural prices with time-varying impacts according to the level of risk aversion

The model specification is as follows:

$$\frac{P_t^i - P_{t-1}^i}{P_{t-1}^i} = \alpha + \beta_1 \frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i} + \beta_2 \frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i} * 1(RA_{t-1} > 0) + \gamma_1 Inv Proxy_t^i + \gamma_2 Cycl Inv Proxy_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \varepsilon_t^i$$

$\frac{P_t^i - P_{t-1}^i}{P_{t-1}^i}$ represents the return of the rolled futures price series of commodity i in week t and $\frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i}$ refers to net index flows to commodity i in week t divided by lagged Open Interests. ΔRA_t stands for the change in risk aversion in week t , $\frac{\Delta Dollar_t}{Dollar_{t-1}}$ refers to the dollar index weekly return. $Inv Proxy_t^i$ represents the inventory shock proxy for commodity i in week t , calculated from the return of a strategy longing the one-year-ahead and shorting the prompt-month futures contracts. $Cycl Inv Proxy_t$ stands for the change in the inventory of cyclical commodities from week $t-1$ to week t .

In each case, we report the result of four regressions: the first regression only includes the index flow as independent variable, the second regression includes the index flows and index flows in stressed periods (index flows multiplied by a dummy variable that equals one if the lagged risk aversion indicator is positive), the third regression only includes the risk aversion and dollar effects, the fourth regression includes index flows, inventory proxies, risk aversion and dollar variables simultaneously. We use the net flows towards the three main generalist commodities ETF to represent weekly "index flows". All the variables are rescaled so that they have zero mean and unitary variance. There are 322 weekly observations in each case.

			ETF Flows	ETF Flows RA > 0	Inv Proxy	Cycl Inv Proxy	RA	Dollar	Adj. R ²
Corn	Reg1	Coeff	0.09						0.00
		Std	(0.06)						
	Reg2	Coeff	-0.15*	0.46***					0.05
		Std	(0.08)	(0.11)					
	Reg3	Coeff					-0.15***	-0.27***	0.12
		Std					(0.05)	(0.05)	
	Reg4	Coeff	-0.14**	0.28***	-0.57***	-0.19***	-0.11***	-0.17***	0.52
		Std	(0.06)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)	
Wheat CBOT	Reg1	Coeff	0.11*						0.01
		Std	(0.06)						
	Reg2	Coeff	0.00	0.21*					0.02
		Std	(0.08)	(0.12)					
	Reg3	Coeff					-0.13**	-0.29***	0.12
		Std					(0.05)	(0.05)	
	Reg4	Coeff	-0.02	0.12	-0.61***	-0.08**	-0.17***	-0.22***	0.54
		Std	(0.06)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)	
Wheat KCBT	Reg1	Coeff	0.10*						0.01
		Std	(0.06)						
	Reg2	Coeff	-0.01	0.22*					0.01
		Std	(0.08)	(0.11)					
	Reg3	Coeff					-0.15***	-0.28***	0.12
		Std					(0.05)	(0.05)	
	Reg4	Coeff	-0.04	0.16*	-0.52***	-0.15***	-0.17***	-0.21***	0.43
		Std	(0.06)	(0.09)	(0.04)	(0.04)	(0.04)	(0.05)	

Table 8 (continued)		ETF Flows	ETF Flows RA > 0	Inv Proxy	Cycl Inv Proxy	RA	Dollar	Adj. R ²	
Soybeans	Reg1	Coeff	0.22***					0.04	
		Std	(0.06)						
	Reg2	Coeff	-0.01	0.44***				0.08	
		Std	(0.08)	(0.11)					
	Reg3	Coeff				-0.24***	-0.21***	0.13	
		Std				(0.05)	(0.05)		
	Reg4	Coeff	-0.08	0.34***	-0.51***	-0.11**	-0.2***	-0.21***	0.45
		Std	(0.06)	(0.09)	(0.04)	(0.04)	(0.04)	(0.05)	
Bean Oil	Reg1	Coeff	0.27***					0.07	
		Std	(0.05)						
	Reg2	Coeff	0.00	0.52***				0.13	
		Std	(0.08)	(0.11)					
	Reg3	Coeff				-0.19***	-0.31***	0.17	
		Std				(0.05)	(0.05)		
	Reg4	Coeff	-0.06	0.45***	-0.46***	-0.18***	-0.17***	-0.17***	0.46
		Std	(0.06)	(0.09)	(0.05)	(0.04)	(0.04)	(0.05)	
Feeder Cattle	Reg1	Coeff	0.06					0.00	
		Std	(0.06)						
	Reg2	Coeff	0.00	0.11				0.00	
		Std	(0.08)	(0.11)					
	Reg3	Coeff				-0.07	-0.08	0.01	
		Std				(0.06)	(0.06)		
	Reg4	Coeff	-0.02	0.1	-	0.00	-0.08	-0.07	0.00
		Std	(0.08)	(0.11)	-	(0.06)	(0.06)	(0.06)	
Lean Hogs	Reg1	Coeff	-0.09					0.00	
		Std	(0.06)						
	Reg2	Coeff	-0.11	0.04				0.00	
		Std	(0.08)	(0.12)					
	Reg3	Coeff				-0.07	0.11*	0.01	
		Std				(0.06)	(0.06)		
	Reg4	Coeff	-0.10	0.05	-	-0.05	-0.07	0.10	0.00
		Std	(0.08)	(0.12)	-	(0.06)	(0.06)	(0.06)	
Live Cattle	Reg1	Coeff	0.07					0.00	
		Std	(0.06)						
	Reg2	Coeff	0.03	0.07				0.00	
		Std	(0.08)	(0.11)					
	Reg3	Coeff				-0.05	-0.09	0.01	
		Std				(0.06)	(0.06)		
	Reg4	Coeff	0.01	0.06	-	-0.07	-0.06	-0.05	0.01
		Std	(0.08)	(0.11)	-	(0.06)	(0.06)	(0.06)	

Table 8 (continued)		ETF Flows	ETF Flows RA > 0	Inv Proxy	Cycl Inv Proxy	RA	Dollar	Adj. R ²	
Cocoa	Reg1	Coeff	0.21***					0.04	
		Std	(0.06)						
	Reg2	Coeff	0.16**	0.11				0.04	
		Std	(0.08)	(0.11)					
	Reg3	Coeff				-0.05	-0.34***	0.12	
		Std				(0.05)	(0.05)		
	Reg4	Coeff	0.09*	0.05	-0.6***	-0.04	-0.04	-0.28***	0.51
		Std	(0.06)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)	
Coffee	Reg1	Coeff	0.11*					0.01	
		Std	(0.06)						
	Reg2	Coeff	0.01	0.19*				0.01	
		Std	(0.08)	(0.11)					
	Reg3	Coeff				-0.19***	-0.27***	0.14	
		Std				(0.05)	(0.05)		
	Reg4	Coeff	-0.01	0.12	-0.65***	-0.08**	-0.16***	-0.1**	0.55
		Std	(0.05)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)	
Cotton	Reg1	Coeff	0.15***					0.02	
		Std	(0.06)						
	Reg2	Coeff	0.00	0.30**				0.03	
		Std	(0.08)	(0.12)					
	Reg3	Coeff				-0.15***	-0.18***	0.06	
		Std				(0.05)	(0.05)		
	Reg4	Coeff	-0.01	0.21***	-0.73***	-0.08**	-0.1***	-0.11***	0.64
		Std	(0.05)	(0.07)	(0.03)	(0.04)	(0.04)	(0.04)	
Sugar	Reg1	Coeff	0.02					0.00	
		Std	(0.06)						
	Reg2	Coeff	-0.09	0.21*				0.00	
		Std	(0.08)	(0.12)					
	Reg3	Coeff				-0.04	-0.15***	0.02	
		Std				(0.06)	(0.06)		
	Reg4	Coeff	-0.01	0.15**	-0.76***	-0.09**	-0.08**	-0.08**	0.64
		Std	(0.05)	(0.07)	(0.03)	(0.04)	(0.04)	(0.04)	
Aggregate	Reg1	Coeff	0.19***					0.03	
		Std	0.06						
	Reg2	Coeff	-0.03	0.44***				0.07	
		Std	(0.08)	(0.11)					
	Reg3	Coeff				-0.22***	-0.37***	0.23	
		Std				(0.05)	(0.05)		
	Reg4	Coeff	-0.05	0.30***	-0.52***	-0.16***	-0.21***	-0.26***	0.58
		Std	(0.05)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)	

Table 9: OLS regressions representing the impact of index flows on speculative flows with time-varying impact according to the level of risk aversion

The model specification is as follows:

$$\Delta NonCom_t^i = \alpha + \beta_1(CIT_t^i - CIT_{t-1}^i) + \beta_2(CIT_t^i - CIT_{t-1}^i) * 1(RA_{t-1} > 0) + \varepsilon_t^i$$

where $\Delta NonCom_t^i$ ($CIT_t^i - CIT_{t-1}^i$) stand for the speculative (index) flows to commodity i in week t and RA_{t-1} for the risk aversion indicator in week $t - 1$. In each case, we report the result of two regressions: one regression including only the index flows as independent variable and one including both index flows and index flows in stressed periods (index flows multiplied by a dummy variable that equals one if the lagged risk aversion indicator is positive). We use the net flows towards the three main generalist commodities ETF to represent weekly "index flows". All the variables are rescaled so that they have zero mean and unitary variance. There are 322 weekly observations in each case.

			ETF Flows	ETF Flows RA > 0	Adj. R ²
Corn	Reg 1	Coeff	0.10*		0.01
		Std	(0.05)		
	Reg 2	Coeff	-0.08	0.35***	0.03
		Std	(0.08)	(0.11)	
Wheat CBOT	Reg 1	Coeff	0.07		0.00
		Std	(0.06)		
	Reg 2	Coeff	0.09	-0.04	0.00
		Std	(0.08)	(0.11)	
Wheat KCBT	Reg 1	Coeff	0.04		0.00
		Std	(0.05)		
	Reg 2	Coeff	0.00	0.08	0.00
		Std	(0.08)	(0.11)	
Soybeans	Reg 1	Coeff	0.11**		0.01
		Std	(0.06)		
	Reg 2	Coeff	-0.04	0.31***	0.03
		Std	(0.08)	(0.11)	
Bean Oil	Reg 1	Coeff	0.15***		0.02
		Std	(0.05)		
	Reg 2	Coeff	0.04	0.23**	0.03
		Std	(0.08)	(0.11)	
Feeder Cattle	Reg 1	Coeff	0.05		0.00
		Std	(0.06)		
	Reg 2	Coeff	0.13	-0.15	0.00
		Std	(0.08)	(0.11)	
Lean Hogs	Reg 1	Coeff	0.00		0.00
		Std	(0.06)		
	Reg 2	Coeff	0.13*	-0.25**	0.01
		Std	(0.08)	(0.11)	
Live Cattle	Reg 1	Coeff	0.08		0.00
		Std	(0.06)		
	Reg 2	Coeff	0.05	0.05	0.00
		Std	(0.08)	(0.11)	

Table 9 (continued)			ETF Flows	ETF Flows RA > 0	Adj. R ²
Cocoa	Reg 1	Coeff	0.14***		0.02
		Std	(0.05)		
	Reg 2	Coeff	0.10	0.07	0.02
		Std	(0.07)	(0.10)	
Coffee	Reg 1	Coeff	0.13**		0.01
		Std	(0.06)		
	Reg 2	Coeff	0.06	0.13	0.01
		Std	(0.08)	(0.11)	
Cotton	Reg 1	Coeff	0.10*		0.01
		Std	(0.06)		
	Reg 2	Coeff	-0.06	0.31***	0.03
		Std	(0.08)	(0.11)	
Sugar	Reg 1	Coeff	0.06		0.00
		Std	(0.06)		
	Reg 2	Coeff	-0.11	0.34***	0.02
		Std	(0.08)	(0.12)	
Aggregate	Reg 1	Coeff	0.17***		0.03
		Std	(0.06)		
	Reg 2	Coeff	-0.03	0.39***	0.06
		Std	(0.08)	(0.11)	

Figure 5: *Sensitivity of price returns to index flows against sensitivity of commercial flows to index flows for the twelve agricultural commodities and global agricultural returns/flows.* The price and flows sensitivities are obtained from the regressions 1 of Tables 8 and 9 respectively. In all cases, we take the ETF flows as the variable representing index flows. The adjusted R^2 of the linear model is 69% and the correlation between the two series 85%.

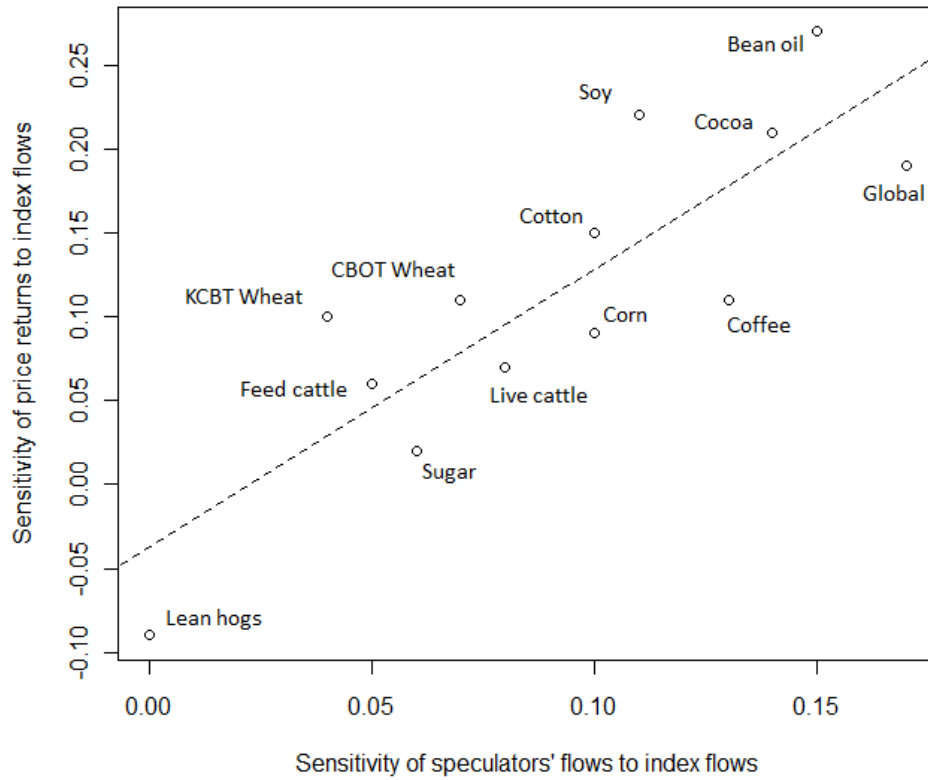


Figure 6: **Excess sensitivity of price returns to index flows against excess sensitivity of speculators' flows to index flows in stressed periods for the twelve agricultural commodities and global agricultural returns/flows.** In top and bottom graphs, the excess sensitivity of speculative flows is obtained from the coefficient of the stressed period index flows variable in "Regression 2" of Table 9. In the top (resp. bottom) graph, the "excess sensitivity of price returns" is defined as the coefficient of the stressed periods index flows variable in the "Regression 2" of Table 8 (resp. Table 11). Hence, the index flows impact is calculated after controlling for Brent and dollar effects in the bottom graph. The adjusted R^2 of the linear model is 54% (resp. 48%) in the top (resp. bottom) graph and the correlation between the two series 76% (resp. 72%).

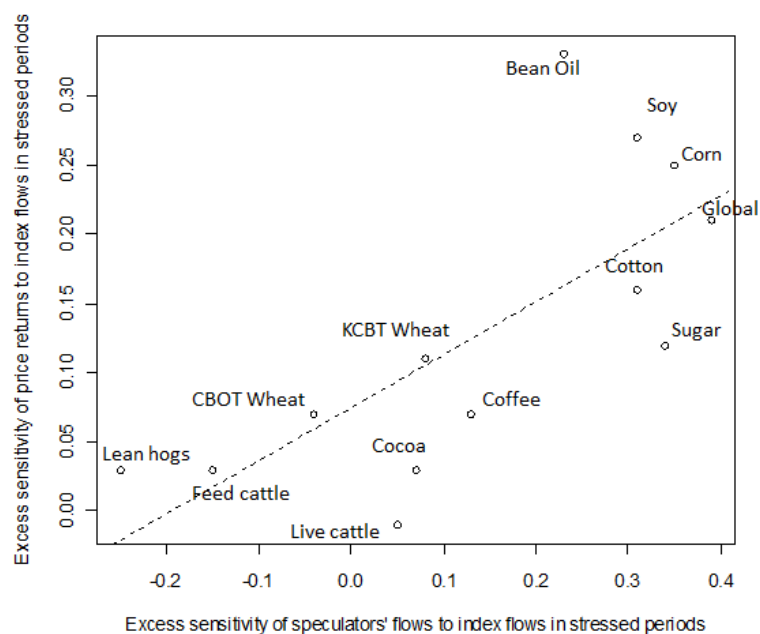
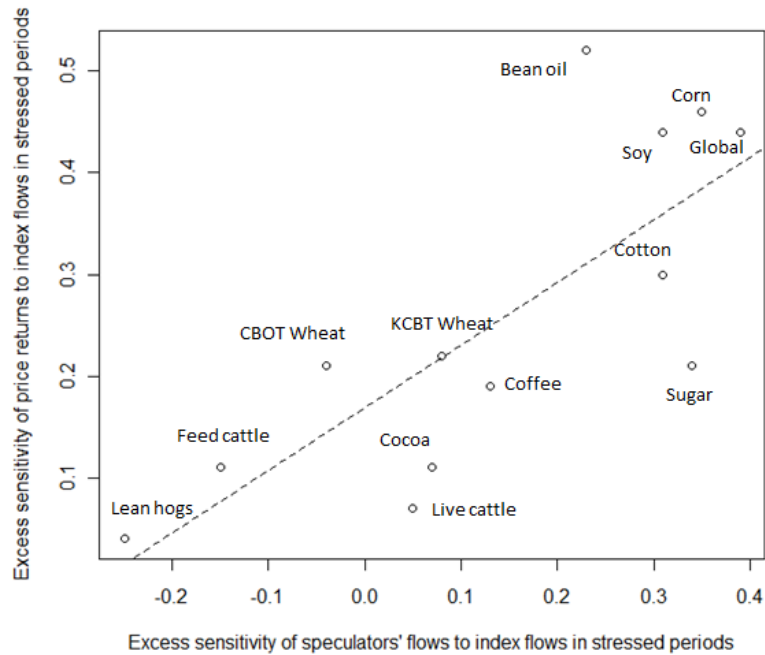


Figure 7: Sensitivity of speculative flows to index flows against correlation to the dollar index (top graph) and the Brent (bottom graph) for the twelve agricultural commodities and global agricultural returns/flows. The flows sensitivities are obtained from regressions 1 of Table 8. Correlations are computed on weekly returns. We have taken the opposite of the correlation to the dollar in the top graph so that the relation is positive between the two variables. The adjusted R^2 of the linear model is 58% (49%) in the top (bottom) graph and the correlation between the two series 79% (73%).

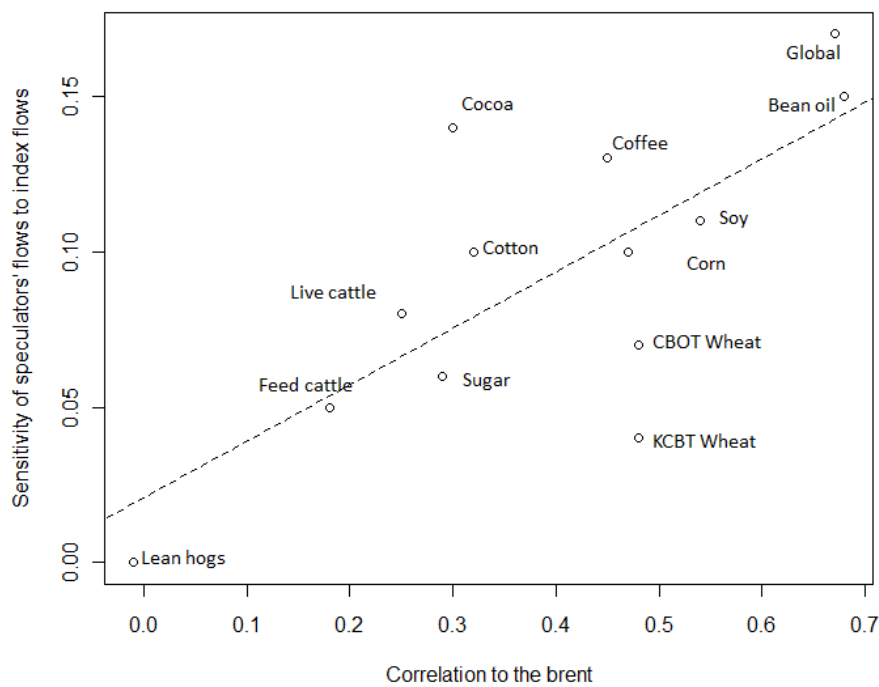
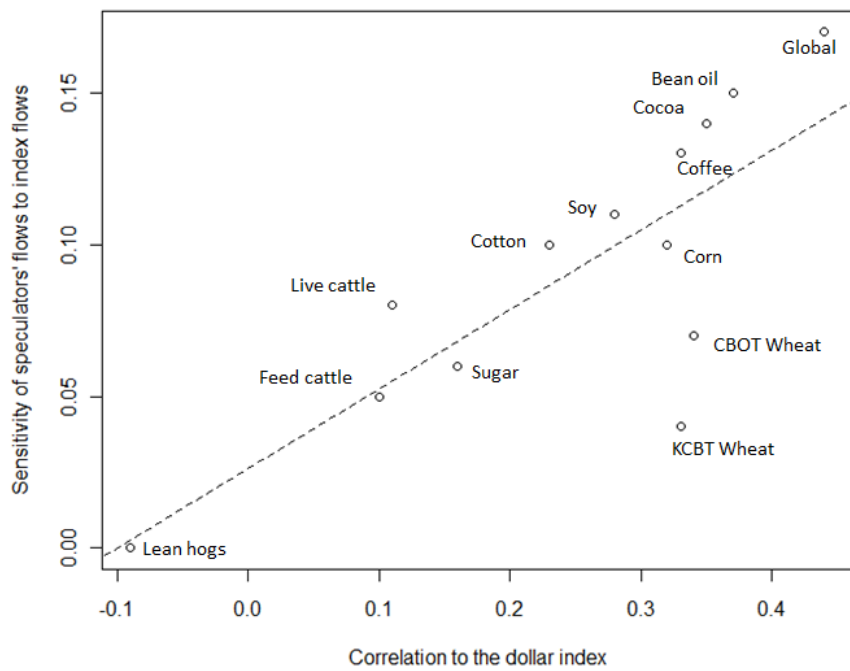


Table 10: OLS Regressions of net aggregate index/speculative weekly flows on changes in risk aversion, dollar index returns and lagged weekly flows, with varying coefficients according to the level of risk aversion

We use four different models, defined as follows:

Model 1 (linear sensitivity to dollar and risk aversion effects):

$$Flows_t = \alpha + \gamma_1 Inv Shock Proxy_t + \gamma_2 Cycl Inv Shock Proxy_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \varepsilon_t$$

Model 2 (time varying dollar and risk aversion sensitivities according to the level of risk aversion):

$$Flows_t = \alpha + \gamma_1 Inv Shock Proxy_t + \gamma_2 Cycl Inv Shock Proxy_t + \gamma_3 \Delta RA_t + \gamma_{3.RA} \Delta RA_t * 1(RA_{t-1} > 0) + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \gamma_{4.RA} \frac{\Delta Dollar_t}{Dollar_{t-1}} * 1(RA_{t-1} > 0) + \varepsilon_t$$

Model 3 (linear sensitivity to lagged flows):

$$Flows_t = \alpha + \gamma_1 Inv Shock Proxy_t + \gamma_2 Cycl Inv Shock Proxy_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \gamma_5 Flows_{t-1} + \varepsilon_t$$

Model 4 (time varying lagged flows sensitivity according to the level of risk aversion):

$$Flows_t = \alpha + \gamma_1 Inv Shock Proxy_t + \gamma_2 Cycl Inv Shock Proxy_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \gamma_5 Flows_{t-1} + \gamma_{5.RA} Flows_{t-1} * 1(RA_{t-1} > 0) + \varepsilon_t$$

ΔRA_t stands for the change in risk aversion in week t , $\frac{\Delta Dollar_t}{Dollar_{t-1}}$ refers to the dollar index weekly return.

$Inv Proxy_t$ represents the average inventory shock proxy across the eleven commodities for which it is available. $Cycl Inv Proxy_t$ stands for the change in the inventory of cyclical commodities from week $t-1$ to week t . All regressions use the aggregate index/speculative flows to aggregate lagged Open Interest as dependent variable and average inventory news proxy as independent variable. Regressions 1, 2, 4 and 5 use index flows as dependent variables while regressions 3 and 4 use speculative flows as dependent variables.

All the variables are rescaled so that they have zero mean and unitary variance. Below the regression coefficient is reported the standard error in parentheses and to the right of the regression coefficient its significance (***) significant at 1%, ** significant at 5%, * significant at 10%). There are 351 weekly observations in each case.

		Inv Proxy	Cycl Inv Proxy	RA	RA RA>0	Dollar	Dollar RA >0	Lagged flows	Lagged flows RA>0	Adj. R ²
Index flows	Coeff	-0.04	-0.10*	-0.05		-0.25***				0.09
Model 1	Std	(0.05)	(0.05)	(0.05)		(0.06)				
Index flows	Coeff	-0.05	-0.10*	0.10	-0.18	-0.32***	0.10			0.09
Model 2	Std	(0.05)	(0.05)	(0.13)	(0.15)	(0.09)	0.11			
Spec flows	Coeff	-0.29***	-0.03	-0.20***		-0.18***				0.19
Model 1	Std	(0.05)	(0.05)	(0.05)		(0.05)				
Spec flows	Coeff	-0.29***	-0.03	-0.29**	0.11	-0.11	-0.11			0.19
Model 2	Std	(0.05)	(0.05)	(0.12)	(0.14)	(0.09)	(0.11)			
Index flows	Coeff	-0.07	-0.16***	-0.09*		-0.20***		0.42***		0.26
Model 3	Std	(0.05)	(0.05)	(0.05)		(0.05)		(0.05)		
Index flows	Coeff	-0.09*	-0.15***	-0.10**		-0.19***		0.35***	0.15*	0.26
Model 4	Std	(0.05)	(0.05)	(0.05)		(0.05)		(0.05)	(0.08)	

Table 11: OLS estimate of the impact of index flows on agricultural prices with brent effect and time-varying impacts according to the level of risk aversion

The model specification is as follows:

$$\frac{P_t^i - P_{t-1}^i}{P_{t-1}^i} = \alpha + \beta_1 \frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i} + \beta_{1.RA} \frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i} * 1(RA_{t-1} > 0) + \beta_2 \frac{Brent_t - Brent_{t-1}}{Brent_{t-1}} + \gamma_1 Inv Proxy_t^i + \gamma_2 Cycl Inv Proxy_t + \gamma_3 \Delta RA_t + \gamma_4 \frac{\Delta Dollar_t}{Dollar_{t-1}} + \varepsilon_t^i$$

$\frac{P_t^i - P_{t-1}^i}{P_{t-1}^i}$ represents the return of the rolled futures price series of commodity i in week t and $\frac{Brent_t - Brent_{t-1}}{Brent_{t-1}}$ is defined accordingly. $\frac{CIT_t^i - CIT_{t-1}^i}{OI_{t-1}^i}$ refers to net index flows to commodity i in week t divided by lagged Open Interests. ΔRA_t stands for the change in risk aversion in week t , $\frac{\Delta Dollar_t}{Dollar_{t-1}}$ refers to the dollar index weekly return. $Inv Proxy_t^i$ represents the inventory shock proxy for commodity i in week t , calculated from the return of a strategy longing the one-year-ahead and shorting the prompt-month futures contracts. $Cycl Inv Proxy_t$ stands for the change in the inventory of cyclical commodities from week $t-1$ to week t .

In each case, we report the result of two regressions (omitting the coefficients of control variables related to inventory and liquidity effect): the first regression includes the brent variable only, the second regression includes index flows, brent and control variables simultaneously.

We use the net flows towards the three main generalist commodities ETF to represent weekly "index flows". All the variables are rescaled so that they have zero mean and unitary variance.

There are 322 weekly observations in each case.

			ETF Flows	ETF Flows RA >0	Brent	Adj. R ²
Corn	Reg1	Coeff			0.38***	0.14
		Std			(0.05)	
Corn	Reg2	Coeff	-0.16***	0.25***	0.14***	0.53
		Std	(0.06)	(0.06)	(0.08)	
Wheat CBOT	Reg1	Coeff			0.38***	0.14
		Std			(0.05)	
Wheat CBOT	Reg2	Coeff	-0.04	0.07	0.18***	0.56
		Std	(0.06)	(0.06)	(0.08)	
Wheat KCBT	Reg1	Coeff			0.39***	0.15
		Std			(0.05)	
Wheat KCBT	Reg2	Coeff	-0.05	0.11	0.2***	0.45
		Std	(0.06)	(0.06)	(0.09)	
Soybeans	Reg1	Coeff			0.45***	0.2
		Std			(0.05)	
Soybeans	Reg2	Coeff	-0.1*	0.27***	0.29***	0.5
		Std	(0.06)	(0.06)	(0.08)	
Bean Oil	Reg1	Coeff			0.62***	0.38
		Std			(0.04)	
Bean Oil	Reg2	Coeff	-0.1*	0.33***	0.44***	0.57
		Std	(0.05)	(0.05)	(0.08)	

Table 11 (continued)		ETF Flows	ETF Flows RA >0	Brent	Adj. R ²	
Feeder Cattle	Reg1	Coeff Std			0.21*** (0.05)	0.04
	Reg2	Coeff Std	-0.04 (0.08)	0.03 (0.08)	0.25*** (0.11)	0.04
Lean Hogs	Reg1	Coeff Std			-0.01 (0.05)	0
	Reg2	Coeff Std	-0.11 (0.08)	0.03 (0.08)	0.07 (0.12)	0
Live Cattle	Reg1	Coeff Std			0.23*** (0.05)	0.05
	Reg2	Coeff Std	-0.01 (0.08)	-0.01 (0.08)	0.25*** (0.11)	0.04
Cocoa	Reg1	Coeff Std			0.25*** (0.05)	0
	Reg2	Coeff Std	0.09 (0.06)	0.03 (0.06)	0.09* (0.08)	0.51
Coffee	Reg1	Coeff Std			0.39*** (0.05)	0.15
	Reg2	Coeff Std	-0.03 (0.05)	0.07 (0.05)	0.19*** (0.08)	0.57
Cotton	Reg1	Coeff Std			0.26*** (0.05)	0.06
	Reg2	Coeff Std	-0.03 (0.05)	0.16** (0.05)	0.17*** (0.07)	0.65
Sugar	Reg1	Coeff Std			0.21*** (0.05)	0.04
	Reg2	Coeff Std	-0.02 (0.05)	0.12* (0.05)	0.13*** (0.07)	0.64
Aggregate	Reg1	Coeff Std			0.56*** 0.04	0.31
	Reg2	Coeff Std	-0.07 (0.05)	0.21*** (0.05)	0.33*** (0.07)	0.64

APPENDIX 1: PROPERTIES OF THE REAL-TIME GRAINS INVENTORY INDEX

We create a smooth inventory proxy from the performance of a strategy shorting the first maturity after the closest harvest (denoted F1), while buying the first maturity after the second closest harvest (F2)¹²:

$$W_t = \prod_{\tau \leq t - \Delta t} \left(1 + \frac{\Delta F_{2\tau}}{F_{2\tau}} - \frac{\Delta F_{1\tau}}{F_{1\tau}}\right)$$

where $\Delta F_\tau = F_{\tau + \Delta t} - F_\tau$ stands for the daily futures price variation between τ and $\tau + \Delta t$. The inventory shock proxy between dates t1 and t2 is then defined by:

$$Inv\ shock\ proxy_{[t1:t2]} = \ln\left(\frac{W_{t2}}{W_{t1}}\right)$$

In this annex, we show on the case of corn at the CBOT that:

- i) The annual observations of $\frac{F_2 - F_1}{F_1}$ just before the completion of the harvest (i.e. between September and December months of each year) have a strong positive correlation to the USDA forecast of the residual stock-to-use in the US at the end of the marketing year (the projected residual inventory at the end of the next August month just before the beginning of the following harvest); see figure A.1.1 and Table A.1.1
- ii) $\ln\left(\frac{W_{t2}}{W_{t1}}\right)$ (which can be interpreted as the variation of the ratio F2/F1 between dates t1 and t2) has a strong positive correlation to the monthly USDA revisions of the projected stock-to-use when the dates t1 and t2 are located just after the releases dates of consecutive monthly USDA (WASDE) reports; see figure A.1.2 and Table A.1.1

These two properties allow us to interpret the changes in $\ln(W_t)$ as a proxy for the revisions in the projected stock-to-use at daily or weekly frequency.

¹² For example, in the case of corn (resp. wheat) futures at the CBOT, the strategy shorts the prompt December (resp. July) month and longs the subsequent December (resp. July) month. When reaching the last trading day of the prompt December contract, the strategy moves to the next two December contracts available. For soybeans, we use the November contract instead of the December contract.

Figure A.1.1: End-of-year relation between CBOT corn forward curve and USDA stock-to-use projections with best linear fit

The x-axis displays, for each year Y, the average Stock-to-Use projections found in the September to December USDA (WASDE) reports of year Y (i.e. the projected residual stock-to-use at the end of the marketing year Y just before the harvest of year Y+1); the y-axis reports, for each year Y, the average forward December to prompt December calendar spread observed from the last trading day of the September contract to the last trading day of the December contract of year Y.

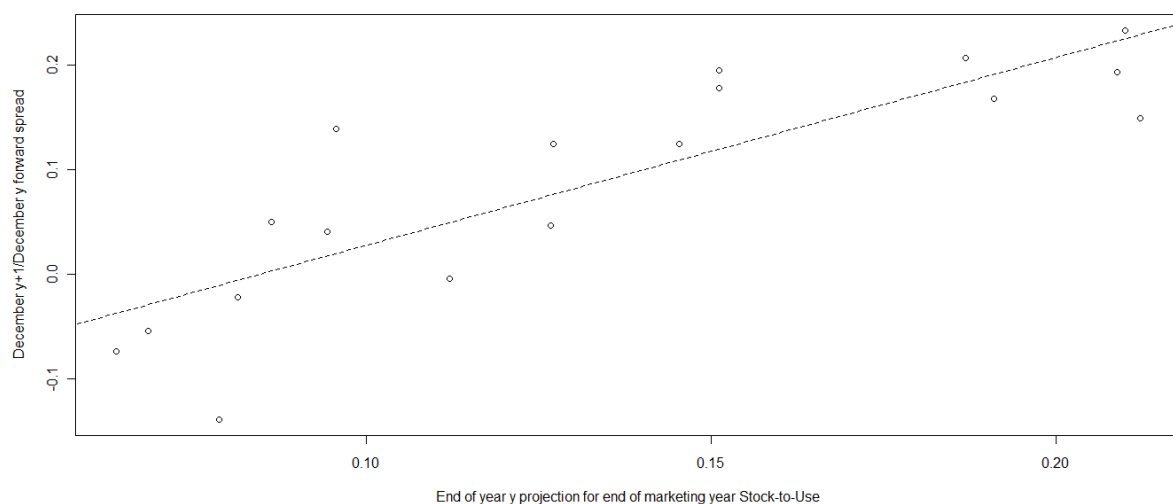


Figure A.1.1: Relation between the monthly dynamics of the CBOT corn forward curve and the monthly revisions of USDA stock-to-use projections with best linear fit

The x-axis corresponds to the monthly revisions in the projected residual stock-to-use at the end of the following marketing year (in the case of the June to August USDA (WASDE) reports) or the current marketing year (in the case of the September to January reports); the y-axis corresponds to the monthly dynamics of the forward December to prompt December calendar spread (the dynamics is calculated between the two dates immediately following the publication of the USDA report); the plot is restricted to the months of June to January as the USDA projections have very little volatility outside this period of the year.

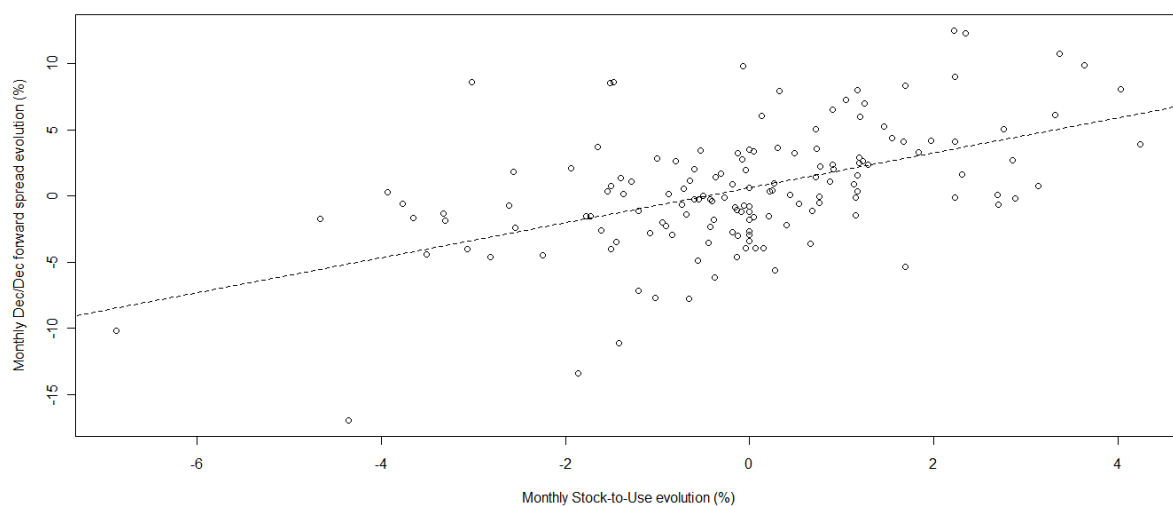


Table A.1.1: **OLS regressions corresponding to the relations displayed in Figures A.1.1 and A.A.2**

End of year regression specification:

$$\left(\frac{F2 - F1}{F1}\right)_y = \alpha + \gamma_1 STU_y + \varepsilon_t$$

Monthly dynamics regression specification:

$$\ln\left(\frac{W_{t2}}{W_{t1}}\right) = \alpha + \gamma_1 (STU_{t2} - STU_{t1}) + \varepsilon_t$$

$\left(\frac{F2-F1}{F1}\right)_y$ represents, for each year y , the average forward December to prompt December calendar spread observed from the last trading day of the September contract to the last trading day of the December contract of year y .

STU_y represents the average Stock-to-Use projections found in the September to December USDA (WASDE) reports of year Y (i.e. the projected residual stock-to-use at the end of the marketing year Y just before the harvest of year $Y+1$).

$\ln\left(\frac{W_{t2}}{W_{t1}}\right)$ corresponds to the monthly dynamics of the forward December to prompt December calendar spread (the dynamics is calculated between the two dates immediately following the publication of the USDA report).

$STU_{t2} - STU_{t1}$ corresponds to the monthly revisions in the projected residual stock-to-use at the end of the following marketing year (in the case of the June to August USDA (WASDE) reports) or the current marketing year (in the case of the September to January reports).

Below the regression coefficient is reported the standard error in parentheses and to the right of the regression coefficient its significance (***) significant at 1%, ** significant at 5%, * significant at 10%). There are 351 weekly observations in each case.

		End of year regression	Monthly dynamics regression
Intercept	Coeff	0.0061	-0.15**
	Std	(0.0033)	(0.041)
Stock-to-Use	Coeff	1.32***	1.8***
	Std	(0.18)	(0.29)
Period		1994-2011 (yearly obs)	1994-2011 (monthly obs from June to January only)
Obs.		18	148
Adj.R ²		29%	69%

APPENDIX 2: COMMODITY INDEX ETFs

The calculation of the assets tracking commodity indices in Figure A.2.1 proceeds in three steps: first, we infer the assets invested in agricultural contracts from the 12 Supplemental Reports; second, we compute the approximate weight of agricultural commodities in global index investing from the CFTC monthly “Special Call”, which reports (with some time lag) the assets invested in each group of commodities¹³; third, we extrapolate the global assets tracking commodity indices by dividing the assets invested in the agricultural contracts by the weight of agricultural commodities in global index investing.

The flows towards the three ETFs of Table A.2.1 between weeks t and t+1 are computed as follows:

$$Flows_{t;t+1} = \sum_{i=1}^3 (N_{t+1}^i - N_t^i) \cdot S_{t+1}^i$$

where N_t^i denotes the number of outstanding shares in ETF i in week t and S_{t+1}^i the ETF share price in week t+1.

Table A.2.1: Three main global commodity index ETFs

In each case, the table provides the underlying commodity index, the name of share issuer, the number of shares outstanding, the Assets Under Management, and the agriculture weight in the index; the data are observed on Jan 15, 2013.

ETF Name	POWERSHARES DB	IPATH DOW JONES-UBS	ISHARES S&P GSCI
Underlying Commodity Index	DB	DJ UBS	GSCI
Parent Comp Name	PowerShares DB ETFs/USA	iPath ETNs/USA	iShares/USA
Outstanding Shares	244 000 000	47 795 190	34 700 000
Last Price (USD)	27.77	41.48	33.16
Total AUM (bln USD)	6.78	1.98	1.15
Agriculture Weight	23%	36%	20%

¹³ This ratio is relatively stable, ranging between 26% and 32% according to the periods

Figure A.2.1: Assets tracking commodity indices

The plain line corresponds to the assets extrapolated from the CFTC Supplemental Report and "Special Call". The dotted line refers to the assets tracking the three main generalist commodity index ETFs. Both series are expressed in billion USD.



Figure A.2.2: Flows towards the three ETFs against the index flows towards the 12 agricultural contracts with best linear fit

The adjusted R^2 and slope of the relation are respectively 17% and 1.7; the correlation between the two series is 42%

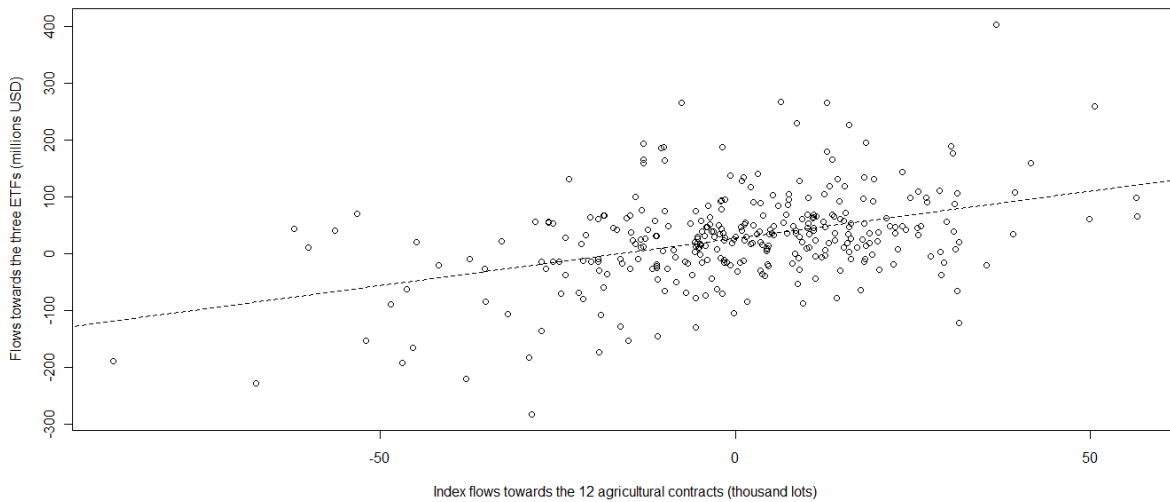


Figure A.2.3: Cumulated index flows towards the 12 agricultural contracts (plain line) and cumulated flows towards the three ETFs (dotted line)

The second series starts in August 2006 as the IShares S&P GSCI ETF was not listed before this date; we observe a neat contrast between the two series in the outflows in the second half of the year 2008

