

The role of financial investments in agricultural commodity derivatives markets

Alessandro Borin and Virginia Di Nino *

(15-October-2009)

Abstract

This empirical work investigates returns and volatilities of futures of eleven agricultural commodities in relation to the outstanding positions held by various type of operators on the derivative markets, in particular commodity index traders. A VAR model of future returns and outstanding positions provides only sparse evidence of causality going from commodity index traders and other operators positions to future returns and no evidence of the reverse causality. The existence of herding behaviour by financial operators is weakly supported in a limited number of markets. When GARCH models are adopted to study jointly the mean and the variance of agricultural commodity prices, the few causal effects found in VAR estimations disappear. Moreover in the few markets where CIT investments appear to significantly affect returns volatility, their impact is rather a stabilizing one.

1. Introduction

The volume of outstanding positions on commodity futures markets has increased almost fourfold in the last ten years; moreover the composition of commodity market participants has changed. During the last commodity boom, the level and volatility of many commodity prices reached unprecedented values, raising concerns that growing financial investment in commodity future markets could have determined price spikes and misalignment from fundamentals. Along with oil and metals, agricultural commodity prices were noticeably involved in this recent boom, after a long lasting period of declining prices. This fuelled the fears that financial market imperfections, affecting primary commodity prices, may threaten food security in various countries. In fact, high volatility of agricultural commodity prices may entail further instability for emerging economies, both as producers and large consumers of these goods. Furthermore, high prices of primary goods may imply undesirable redistribution effects also in advanced countries. The impressive food price levels reached in mid 2008, as well as the concerns for new commodity price surges, have also favoured the current policy debate about the necessity of more restrictive regulations on financial commodity markets. However so far most of the contributions to the debate have been rarely based more on general considerations and personal opinion rather than robust empirical evidence .

*Bank of Italy , Via Nazionale 91 Roma, Italy. alessandro.borin@bancaditalia.it , virginia.dinino@bancaditalia.it .
The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Bank of Italy.

Economic research on the effects of financial investment on commodity futures price movements is rather inconclusive¹. One reason could be the uncertain causal direction, as financial investors may simply react endogenously to price movements brought about by changes in fundamentals; moreover, the quality and availability of data on commodity asset investment are generally poor. The IMF recognized the possible influence of financial investors on commodity indices, but its empirical analyses failed to draw clear conclusions.

In a very recent study² the IMF investigates, along with other factors, the effects of financial investments on long term volatility³ in commodity prices. They identify four main significant determinants that positively affect food price volatility: the index of real activity, the volatility of the US inflation and exchange rate (commodities are mainly quoted in US dollars) and, although with a much smaller effect, total volumes traded in commodity derivative markets.

Our work aims first at providing a comprehensive description of the commodity derivative market functioning; in particular, we will identify three kinds of operators, each with different strategies and instruments. Second, we will further investigate whether financial investment has played a systematic influence on futures price movements of agricultural commodities; for this scope we will employ a new set of data and information available for the agricultural products traded in the main U.S. financial markets.

Initially we will take on Gilbert (2008) approach. He uses positions on futures markets (the Chicago Board of Trade) for some agricultural products (corn, soybeans, soybeans oil and wheat) in order to analyse the influence of financial investors, divided into Commodity Index Traders (CIT) and traditional speculators, on futures price movements between the end of July 2007 and the end of August 2008. The investigation is carried via Granger causality tests, based on the outcome of a VAR model. Gilbert (2008) finds evidence of a systematic influence of CIT positions on futures prices only for soybeans, while in other cases such a link is rejected. Quite importantly, Gilbert (2008) investigates *price level* effects, while *price volatility*, a key feature of the last commodity boom, is not considered. In this work, moving from the recent IMF evidence that traded volumes have an effect on long term volatility of agricultural commodities, we try to identify whether for a given outstanding volume of positions, the impact on short term volatility differs depending on the nature of the investor.

In the paper we apply Gilbert (2008) methodology to the analysis of a larger number of agricultural commodities futures markets, based on data published by the Commodity Futures Trading

¹ See Gilbert (2008); Ch.3 in IMF WEO October 2008; box 5.1 in WEO September 2006.

² World Economic Outlook October 2009.

³ They apply a spline garch model like in Engle and Rangels (2006) which consents variation in long run volatility assumed fixed in simpler garch model.

Commission (CFTC). We look at developments since beginning of 2006 (when detailed information on positions by different types of financial investors became available). The study will examine the influence of both CIT and traditional speculator positions on both the *level* and the *volatility* of futures prices. It is crucial to be able to distinguish between the two different kinds of investors, since their strategies are different and may entail a dissimilar impact on price level and volatility.

2. Evolution of commodity derivatives markets.

The markets of commodity derivatives have grown dramatically during the last ten years (fig.1.a), showing an exceptional acceleration at the beginning of 2006, when the number of outstanding positions in regulated commodity futures markets almost doubled in only six months (Bank of International Settlement 2009). Similar patterns occurred also in other derivatives markets (interest rates, equity indices, exchange rates) as a consequence of the recent financial innovation. Moreover, in the commodity markets the increase in derivatives trading came with a widespread rise in the quotations (fig.1.b), that contributed to bring the value of outstanding positions in the main commodity futures markets from about 100 billions of dollars in 2002, to almost 700 billions at the middle of 2008 (Masters 2008). This amount is comparable with the money invested in organized futures markets of equity indices (1.150 billions of dollars in June 2008 and 730 in December 2008, according to BIS estimates), while it is much smaller than the value of outstanding positions in organized exchanges of interest rate futures (about 20.000 billions of dollars in 2008, base on BIS data).

Figure 1.a Derivative market dimension – Open Interest

(index 1999=100, 3-months moving average, futures-and-options combined)

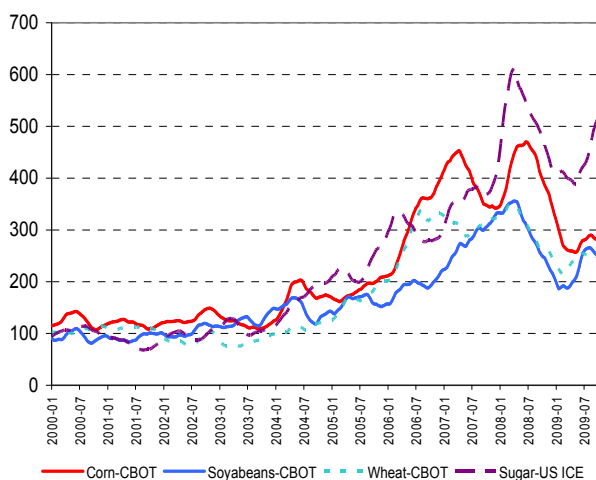
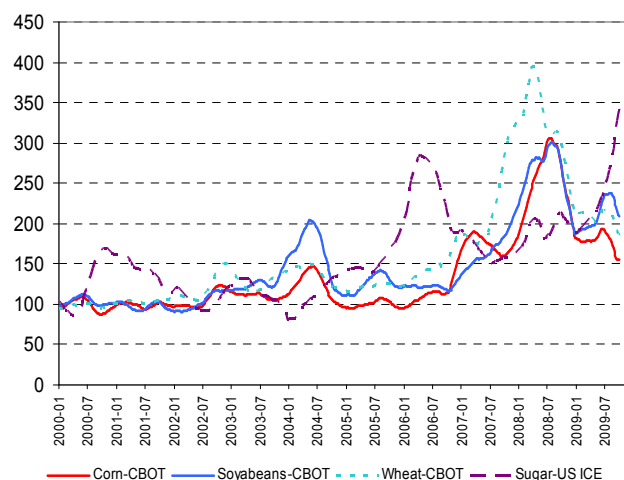


Figure 1.b Nearby futures prices

(index 1999=100, 3-months moving average,)



Source: Commodity Future Trading Commission (CFTC). Source: Thomson Datastream.

Moreover, investments in commodity derivatives are often realized through over the counter (OTC) financial instruments, that have seen a remarkable development in the past few years. According to data provided by the BIS, the notional amounts of outstanding forward and swap contracts on OTC markets reached about 7 trillions of dollars at June 2008. Therefore, nowadays the money invested in the main regulated commodity futures markets represent about one tenth of the overall phenomenon⁴.

The regulated and the OTC markets are interconnected because of the possibility of arbitrage; moreover, the operators on the OTC markets very often hedge their net exposures in the regulated exchanges.

Even for the regulated commodity futures markets in the US, it is however extremely difficult to get precise estimates of the resources invested categorized by investment purpose. First, investors in futures markets may act with multiple scopes. Furthermore, the proportion of contracts traded in organized exchanges with respect to those outstanding in the OTC markets varies substantially among the different types of investments, and we do not have any direct measure of OTC positions by type of investors.

Investments in commodity indices have become relevant only in recent years (since 2002-2003). However, they rapidly gained weight as institutional investors (like pension funds or sovereign wealth funds) were seeking portfolio diversification into commodity derivatives, as it will be treated in more detail in the next section. Most of the investments in commodity indices are made through OTC intermediaries (CFTC 2008). According to some CFTC estimates, based on contracts traded in the main organized exchanged, commodity index investments grew from 75 billion of US dollars in 2006 (Radetzky, 2008) to 146 billion at the end of 2007, and 200 billion in June 2008.

Around a fifth of their investment concerns agricultural commodity wheat, corn, sugar, and live cattle in first place⁵. Cleaning the notional amount of this investments from the effect of the large commodity price increase, these figures imply a growth of the commodity index positions equal to 50 per cent in 2007 followed by a stabilization during the first half of 2008.

⁴ This proportion is in line with those of other financial derivatives markets, like that of interest rates (BIS 2009).

⁵ According to the components and dollar weights published the 14th October 2009 18.3 per cent of all positions are held in agricultural commodities, 3,8 per cent in wheat, 3,3 per cent in corn 2,5 in sugar and 2,5 in live cattle and soybeans 2,4 per cent..

3. Types of participants on commodity derivatives markets.

In principle, we can distinguish among three main types of participants on futures commodity markets, depending on their investment scope and time horizon.

- Hedgers, which use derivative markets to hedge business risks. They are usually supposed to have an exposure to the physical commodity market, for instance mining companies and agricultural producers, refiners of oil and metals or air companies whose costs are heavily affected by fuel prices.
- “Traditional” speculators, which enter the commodity derivative market to make profits, exploit temporary arbitrage opportunities or take positions according to their expectations on future price movements. Their investment horizon usually is relatively short (from few minutes, up to some weeks or months), and they are supposed to revert their positions before the delivery date⁶. In general, they should play a stabilizer role: they contribute liquidity, being also counterparts for hedging transactions; improve market efficiency, aiding price discovery through their efforts to gather information on underlying commodities; since they invest according to expectations over market fundamentals, their behaviour should not distort futures prices. However, in a world with imperfect and asymmetric information, they may adopt procedures to predict price movements not necessarily based on market fundamentals, such as trend extraction techniques (in this case they are named trend followers). In the latter case, their actions may amplify misalignments from fundamental conditions and feed speculative bubbles.
- Commodity index investors, who use commodity derivatives as alternative investment assets in a portfolio diversification strategy and are less concerned with the evolution of fundamentals. Commodity price variations have historically shown a positive correlation with inflation and low correlation with equity returns, which makes their inclusion a natural choice in a long-term optimization strategy. Exposures by these investors tend to reproduce indices that compound different commodities (the two main indices are the Dow Jones-AIG⁷ and the S&P-GSCI). Commodity index investors are characterized by a longer-term horizon than traditional speculators, and their investment strategy would always correspond to acquiring long positions in futures markets (directly, or through intermediaries or other financial instruments) and, in such a way, they may represent a natural counterpart of commercial hedgers, that are usually net short. Differently from traditional speculators,

⁶ There is another group of speculators, named scalpers which often trade in and out of a position within a second and exploit small differentials to earn. They guarantee the immediacy of execution to a trade.

⁷ This index has recently changed name in Dow Jones UBS after the UBS Securities LLC acquired AIG Financial Product Corp.

commodity index investors tend to be passive, to the extent that they do not express any particular belief through their operations but simply replicate a given commodity index.

The role of commodity index investors (or CIT investors) on futures markets is quite controversial. Masters (2008) compares the entry of CIT investors to a physical demand shock, which tends to be quite price-inelastic, as their primary objective is to allocate a given amount of money into commodities, no matter what is the cost of this strategy.⁸

In general the risk is that commodity index investors may affect price quotations through investment strategies irrespective of expectations over fundamentals in commodity markets. Soros (2008) pointed out that during the last commodity price boom CIT investors, looking for higher returns, intensified the trend generated by market fundamentals. Their distorting influence was thus similar to a “traditional” speculative bubble, but with a much larger magnitude and long-lasting consequences⁹.

Moreover, one could also argue that CIT investors may induce “traditional” speculators to follow after the trend they set, as long as the latter believe it will be long-lasting. Thus, even informed speculators may be induced to de-link themselves from market fundamentals, exacerbating a bubble spiral or increasing price volatility.

According to other studies (Radetzki 2008, Greely and Currie 2008), the “passive” investment strategy of index investors prevent them from having an effect on price quotations; quite on the contrary, they are a natural counterpart to commercial hedgers and consequently may improve market liquidity and contribute to price volatility.

These contributions enter the policy debate that followed the last price surge about the necessity of more stringent regulation in commodity derivative markets. In particular for food commodity prices there have been proposals of setting new speculative position limits for operators non involved in the physical market, of requiring higher margins for transactions¹⁰ and increasing transparency also by gathering information from swap dealers and index traders regarding their OTC market activities (CFTC June 2008) or removing swap dealers from commercials to create a specific classification

⁸ In his words: “There is a crucial distinction between Traditional Speculators and Index Speculators: Traditional Speculators provide liquidity by both buying and selling futures. Index Speculators buy futures and then roll their positions by buying calendar spreads. They never sell. Therefore, they consume liquidity and provide zero benefit to the futures markets.”

⁹ Soros (2008), in his report to the U.S. Senate Commerce Committee says, “I shall focus on financial institutions investing in commodity indexes as an asset class because this is a relatively recent phenomenon and it has become the “elephant in the room” in the futures market”.

¹⁰ On the topic Hardouvelis(2003) investigating the effect of margin requirement in the US stock market finds them to be an effective policy tool in curbing destabilizing speculation since they are associated with lower stock price volatility, lower excess volatility and smaller deviation from fundamental values of stock prices.

(CFTC September 2008). In the light of the renewed debate it becomes even more urgent understanding which role the financialization of commodity market holds. A major issue is to obtain data suitable to examine the lack of ability to dispose

4. Data sources.

The Commodity Future Trading Commission (CFTC), which is in charge of publishing, on a weekly basis¹¹, data on the positions taken by each type of investors on the US futures markets (the commitment of traders), used to classify them according to their main economic activity: “Commercials” and “Non commercial”. However, the association between “Commercials” and hedgers of physical market exposures has indeed weakened. By now, this category includes many non-traditional hedgers, as the “swap dealers”, who operate also as counterparts of various types of clients (both commercial and non commercials, including commodity index investors) in the OTC markets. Swap dealers tend to hedge their net exposures in the OTC markets with exposures in the regulated futures markets. For this reason they have been so far associated to commercial operators and granted a special exemption from position limits imposed to other non commercial operators whose modification is now under discussion at the CFTC board¹².

Starting from 2007 the CFTC responded to the need of more transparency by publishing, for a limited number of agricultural products,¹³ a supplement to the standard weekly report on futures positions, in which operators are categorized either as “Commodity Index Traders” (CIT), “non-CIT Commercials”, “non-CIT Non commercials” (also called “other speculators”) and a residual non reportable category. Quoting from CFTC (2006), *“these so-called Index Traders will be drawn from both previous Noncommercial and Commercial categories. Coming from the former there will be managed funds, pension funds and other institutional investors that generally seek exposure to commodity prices as an asset class in an unleveraged and passively-managed manner using a standardized commodity index. Coming from the second category there will be entities whose positions predominantly reflect hedging of OTC transactions (swap dealers, holding long futures positions to hedge short OTC commodity index exposure, opposite institutional traders such as pension funds).”*

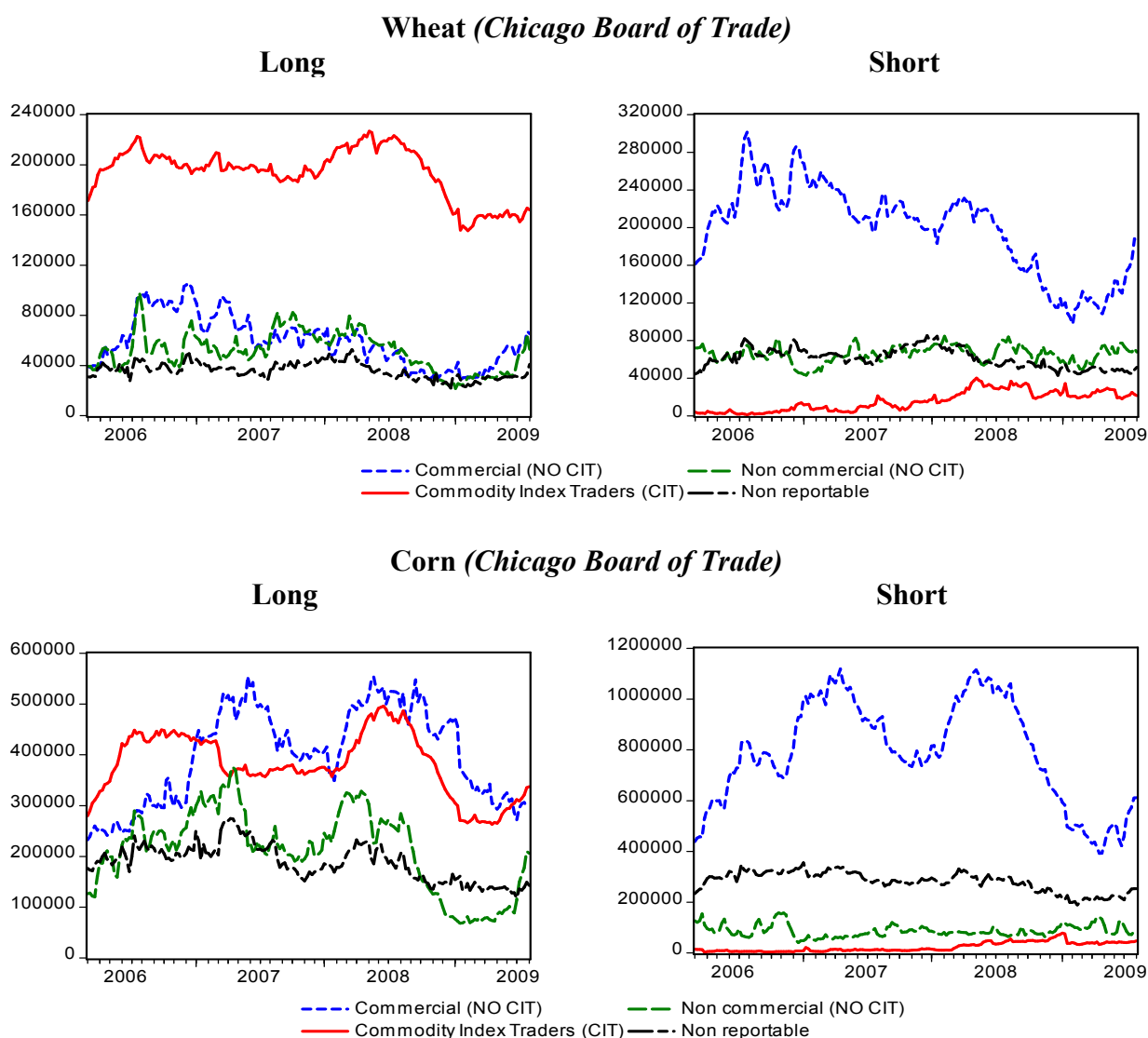
¹¹ The publication is made available each Friday and concerns the outstanding position of each Tuesday.

¹² The recommendation of September 2008 issued by the CFTC asked for a shift from “bona fide hedge exemption” to a “limited risk management exemption” which is conditioned on an obligation to report to the CFTC when non commercial clients reach position limits or certify that none of the swap clients exceed specified position limits in related exchange-regulated commodities.

¹³ The complete list includes: cocoa ICE, cocoa NYBOT, coffee NYBOT, Corn CBOT, Cotton ICE Cotton NYBOT, Feeder Cattle CBOT, Live Cattle CBOT, soybean CBOT, Soybean oil CBOT, sugar NYBOT, wheat CBOT, wheat Kansas City.

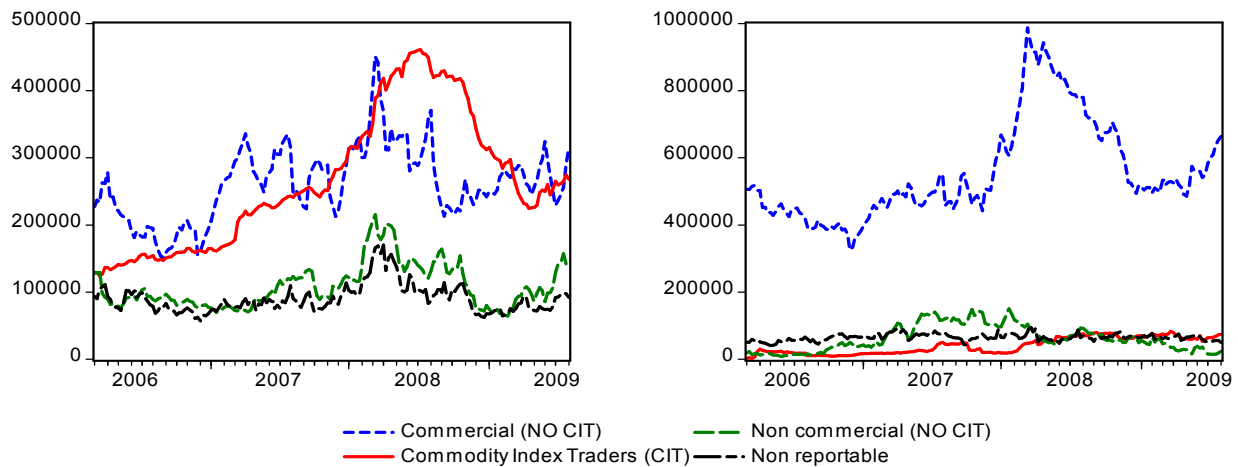
In September 2009 the CFTC started publishing a new Commitment of Traders report, which provides the volume of long and short positions held by four type of operators: proper commercial (producer, merchant, processor, user), swap dealers, money manager and other reportables. This report makes a step forward toward reconciling a operator’s trading activity, as illustrated in section (1), with their filing. Nonetheless a warning issued by the CFTC clarifies potential limitations of the data to the extent that operators may engage in different type of activity: producers may decide to operate swaps activities and operators classified among swap dealers may also engage in commercials activities¹⁴.

Figure 2: Number of outstanding positions, futures-and-options combined, by type of operator.



¹⁴ We meant completing this analysis of the agricultural commodity “financialization” by comparing results obtained employing the two alternative classifications: the CIT supplement and the disaggregated report. Unfortunately the time series of data published so far by the CFTC in the disaggregated report starts only from September 2009. We deem interesting to know what results one may obtain in the same type of analysis employing the disaggregated classification.

Sugar (NY Board of trade and ICE Futures)



Source: Commodity Future Trading Commission (CFTC).

Figure 2 shows the evolution of long and short positions by type of investor for main agricultural commodities: wheat, corn and sugar. It also provides an idea of the data we use in the estimations. The CIT appear as the most important buyers, they almost do not hold short positions but are the largest net holder in each market. Commercial operators and non commercials are more balanced in their investment strategy. Non reportable, a category including small operators not subject to position reporting, are a non negligible fraction of the market.

Our dependent variable consists of weekly nearby future prices going from the beginning of 2006 to October 2009¹⁵. We follow the convention of rolling on the first day of the delivery month. The quotation refers to every Tuesday, the day when data on operator positions are gathered.

5. The econometric modelling of the expected values and empirical estimates.

This study investigates the relation of future prices and the positions held by different types of speculators employing a vector autoregressive model with the scope of ascertaining whether speculative position of CIT or the behaviour of traditional speculators tend to cause (in a statistical sense) price movements rather than being induced by price changes.

Differently from previous literature we have opted for an econometric specification in logarithmic differences. This choice consents to control for the presence of heteroskedasticity, engendered by changes in market dimension and price level, and allows a direct study of market returns and their variability which is, after all what drives the actions of derivative market investors. In addition long and short positions of non commercials operators enter our econometric model separately. The

¹⁵ The use of weekly financial data to analyse financial markets, characterized by very quick operator reactions, is a drawback of our approach which can not be overcome. It makes more difficult obtaining robust estimates of the relations between an operator behaviour and the future price.

reason is twofold: first net positions (long minus short) may be negative and the logarithmic value of negative numbers can not be computed. More importantly our specifications permits to verify effectively whether a positive change in long position by an operator has a similar impact of a negative change in short positions by the same type of operator or rather the two are differentiated. We do not impose any a-priori parameter restriction nor contemporaneous restriction on the endogenous variables as the use of weekly data made impossible to find a valid one. We first investigated the stationarity properties of the variables and found that future prices and speculative positions have a clear non stationary path¹⁶; therefore we estimated the VAR model in logarithmic differences¹⁷:

$$y_t = \gamma_0 + \Gamma y_{t-1} + e_t$$

where the vector of endogenous variables is $y_t = \begin{bmatrix} r_t \\ CIT_t \\ nclong_t \\ ncshort_t \\ nrept_t \end{bmatrix}$, $\Gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \dots & \dots & \gamma_{15} \\ \vdots & \ddots & & & \vdots \\ \vdots & & \ddots & & \vdots \\ \vdots & & & \ddots & \vdots \\ \gamma_{51} & \dots & \dots & \dots & \gamma_{55} \end{bmatrix}$, the

error term is e_t and r represents the futures return. CIT indicates the long position of commodity index traders, $nclong$ represents the long positions of non commercial, similarly $ncshort$ are the short positions of non commercials and $nrept$ stays for long positions of non reportable operators. We excluded from the equation short positions of CIT and non reportable ones which are few and those of commercial operators that should identify actors on the physical market like refiners.

The optimal number of lags has been determined according to selection criteria (our *a priori* is that we may find direct effects of past innovations up to two weeks lag). Based on AIC values we included only one lag for all the eleven commodities considered. In this case (lag=1) the Granger causality test¹⁸, which consists of a likelihood ratio test on the unrestricted model (including all the regressors) and the restricted one (which excludes all the lags of the regressor whose causality we are testing), yields the same results of the simple test of significance of a single regressor. For this reason we preferred reporting in the text the estimated coefficient (Granger test will be provided upon request) that also indicates the covariance sign.

¹⁶ This is confirmed by the value of the AR(1) coefficient obtained from a VAR model in levels and by tests for the existence of unit roots. It does not seem to exist a co-integrating relationship between futures and speculative positions (the Johansen co-integration tests indicate zero as co-integrating vector-rank).

¹⁷ Gilbert (2008) also employs a var model to study the impact of CIT positions on future prices but his econometric specification is first differences.

¹⁸ The ‘‘Granger causality’’ is just a statistical concept of causality that is based on the ability of past values of a variable to help predicting current values of another beyond the information contained in its own lagged values. If two variables are both driven by a common third process, but with a different lag, there would be Granger causality. Yet, manipulation of one process would not change the other.

In table 1 regressors are reported in rows and regressions in columns. The first column shows the estimates obtained from regression on future return, the second on CIT positions and so on so forth. Each row collects estimates afferent to a single regressor; for instance in the second row are reported the covariance of CIT positions percentage change at $t-1$ with future returns at time t and other operators positions at time t .

There are three kinds of relationship particularly interesting to analyze in this exercise. We would like to see (1) whether future return are affected by changes in outstanding positions of various operators, (2) whether returns react differently to some extent to CIT dis/investments and finally (3) whether there are herding behaviour across operators, i.e. an operator's behaviour influences other operators decisions.

At a glance a significant path, valid across markets, does not appear. There are sparse significant coefficient which in many cases point out to the presence of a regressor autocorrelation.

Concerning our first issue, out of the eleven commodity markets investigated, the percentage change of index traders and non-commercials positions in the previous week seem to granger cause future returns in the market of live cattle. A significant covariance with next period future return is also found in the market of soybean oil and cotton with changes in CIT and small operators positions and in the sugar market with non commercial and small operators (with a negative counterintuitive sign) positions. A rise in long non-commercial positions cause an increase in futures returns in the corn market. Finally the derivative positions of non commercials in the cocoa and coffee market show a significant coefficient but with a counterintuitive sign on non commercial positions (long and short respectively).

In general the actions of commodity index traders impact on a few selected market returns and to such extent their role in the market is not different from that of other investors; it is definitely true that provided a significant impact is found, its size is generally much larger (see cotton, soyabean oil and live cattle).

With respect to our last issue on possible herding behaviour of operators, CIT buying is followed within a week by other operators buying in the market of cotton and in a few other cases by small operators. Plastina (2008) analyzes the role of commodity index traders in the cotton market and finds that their investments exert a significant upward pressure on nearby future price. In this work not only we confirm his finding but we also discover that other operators both non commercials and small ones closely follow its investment strategy; they act as a trend followers.

From our analysis we conclude that the opposite is never true (except in feeder cattle but with the wrong sign), CIT never follow other operators strategy. This last finding tends to reinforce the idea that CIT are passive operators interested in balancing a portfolio rather than looking after short run

profit opportunities. Finally we can find significant herding effects among non commercials and non reportable in coffee, sugar, wheat (both Chicago and Kansas) and again cotton.

The limit of such analysis stands in the impossibility of going beyond a statistical causality. We do not have well defined theoretical restrictions on contemporaneous response to shape our empirical approach; moreover although we corrected standard errors for the presence of heteroskedasticity, we have not controlled for a classical feature of financial data: the presence of autocorrelated conditional heteroskedastic volatility of the error term. This will be done in next section.

Table 1.a: Results from Vector Autoregressive estimation.

		Cocoa					Coffee					Corn					Cotton				
All variables are in Δ -log		FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG	FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG	FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG	FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG
Future price (-1)	coef.	<i>0.21</i>	-0.19	<i>0.74</i>	-0.14	<i>0.93</i>	0.06	-0.04	<i>0.65</i>	-0.36	<i>0.59</i>	-0.15	0.00	-0.15	-0.01	-0.13	0.11	0.07	-0.14	0.00	<i>0.46</i>
	t-stat.	<i>2.51</i>	-1.57	<i>4.33</i>	-0.51	<i>3.68</i>	0.62	-0.62	<i>2.40</i>	-0.94	<i>1.64</i>	-1.54	-0.01	-1.05	-0.06	-1.15	1.19	1.39	-0.76	0.01	<i>2.42</i>
CIT pos. LONG(-1)	coef.	-0.01	0.11	-0.03	0.16	0.10	-0.06	<i>0.33</i>	-0.26	-0.26	0.02	-0.02	<i>0.31</i>	0.18	0.37	0.18	<i>0.35</i>	<i>0.27</i>	<i>0.80</i>	-0.54	<i>0.75</i>
	t-stat.	-0.13	1.48	-0.31	0.94	0.63	-0.48	<i>4.45</i>	-0.86	-0.60	0.05	-0.14	<i>4.24</i>	0.66	0.84	0.84	<i>2.62</i>	<i>3.64</i>	<i>3.01</i>	-0.92	<i>2.67</i>
Non commercial pos. LONG(-1)	coef.	<i>-0.11</i>	0.07	<i>0.13</i>	-0.17	-0.03	0.02	0.00	0.21	<i>-0.26</i>	0.17	<i>0.12</i>	0.03	<i>0.27</i>	<i>-0.34</i>	0.11	0.01	0.00	-0.01	0.03	<i>0.23</i>
	t-stat.	<i>-2.96</i>	1.24	<i>1.72</i>	-1.39	-0.30	0.47	0.14	<i>2.49</i>	<i>-2.13</i>	1.47	<i>1.99</i>	1.42	<i>2.90</i>	<i>-2.28</i>	1.50	0.32	0.16	-0.15	0.15	<i>2.40</i>
Non commercial pos. SHORT(-1)	coef.	0.04	0.01	-0.01	<i>0.26</i>	-0.01	<i>0.05</i>	0.00	<i>0.11</i>	<i>0.23</i>	<i>0.15</i>	0.02	0.00	0.01	0.08	0.04	0.00	<i>0.02</i>	<i>-0.07</i>	<i>0.27</i>	0.01
	t-stat.	1.62	0.39	-0.26	<i>3.62</i>	-0.08	<i>2.48</i>	0.06	<i>2.10</i>	<i>3.22</i>	<i>2.19</i>	0.68	-0.33	0.30	1.04	1.05	-0.25	<i>1.91</i>	<i>-1.88</i>	<i>3.30</i>	0.28
Non reportable pos. LONG(-1)	coef.	0.01	0.01	0.06	-0.11	<i>-0.21</i>	<i>0.03</i>	-0.01	<i>0.13</i>	<i>-0.14</i>	<i>-0.27</i>	0.08	0.00	<i>0.17</i>	-0.26	-0.08	<i>-0.07</i>	-0.01	<i>0.19</i>	<i>-0.49</i>	<i>-0.28</i>
	t-stat.	0.45	0.24	1.18	-1.40	<i>-2.91</i>	<i>1.64</i>	-0.84	<i>2.40</i>	<i>-1.81</i>	<i>-3.77</i>	1.12	0.09	<i>1.71</i>	-1.59	-0.97	<i>-2.04</i>	-0.70	<i>2.71</i>	<i>-3.19</i>	<i>-3.76</i>
constant	coef.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	t-stat.	0.88	0.85	-0.28	0.16	-0.43	0.17	0.90	-0.25	0.29	-0.36	0.60	0.58	0.02	0.05	-0.42	-0.20	0.78	-0.10	-0.17	-0.67
Adj. R ²		0.04	0.00	0.18	0.08	0.08	0.02	0.08	0.16	0.18	0.11	0.01	0.11	0.06	0.07	0.01	0.05	0.09	0.10	0.14	0.16

Note: 10, 5, 1 per cent significance are indicated with italic, bold and italic and bold scripts. White heteroskedastic robust standard error.

Table 1b : Results from Vector Autoregressive estimation.

		Feeder Cattle					Live Cattle					Soyabeans					Soyabean Oil				
All variables are in Δ -log		FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG	FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG	FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG	FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG
Future price (-1)	coef.	0.04	0.07	0.44	-2.27	-0.22	-0.10	0.02	-0.07	-0.35	-0.43	-0.01	0.01	0.23	<i>-0.56</i>	0.07	0.03	0.01	0.48	-0.29	0.17
	t-stat.	0.51	0.61	0.98	-4.08	-0.83	-1.48	0.40	-0.30	-1.11	-1.59	-0.09	0.26	1.08	<i>-1.84</i>	0.32	0.38	0.15	1.53	-0.76	0.90
CIT pos. LONG(-1)	coef.	-0.06	0.03	0.10	0.01	0.39	0.21	0.32	0.23	0.01	0.58	0.06	0.16	0.40	0.66	0.48	0.22	0.19	0.21	-0.23	-0.19
	t-stat.	-1.31	0.36	0.36	0.02	2.44	2.95	4.70	0.94	0.04	2.00	0.43	2.14	1.23	1.47	1.54	2.12	2.71	0.57	-0.53	-0.89
Non commercial pos. LONG(-1)	coef.	-0.01	0.02	0.08	-0.06	0.00	0.10	0.03	0.24	-0.09	<i>0.17</i>	-0.03	0.03	0.02	<i>0.24</i>	0.07	-0.03	-0.01	0.03	-0.01	<i>0.09</i>
	t-stat.	-0.44	0.96	1.08	-0.67	0.10	4.89	1.57	3.25	-0.89	<i>1.96</i>	-0.71	1.61	0.17	<i>1.89</i>	0.84	-1.31	-0.46	0.38	-0.07	<i>1.68</i>
Non commercial pos. SHORT(-1)	coef.	-0.01	0.03	-0.06	0.21	-0.03	-0.05	0.00	0.00	0.32	0.07	-0.03	0.01	<i>-0.11</i>	0.11	0.01	-0.01	0.00	-0.09	0.02	-0.02
	t-stat.	-0.65	1.61	-1.12	3.02	-0.76	-3.28	0.18	0.04	4.47	1.09	-1.23	0.70	<i>-1.81</i>	1.32	0.16	-0.79	-0.03	-1.39	0.28	-0.66
Non reportable pos. LONG(-1)	coef.	0.01	-0.08	0.25	-0.06	-0.10	-0.01	-0.01	-0.04	-0.04	<i>-0.12</i>	0.02	0.00	0.06	-0.04	-0.06	0.08	0.00	0.25	-0.34	-0.20
	t-stat.	0.66	-2.47	2.05	-0.37	-1.34	-0.74	-0.80	-0.64	-0.49	<i>-1.70</i>	0.66	0.24	0.71	-0.33	-0.82	2.10	0.18	1.97	-2.20	-2.67
constant	coef.	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	t-stat.	-0.33	0.30	-0.30	0.49	0.02	-0.48	0.96	-0.21	0.61	-0.43	0.73	1.29	-0.12	-0.12	-0.45	0.61	0.45	-0.01	0.27	-0.03
Adj. R ²		-0.01	0.02	0.01	0.15	0.02	0.17	0.10	0.03	0.10	0.04	-0.02	0.04	0.04	0.02	0.00	0.03	0.01	0.07	0.02	0.04

Note: 10, 5, 1 per cent significance are indicated with italic, bold and italic and bold scripts. White heteroskedastic robust standard error.

Table 1.c : Results from Vector Autoregressive estimation.

		Sugar					wheat Chicago					Wheat Kansas				
All variables are in Δ -log		FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG	FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG	FUT	CIT LONG	NC LONG	NC SHORT	NREPT LONG
Future price (-1)	coef.	-0.13	-0.03	-0.14	-0.18	-0.03	0.03	0.03	0.15	-0.11	-0.20	0.06	0.05	-0.08	<i>-0.47</i>	0.17
	t-stat.	-1.79	-0.76	-1.29	-0.72	-0.25	0.35	0.90	0.94	-0.98	-1.38	0.71	0.77	-0.56	<i>-1.64</i>	0.80
CIT pos. LONG(-1)	coef.	0.02	0.27	0.00	0.75	-0.04	-0.07	0.03	0.45	0.12	<i>0.66</i>	-0.04	0.11	-0.21	0.92	-0.33
	t-stat.	0.12	3.64	0.02	1.55	-0.16	-0.34	0.37	1.16	0.43	<i>1.91</i>	-0.43	1.49	-1.29	2.78	-1.30
Non commercial pos. LONG(-1)	coef.	0.15	0.00	<i>0.13</i>	-0.15	0.24	0.02	-0.01	0.10	0.01	0.22	0.07	<i>0.06</i>	0.28	-0.02	0.25
	t-stat.	2.88	0.12	<i>1.68</i>	-0.85	2.61	0.42	-0.77	1.23	0.15	3.01	1.52	<i>1.82</i>	3.52	-0.15	2.05
Non commercial pos. SHORT(-1)	coef.	-0.04	0.00	-0.03	-0.12	-0.01	0.01	0.03	-0.03	0.02	-0.07	0.01	-0.03	-0.03	0.08	<i>0.10</i>
	t-stat.	-1.96	0.29	-0.83	-1.51	-0.35	0.12	1.45	-0.30	0.30	-0.69	0.39	-1.60	-0.72	1.11	<i>1.74</i>
Non reportable pos. LONG(-1)	coef.	0.15	0.01	0.15	-0.12	-0.09	0.07	0.00	0.02	-0.11	-0.25	-0.03	-0.01	<i>-0.09</i>	-0.06	-0.27
	t-stat.	3.21	0.41	2.11	-0.74	-1.14	1.52	-0.14	0.27	<i>-1.85</i>	-3.49	-1.14	-0.33	<i>-1.95</i>	-0.67	-3.74
constant	coef.	0.00	<i>0.00</i>	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
	t-stat.	0.77	<i>1.93</i>	-0.07	-0.24	0.04	0.44	0.29	-0.16	0.38	-0.02	0.43	0.90	-0.48	0.62	-0.34
Adj. R ²		0.16	0.05	0.05	0.00	0.02	-0.01	-0.01	0.02	0.00	0.07	0.00	0.04	0.07	0.05	0.08

Note: 10, 5, 1 per cent significance are indicated with italic, bold and italic and bold scripts. White heteroskedastic robust standard error.

6. Volatility analysis

Empirical research in the field has mainly concentrated on the effect that financial operators have on commodities price level, much less attention has been paid to the link between commodity “financialization” and price volatility. In fact, high volatile commodity prices may involve critical consequences both for the economies specialized in the production of these goods, as well as for the individuals whose expenditure is mainly spent for primary good consumption. Moreover, per se the uncertainty on future price developments entail further costs in terms of hedging, misalignment of investment decision from optimal choices based on the evolution of market fundamentals etc.

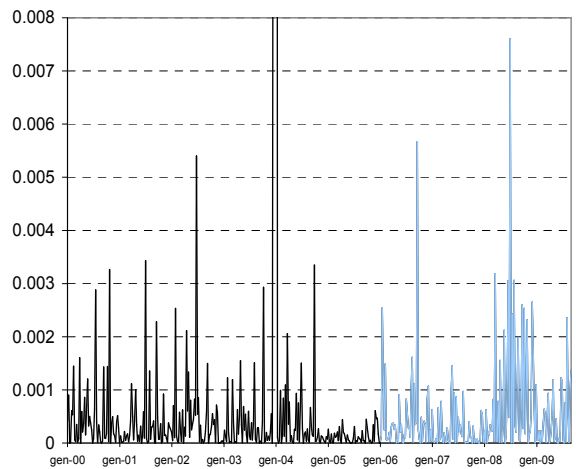
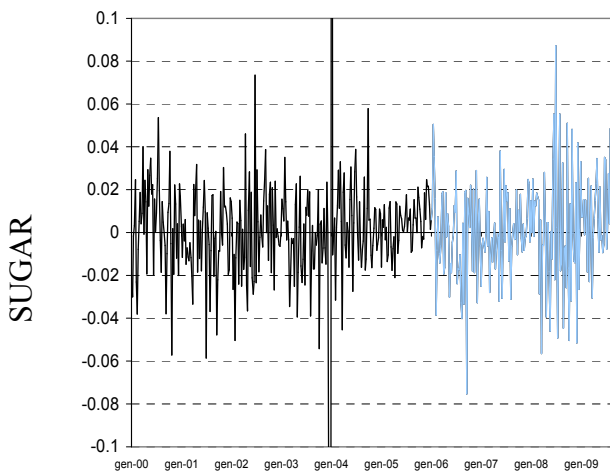
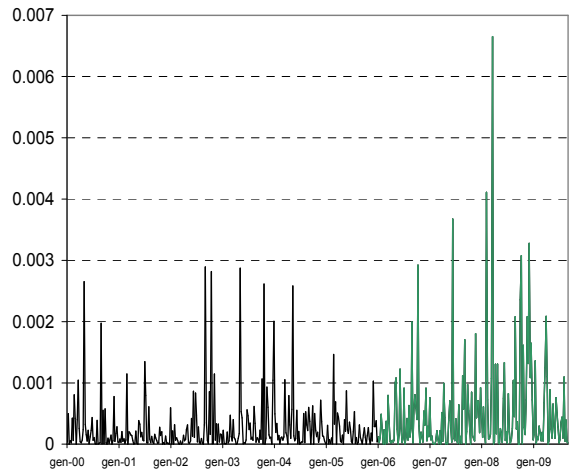
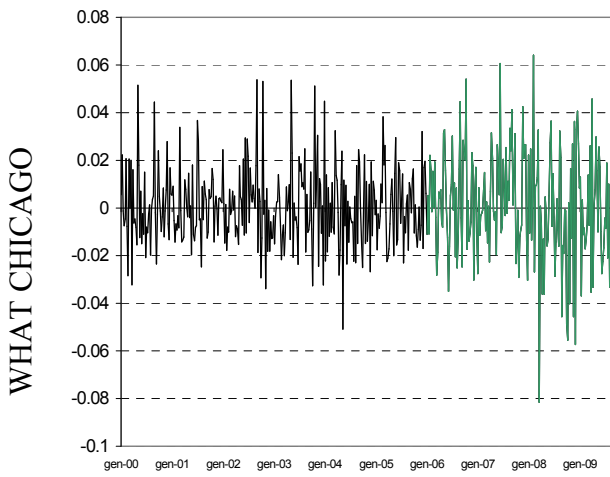
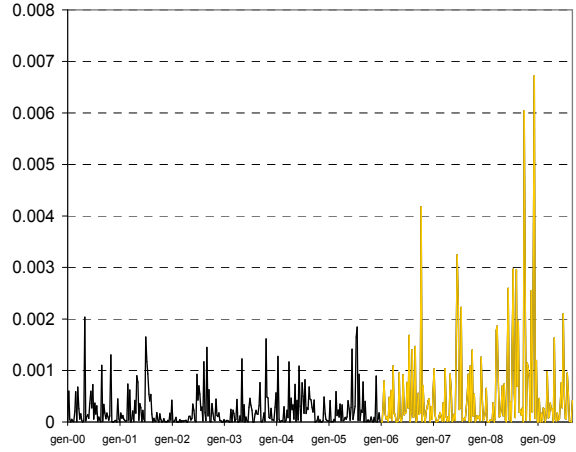
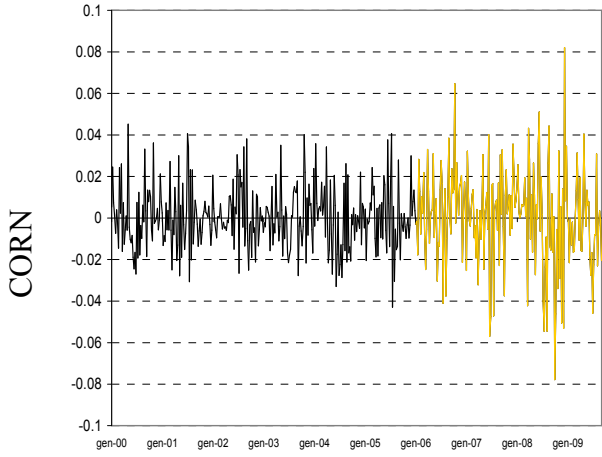
We will then consider the hypothesis that trading in commodity derivatives may be related with price volatility, more than the variations in levels. Before analysing the relationship between derivatives positions and price volatility, it is necessary to analyse the characteristics of the volatility in futures returns. In fact, it is well known that daily returns of futures derivatives, as those of many other financial assets, tend to show a certain degree of autocorrelation in volatility. It means that relative large positive or negative variations are often concentrated in certain periods, while other phases are characterized by a low price volatility. This phenomenon, known as *volatility clustering*, is at the basis of the models of autoregressive conditional heteroskedasticity (ARCH, GARCH, Engle 1982, Bollerslev 1986) developed for the financial series. As our aim is to relate price volatility to the dynamic of investment positions in commodity derivatives market, that are available only at weekly frequencies, we first check for the presence of volatility clustering and GARCH effects also in weekly returns.

To provide a graphical evidence of the presence of volatility clustering, we plot weekly log-differences of nearby futures prices and their squares of the main agricultural commodities from January 2000 to October 2009. As shown in Fig. 3 and in Appendix A, for the other commodities included in the analysis, during the ten year period there is evidence of volatility clustering also in weekly returns in most of the products, as months of relatively high volatility alternates with others of lower volatility. Considering only the period for which the detail of CIT positions are available in CFTC data (from January 2006 to October 2009), we note that it is also a period characterized by general high volatility, while volatility clustering is sometimes less evident.

Figure 3: Graphical evidence of volatility clustering

Logarithmic differences of nearby future prices

Square of logarithmic differences of nearby future prices



Source: Thomson Reuters Datastream .

Source: Thomson Reuters Datastream.

These graphs also show that the presence of GARCH effects is heterogeneous across commodities and it is confirmed by a more formal analysis of the autocorrelations in the squared returns series. While in the futures returns of products like corn, soybeans, soybean-oil and sugar, there is a clear evidence of volatility clustering, it is much weaker in other series (coffee, cotton and live cattle). On the basis of this evidence, we think that it is generally possible to model weekly return volatility (jointly with return means) through the class of models of autoregressive conditional heteroskedasticity (GARCH), developed in the analysis of financial markets.

We adopt different econometric specifications, all based on the following GARCH setting:

$$r_t = \mu + \alpha r_{t-1} + \beta_1 CIT_long_{t-1} + \beta_2 ncomm_long_{t-1} + \beta_3 ncomm_short_{t-1} + \varepsilon_t$$

where $\varepsilon_t = u_t \sqrt{h_t}$ with $u_t \approx N(0,1)$
and $h_t = c + a\varepsilon_t^2 + bh_{t-1} + \sum_i \gamma_i X_i$

X_i represent the set of regressors included in the specification of the conditional variance equation in addition to the ARCH and GARCH components ($\varepsilon_{t-1}^2, h_{t-1}$).

We first estimate a simple GARCH (1,1) model, including only the constant term among the mean regressors ($\beta_j=0$ and $\gamma_i=0$). This represents our baseline specification (model 1) and it is also necessary to check whether a general model of conditional heteroskedasticity may fit the data on futures weekly returns in our sample. Then we extend this specification to include the percentage variations in the positions held by different operators both in the mean and in the variance equation. It addresses the double purposes of accounting for the existence of autoregressive heteroskedasticity in the mean equation, that was not considered in the VAR estimates presented in the previous section, and investigating whether the positions have any impact on volatility. In absence of valid restrictions to identify some structural relation between speculative positions and futures returns (at least on the basis of the available weekly observations), we chose to impose a lag of one period also on the variables on speculative positions included in the variance equation. Thus, any significant coefficient (γ_i), may be interpreted as a sort of “Granger causality” of the variable X_i on the conditional variance of futures returns; in other words this information significantly contributes to predict future volatility. We consider two alternative econometric specifications of the variance equation. In the first case (model 2), we consider the same regressors included in the mean equation - the percentage change of long positions of CIT investors and the percentage change of short and long positions of non commercial operators - in addition to the ARCH and GARCH

components $(\varepsilon_{t-1}^2, h_{t-1})$. Finally, we consider some non linear relationships in volatility including the squared terms of CIT and non commercial long positions (model 3).

The results of the GARCH estimations for the three specifications are reported in table 2.a and 2.b. Considering the simple GARCH (1,1) model, we can see that the estimates parameters for the GARCH component (h_{t-1}) are significant and with the expected sign in eight out of eleven market, with the exceptions of coffee, wheat-CBOT and wheat-Kansas. Thus a specification with autoregressive conditional heteroskedasticity seems, in general, appropriate to model the variance of futures returns in our sample.

Considering the relations between changes in trading volumes of different operators and the volatility of commodity futures prices, we note that the coefficient of CIT operators are significant only in four cases. Furthermore for three of these markets (cocoa, coffee and corn) the coefficient is negative, that means that an increase in the long positions held by commodity index operators is associated with a decrease in volatility. The variations in gross long positions of the other commercial operators do not show any significant correlation with price volatility at week frequency, while in the case of coffee there is a significant negative relation between short positions of non commercial operators and futures returns volatility.

In general our empirical analysis does not find strong correlation between trading activity in futures markets of pure financial operators and commodity price volatility. Furthermore, considering the mean equations of the GARCH estimates, we note that some significant relations found in the VAR regressions, are not robust to specifications that model the heteroskedasticity in the error term.

Table 2.a Results of GARCH estimations

	Cocoa			Coffee			Corn			Cotton			Feeder cattle			Livecattle		
All variables are in Δ -log Dep. variable: Future price	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
constant	0.004 <i>(0.003)</i>	0.003 <i>(0.003)</i>	0.002 <i>(0.003)</i>	0.001 <i>(0.003)</i>	0.001 <i>(0.00)</i>	0.002 <i>(0.003)</i>	<i>0.006</i> <i>(0.004)</i>	0.004 <i>(0.004)</i>	0.002 <i>(0.004)</i>	0.001 <i>(0.003)</i>	0.000 <i>(0.007)</i>	-0.003 <i>(0.004)</i>	-0.001 <i>(0.002)</i>	-0.003 <i>(0.009)</i>	0.000 <i>(0.002)</i>	-0.001 <i>(0.002)</i>	0.000 <i>(0.002)</i>	-0.001 <i>(0.003)</i>
Future price (-1)		0.170 <i>(0.085)</i>	0.173 <i>(0.079)</i>		0.095 <i>(0.126)</i>	0.091 <i>(0.107)</i>		0.000 <i>(0.111)</i>	-0.072 <i>(0.094)</i>		0.001 <i>(0.147)</i>	0.043 <i>(0.106)</i>		0.008 <i>(0.323)</i>	0.060 <i>(0.042)</i>		0.014 <i>(0.113)</i>	0.007 <i>(0.135)</i>
CIT pos. LONG(-1)		0.028 <i>(0.039)</i>	0.084 <i>(0.046)</i>		-0.109 <i>(0.097)</i>	-0.113 <i>(0.144)</i>		0.000 <i>(0.205)</i>	-0.151 <i>(0.142)</i>		0.001 <i>(0.29)</i>	0.293 <i>(0.185)</i>		-0.020 <i>(0.215)</i>	-0.088 <i>(0.076)</i>		-0.010 <i>(0.080)</i>	0.001 <i>(0.108)</i>
Non commercial pos. LONG(-1)		-0.073 <i>(0.037)</i>	-0.050 <i>(0.034)</i>		0.009 <i>(0.045)</i>	0.010 <i>(0.030)</i>		0.000 <i>(0.076)</i>	0.053 <i>(0.042)</i>		0.003 <i>(0.059)</i>	0.004 <i>(0.036)</i>		0.003 <i>(0.043)</i>	-0.020 <i>(0.016)</i>		-0.031 <i>(0.026)</i>	-0.005 <i>(0.017)</i>
Non commercial pos. SHORT(-1)		0.000 <i>(0.000)</i>	0.022 <i>(0.022)</i>		0.048 <i>(0.020)</i>	0.045 <i>(0.029)</i>		0.000 <i>(0.000)</i>	0.041 <i>(0.034)</i>		0.000 <i>(0.000)</i>	-0.009 <i>(0.028)</i>		0.000 <i>(0.000)</i>	-0.010 <i>(0.014)</i>		0.014 <i>(0.016)</i>	-0.001 <i>(0.021)</i>
	<i>Variance Eq.</i>			<i>Variance Eq.</i>			<i>Variance Eq.</i>			<i>Variance Eq.</i>			<i>Variance Eq.</i>			<i>Variance Eq.</i>		
constant	0.000 <i>(0.000)</i>	0.001 <i>(0.000)</i>	0.001 <i>(0.000)</i>	0.001 <i>(0.000)</i>	0.001 <i>(0.000)</i>	0.001 <i>(0.001)</i>	0.000 <i>(0.000)</i>	0.000 <i>(0.000)</i>	0.00 <i>(0.001)</i>	0.000 <i>(0.000)</i>	0.001 <i>(0.000)</i>	0.001 <i>(0.001)</i>	0.000 <i>(0.000)</i>	0.001 <i>(0.000)</i>	0.000 <i>(0.000)</i>	0.000 <i>(0.000)</i>	0.000 <i>(0.000)</i>	0.000 <i>(0.000)</i>
Residual(-1)^2	0.020 <i>(0.018)</i>	-0.063 <i>(0.045)</i>	-0.097 <i>(0.036)</i>	0.109 <i>(0.111)</i>	0.063 <i>(0.120)</i>	0.101 <i>(0.119)</i>	0.067 <i>(0.037)</i>	0.008 <i>(0.042)</i>	0.01 <i>(0.055)</i>	0.070 <i>(0.046)</i>	-0.005 <i>(0.087)</i>	0.084 <i>(0.131)</i>	0.095 <i>(0.064)</i>	-0.151 <i>(0.15)</i>	-0.013 <i>(0.089)</i>	0.024 <i>(0.048)</i>	0.092 <i>(0.060)</i>	-0.039 <i>(0.043)</i>
GARCH(-1)	0.971 <i>(0.035)</i>	0.752 <i>(0.082)</i>	0.550 <i>(0.103)</i>	0.366 <i>(0.628)</i>	0.172 <i>(0.208)</i>	0.268 <i>(0.482)</i>	0.888 <i>(0.064)</i>	0.887 <i>(0.055)</i>	0.544 <i>(0.214)</i>	0.918 <i>(0.066)</i>	0.857 <i>(0.122)</i>	0.337 <i>(0.649)</i>	0.831 <i>(0.097)</i>	0.825 <i>(0.124)</i>	-0.084 <i>(0.136)</i>	0.817 <i>(0.168)</i>	0.886 <i>(0.062)</i>	0.484 <i>(0.619)</i>
CIT pos. LONG(-1)		-0.007 <i>(0.003)</i>	-0.012 <i>(0.003)</i>		-0.008 <i>(0.003)</i>	-0.010 <i>(0.006)</i>		-0.003 <i>(0.000)</i>	-0.01 <i>(0.007)</i>		-0.007 <i>(0.009)</i>	-0.006 <i>(0.015)</i>		-0.006 <i>(0.008)</i>	-0.002 <i>(0.003)</i>		0.001 <i>(0.001)</i>	-0.002 <i>(0.003)</i>
Non commercial pos. LONG(-1)		-0.001 <i>(0.001)</i>	0.000 <i>(0.001)</i>		0.001 <i>(0.002)</i>	0.002 <i>(0.002)</i>		-0.003 <i>(0.002)</i>	0.00 <i>(0.004)</i>		-0.002 <i>(0.001)</i>	-0.001 <i>(0.004)</i>		0.002 <i>(0.001)</i>	0.001 <i>(0.001)</i>		0.000 <i>(0.000)</i>	0.000 <i>(0.001)</i>
Non commercial pos. SHORT(-1)		-0.002 <i>(0.001)</i>			-0.003 <i>(0.001)</i>			0.000 <i>(0.001)</i>			0.000 <i>(0.001)</i>			-0.001 <i>(0.001)</i>			0.000 <i>(0.000)</i>	
CIT pos. LONG(-1)²			0.027 <i>(0.024)</i>			0.089 <i>(0.103)</i>			-0.18 <i>(0.164)</i>			-0.015 <i>(0.195)</i>			0.128 <i>(0.071)</i>			-0.019 <i>(0.066)</i>
Non commercial pos. LONG(-1)²			0.000 <i>(0.003)</i>			-0.004 <i>(0.006)</i>			-0.02 <i>(0.013)</i>			-0.010 <i>(0.016)</i>			0.004 <i>(0.004)</i>			-0.009 <i>(0.008)</i>
<i>for the mean equation</i>																		
Adj. R ³	-0.02	0.01	-0.02	-0.02	-0.05	-0.06	-0.02	-0.06	-0.06	-0.02	-0.06	-0.02	0.00	-0.06	-0.05	-0.02	-0.07	0.07
DW	1.70	1.92	1.99	1.94	2.03	2.03	2.10	2.09	1.91	1.76	1.83	1.92	1.92	1.99	2.02	2.01	1.95	1.91
F.-stat.		1.22	0.70		0.16	0.14		0.02	0.10		0.07	0.70		0.05	0.25			0.01
P.-value		0.28	0.73		1.00	1.00		1.00	1.00		1.00	0.74		1.00	0.99			1.00

Note: 10, 5, 1 per cent significance are indicated with italic, bold, italic and bold scripts.

Table 2.b Results of GARCH estimates

	Soyabeans			Soyabean-oil			Sugar			Wheat-Chicago			Wheat-Kansas		
All variables are in Δ -log Dep. variable: Future price	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
constant	0.006 <i>(0.002)</i>	0.006 <i>(0.003)</i>	0.007 <i>(0.003)</i>	0.008 <i>(0.003)</i>	0.006 <i>(0.000)</i>	0.008 <i>(0.003)</i>	0.001 <i>(0.004)</i>	0.001 <i>(0.002)</i>	-0.002 <i>(0.005)</i>	0.003 <i>(0.003)</i>	0.003 <i>(0.005)</i>	0.002 <i>(0.004)</i>	0.003 <i>(0.002)</i>	0.004 <i>(0.003)</i>	0.002 <i>(0.006)</i>
Future price (-1)		0.126 <i>(0.107)</i>	0.062 <i>(0.103)</i>		0.119 <i>(0.079)</i>	0.169 <i>(0.092)</i>		-0.185 <i>(0.068)</i>	-0.050 <i>(0.088)</i>		0.040 <i>(0.087)</i>	-0.003 <i>(0.086)</i>		0.034 <i>(0.091)</i>	0.060 <i>(0.118)</i>
CIT pos. LONG(-1)		-0.067 <i>(0.132)</i>	-0.001 <i>(0.148)</i>		0.137 <i>(0.107)</i>	0.063 <i>(0.091)</i>		0.002 <i>(0.117)</i>	-0.015 <i>(0.140)</i>		0.214 <i>(0.214)</i>	0.035 <i>(0.244)</i>		-0.099 <i>(0.083)</i>	-0.042 <i>(0.107)</i>
Non commercial pos. LONG(-1)		-0.051 <i>(0.036)</i>	-0.025 <i>(0.02)</i>		-0.041 <i>(0.023)</i>	-0.086 <i>(0.011)</i>		0.202 <i>(0.037)</i>	0.227 <i>(0.048)</i>		0.036 <i>(0.038)</i>	0.076 <i>(0.048)</i>		0.065 <i>(0.042)</i>	0.074 <i>(0.073)</i>
Non commercial pos. SHORT(-1)		0.000 <i>(0.000)</i>	-0.018 <i>(0.019)</i>		-0.015 <i>(0.018)</i>	-0.015 <i>(0.015)</i>		-0.061 <i>(0.015)</i>	-0.065 <i>(0.031)</i>		0.024 <i>(0.054)</i>	0.037 <i>(0.056)</i>		-0.014 <i>(0.011)</i>	0.016 <i>(0.038)</i>
	Variance Eq.			Variance Eq.			Variance Eq.			Variance Eq.			Variance Eq.		
constant	0.000 <i>(0.000)</i>	0.000 <i>(0.000)</i>	0.001 <i>(0.000)</i>	0.000 <i>(0.000)</i>	0.000 <i>(0.000)</i>	0.000 <i>(0.000)</i>	0.000 <i>(0.000)</i>	0.000 <i>(0.000)</i>	0.002 <i>(0.001)</i>	0.000 <i>(0.000)</i>	0.001 <i>(0.001)</i>	0.001 <i>(0.001)</i>	0.000 <i>(0.000)</i>	0.002 <i>(0.000)</i>	0.002 <i>(0.002)</i>
Residual(-1)^2	0.140 <i>(0.08)</i>	0.036 <i>(0.04)</i>	0.306 <i>(0.132)</i>	0.169 <i>(0.082)</i>	0.201 <i>(0.031)</i>	0.493 <i>(0.180)</i>	0.146 <i>(0.065)</i>	0.403 <i>(0.122)</i>	0.111 <i>(0.088)</i>	-0.022 <i>(0.001)</i>	0.089 <i>(0.110)</i>	0.090 <i>(0.105)</i>	-0.025 <i>(0.001)</i>	0.443 <i>(0.149)</i>	0.039 <i>(0.142)</i>
GARCH(-1)	0.826 <i>(0.097)</i>	0.937 <i>(0.033)</i>	0.354 <i>(0.206)</i>	0.813 <i>(0.067)</i>	0.657 <i>(0.110)</i>	0.361 <i>(0.182)</i>	0.804 <i>(0.074)</i>	0.672 <i>(0.097)</i>	0.499 <i>(0.235)</i>	1.019 <i>(0.007)</i>	0.400 <i>(0.410)</i>	0.210 <i>(0.278)</i>	1.033 <i>(0.000)</i>	-0.089 <i>(0.184)</i>	0.514 <i>(0.573)</i>
CIT pos. LONG(-1)		-0.004 <i>(0.003)</i>	-0.013 <i>(0.014)</i>		-0.002 <i>(0.004)</i>	0.000 <i>(0.007)</i>		0.002 <i>(0.003)</i>	-0.005 <i>(0.011)</i>		0.014 <i>(0.015)</i>	0.025 <i>(0.022)</i>		0.017 <i>(0.006)</i>	-0.001 <i>(0.013)</i>
Non commercial pos. LONG(-1)		-0.001 <i>(0.001)</i>	0.000 <i>(0.001)</i>		0.000 <i>(0.001)</i>	0.002 <i>(0.001)</i>		0.000 <i>(0.001)</i>	-0.001 <i>(0.003)</i>		-0.002 <i>(0.002)</i>	-0.008 <i>(0.005)</i>		-0.003 <i>(0.003)</i>	0.002 <i>(0.005)</i>
Non commercial pos. SHORT(-1)		0.001 <i>(0.001)</i>			0.001 <i>(0.001)</i>			-0.001 <i>(0.001)</i>			-0.007 <i>(0.004)</i>			0.001 <i>(0.002)</i>	
CIT pos. LONG(-1)²			0.329 <i>(0.335)</i>			0.018 <i>(0.170)</i>			-0.141 <i>(0.105)</i>			0.829 <i>(0.955)</i>			-0.064 <i>(0.084)</i>
Non commercial pos. LONG(-1)²			-0.014 <i>(0.004)</i>			-0.007 <i>(0.003)</i>			-0.051 <i>(0.014)</i>			0.045 <i>(0.036)</i>			-0.033 <i>(0.037)</i>
<i>for the mean equation</i>															
Adj. R ³	-0.02	-0.03	-0.06	-0.03	-0.04	-0.06	-0.02	0.11	0.10	-0.02	-0.04	-0.05	-0.02	-0.04	-0.05
DW	1.80	2.03	1.90	1.88	1.94	1.92	2.05	1.88	2.16	2.02	2.04	1.99	1.82	2.09	1.98
F.-stat.		0.06	0.12		0.51	0.03		3.10	2.75		0.32	0.26		0.29	0.25
P.-value		1.00	1.00		0.88	1.00		0.00	0.00		0.98	0.99		0.98	0.99

Note: 10, 5, 1 per cent significance are indicated with italic, bold, italic and bold scripts.

7. Concluding Notes

This work originates within the debate around the fast and extraordinary expansion of commodity derivative markets and the contemporaneous generalised boom of commodity prices. In a first part the paper reviews the principal stylized facts, provide a definition for each major operator and describes the market functioning. The focus is on a special type of investor which tracks commodity indices. Due to their relative novelty on the market, to the fact that their investment decisions are based upon different considerations from those of speculators and hedgers and to the fact that they represent the major investors, in terms of trading volumes, in many commodity markets, their action have been subject to a long discussion on possible repercussion on prices. People is mainly worried about their possible ability to push commodity prices away from the pattern designed by fundamental values and generate bubbles. Large swings in commodity prices have deep welfare repercussions, and wealth distribution consequences in major consumer and producer countries; often identifiable with developing countries.

The paper investigates price level and volatility of eleven agricultural commodities in connection with the evolution of outstanding positions held by major type of traders (CIT but also other type of investors). Beginning with the study of statistical causality effects of positions on future returns and of returns on positions, we enrich the analysis with a set of GARCH estimations. We achieve the twofold purpose of correctly controlling in our econometric model for the existence of conditional heteroskedasticity and of investigating whether the positions held by operators on the market have a whatever impact on volatility.

From the VAR estimates we obtain sparse evidence of the existence of Granger causality between future prices and traders investment decisions. Empirical findings are rather weak. There are a few exceptions when change in positions of both non commercials and commodity index traders granger cause a change in future prices but we were unable to find a common effect of CIT operations across markets. It is also scarce the evidence of herding behaviour except in the cotton market. When the analysis control for the presence of volatility clustering and we estimate jointly a return and a volatility equation for each market, we notice that the few significant relations found in the VAR regressions, do not prove robust to specifications that model the heteroskedasticity in the error term volatility. Garch estimates support the general idea that CIT operators do not have any impact on the level nor on the volatility of commodity prices. Within the few cases when their coefficient in the variance equation is significant, the sign indicate a stabilizing role of these operators rather than a destabilizing one.

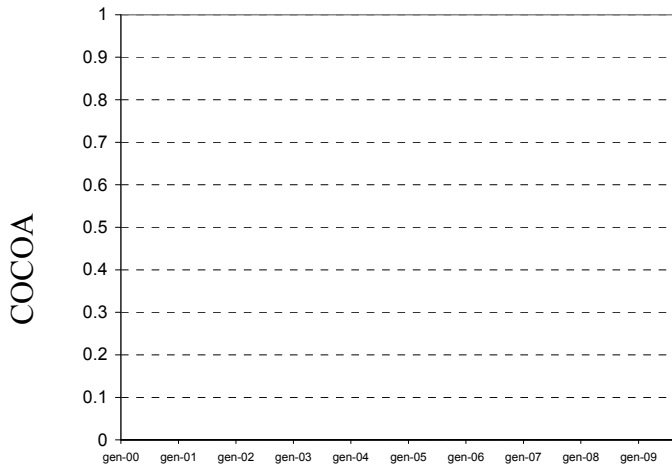
References:

- Alquist R. Kilian L., (2007), “What do we Learn from the Price of Crude Oil futures?”, CEPR discussion paper n.6548, November.
- Bank of International Settlements, Quarterly review December 2008. Statistical Annex.
- Bollerslev T. "Generalized Autoregressive Conditional Heteroskedasticity", *Journal of Econometrics*, 31:307-327, 1986.
- CFTC, (2006), Commission Actions in Response to the “Comprehensive Review of the Commitments of Traders Reporting Program (June 21, 2006), Washington DC, CFTC.
- CFTC, (2008), Staff Report on Commodity Swap Dealers and Index Traders, with Commission Recommendations (September, 2008), Washington DC, CFTC.
- Cashin P. and Mcdermott J.C., (2002), “The Long-Run Behaviour of Commodity Prices: Small Trends and Big variability”, *IMF Staff Papers*, Vol. 49, No.2.
- Engle R. F. "Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation", *Econometrica* 50:987-1008, 1982.
- Gilbert C. L., (2008), “Commodity Speculation and Commodity Investments”, Forthcoming in *Journal of Commodity Markets and Risk Managements* (2009).
- Greely D. and Currie J. (2008), “ Speculator, Index Investors and Commodity Prices”, Goldman Sachs – Commodities.
- Interagency Task Force on Commodity Markets (ITF) (2008), Interim Report of the ITF, Washington DC, CFTC.
- IMF, “What Explains the rise in Food Price volatility?”, *World Economic Outlook* October 2009, Chapter 1 Box. 1.7 pp.84-87.
- IMF, “Commodity Market Developments and Prospects?”, *World Economic Outlook*, April 2009, Chapter 1 Appendix 1.1 pp.44-57.
- Irwin, S.H., and B.R. Holt (2004), “The effect of large hedge fund and CTA trading on futures market volatility”, in Gregoriou et al. (2004), 151-82.
- Masters M.W., (2008), Testimony before the U.S. Senate Committee of Homeland Security and Government Affairs, Washington, DC, 20 May 2008.
- Radetzki M., (2008), “A Handbook of Primary Commodities in the Global Economy” Cambridge University Press.
- Soros G., (2008), Testimony before the U.S. Senate Commerce Committee Oversight Hearing on FTC Advanced Rulemaking on Oil Market Manipulation, Washington D.C., 4 June 2008.

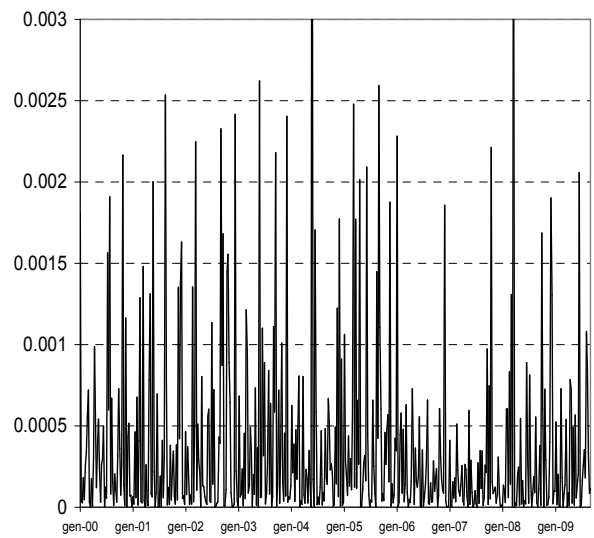
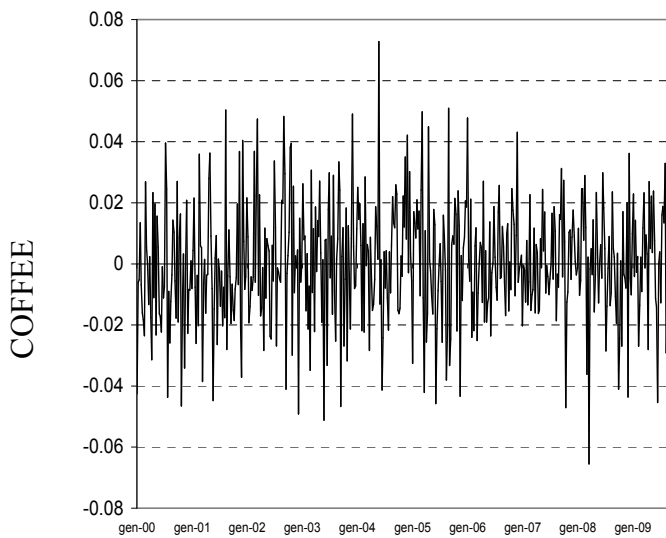
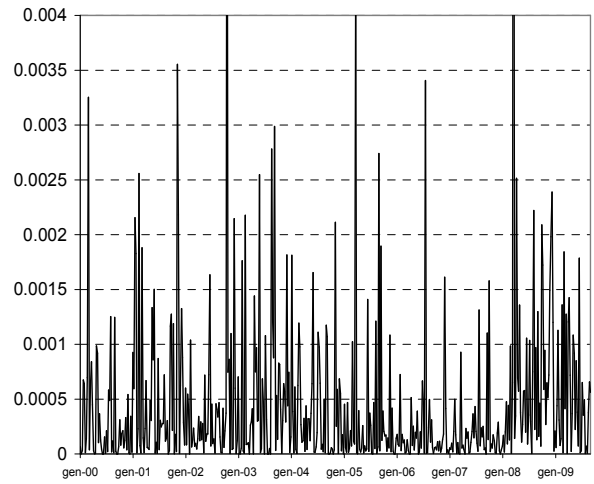
Appendix A

The presence of volatility clustering in agricultural commodities is testified by graphs below which depict price log differences and their square. In some cases the phenomenon is particularly evident like soybeans oil or

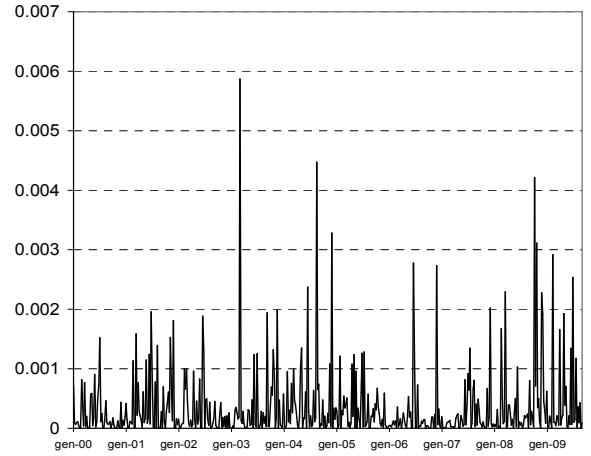
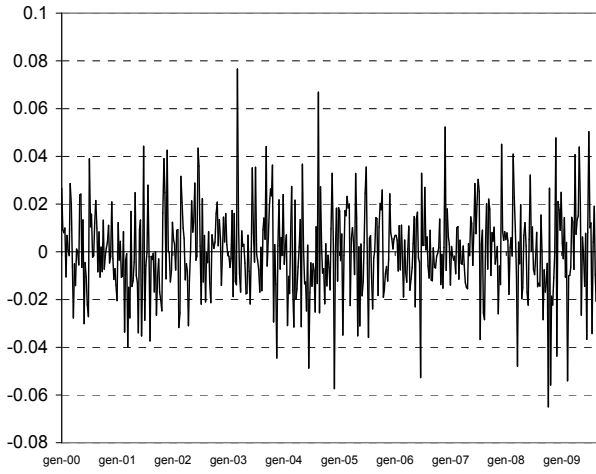
Logarithmic differences of nearby future prices



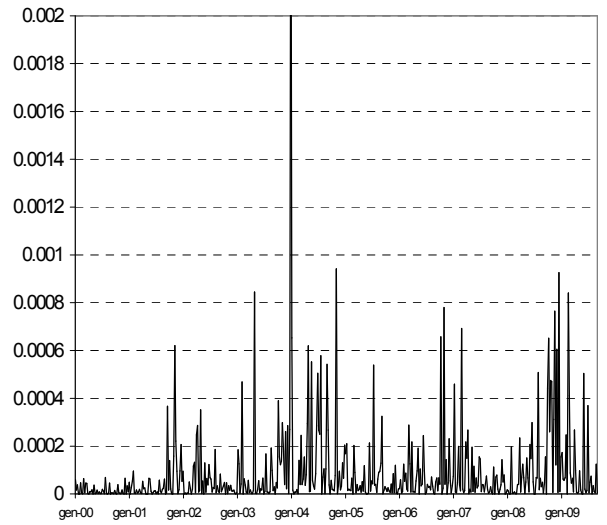
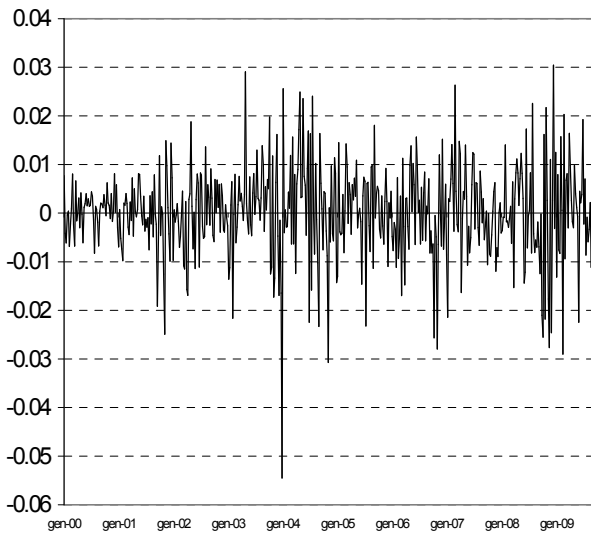
Square of logarithmic differences of nearby future prices



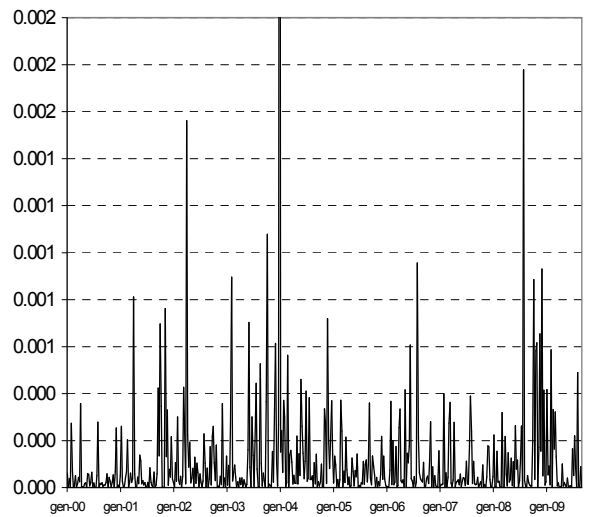
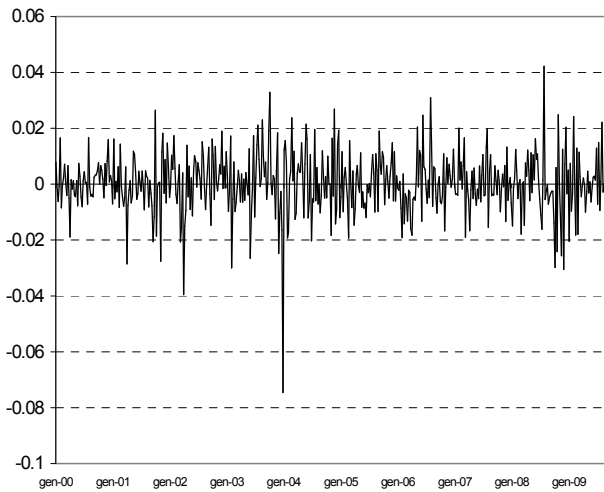
COTTON



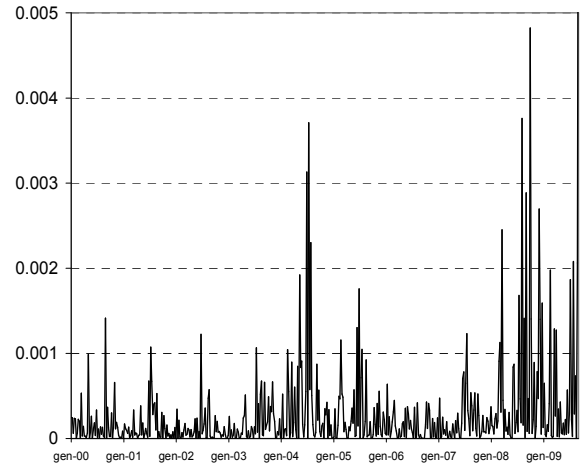
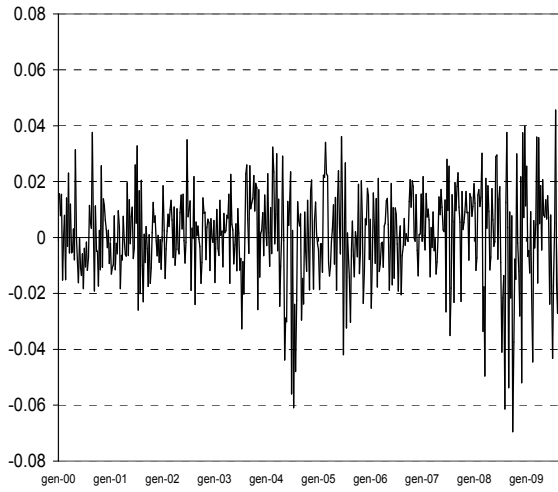
FEEDER CATTLE



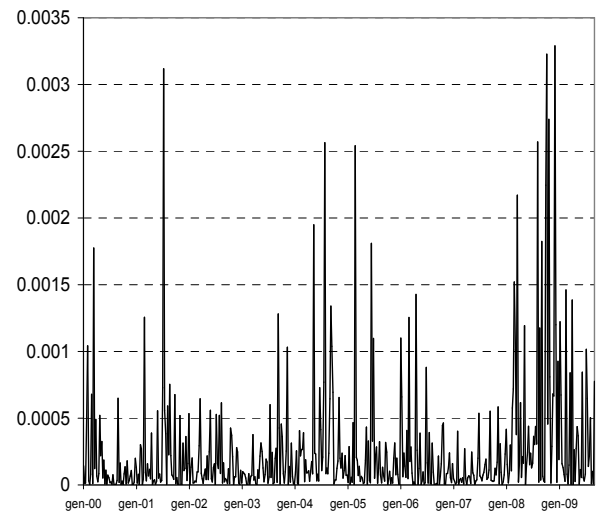
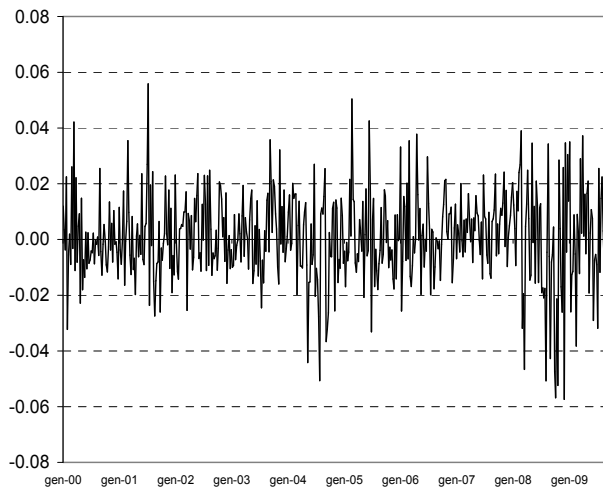
LIVE CATTLE



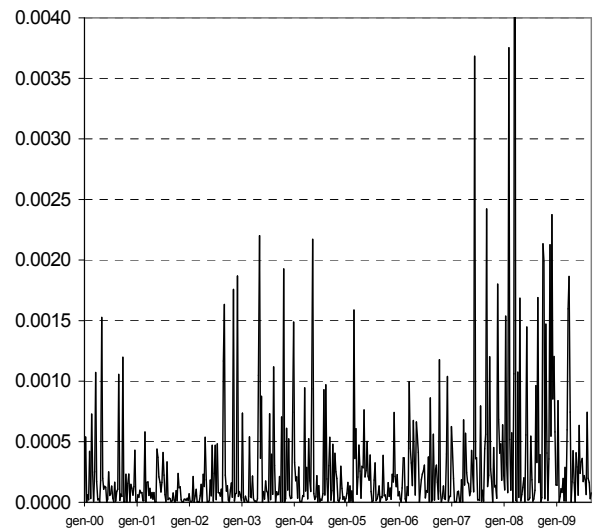
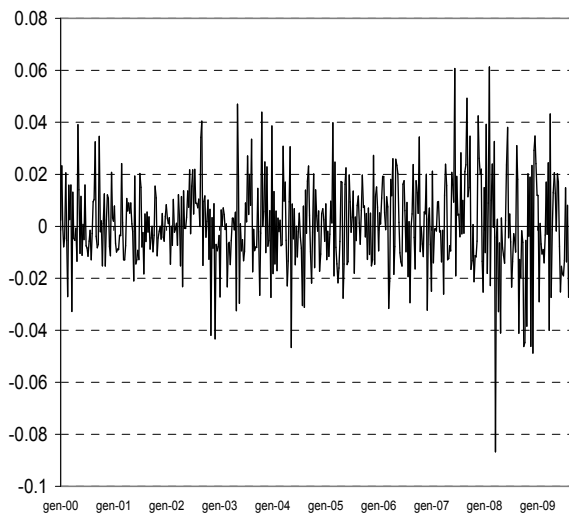
SOYBEANS



SOYBEAN OIL



WHEAT KANSAS



Source: Thomson Reuters Datastream.

Source: Thomson Reuters Datastream.