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Price Volatility, Speculation and Excessive Speculation in Commodity Markets: sheep or shepherd behaviour?

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Abstract

The present study aims to investigate the dynamics of primary commodity prices and the role of speculation over time. In particular the relationship between speculation and price volatility on the one side, and the linkage between excessive speculation and price volatility on the other side, is carefully examined with the scope to establish whether volatility drives speculation or speculation drives price volatility, or whether there are no linkages between the two variables. In order to identify the presence of any lead-lag relationships, two batteries of Granger causality tests are carried out for the period 1995-2012. The investigation complements a preliminary index analysis on speculation and excessive speculation in the commodity market. Unlike several academic researches that reject any causal relationship between the two variables, this study shows that excessive speculation drives price volatility, and that often bilateral relationships exist between price volatility and speculation. In addition, the lead-lag relationships are found not for the entire sample period 1995-2012, but when small sub-periods are taken into account. It turns out, in fact, that excessive speculation has driven price volatility for maize, rice, soybeans, and wheat in particular time frames, but the relationships are not always overlapping for all the considered commodities.

Keywords: Price volatility, excessive speculation, Granger analysis

1. Introduction*

Over the last decades, economic integration has led to significant increases in global trade volumes and cross-border financial flows with the exception of the period 2008-2009 when the financial and economic crisis caused a severe contraction in world trade. Contextually, from 2002 to mid-2008, commodity prices strongly increased and were accompanied by high volatility, sometimes varying by as much as 80 per cent in a single year. Commodity price, and price volatility hikes have been shown to be economically detrimental as they could impede the economic growth in poor countries (Jacks et al., 2011), increase poverty (Ahmed et al, 2008; von Braun and Tadesse, 2012), create worldwide unrest (protests and riots), and threaten political stability. During 2007-2008 several emerging economies like India, Indonesia, and Mexico, experienced social unrest when consumers protested against price increases in basic goods such as bread and rice (Zawojska, 2009). Lack of predictability and uncertainty associated with increased volatility may influence both producers and consumers. High fluctuations in prices might limit the ability of consumers to secure supplies and control input costs, while producers could face the dual problem of low returns and high risks (Page and Hewitt, 2001). In macroeconomic terms, price surges are beneficial for net exporting countries, which experience surpluses in their balance of payments, but they augment the import bill of net importing countries. Volatile prices also have a negative effect on livelihoods. The inherent uncertainty of unstable prices complicates financial planning and environmental management for commodity-dependent countries and producers, deepening commodity dependence and widening existing inequalities. In addition, the empirical evidence suggests that volatility has a considerable influence on economic output (Yang et al., 2002; Hamilton, 2000). For example, according to the Energy Information Administration (2002), oil price volatility produced a loss of 0.2 percentage points of GDP growth in the U.S. economy between 1997 and 2001. This has in turn generated a negative impact on the labour market (Ferderer, 1996; Hamilton, 2000; Papapetreu, 2001). Further, high volatility increases uncertainty over whether to invest or not (Ferderer, 1996), i.e. companies postpone investment expenditures when they experience increased uncertainty concerning future commodity prices.

Against this background, the present research aims at analysing the evolution of commodity prices and their volatilities over time, the role of financial traders in commodity markets, the changes in motivations of market participants, and the causal relationship between volatility and speculation. Despite the increasing interest for the financialisation of commodity markets, there has been a limited research on how speculative trading activity has impacted price volatility and the existing studies have given contrasting results. I will, therefore, extend the present debate distinguishing between speculation and excessive speculation and I will test the causal relationships between speculation and price volatility on the one side and excessive speculation and price volatility on the other side. In this way it will be clear if speculation/excessive speculation drive price, so that speculators can be defined as

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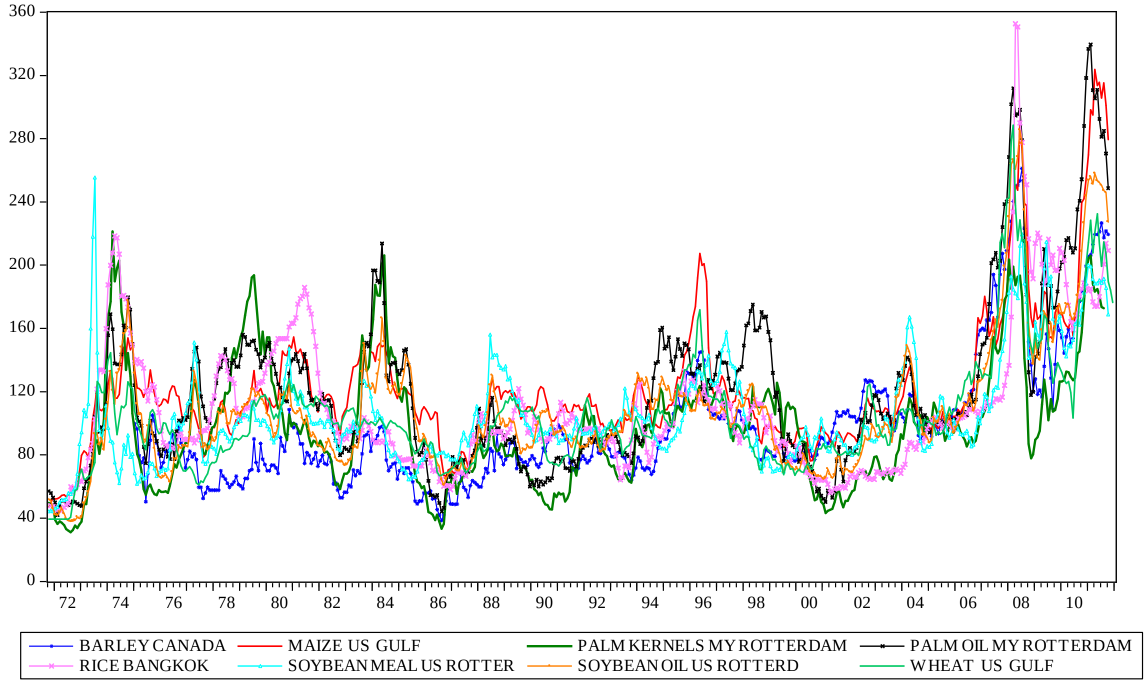
shepherd; or if rising price volatility pushes speculation, so that speculators engage in a herd-like behaviour and can be defined as sheep.

The rest of the paper is organised as follows. Section 2 gives an overview of commodity price trends and presents some stylised facts. Section 3 briefly discusses the meaning and measurements of volatility. Section 4 reviews the literature on the linkages between speculation and price volatility in the largest non-oil commodity futures markets. Section 5 offers a set of indices to measure speculation in excess and speculative pressure. Section 6 presents the econometric evaluation of the linkages between speculation and price. Section 7 concludes.

2. Selected Commodity Price Trends

Chart 1 reports the monthly price indices for the major grains and oilseeds namely wheat, rice, maize, barley, soybeans, palm kernel, and palm oil back to 1971.

Chart 1 Market price index 2005=100. Monthly basis



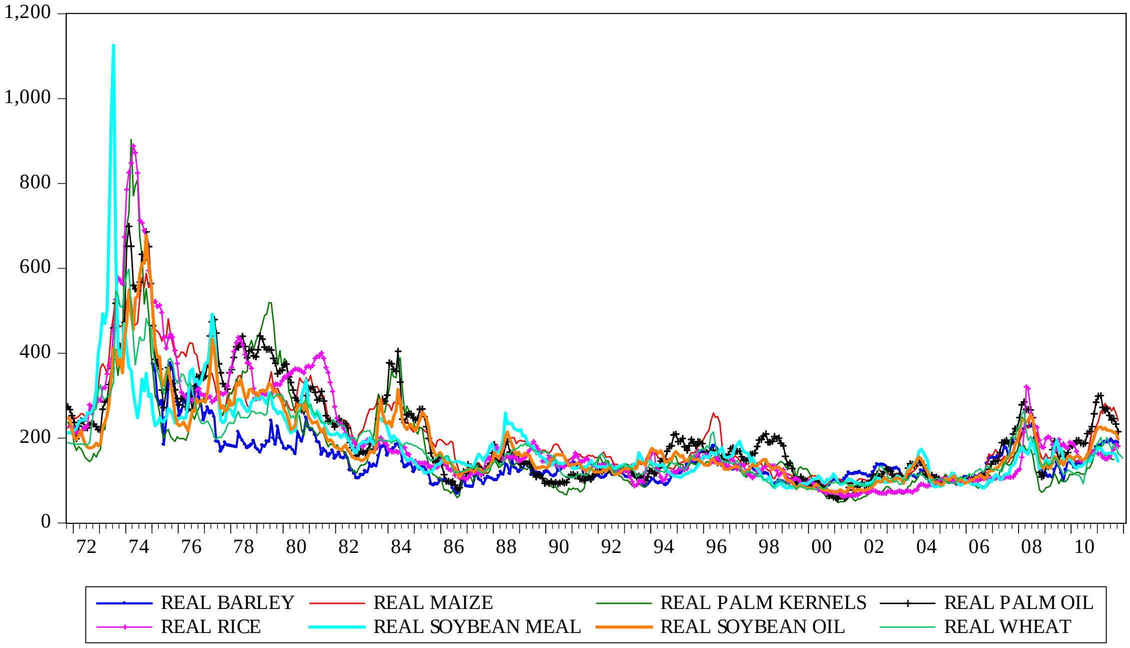
Source: Own elaborations on Datastream data.

Wheat and rice account for much of the world food consumption of grains. Corn is used for both food and livestock feed. Barley is ranked fourth among the cereal grain crops after wheat, maize, and rice in terms of cultivated area and production level. It is the staple food diet of many countries and is largely required for making breads and beer. Animal food and livestock feed is the primary use of barley crop. Soybeans, palm oil and kernel provide vegetable oil for human consumption and protein feed for animals. Palm and palm kernel oil are also found in many non-food items such as soaps, detergents, candles, and cosmetics. Combined, all these crops account for a large share of the staple foods that are consumed globally.

Three striking aspects appear from the graphical inspection. First, there have been periodic spikes in the prices of the considered commodities during the last 40 years. This means that commodity prices show cyclical movements. Second, the size of price increases during the period 2006-2008 was impressive. Afterward, the global recession induced a significant price drop from "the 2008 spike". The significant price fall has accompanied the contraction in world trade. Since the summer of 2010, commodity prices have been rising again. Third, price hikes across all types of commodities occurred simultaneously as well as the falls. Put differently, there is a tendency of commodity prices to co-move, which is likely to put import countries under significant inflation pressure. One reason for this behaviour is that buyers can easily substitute among grains and oilseeds and purchase whichever is cheap. Besides, the synchronisation of price movements across a range of commodities has induced some observers to believe that commodity price boom is a bubble (Stewart, 2008; Gilbert, 2010), driven predominantly by very low interest rates and excessive speculation in commodity future markets. Therefore, the recent run-up in commodity prices may in part be driven by factors that are unrelated to supply and market forces. According to a different view, market fundamentals, i.e. demand and supply for the commodities, can fully explain the price gains (The Regional Economist, 2011).

Chart 2 displays the international prices for the same food commodities in real terms. Each commodity price expressed in US$ has been deflated using the U.S. unadjusted consumer price index for all items. These figures, however, should be viewed with caution because the use of the CPI as deflator has been highly debated. According to the Boskin Commission Report issued on December 4, 1996, measurement errors in the U.S. CPI have resulted in overstatement of the inflation rate by roughly 1.1 percent over the period from 1970-1995. This implies that the decline in real commodity prices should be smaller than the values suggested by the data.

Chart 2 Real commodity price indices



Source: Own elaborations on Datastream data.

3. Price Volatility and volatility measurements

Volatility is a measure of the extent of the variability of a price or quantity that occurs on a day-to-day, week-to-week, month-to-month or year-to-year basis. The concept of volatility may be confused simply with rising prices; however, volatility can equally result in prices that are significantly lower than historical average levels. Technically, volatility measures how much a price changes either with regard to its constant long-term level, or to its trend. That is to say, volatility measures dispersion about a central tendency. In this respect, it is important to note that volatility does not measure the direction of price changes; rather it quantifies variation of prices around the mean. When price movements over a short period of time are extremely wide, we have “high volatility” (European Commission, 2009). Data with higher frequencies show higher volatility. Volatility diminishes when frequencies decrease. Annual data are less volatile than quarterly data; quarterly data are less volatile than monthly data.

Volatility can be distinguished in historical, conditional, or implied volatility. *Historical volatility*, also called *realised volatility*, is based on the observed movements of prices over the long term, and indicates how volatile an asset or commodity price has been in the past. It involves calculating the historical average variance or standard deviation of log price returns (growth rate). For low levels of volatility, the log standard deviation is approximately equal to the coefficient of variation. *Conditional volatility* is the standard deviation of a future return that is conditional on known information such as the history of past returns (Taylor, 2007). This measure, thus, quantifies uncertainty about future observations, given a certain information set. *Implied volatility* is the market’s forecast of the volatility of underlying asset returns. It shows how volatile an asset will be in the future (Brooks, 2008). It is called “implied” because, by dealing with future events, it cannot be observed, and can only be inferred from the price of an “option” (FAO, 2011). Implicit volatility is inferred from the prices of call options using the Black-Scholes model.

Put differently, historical volatility models use time series of past market prices, conditional volatility uses ARCH-GARCH and extended GARCH models for estimating volatility expectations, and implied volatility uses traded option prices. Therefore, we can say that historical volatility is a “backward-looking” measure of volatility, while conditional and implied volatility are respectively a “backward-looking” historical forecast of future volatility and a “forward-looking” forecast of volatility reflected in current option prices.

Technically, to gauge the historical volatility first the price series for individual goods are transformed into index form (e.g. base 2000=100), then, as for stock price volatility, the continuously compounded return (r and R), i.e. the logarithmical changes in consecutive daily or monthly prices, is computed by using the following formula:

$$r_i^{day} = \ln\left(\frac{P_i^{day}}{P_{i-1}^{day}}\right) \text{ or } R_n^{month} = \ln\left(\frac{P_n^{month}}{P_{n-1}^{month}}\right) \tag{1}$$

with i=1….K, K=number of trading days, usually 21
n=1…T, T=number of months

Then the standard deviation of the logarithmic change in daily or monthly prices is calculated, so to obtain the daily volatility referred to a month and the monthly volatility referred to a year:

$$\sigma^{daily}_{volatility} = \sqrt{\frac{\sum_{i=1}^{K}\left(r_i^{day} - \bar{r}\right)^2}{K}} \cdot 100 \text{ with } \bar{r} = \sum_{i=1}^{K}\left(\frac{r_i^{day}}{K}\right) \quad (2)$$

$$\sigma^{monthly}_{volatility} = \sqrt{\frac{\sum_{n=1}^{T}\left(R_n^{month} - \bar{R}\right)^2}{T}} \cdot 100 \text{ with } \bar{R} = \sum_{n=1}^{T}\left(\frac{R_n^{month}}{T}\right) \quad (3)$$

It is conventional to quote return volatilities at an annual rate following the Chicago Mercantile Exchange. This implies that daily volatilities can be annualised multiplying by radical 250 or 252 trading days in the year, while monthly volatilities can be annualised multiplying by radical 12 (Gilbert and Morgan, 2011).

The most popular model used in the empirical literature to assess conditional volatility is the GARCH(1,1) model developed by Bollerslev (1986), in which the distribution of the return (r) for period t, conditional on all the previous returns is given by:

$$r_t \mid r_{t-1}, r_{t-2}, \ldots.. \quad \mathrm{N}(\mu, \sigma_t^2) \quad (4)$$

Where μ and σ_t^2 are the conditional mean and the conditional variance respectively. The conditional variance, i.e. the one-period ahead forecast variance based on past information is specified as:

$$\sigma_t^2 = \omega + \alpha(r_{t-1} - \mu)^2 + \beta\sigma_{t-1}^2 \quad (5)$$

This equation shows that conditional variance is a function of a constant term ω, news about volatility from the previous period, measured as the lag of the squared residuals from the mean (r_{t-1}-μ) (the ARCH term) and the previous conditional variance (σ_{t-1}^2) (the GARCH term).

The conditional variance equation can be alternatively rewritten in terms of unconditional variance (h^2) as:

$$\sigma_t^2 = \gamma h^2 + \alpha(r_{t-1} - \mu)^2 + \beta\sigma_{t-1}^2 \quad (6)$$

given that the unconditional variance is expressed as:

$$h^2 = \mathrm{var}(\mathrm{r_t}) = \mathrm{E}\left[(r_{t-1} - \mu)^2\right] = \frac{\omega}{1-\alpha-\beta} \quad (7)$$

with $\gamma = 1-\alpha-\beta$ (8)

Measures of conditional volatility imply that the volatility of an asset price is not the same at all times, but varies considerably across time; i.e., it is stochastic.

Generally, stock market volatility increases during crises and then decreases in due course. For instance the Great Depression was accompanied by very high volatility. The stock market crash of October 1987 was a financial crisis that was followed by a short period of extraordinary high volatility. Volatility was high before the terrorist attacks on September

11, and went much higher when the U.S. markets reopened six days later (Taylor, 2007). Again volatility increased substantially during the 2008 financial crisis.

For the purpose of this analysis, I have computed the historical and the conditional volatility in order to have both an index that looks backwards as it captures the amplitude of price movements for a given period of time in the past and an index that takes into account current expectations on future returns conditioned by past information.

Chart 3 plots the period-over-period difference in the logged commodity price index, or ln (P_t/P_{t-1}). Monthly changes in commodity price summary statistics are reported in table 1. Data definitions and sources are presented in the Appendix.

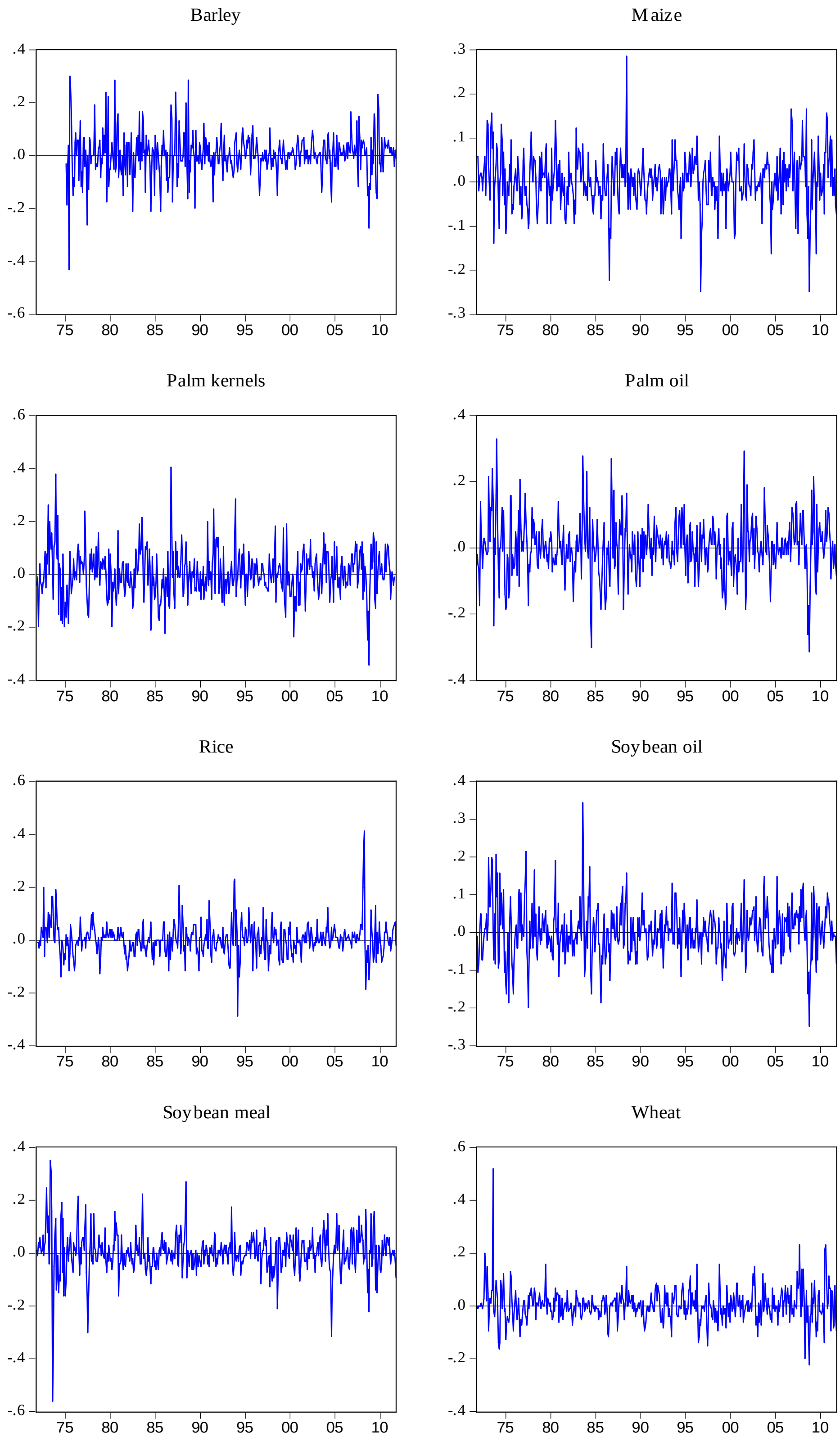
Table 1 Commodity Price, 1971-2011
(Monthly log changes)

	BARLEY	MAIZE	PALMKER	PALMOIL	RICE	SOYOIL	SOYMEAL	WHEAT
Mean	0.001895	0.003661	0.002675	0.003087	0.003305	0.003175	0.002431	0.003378
Maximum	0.300105	0.285179	0.405465	0.329304	0.412110	0.343590	0.350657	0.518794
Minimum	-0.430783	-0.248461	-0.342490	-0.314711	-0.287682	-0.248461	-0.562119	-0.223144
Std. Dev.	0.081204	0.058800	0.087667	0.083612	0.061990	0.067449	0.078370	0.062381
Skewness	-0.128577	-0.182039	0.296404	0.042319	1.028119	0.351121	-0.817652	1.357076
Sum Sq. Dev.	2.901411	1.656115	3.665947	3.348667	1.836868	2.179152	2.941933	1.863984
Observations	441	480	478	480	479	480	480	480

Source: Own elaborations on Datastream data.

Table 1 provides information on the mean price change values, their minimum and maximum values, the dispersion of price changes with respect to the mean. Skewness measures how symmetric the data is, in other words is there a tendency for the data to be positive or negative. For a symmetric distribution, like the normal, the median is the average and so the skewness is zero. A non-symmetrical or skewed distribution occurs when one side of the distribution does not mirror the other. Negatively skewed distributions, as in the cases of barley, maize, and soybean meal have a long left tail. Positively skewed distributions, such as palm oil and kernel, rice and wheat, have a long right tail. Applied to investment returns, non-symmetrical distributions are generally described as being either positively skewed (meaning frequent small losses and a few extreme gains) or negatively skewed (meaning frequent small gains and a few extreme losses). Negative skewness means there is a substantial probability of a big negative return. Positive skewness means that there is a greater than normal probability of a big positive return. Applied to prices, positive skewed distribution means frequent small price drops and few extreme price run-ups, while negative skewed distribution means frequent small increases in price and few extreme drops. Positive skewness implies big price increases, while negative skewness means large price drops.

Chart 3 Monthly Changes in Commodity Prices



Source: Own elaborations on Datastream data.

Table 2 offers more evidence on historical price volatility at an annual rate for selected food commodities computed according to equation 3. Explicitly, for each commodity the annualised standard deviation over the marketing year is calculated from the monthly estimates of σ. The 1970s appear as a period of high volatility compared to what went after. Especially, the years 1972-1975 recorded the strongest price movements, likely triggered by the collapse of the Bretton Woods exchange regime. Food prices were also very volatile over 2006-2009, with an exceptional volatility experience in 2008. In that year, rice recorded the highest price volatility of above 60%. Generally, volatility remained low in the first half of the '90s for soybean, wheat, maize, and palm oil. Over rolling 4-5 year period annualised volatility for soybean meal, soybean oil, wheat, and maize has ranged from a low of 12-13% to over 44%, 28%, 33% and 25% respectively. Volatility for palm kernels and palm oil varied from a minimum of 14-15% to a maximum of 35-36%. Volatility for barley and rice swung from about 11% to 33% and 25% respectively.

Table 2 Commodity Price Annualised Volatility.

	SOYBEAN MEAL	SOYBEAN OIL	WHEAT	MAIZE	PALM KERNELS	PALM OIL	BARLEY	RICE
1972-1975	44.32	28.16	33.23	21.33	35.20	36.64	-	22.14
1976-1979	25.99	21.65	14.06	17.58	24.13	22.20	31.86	13.77
1980-1984	19.32	24.06	10.67	15.91	26.88	26.47	29.19	12.53
1985-1989	16.98	19.90	12.87	19.50	28.88	30.58	33.13	17.55
1990-1994	12.84	15.96	15.34	13.05	27.92	16.60	18.04	23.77
1995-1999	18.15	14.06	19.68	17.52	20.36	21.41	15.56	19.36
2000-2005	21.84	19.07	15.62	16.23	23.04	23.19	15.33	11.24
2006-2009	25.89	22.35	24.89	25.79	27.27	29.11	29.89	24.92
2010-2011	13.87	12.65	29.48	20.04	14.04	15.44	11.02	13.28

Source: Own elaborations on Datastream price market data.

To assess the conditional volatility, a more rigorous GARCH(1,1) model (equations 4-8) has been estimated for the same commodities. The results are reported in table 3.

Table 3 GARCH (1;1) Conditional Volatility.

Sample (adjusted): 1971M11 2011M10

	Barley		Maize		Palmker		Palmoil	
	monthly	**yearly**	**monthly**	**yearly**	**monthly**	**yearly**	**monthly**	**yearly**
μ	0.00397	0.999	0.00443	1.117	0.0063	1.588	0.0057	1.436
σ_t^2	0.00982		0.00333		0.01003		0.00808	
σ_t	0.09907	1.5727	0.0577	0.9159	0.10015	1.5898	0.08987	1.4267
Likel.	1469.53		2148.77		1595.75		1861.15	

	Rice		Soymeal		Soyoil		Wheat	
	monthly	**yearly**	**monthly**	**yearly**	**monthly**	**yearly**	**monthly**	**yearly**
μ	0.00403	1.016	0.00698	1.759	0.00403	1.016	0.00698	1.759
σ_t^2	0.00311		0.00755		0.00311		0.00755	
σ_t	0.05579	0.8856	0.08688	1.3791	0.05579	0.8856	0.08688	1.3791
Likel.	2152.18		1992.06		2152.18		1992.06	

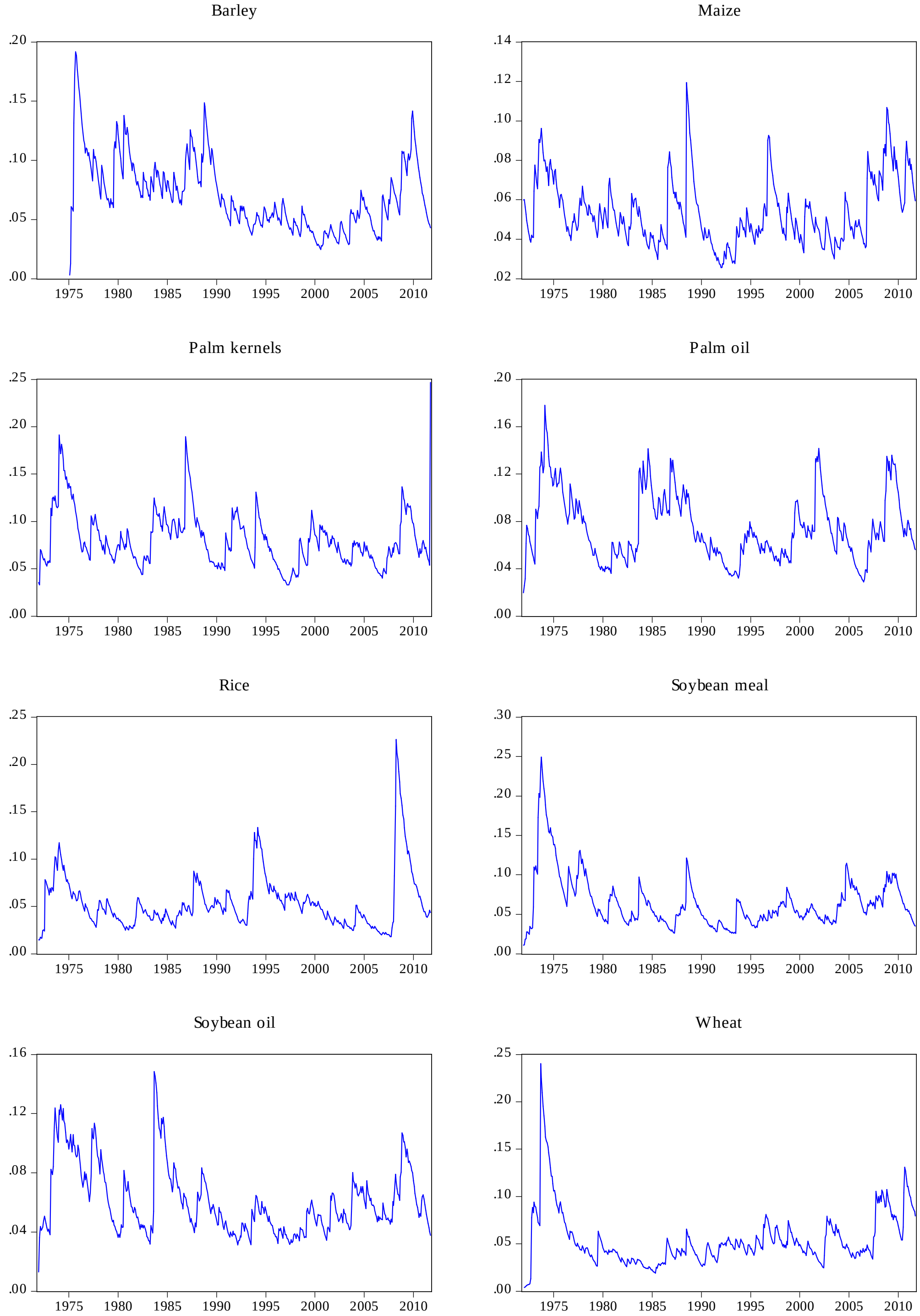
Maximum likelihood estimation is used to calibrate the GARCH process.

Parameters set		Max			Max
ω	9.75E-06	1	γ	0.015	1
α	0.116	1	h	0.0259	
β	0.869	1			

Specifically, table 3 displays the conditional mean μ, the conditional variance σ^2, the conditional standard deviation σ, and the likelihood estimation of the parameters. As before, the resulting volatilities are expressed as standard deviations. By comparing the "backward-looking" historical volatility with the forecasts of future volatility conditioned by past information, it emerges that the standard deviations are almost identical; therefore, when taking into account stochastic movements of returns the scenario does not change very much. In particular, barley shows a monthly conditional standard deviation of 9.91% against a realised standard deviation of 8.12%; palm oil has a monthly conditional standard deviation of 8.99% against a value of 8.36% for realised volatility; soybean oils have a conditional standard deviation of 7.70% per month against a realised standard deviation of 6.74%; and wheat shows a monthly conditional standard deviation of 6.61% against a realised value of 6.24%. Rice and maize are the only two commodities that show a historical standard deviation larger than the conditional standard deviation (5.88% against 5.77% and 6.20% against 5.58%). Palm kernel registers the major differences in the conditional and historical standard deviations, with values of 10.01% and 8.77%, respectively. These results corroborate to a certain extent the findings obtained from historical volatility, and could be considered as a robustness check to model commodity price volatility[1]. The evolution of the monthly conditional volatility is reported in Chart 4.

[1] It should be noted that the two estimations depart from different assumptions regarding the nature of the stochastic process that generates returns.

Chart 4 Monthly Conditional Volatility



Source: Own elaborations on Datastream data.

4. Literature on Speculation

It is possible to distinguish two different strands of literature regarding the role of speculation in the financial markets and its effects on price volatility: the traditional and non-traditional theory.

The traditional speculative theory highlights that speculation, which entails buying when the price is low and selling when the price is high, has a stabilising effect on the financial markets. This is because when buying, speculators increase depressed prices, while when they sell they decrease inflated prices. In this vision speculation activity smoothes the price process thus reducing volatility (Keynes, 1923; Friedman, 1953). Additionally, speculators would fill any hedgers' demand-supply imbalances and provide liquidity to the market thus facilitating its functioning. Commercial traders liquidate contract positions paying for commodities at delivery or selling contracts to offset the risk of other contract positions they hold. Put differently, in a well-functioning futures market, hedgers, who are trying to reduce their exposure to price risk, will trade with someone who is willing to accept the risk by taking opposing positions. By taking the opposing positions, these traders facilitate the needs of hedgers to mitigate their price risk, while also adding to overall trading volume, which contributes to the formation of liquid and well-functioning markets. Kaldor (1939) put forward that moderating price fluctuations, speculators automatically act in a way that leads to the transfer of goods from uses where they have a lower utility to uses where they lead to higher utility. In this view speculative gains are similar to entrepreneurial gains. It is interesting to notice that Kaldor specifies that speculation could be sometimes stabilising and other times destabilising. In his words:

> "Does speculation exert a price-stabilising influence or the opposite? The most likely answer is that it is neither, or rather that it is both simultaneously. It is probable that in every market there is a certain range of price-oscillation within which speculation works in a destabilising direction while outside that range it has a stabilising effect…Speculation is much more likely to operate in a destabilising direction when we consider price-fluctuations within smaller ranges, than larger ranges; and when we consider the movements over a shorter period than over a longer period. This is so not only because it is the short-period expectations which are most elastic (show the strongest reaction to price changes), but also because it is these short-period expectations which are most flexible."

More recent studies belonging to the traditional speculative theory are those by Brunetti et al. (2011) and Deuskar and Johnson (2011), which have found that speculative activity does not lead to any price changes, but it rather reduces market volatility and illiquidity. Stoll and Whaley (2010) have obtained no evidence that the position of commodity index traders impacts prices in agricultural futures markets. Irwin and Scott (2012) using Granger causality and long-horizon regression tests have also demonstrated that there are no causal links between daily volatility in the crude oil and natural gas futures markets, and the positions for two large energy exchange-traded index funds. Dale and Zyren (1996) claim that speculative funds are price followers. Another interesting study which looks in a different perspective has been carried out by Jacks, who analysed the linkages between the presence of futures markets and commodity price volatility. The author drawing from the historical record on the establishment and prohibition of futures markets has asserted that there is no evidence for the claim that futures markets are associated with higher commodity price volatility, rather they dampen price volatility. This means that commodity prices were more volatile in those periods in which futures markets were prohibited or closed for a period.

Conversely, the non-traditional theory suggests that increased participation of traditional speculators in futures markets has produced a detrimental effect and has finished to destabilise markets. In this view, speculators could drive prices away from fundamental values, thus causing "bubbles", or they could manipulate the market, or when they are poorly informed, they could trade in response to supply and demand shocks by extrapolating past trends or by observing each other ("herding"), rather than on the basis of market fundamentals (Weiner, 2002). Kraples (1995; 1996), Verleger (1995), Masters (2008) and

Hamilton (2009) have for instance shown that price fluctuations in oil markets have been driven by speculative activities. In particular, Masters (2008) has argued that massive buy-side "demand" from index funds has created a bubble in commodity prices, with the result that oil prices have far exceeded fundamental values. Gilbert and Morgan (2011), Tang and Xiong (2011), and Stewart (2008) have suggested that speculation has raised non-oil commodity volatility.

In order to evaluate these different positions, the next paragraphs will investigate the financialisation of the commodity markets and the lead-lag relationship between volatility and speculation. Unlike many studies I do not consider any measurement of index fund investment in commodity futures markets to mirror speculation, but specific metrics will be computed.

5.1 Financialisation of Commodity Markets

The U.S. Commodity Futures Trading Commission (CFTC), a government regulatory agency, identifies three categories of futures traders: "commercial traders"[2], also known as hedgers, which hold position in the underlying commodity and attempt to offset risk exposure through future transactions; "non-commercial traders"[3], the so called speculators, which hold only positions in futures contracts and do not have any involvement in the physical commodity trade; "non-reportables", which do not meet the reporting thresholds set by the CFTC. The latter traders are usually small traders, while commercials and non-commercials are reportable traders[4], i.e. they hold positions in futures and options at or above specific reporting levels set by CFTC. Futures markets facilitate the transfer of price risk from commercial to non-commercials. Thereby, likewise in insurance markets, hedgers expect to pay for the risk transfer, while speculators expect to profit. Traders could take long, as well as short, positions in commodity futures markets depending on whether commodity prices are expected to appreciate (long=>buy) or depreciate (short=>sell).

To evaluate the financialisation of commodity markets, open interest dynamics have been considered. Open interest describes the total number of futures contracts long (purchased contracts outstanding) or short (sold contracts outstanding) for a given commodity in a delivery month or market that has been entered into and not yet liquidated by an offsetting transaction or fulfilled by delivery of the commodity. For each seller of a futures contract there must be a buyer of that contract. Thus a seller and a buyer combine to create only one contract. Therefore, to determine the total open interest for any given market we need only to know the totals from one side or the other, buyers or sellers, not the sum of both. The open interest position that is reported each day represents the increase or decrease in the number of contracts for that day, and it is shown as a positive or negative number. Each trade completed on the exchange has an impact upon the level of open interest for that day.

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[2] Commercials include a) producers, merchants, processors, manufacturers (refiners, fabricators, etc.), dealers (wholesalers, exporter/importers, marketers, shippers, etc.) b) swap dealers (includes arbitrageurs).

[3] Non-Commercials include Hedge Funds (Commodity Pool Operators, Commodity Trading Advisors, Associated Persons who control customer accounts, and other Managed Money Traders); Floor Brokers & Traders and Non-Registered Participants (Traders not registered under the Commodity Exchange Act).

[4] It is estimated that the aggregate of reportables account for 70% to 90% of the open interest in any given futures markets (Miffre, 2011).

For example, open interest will increase by one contract if both parties to the trade are initiating a new position (one new buyer and one new seller).

If both traders are closing an existing or old position (one old buyer and one old seller) open interest will decline by one contract. If one old trader passes off his position to a new trader (one old buyer sells to one new buyer), the open interest will not change.

Increasing open interest means that new money is flowing into the marketplace. In analytical terms, the market's total open interest is the sum of reporting and non-reporting positions.

$$TOT\ OI = [NCL+NCS+2*NCSP]+[CL+CS]+[NRL+NRS]$$

Where non-commercial open interest (NC) is distinguished in long (NCL), short (NCS) and spreading[5] (NCSP), while for commercials (C) and non-reportables (NR) open interest is divided in long and short. Thus the composition of the open interest (hedging or speculation) gives a measure of the use being made of the market by various trader types. Data on the composition of open interest for all futures contracts are collected by the Commodity Futures Trading Commission (CFTC) and a subset of this data is realised by CFTC's Commitments of Traders (COT) report.

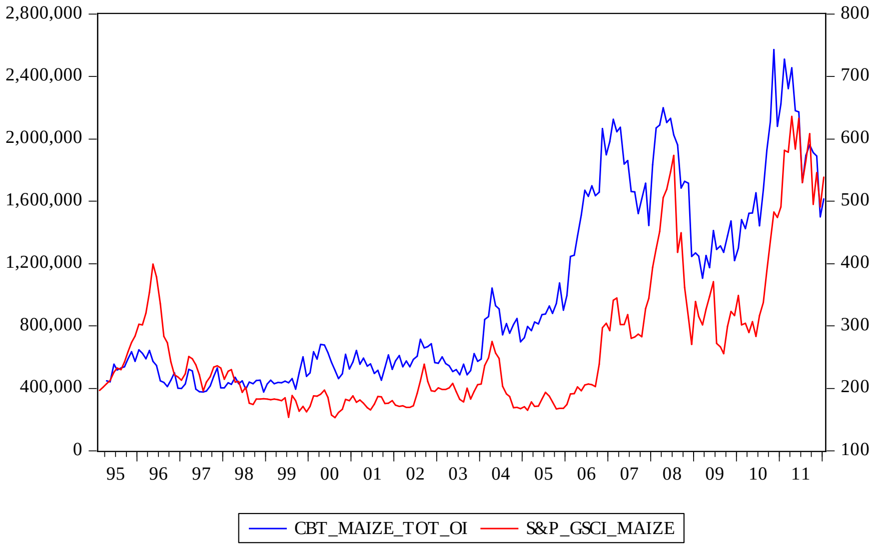
The financialisation of the commodity futures market is sketched in Chart 5.

Chart 5 portrays the total open interest and the level of the Standard and Poor's Goldman Sachs Commodity price Index (S&P GSCI)[6] for maize, rice, soybeans, and wheat. Open interest recorded significant raises. Maize raised contracts from 367,259 in April 1995 to 1,146,906 contracts in December 2011, rice contracts went from 2,211 to 18,114; soybean meal grew from 101,916 to 207,046 contracts and wheat from 260,505 contracts to 386,401 during the same period. The reported correlation matrix suggests a positive and significant relationship between total open interest and S&P GSCI commodity index. This means that the number of contracts moves in the same direction of prices, hence changes in the open interest mirrors the ups and downs of S&P GSCI. It should be noticed that for the whole sample the highest correlation value is found for maize, followed by wheat, rice and soybeans. Shrinking the period to only two years (1998:2-2012:1) the correlation values increase notably for all the commodities. This could support the view according to which changes in open interests could have increased volatility of S&P GSCI.

[5] Spreading is the simultaneous buying and selling of two futures contracts of differing maturities (e.g. buy one June maize contract and sell one March maize contract).

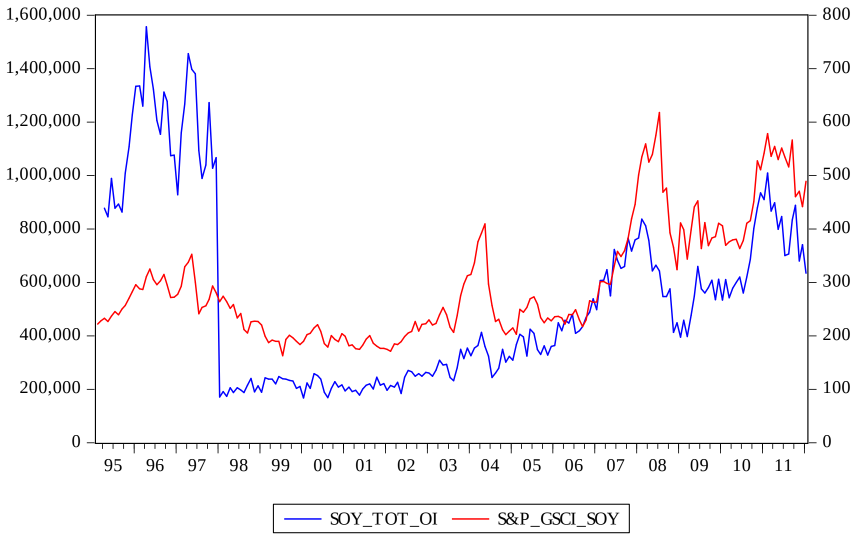
[6] Another popular index is the Dow-Jones UBS Commodity Index (DJ-UBS)

Chart 5 Role of financial players



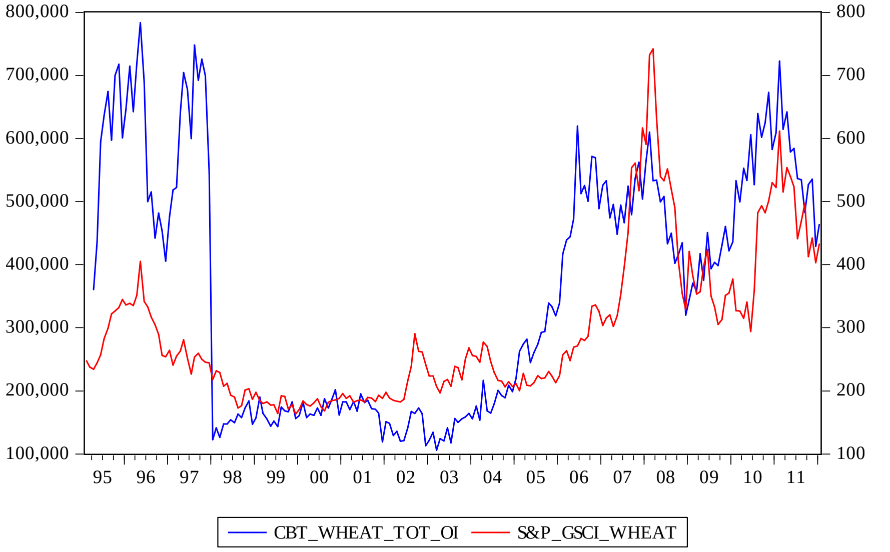
Correlation Matrix	S&P MAIZE	CBT MAIZE TOT OI	
S&P MAIZE	1.000000	0.782498	
CBT MAIZE TOT OI	0.782498	1.000000	t-stat=17.77

Correlation Matrix 98:2-12:1	S&P MAIZE	CBT MAIZE TOT OI	
S&P MAIZE	1.000000	0.840592	
CBT MAIZE TOT OI	0.840592	1.000000	t-stat=19.99



Correlation Matrix	SOY TOT OI	S&P SOY	
SOY TOT OI	1	0.471833	
S&P SOY	0.471833	1	t-stat=7.57

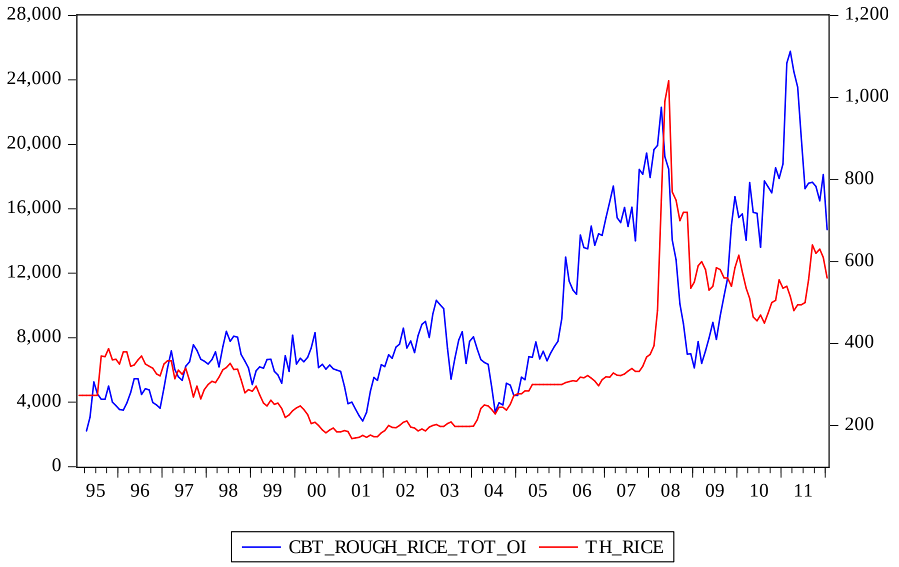
Correlation Matrix 98:2-12:1	SOY TOT OI	S&P SOY	
SOY TOT OI	1	0.892416	
S&P SOY	0.892416	1	t-stat=25.48



Correlation Matrix	CBT WHEAT TOT OI	S&P WHEAT	
CBT WHEAT TOT OI	1.000000	0.658421	
S&P WHEAT	0.658421	1.000000	t-stat=25.48

t-stat=12.37

Correlation Matrix 98:2-12:1	CBT WHEAT TOT OI	S&P WHEAT	
CBT WHEAT TOT OI	1.000000	0.819669	
S&P WHEAT	0.819669	1.000000	t-stat=18.43



Correlation Matrix	CBT ROUGH RICE TOT OI	TH RICE	
CBT ROUGH RICE TOT OI	1.000000	0.568140	
TH RICE	0.568140	1.000000	t-stat=9.76

Correlation Matrix 98:2-12:1	CBT ROUGH RICE TOT OI	TH RICE	
CBT ROUGH RICE TOT OI	1.000000	0. 606494	
TH RICE	0.606494	1.000000	t-stat=9.83

Note: Left axis: total open interest contracts, Right axis: Spot price index valued by S&P GSCI, except for rough rice valued at Thai Burse.

To have a better understanding of the financialisation of markets, the position of trader group (long and short futures) measured as their percentage of total open interest for the whole period of analysis 1995-2012 and the sub-periods 1995-2000, 2001-2006, 2007-2012 has been computed. Hedgers and speculators are the most influential players in the futures markets both short and long. Indeed, reportables accounts for 78.98% in maize long market, 68.43% in rice long markets, 72.33% in soybean long market, and 77.44% in wheat long market in the period 1995-2012. This percentage increases if one considers only the sub-sample 2007-2012. The same dynamics hold true for short market: reportables cover 70.23% in maize short market, 77.71% in rice short market, 82.46% in soybeans short market, and 78.95% in wheat short market. The percentage share of reportables in the short markets is higher than the share recorded in long markets; the only exception is for maize.

Table 4 Position Share of Reportable and non-Reportable Traders (Long)

	Commercials OI %	**Non-Commercials OI %**	**Non-Reportables OI %**		**Commercials OI %**	**Non-Commercials OI %**	**Non-Reportables OI %**
	Maize				**Rice**		
1995:4 2000:12	53.67481	17.53988	28.78530	**1995:4 2000:12**	50.77797	13.00551	36.21710
2001:1 2006:12	56.91122	22.59289	20.49589	**2001:1 2006:12**	37.62181	27.17722	35.20236
2007:1 2012:1	54.24208	32.90143	12.85650	**2007:1 2012:1**	47.76541	30.21098	22.02459
1995:4 2012:1	**54.99969**	**23.97984**	**21.02048**	**1995:4 2012:1**	**45.17891**	**23.25252**	**31.56955**
	Soybean				**Wheat**		
1995:4 2000:12	46.84129	16.42326	36.73545	**1995:4 2000:12**	40.99299	22.95836	36.04866
2001:1 2006:12	55.50935	19.41973	25.07092	**2001:1 2006:12**	53.96552	25.76534	20.26914
2007:1 2012:1	48.97593	30.54184	20.48223	**2007:1 2012:1**	64.54518	25.45651	9.998309
1995:4 2012:1	**50.57551**	**21.75484**	**27.66965**	**1995:4 2012:1**	**52.72915**	**24.71326**	**22.55759**

Table 5 Position Share of Reportable and non-Reportable Traders (Short)

	Commercials OI %	Non-Commercials OI %	Non-Reportables OI %		Commercials OI %	Non-Commercials OI %	Non-Reportables OI %
	Maize				**Rice**		
1995:4 2000:12	49.11267	11.16752	39.71981	**1995:4 2000:12**	55.63051	13.43365	30.93583
2001:1 2006:12	56.72933	16.74337	26.52730	**2001:1 2006:12**	61.50793	15.62845	22.86362
2007:1 2012:1	65.57321	12.09897	22.32781	**2007:1 2012:1**	74.47884	13.70656	11.81460
1995:4 2012:1	**56.79828**	**13.43623**	**29.76549**	**1995:4 2012:1**	**63.41726**	**14.29837**	**22.28438**
	Soybean				**Wheat**		
1995:4 2000:12	67.52290	8.590364	23.88673	**1995:4 2000:12**	53.82450	18.35902	27.81648
2001:1 2006:12	73.20902	11.47967	15.31131	**2001:1 2006:12**	55.56512	26.06382	18.37106
2007:1 2012:1	76.07067	10.95440	12.97493	**2007:1 2012:1**	55.98069	27.47381	16.54551
1995:4 2012:1	**72.13089**	**10.33411**	**17.53500**	**1995:4 2012:1**	**55.09604**	**23.85777**	**21.04619**

Source: Own elaborations on Datastream data.

In addition, Table 4 highlights that hedging is the largest position of the three categories. Hedging is more than 54% of the long open interest in maize market, about 53% in wheat market, more than 50% in soybean market and about 45% in rice market for the period 1995-2012. These values increase to about 57% of the short open interest in maize, to 72% in soybean short market, to 63% in wheat and 55% in rice markets. Considering the sub-samples, the commercial percentage of long open interest share has surged over time for wheat; it has been almost stable for maize, and it has gone to a wave-like dynamics for soybean and rice. For short markets, the percentage share of commercials has trended up for rice, maize, and soybean, and it has been constant for wheat. Besides, another significant aspect revealed in Table 4 is that the share of speculators (non-commercials) in all the considered long futures markets has increased significantly. For rice the percentage values have more than doubled going from 13% to 30% of the long open interest during our sample period. This trend is different in the short market where speculators position experienced an up-and-down trend with the exception of wheat. Comparing tables 4 and 5 it emerges that hedgers are more concentrated in short markets, whilst speculators are more widespread in long category. According to Keynes' theory of normal backwardation, the net supply of commercial futures contracts, or hedging pressure, affects the equilibrium futures prices. This can lead to rises or falls in futures prices over time. When hedgers take long positions, the equilibrium achieved is such that futures prices tend to decrease over time. Conversely, in a market where short hedging dominates, futures prices tend to increase over time. Finally, the percentage values for non-reportables have decreased both for long and short positions, testifying that the number of smaller traders has been overcome by speculators and hedgers. The evolution of the positions of each trader group operating in the long markets in percentage share is reported in Chart 6 (Appendix).

The changing trading positions can be also analysed considering the hedging or speculative pressure (De Roon et al., 2000; Sanders et al., 2004) in futures markets. The hedging (speculative) pressure is defined as the difference in commercial (non-commercial) short and commercial (non commercial) long positions divided by total commercial (non commercial) positions, namely:

$$\textit{Hedging}\ \text{pressure} = \frac{(HL - HS)}{(HL + HS)} \qquad \text{Speculative pressure} = \frac{(SL - SS)}{(SL + SS)}$$

Each index represents the net long position held by the groups (hedgers-speculators) normalised by their total size in percentage.

Table 6 Speculative Pressure

SPEC PRESS % MAIZE	1995-2012	1995 2000	2001 2006	2007 2012	2007 2009
Mean	27.92366	23.73609	16.51236	46.12951	49.98080
Median	34.96500	24.09000	9.155000	53.20000	54.49000
Maximum	95.66000	95.66000	73.21000	70.88000	68.68000
Minimum	-68.14000	-68.14000	-43.76000	2.840000	9.900000
Std. Dev.	38.48089	49.34368	32.80159	20.36088	15.57835
Skewness	-0.316493	-0.058867	0.112910	-0.674660	-0.964333
SPEC PRESS % RICE	**1995-2012**	**1995 2000**	**2001 2006**	**2007 2012**	**2007 2009**
Mean	20.14371	-0.449565	22.88167	40.20607	59.36320
Median	27.40500	0.560000	26.07500	33.78000	54.52000
Maximum	98.36000	83.60000	92.17000	98.36000	98.36000
Minimum	-91.03000	-91.03000	-69.64000	-27.45000	21.26000
Std. Dev.	44.28828	46.90529	43.14277	31.12836	24.89141
Skewness	-0.410419	-0.176745	-0.221256	0.056861	0.029725
SPEC PRESS % SOY	**1995-2012**	**1995 2000**	**2001 2006**	**2007 2012**	**2007 2009**
Mean	35.85292	29.48478	31.25014	48.48902	56.94880
Median	48.40000	44.57000	42.39500	54.04000	65.62000
Maximum	94.95000	94.95000	87.26000	84.79000	84.79000
Minimum	-69.66000	-69.66000	-67.63000	-34.06000	1.710000
Std. Dev.	41.34111	46.81100	43.61730	27.50197	23.31046
Skewness	-0.847053	-0.621730	-0.604778	-1.020474	-0.803803
SPEC PRESS % WHEAT	**1995-2012**	**1995 2000**	**2001 2006**	**2007 2012**	**2007 2009**
Mean	3.847322	12.29430	1.588806	-3.041672	4.010160
Median	-1.340000	2.469000	-2.395500	-0.897000	4.502000
Maximum	77.79200	77.79200	59.50900	18.98400	18.98400
Minimum	-48.41600	-48.41600	-47.88000	-29.42800	-13.81400
Std. Dev.	28.30259	34.26814	29.64549	13.27368	8.929135
Skewness	0.795354	0.530198	0.432855	-0.166020	-0.177120
Observations	202	69	72	61	25

Source: Own elaborations on Datastream data.

From the previous table, one can see that speculative pressure has maintained almost always a mean positive value over the sample period. Positive values indicate that commodity markets can be regarded as speculative markets. If negative values would prevail they could have been considered as hedging markets. High standard deviations suggest that speculative pressure is considerably volatile. The skewness is highly negative for all commodities with the exception of wheat, suggesting that, despite the high mean value many of the observations are considerably less than the mean.

The speculative pressure index reveals that on average soybean is the commodity to register the highest speculative pressure at 48.4% while wheat has the lowest pressure of about 4% during the period 1995-2012. It is interesting to notice that if we consider the years with the highest economic turbulence, 2007-2009 then the speculative pressure for all commodities is significantly high.

5.2 Excessive Speculation

It is important to note that increased participation of non-commercials (traditional speculators) does not imply extreme speculation. As testified by the traditional theory, speculative trading is essential for the proper execution of hedging activities. The speculative trader provides the necessary level of trading activity or “liquidity” to the market to prevent the occurrence of added risk from failure to establish or terminate a contract. Hitherto, “market liquidity” or the necessary level of speculation relative to the hedging positions represents a crucial element to the overall performance of a futures market (Ward, 1974). Put differently, speculation brings some potential benefits such as: liquidity increasing, ability for commercial entities to transfer risk of price changes, and finances storage. However, it has also potential disadvantages: if it is excessive it could cause prices to deviate from the supply and demand fundamentals. What is problematic is an excessive level of speculation that is a level of speculation that overcomes the need to satisfy net hedging transactions and market liquidity, because the excess may distort price dynamics. For this reason the U.S. Commodity Futures Trading Commission has stated that because excessive speculation may cause “sudden or unreasonable fluctuations or unwarranted changes in the price of commodity” the Commission is authorised to impose limits on the size of speculative positions in futures markets.

Specifically, to evaluate the extra speculation, the excessive speculative index (ESPI) as developed by Working (1953, 1962) has been computed. The ESPI measures the relative importance of speculative positions with respect to hedging positions. This index has been used also by Sanders et al. (2010), Buyuksahin and Harris (2011) to examine the adequacy or excessiveness of speculative participation in the commodity futures markets. Sanders et al. (2010) show that the level of speculation in nine agricultural futures markets from 2006-08 (adjusting for index fund positions) was not extreme, but ranged within the historical norms. Across most markets, the increase in index buying was more than offset by commercial (hedger) selling. Buyuksahin and Harris (2011) demonstrate that Working’s index in the crude oil futures market increased in parallel with crude oil prices over 2004-09, and the peak of the index was still well within historical norms.

In formal terms the excessive speculation index is expressed as follows:

$$ESPI = \left[1 + \frac{NC\ \mathrm{OI\ Short}}{\left(C\ \mathrm{OI\ Short} + \mathrm{C\ OI\ Long}\right)}\right] \cdot 100 \qquad \text{if} \qquad \mathrm{C\ OI\ Short} \geq \mathrm{C\ OI\ Long}$$

$$ESPI = \left[1 + \frac{NC\ \mathrm{OI\ Long}}{\left(C\ \mathrm{OI\ Short} + \mathrm{C\ OI\ Long}\right)}\right] \cdot 100 \qquad \text{if} \qquad \mathrm{C\ OI\ Short} \prec \mathrm{C\ OI\ Long}$$

where *NC OI Short* = open futures position of short speculators, *NC OI Long* = open futures position of long speculators, *C OI Short* = open futures position of short hedgers and *C OI Long* = open futures position of the long hedgers. Put differently, the nominator represents the speculation positions short and long. The denominator is the total amount of futures open interest resulting from hedging activity.

The excessive speculation index is silent on the direction of speculation (long versus short). Instead, the amount of speculation is gauged relative to what is needed to balance hedging positions.

Table 7 reports the statistics for the excessive speculation index calculated for maize, rice, soybeans, and wheat for the entire sample and sub-sample.

Table 7 Excessive Speculation Index Complete Sample (1995:4-2012:1) and Sub-samples.

Complete sample	SPECULATION INDEX MAIZE	SPECULATION INDEX RICE	SPECULATION INDEX SOYBEAN	SPECULATION INDEX WHEAT
Mean	119.2851	112.7009	110.3857	119.2063
Median	118.3272	110.5650	108.9993	118.4291
Maximum	150.7940	164.4600	131.8522	145.8218
Minimum	101.5925	100.2600	100.5640	103.4452
Sub-sample 1995:4 2000:12	**SPECULATION INDEX MAIZE**	**SPECULATION INDEX RICE**	**SPECULATION INDEX SOYBEAN**	**SPECULATION INDEX WHEAT**
Mean	113.1225	110.2946	107.4836	118.1487
Median	112.5071	107.8900	107.0573	118.3823
Maximum	129.2976	146.1200	122.0625	135.2880
Minimum	101.5925	101.2100	100.5640	103.4452
Sub-sample 2001:1 2006:12	**SPECULATION INDEX MAIZE**	**SPECULATION INDEX RICE**	**SPECULATION INDEX SOYBEAN**	**SPECULATION INDEX WHEAT**
Mean	122.1821	116.0600	110.1144	119.1181
Median	121.6821	111.8250	108.2511	117.1051
Maximum	136.7152	164.4600	127.8115	145.8218
Minimum	109.2769	101.2500	101.5919	108.5406
Sub-sample 2007:1 2012:1	**SPECULATION INDEX MAIZE**	**SPECULATION INDEX RICE**	**SPECULATION INDEX SOYBEAN**	**SPECULATION INDEX WHEAT**
Mean	122.8364	111.4579	113.9884	120.5068
Median	118.4707	111.5900	112.8361	119.7040
Maximum	150.7940	131.5400	131.8522	129.0079
Minimum	111.0724	100.2600	104.8145	113.9259

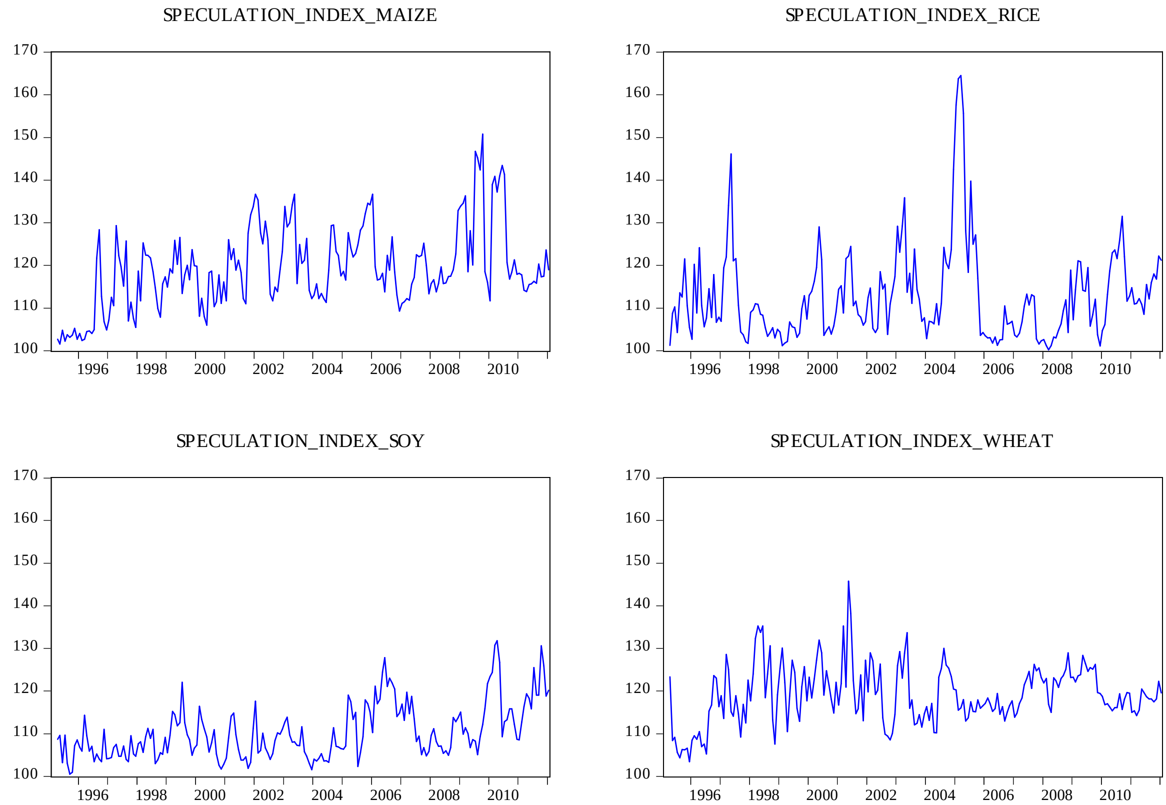
Source: Own elaborations on Datastream data.

For the whole sample, the average ESPI for maize and wheat is 119 - indicating speculation in the two markets is 19% greater than that desirable to meet hedging needs. Speculation was about 13% in excess for rice, and 10% in excess for soybeans. The first block of the table indicates also the maximum values recorded during the years 1995-2012, maize market recorded more than 50% excess speculation, rice market more than 64%, soybeans more than 31% and wheat more than 45% excess speculation. Considering the sub-samples, the speculative index values have risen over time for soybean and wheat to average 114 and 120, respectively in 2007-2012, implying that speculation in excess of minimal short and long hedging needs increased to 14% and 20%. This increase can be due to the growing spread trades of speculators (higher numerator) or the declining rate in hedging demand (lower denominator).

These values are rather comparable to historical index numbers in other markets (Irwin et al. 2009).

Chart 6 displays the excessive speculative index over time.

Chart 6 Excessive Speculation Index



A drawback of the Working index is that it does not include non-reportable positions, and non-reportables can be speculators or hedgers. In addition, the official distinction in speculators and commercials can be biased because traders may have an incentive to be classified as commercials, due to the speculative position limits placed on non-commercials. Finally, since cash positions for true commercials are unknown, their position may be speculative in nature (Sanders et al., 2004). Despite the limits of the Working index, it remains the best indicator in the empirical literature, in fact alternative indices, in addition to the same shortcomings of the Working index, prove also to be instable. This is the case, for instance, of the measure of excessive speculation proposed by Ward (1974)[7], whose metrics is very sensitive to the levels of long and short hedging. Specifically, explosive upper values of the index are recorded in periods in which short and long hedged commitments are nearly equal. In our sample the extreme upper ranges were very frequent and therefore the index was misleading (Table 11, Appendix).

[7] The Ward index is: SL / (HS-HL) if HS≥HL ; SS / (HL-HS) if HS<HL where H, = short hedge (all trading variables measured in contract units out-standing), HL= long hedging, S = short speculation, St = long speculation. All index values of equation must be equal to or greater than one plus a liquidity factor. Suppose the index were 1.48, then speculation would be 48 percent over the minimum to offset the net hedged position. Index values greater than a necessary liquidity level (to be estimated subsequently) suggest excessive speculation. Index measures greater than that necessary for market liquidity indicate that groups of speculators are interpreting the same information differently or are utilizing market information totally ignored by other speculative groups.

6. Granger causality

To assess whether a trader activity prompts, in a forecasting sense price volatility and/or vice-versa, the Granger causality test has been carried out.

The Granger (1969) approach to the question of whether x causes y is to see how much of the current y can be explained by past values of x and then to see whether adding lagged values of x can improve the explanation. It is said that y is Granger-caused by x if x helps in the prediction of y, or equivalently if the coefficients on the lagged x's are statistically significant. Note that two-way causation is frequently the case; x Granger causes y and y Granger causes x.

It is important to note that the statement "x Granger causes y" does not imply that y is the effect or the result of x. Granger causality measures precedence and information content, but does not by itself indicate causality in the more common use of the term. Rather, the Granger causality test shows whether one variable leads another one.

I have therefore tested two batteries of Granger causality tests: one concerns the relationships between speculation and volatility, i.e. if speculation "causes" price volatility (speculation → volatility), or is it volatility that causes speculation (volatility → speculation), or is there a bilateral causality (speculation ↔ volatility), or is there not a specific relationship between the two variables for maize, rice, soybeans, and wheat markets. The other battery takes into account excessive speculation and volatility.

The empirical literature has examined several factors as proxy indicators of financial speculation. For instance, Robles et al. (2009) have considered a set of indicators of speculation activity, namely the volume of futures contracts, open interest of futures contracts, the ratio of the volume of futures to open interest, the ratio of non-commercial positions to the total positions for long as well as for short positions, and the net long positions. Net long positions held by non-commercial traders have been also used by the IMF (2006), Micu, (2005), and Domanski and Heath (2007). For the purpose of this analysis, I consider two proxies for speculation, namely the share of total open interest positions held by non-commercials and the speculative pressure. These two indicators are selected because they focus directly on speculative behaviours identified by the U.S. Commodity Future Trading Commission and they have proven highly significant. Excessive speculation is instead computed *à la* Working.

Granger causality requires that the series have to be covariance stationary hence, before computing the test, the classical Adjusted Dickey-Fuller and Phillips Perron checks have been performed. For all of the series the null hypothesis H_0 of non-stationarity can be rejected at a 5% confidence level, therefore there is no necessity to consider any first differences and the Granger test can be directly implemented.

Considering the two proxies of speculation for the entire sample (Tables 8 and 9), one cannot reject the hypothesis that speculation does not Granger-cause volatility for rice and soybeans. Likewise, it is not possible to reject the hypothesis that volatility does not Granger-cause speculation for the some commodities. Alternatively, it is possible to reject the hypothesis that volatility does not Granger-cause speculation for wheat. A complex result appears for maize: namely, there is a bidirectional relationship when speculative pressure is considered, while one rejects the hypothesis that speculation does not Granger-cause volatility for maize when the relative share of non-commercial is considered. Therefore, it appears that for wheat Granger causality clearly runs one-way: from volatility to speculation. The results for wheat and maize could be explained by the fact that the correlation coefficients for these commodities were the highest among the other goods between 1995:2-2012:1. In short, the findings indicate that there is no statistically discernible relationship between speculation and volatility for rice and soybeans, while a more complex relationship exists for maize, and a distinct relationship for wheat.

The results become more distinct if one considers shorter subsamples: specifically, several unilateral and bilateral relationships between speculation and volatility have been identified. This means that it is possible to clearly identify two-way directions of causality. When one-way causality is identified, it always moves from volatility to speculation, meaning that increased price volatility has led to more speculation.

Table 8 Pairwise Granger Causality Tests. Speculation (A)
Sample: 1995M02 2012M01

Null Hypothesis	Lags	F-Statistic	Prob.	Decision
SPECULATION does not Granger Cause VOLATILITY_RICE	2	0.15691	0.8549	Do not reject
VOLATILITY_RICE does not Granger Cause SPECULATION		0.02986	0.9706	Do not reject
SPECULATION does not Granger Cause VOLATILITY_MAIZE	1	16.5802	7.E-05	Reject
VOLATILITY_MAIZE does not Granger Cause SPECULATION		0.80922	0.3695	Do not reject
SPECULATION does not Granger Cause VOLATILITY_WHEAT	2	0.78311	0.4585	Do not reject
VOLATILITY_WHEAT does not Granger Cause SPECULATION		3.18830	0.0435	Reject
SPECULATION does not Granger Cause VOLATILITY_SOYBEAN	1	1.69844	0.1941	Do not reject
VOLATILITY_SOYBEAN does not Granger Cause SPECULATION		0.02469	0.8753	Do not reject

Null Hypothesis	Lags	F-Statistic	Prob.	Decision
Sample: 1995M02 2000M12				
SPECULATION does not Granger Cause VOLATILITY_RICE	5	2.72211	0.0292	Reject
VOLATILITY_RICE does not Granger Cause SPECULATION		4.71643	0.0012	Reject
SPECULATION does not Granger Cause VOLATILITY_WHEAT	2	0.67559	0.5126	Do not reject
VOLATILITY_WHEAT does not Granger Cause SPECULATION		5.20370	0.0081	Reject
Sample: 2001M01 2006M12				
SPECULATION does not Granger Cause VOLATILITY_WHEAT	1	2.10874	0.1511	Do not reject
VOLATILITY_WHEAT does not Granger Cause SPECULATION		4.44746	0.0386	Reject
SPECULATIVE PRES does not Granger Cause VOLATILITY_MAIZE	1	0.88419	0.3504	Do not reject
VOLATILITY_MAIZE does not Granger Cause SPECULATIVE PRES		3.08374	0.0836	Reject
Sample: 2005M04 2008M05				
SPECULATIVE PRES does not Granger Cause VOLATILITY_RICE	1	0.57640	0.4530	Do not reject
VOLATILITY_RICE does not Granger Cause SPECULATIVE PRES		8.52968	0.0062	Reject
Sample: 2007M01 2009M01				
SPECULATION does not Granger Cause VOLATILITY_MAIZE	2	2.03473	0.1597	Do not reject
VOLATILITY_MAIZE does not Granger Cause SPECULATION		3.67389	0.0459	Reject
Sample: 2007M01 2008M12				
SPECULATION does not Granger Cause VOLATILITY_RICE	2	3.25853	0.0634	Reject
VOLATILITY_RICE does not Granger Cause SPECULATION		8.95722	0.0022	Reject
SPECULATION does not Granger Cause VOLATILITY_WHEAT	7	15.7113	0.0611	Reject
VOLATILITY_WHEAT does not Granger Cause SPECULATION		58.4788	0.0169	Reject
Sample: 2007M01 2012M01				
SPECULATION does not Granger Cause VOLATILITY_RICE	1	0.03115	0.8606	Do not reject
VOLATILITY_RICE does not Granger Cause SPECULATION		6.67634	0.0127	Reject
SPECULATION does not Granger Cause VOLATILITY_SOYBEAN	1	0.04543	0.8321	Do not reject
VOLATILITY_SOYBEAN does not Granger Cause SPECULATION		4.46102	0.0396	Reject

Notes: Volatility = realised volatility. Speculation = non-commercial long positions divided by total open interest.
Since the Granger causality test is very sensitive to the number of lags included in the regression, the lag order selection criteria based on the sequential modified LR test, the final prediction error, the Akaike information criterion, the Schwarz information criterion, and the Hannan-Quinn information criterion have been used in order to find an appropriate number of lags. When some criteria showed contrasting results, the number of lags was selected on the basis of the highest number of criteria showing the same outcome.
Price volatility for wheat refers to values from the Chicago Board of Trade.

Table 9 Pairwise Granger Causality Tests. Speculation (B)

Sample: 1995M02 2012M01

Null Hypothesis	Lags	F-Statistic	Prob.	Decision
SPECULATIVE PRES does not Granger Cause VOLATILITY_RICE	2	0.73613	0.4803	Do not reject
VOLATILITY_RICE does not Granger Cause SPECULATIVE PRES		0.55861	0.5729	Do not reject
SPECULATIVE PRES does not Granger Cause VOLATILITY_MAIZE	1	3.55345	0.0609	Reject
VOLATILITY_MAIZE does not Granger Cause SPECULATIVE PRES		8.09914	0.0049	Reject
SPECULATIVE PRES does not Granger Cause VOLATILITY_WHEAT	2	0.10330	0.9019	Do not reject
VOLATILITY_WHEAT does not Granger Cause SPECULATIVE PRES		7.20488	0.0010	Reject
SPECULATIVE PRES does not Granger Cause VOLATILITY_SOYBEAN	2	0.34171	0.7110	Do not reject
VOLATILITY_SOYBEAN does not Granger Cause SPECULATIVE PRES		1.92087	0.1493	Do not reject

Null Hypothesis	Lags	F-Statistic	Prob.	Decision
Sample: 1995M02 2000M12				
SPECULATIVE PRES does not Granger Cause VOLATILITY_RICE	5	2.90273	0.0218	Reject
VOLATILITY_RICE does not Granger Cause SPECULATIVE PRES		2.13260	0.0757	Reject
SPECULATIVE PRES does not Granger Cause VOLATILITY_WHEAT	2	0.47548	0.6238	Do not reject
VOLATILITY_WHEAT does not Granger Cause SPECULATIVE PRES		7.12705	0.0016	Reject
Sample: 2001M01 2006M12				
SPECULATIVE PRES does not Granger Cause VOLATILITY_WHEAT	1	2.70158	0.1049	Do not reject
VOLATILITY_WHEAT does not Granger Cause SPECULATIVE PRES		12.1630	0.0009	Reject
SPECULATIVE PRES does not Granger Cause VOLATILITY_MAIZE	1	0.51578	0.4751	Do not reject
VOLATILITY_MAIZE does not Granger Cause SPECULATIVE PRES		20.5203	2.E-05	Reject
SPECULATIVE PRES does not Granger Cause VOLATILITY_SOYBEAN	7	2.76187	0.0166	Reject
VOLATILITY_SOYBEAN does not Granger Cause SPECULATIVE PRES		3.10906	0.0084	Reject
Sample: 2005M04 2007M10				
SPECULATIVE PRES does not Granger Cause VOLATILITY_WHEAT	1	7.92021	0.0090	Reject
VOLATILITY_WHEAT does not Granger Cause SPECULATIVE PRES		4.50029	0.0432	Reject
Sample: 2005M04 2008M05				
SPECULATIVE PRES does not Granger Cause VOLATILITY_RICE	1	4.17163	0.0489	Reject
VOLATILITY_RICE does not Granger Cause SPECULATIVE PRES		6.01890	0.0194	Reject
Sample: 2007M01 2009M01				
SPECULATIVE PRES does not Granger Cause VOLATILITY_MAIZE	2	0.37212	0.6945	Do not reject
VOLATILITY_MAIZE does not Granger Cause SPECULATIVE PRES		4.64786	0.0236	Reject
Sample: 2007M01 2008M12				
SPECULATIVE PRES does not Granger Cause VOLATILITY_RICE	1	2.57740	0.1241	Do not reject
VOLATILITY_RICE does not Granger Cause SPECULATIVE PRES		4.40930	0.0486	Reject
Sample: 2007M01 2012M01				
SPECULATIVE PRES does not Granger Cause VOLATILITY_RICE	1	0.65743	0.4212	Do not reject
VOLATILITY_RICE does not Granger Cause SPECULATIVE PRES		2.86773	0.0965	Reject

Notes: Volatility = realised volatility. Speculation = speculative pressure.

Considering excessive speculation, some interesting results come about. In particular for long periods, as in the case of speculation, a non-distinct relationship is found for rice, maize and soybeans, while a one-way relationship that runs from volatility to excessive speculation is found for wheat. When shorter periods are taken into account, it emerges a clear one-way relationship that moves from excessive speculation to volatility. This confirms the analysis by Kaldor.

Table 10 Pairwise Granger Causality Tests. Excessive Speculation

Sample: 1995M02 2012M01

Null Hypothesis	Lags	F-Statistic	Prob.	Decision
EXCESS SPECULATION does not Granger Cause VOLATILITY_RICE	2	0.03264	0.9679	Do not reject
VOLATILITY_RICE does not Granger Cause EXCESS SPECULATION		0.01590	0.9842	Do not reject
EXCESS SPECULATION does not Granger Cause VOLATILITY_MAIZE	2	0.21181	0.8093	Do not reject
VOLATILITY_MAIZE does not Granger Cause EXCESS SPECULATION		0.64892	0.5238	Do not reject
EXCESS SPECULATION does not Granger Cause VOLATILITY_WHEAT	3	0.71140	0.5463	Do not reject
VOLATILITY_WHEAT does not Granger Cause EXCESS SPECULATION		3.90784	0.0098	Reject
EXC SPECULATION does not Granger Cause VOLATILITY_SOYBEAN	2	0.31681	0.7289	Do not reject
VOLATILITY_SOYBEAN does not Granger Cause EXC SPECULATION		1.61854	0.2009	Do not reject

Null Hypothesis	Lags	F-Statistic	Prob.	Decision
Sample: 2001M01 2002M12				
EXCESS SPECULATION does not Granger Cause VOLATILITY_RICE	4	2.89212	0.0733	Reject
VOLATILITY_RICE does not Granger Cause EXCESS SPECULATION		1.63420	0.2346	Do not reject
Sample: 2004M11 2006M12				
EXCESS SPECULATION does not Granger Cause VOLATILITY_RICE	1	3.45160	0.0766	Reject
VOLATILITY_RICE does not Granger Cause EXCESS SPECULATION		1.69057	0.2070	Do not reject
Sample: 2007M01 2008M05				
EXCESS SPECULATION does not Granger Cause VOLATILITY_RICE	4	6.12068	0.0536	Reject
VOLATILITY_RICE does not Granger Cause EXCESS SPECULATION		0.97344	0.5101	Do not reject
EXCESS SPECULATION does not Granger Cause VOLATILITY_MAIZE	4	5.70002	0.0602	Reject
VOLATILITY_MAIZE does not Granger Cause EXCESS SPECULATION		0.30583	0.8611	Do not reject
Sample: 2007M08 2009M01				
EXCESS SPECULATION does not Granger Cause VOLATILITY_WHEAT	5	37.5175	0.0262	Reject
VOLATILITY_WHEAT does not Granger Cause EXCESS SPECULATION		1.02802	0.5603	Do not Reject
EXC SPECULATION does not Granger Cause VOLATILITY_SOYBEAN	5	17.0131	0.0564	Reject
VOLATILITY_SOYBEAN does not Granger Cause EXC SPECULATION		0.13711	0.9671	Do not reject
Sample: 2008M04 2010M04				
EXCESS SPECULATION does not Granger Cause VOLATILITY_MAIZE	6	3.45131	0.0786	Reject
VOLATILITY_MAIZE does not Granger Cause EXCESS SPECULATION		0.32825	0.8995	Do not reject
EXC SPECULATION does not Granger Cause VOLATILITY_SOYBEAN	1	5.85364	0.0247	Reject
VOLATILITY_SOYBEAN does not Granger Cause EXC SPECULATION		0.47609	0.4978	Do not reject
Sample: 2010M04 2011M07				
EXCESS SPECULATION does not Granger Cause VOLATILITY_WHEAT	3	8.50008	0.0140	Reject
VOLATILITY_WHEAT does not Granger Cause EXCESS SPECULATION		2.70669	0.1383	Do not reject

Notes: Volatility = realised volatility. Excessive speculation = ESPI.

In a nutshell, while speculation and volatility influence reciprocally each other, or tendencially speculation follows price volatility, excessive speculation tends to Granger-cause price volatility, i.e. speculators become shepherds.

7. Conclusions

The rise in commodity prices over the last decade and their volatility has generated considerable interest among academicians, policy makers, and investors for their effects on the real economy and thus on economic growth, food security, and investment decisions. The present study has investigated the changes that occurred in the commodity market and the causal relationship between volatility, speculation, and excessive speculation, where the latter refers to that amount of long (purchased contracts outstanding) or short (sold contracts outstanding) speculation over what is needed to satisfy net hedging transactions and market liquidity.

The results show that the non-commercial positions have increased over time with the most significant surges in the 2007-2008 and 2011 periods. Contemporaneously, trading by commercials has increased, but their trading volume has grown more slowly than non-commercials. Using Commitments of Traders data, a positive correlation emerges between aggregate non-commercial net open interest and the level of commodity prices. This finding gives a first idea that there could be a relationship between speculation and price volatility.

In order to formally verify this outcome, two batteries of Granger causality tests have been carried out: one investigating the relationship of speculation-volatility, the other concerning the linkage between excessive speculation and volatility. Three main interesting results occur.

First, if one considers a large time span, it is difficult to find any discernible linkage between speculation and volatility or excessive speculation and volatility for rice and soybeans. This is in line with several studies that have proved the absence of any relationship between speculation and volatility. For maize and wheat, more long run linkages are found, likely due to the fact that both commodities are widely used in the production of biofuels, and this has increased speculative behaviours over time. However, when one shrinks the periods of analysis to one or to two years, clear relationships appear between the two pairs of variables.

Second, with regard to the linkage between speculation and price volatility, the results show that it is possible to spot some periods in which there are bilateral linkages between the two variables and others in which price volatility leads speculation. Contextually, considering the relation between excessive speculation and price volatility, it is possible to identify times in which excessive speculation Granger-causes price volatility. This implies that when speculation becomes disproportionate it could destabilise futures markets. This outcome gives support to the intuition by Kaldor according to which speculation is much more likely to operate in a destabilising direction when we consider price fluctuations within smaller ranges.

Third, both the one-way and two-way relationships are not overlapping over time for all the commodities taken together.

The results therefore show that it is not speculation that matters for destabilising markets, but excessive speculation, because speculation activity allows hedgers to find counterparties to hedge their positions and, in general, it allows markets to perform their institutional role. However when speculation is above the hedging needs, then it can bring about extreme volatility. The difference between speculation and excessive speculation should be considered the bridge that could combine the traditional and non-traditional speculative theories.

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Appendix

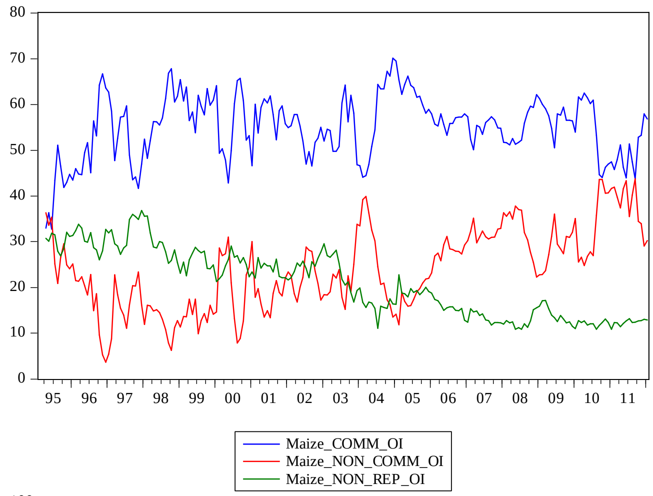
Market price for wheat	This is a market price series for wheat, with values expressed in U.S. dollars and averaged from daily quotations. The commodity and market specifications are: U.S. No. 1 hard red winter, ordinary protein, prompt shipment, FOB Gulf of Mexico ports. The series are compiled by the Commodities and Special Issues Division of the IMF's Research Department, with assistance from the World Bank, UNCTAD, and national sources.
Market price for maize	This is a market price series for maize, with values expressed in U.S. dollars and averaged from daily quotations. The commodity and market specifications are: U.S. No. 2 yellow, prompt shipment, FOB Gulf of Mexico ports. The series are compiled by the Commodities and Special Issues Division of the IMF's Research Department, with assistance from the World Bank, UNCTAD, and national source
Market price for soybean	This is a market price series for soybeans, with values expressed in U.S. dollars. The commodity and market specifications are: Soybean futures contract (first contract forward) No. 2 yellow and par. The series are compiled by the Commodities and Special Issues Division of the IMF's Research Department, with assistance from the World Bank, UNCTAD, and national sources.
Market price for palm kernel	This is a market price series for palm kernel oil, with values expressed in U.S. dollars. The commodity and market specifications are: Malaysia: C.I.F. Rotterdam. The series are compiled by the Commodities and Special Issues Division of the IMF's Research Department, with assistance from the World Bank, UNCTAD, and national sources.
Market price for palm oil	This is a market price series for palm oil, with values expressed in U.S. dollars and averaged from weekly quotations. The commodity and market specifications are: Palm Oil Futures (first contract forward) 4-5 percent FFA Bursa Malaysian Derivatives Berhad. The series are compiled by the Commodities and Special Issues Division of the IMF's Research Department, with assistance from the World Bank, UNCTAD, and national sources.
Market price for barley	This is a market price series for barley, with values expressed in U.S. dollars and averaged from daily quotations. The commodity and market specifications are: Canadian No. 1 Western Barley, spot price. The series are compiled by the Commodities and Special Issues Division of the IMF's Research Department, with assistance from the World Bank, UNCTAD, and national sources.
Market price for rice	This is a market price series for rice, with values expressed in U.S. dollars and averaged from weekly quotations. The commodity and market specifications are: Thai, white milled, 5 percent broken, nominal price quotes, FOB Bangkok. The series are compiled by the Commodities and Special Issues Division of the IMF's Research Department, with assistance from the World Bank, UNCTAD, and national sources.

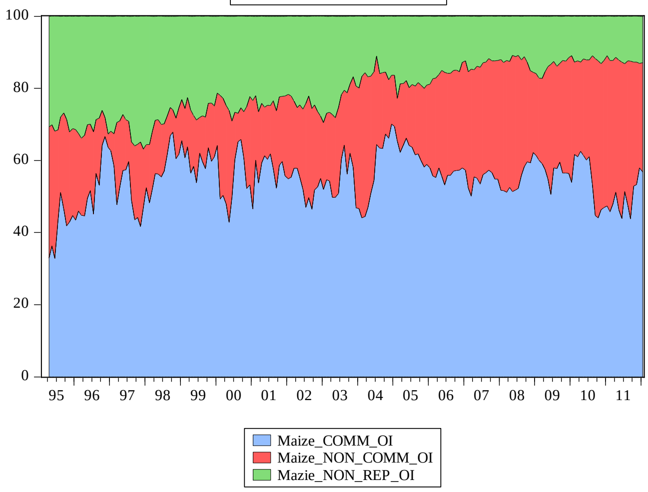
Table 11 Ward's Excessive Speculation Index

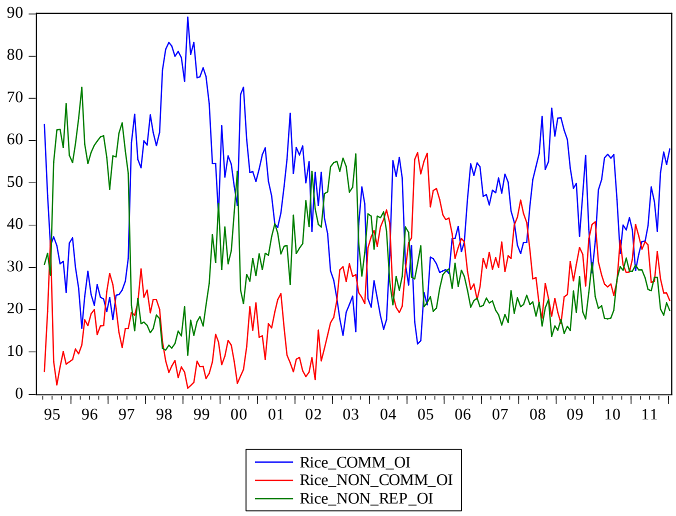
Complete sample				
1995:4 2012:1	MAIZE	RICE	SOY	WHEAT
Mean	329.3579	208.5108	254.8490	1196.603
Median	190.6650	97.31500	91.92500	237.8400
Maximum	3850.940	3994.400	12771.78	71753.13
Minimum	58.03000	21.50000	43.44000	76.33000
Std. Dev.	472.9970	409.3701	990.7373	5823.635
Skewness	5.142558	5.841224	10.70589	9.964447
Kurtosis	34.16454	44.61749	130.0077	113.0492
Sub-sample				
1995:4 2000:12	MAIZE	RICE	SOY	WHEAT
Mean	173.8114	193.1545	202.5439	526.2188
Median	133.4500	96.93000	69.64000	165.2100
Maximum	1083.020	2262.500	4749.670	7900.000
Minimum	58.03000	21.50000	43.44000	76.33000
Std. Dev.	153.7633	365.3845	585.5495	1102.831
Skewness	3.801267	4.340110	7.041131	4.927933
Kurtosis	20.74380	22.33709	54.46796	31.07352
Sub-sample				
2001:1 2006:12	MAIZE	RICE	SOY	WHEAT
Mean	465.8657	179.0418	350.7585	1399.847
Median	212.2850	88.91500	92.97000	235.9700
Maximum	3850.940	1900.000	12771.78	71753.13
Minimum	117.7100	33.78000	60.40000	101.1700
Std. Dev.	716.3233	275.4447	1510.611	8422.689
Skewness	3.546616	4.689182	7.903413	8.263481
Kurtosis	15.47517	27.06412	65.31295	69.52683
Sub-sample				
2007:1 2012:1	MAIZE	RICE	SOY	WHEAT
Mean	344.1798	260.6641	200.8092	1715.014
Median	239.4500	106.8700	101.2600	343.1500
Maximum	1421.190	3994.400	3286.050	32835.67
Minimum	142.0900	64.25000	81.31000	160.8500
Std. Dev.	255.1231	562.3536	426.8349	5239.146
Skewness	2.026680	5.392398	6.470939	4.740972
Kurtosis	7.482026	34.30369	46.50148	25.52600

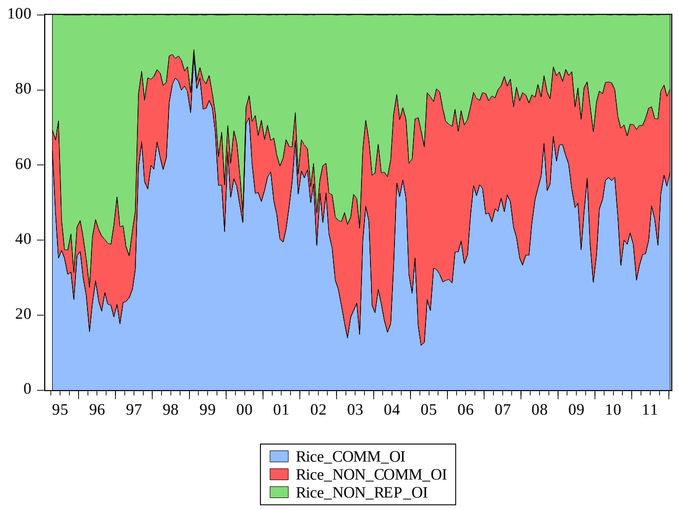
Source: Own elaborations on Datastream data.

Chart 7 Position Share of Reportable and non-Reportable Traders





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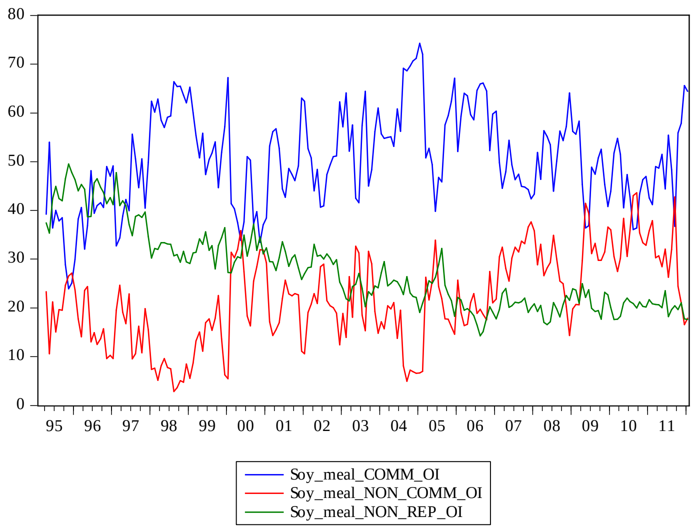
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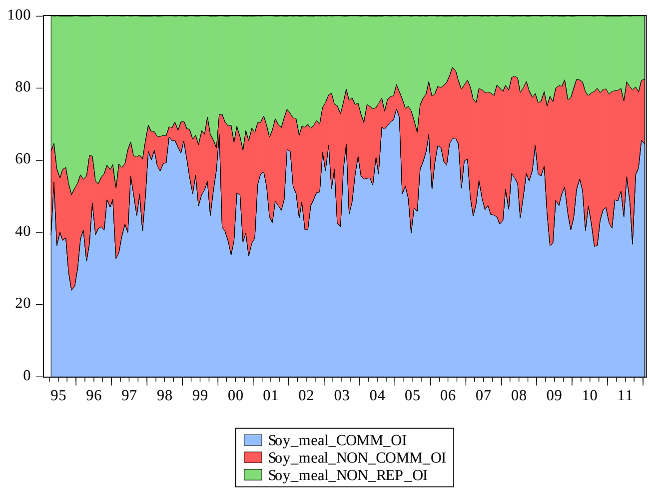
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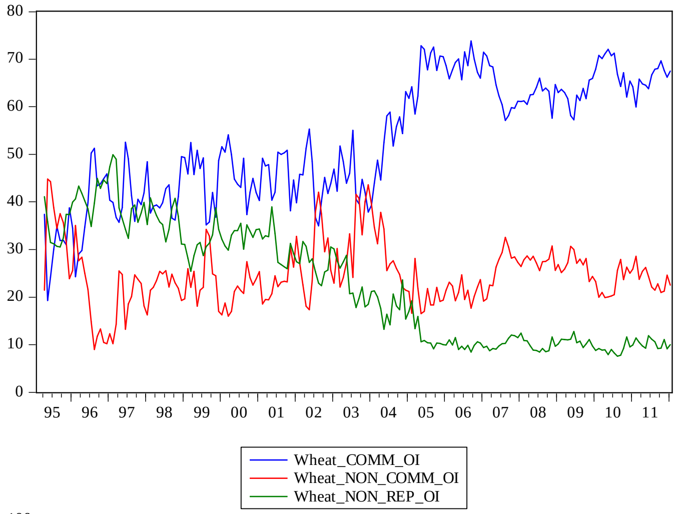
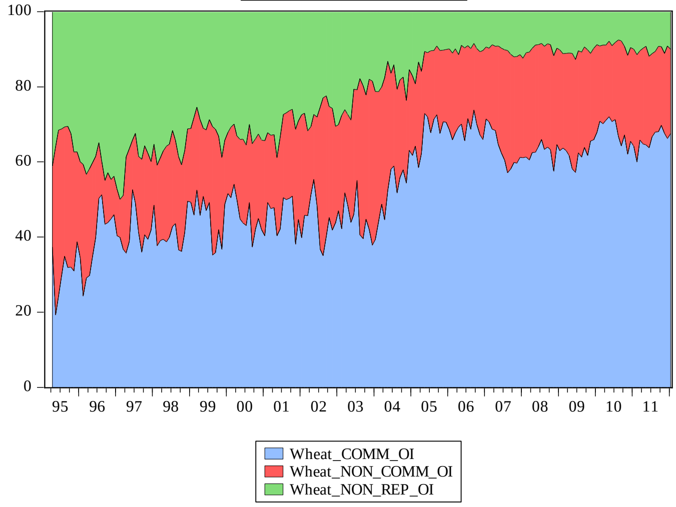
Soy_meal_NON_REP_OI





Source: Own elaborations on Datastream data.