The Impact of Trading Activity in Agricultural Futures Markets

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Summary

The paper examines a causal link between trading activity and market factors as returns and volatility as well. The ratio of volume to open interest in futures contracts performs better than other parameters extensively adopted in literature. The reason probably depends on the daily frequency of information which gives statistical evidence to phenomena which conclude their effect in weekly intervals. The estimations for the contemporaneous model give statistical evidence of a mutual relationship between trading activity and realized volatility. The behaviour of all the twelve futures markets examined is quite similar and uniform respect to the scale of the coefficients and their temporal profile.

Keywords: volatility, trading activity, commodity futures markets, agricultural commodities

JEL Classification codes: G13, Q11, Q13

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1. INTRODUCTION

In recent years the commodity markets, in particular agricultural markets, have experienced a high volatility with prices that boost in a very quick and strong way and drop with the same rapidity and intensity. 2006-2008 and 2010-2011 are the periods where agricultural commodity prices rise to levels worrying for food security mainly for populations who spend a large part of their income for food; these anomalous fluctuations in prices affect also the stability of farm income and the level of incertitude in farmer's production decision and along the food supply chain. Future possible scenarios of similar erratic price movements pushed policy makers to inquire into the determinants of the spikes for prevent them through appropriate regulations.

This market phenomenon that brought in 2008 the price of some important agricultural commodities, such as wheat and corn, to a level almost four times higher than one year before and to halves one year later has been investigated by researchers, market analysts and policy makers without reaching a common interpretation of such a dynamic and a unique explanation of the main determinant. Increase in world food demand induced by the strong economic development of China and India and by the increase of world population are two main reasons sustained by many authors. On the supply side, one important motivation to the price volatility is the growing agricultural soil subtracted to agrifood purposes to produce biomass for the renewable energy sector (e.g. biofuel and biogas). The global fight to the climate change is the main reason for which the European Union (EU) developed a wide and long-run strategy for promoting the diffusion and the enhancement of renewable energy within the Member States introducing high economic incentives; at the same way, in the USA, the internal strategy for reducing the dependency from fossil fuels has given rise to a programme of subsidies for biofuels. According to FAO-OCDE (2008), the public policies on energy and environment in EU and USA represent the main cause of the price bursts in the agricultural commodity markets. Furthermore, some authors argue that price increase is determined also by a lower increase of land productivity than the increase of world population according to the Malthusian postulate of decreasing marginal productivity.

Despite the researches on demand and supply determinants of the spikes, other authors disputed the role of market speculation as the determinant of a market bubble. In particular, the analysis has been addressed to understand the relation between the price dynamics and the trend of a financial activity that much increases its participation in commodity future markets, the index funds. Briefly, a commodity index fund is a financial activity that invests on different commodity future or swap markets with the aim to replicate the return of an index of commodity prices or commodity future prices. In turn, an index fund is a fund whose aim is to track the performance of a commodity index. In 2008, according to the Commodity Future Trading Commission (CFTC), the incidence of the index funds on the commodity index investments was 24% (CFTC, 2008). The huge and quick increase in commodity index fund investments, which in during the period 2006-2007 increased from $90 billion to $210 billion, would seem correlated with the increase in commodity market prices. This assumed correlation brings the name of Masters' hypothesis from the hedge fund manager Michael W. Masters that declared before the US Congress and CFTC as the speculation activity on commodity indices have deeply influenced commodity future prices distancing them from the fundamental values. This observation, which in most cases is not statistically demonstrated but rather sustained by the market operators' sentiment, contributed to reinforce the belief that in the period of boom and bust commodity prices the passive speculators (index fund investors) determined a speculative bubble.

As remarked by Irwin et al. (2009), the Masters' hypothesis even though apparently convincing contains some conceptual flaws and it is inconsistent with the future market operational mechanisms. First, the investments of money in future markets cannot be viewed as a demand for physical quantity of commodities, i.e. the financial flow cannot affect the price of the commodities for which the futures are created. A large part of the future contracts are created at a certain and fixed level of price. Following this argument, the commodity prices can change only if the information on fundamentals perceived by the operators changes. The contemporaneous variation in commodity and future market prices can identify a correlation but it is much more difficult to assert that we are in presence of a causality (Irwin et al., 2009). The well-behaved trade on future markets can operate only if the market is highly transparent and the market participants full informed. The very transparent mechanisms that drive the index fund investments makes little convincing their influence on commodity price dynamics. Secondary, to affect the commodity price movements, index funds should manage the physical quantity of commodities, because the equilibrium price for the commodities is identified only within the cash markets, where the physical commodities are delivered. Only in that market position the demand and supply of physical quantities become relevant for the market price generation. Index funds invest in future markets by exchanging financial instruments and not physical commodities.

Although the previous remarks would seem to confute the bubble theory on commodity markets, some authors discovered a statistical evidence about the effect of the index funds on the commodity prices. Hamilton and Wu (2013) apply a related regression model for 12 agricultural commodities integrating the notion of risk premium. The results indicate the absence of significant influence of the index funds on commodity futures. Repeating the same model for the crude oil future market, the authors identify statistical evidence that the dynamics of index investing can predict crude oil future returns, but only for the period 2006-2009. A more net evidence about the role of index funds on the commodity market is provided by Tang and Xiong (2012) that apply a regression model for testing the hypothesis according which the non-energy commodities included in index funds are more correlated than the off-index commodities. The hypothesis is confirmed by the model outcomes finding that the level of correlation among non-energy commodities increases if they are indexed. This result would demonstrate how the commodity prices be not entirely driven by fundamental information, like physical quantity demand at global level, but also by a trading activity on index funds. Gutierrez (2013) adopts a nonparametric bootstrap methodology for investigating the existence of a price bubble for four agricultural commodities (wheat, corn, soya beans and rough rice) over the period 1985-2011. The outcomes suggest a clear presence of price exuberance for wheat, corn and price and a moderate price explosiveness for soya bean. Even though the lacking of a structural analysis does not allow to identify the main factors behind the market price shocking, according author's conclusion it is likely that trader expectations on price upward had contributed to the price spikes in 2007-2008.

Although a large part of the literature takes the side of the "non-bubble theory", the results of these authors cannot exclude completely the interaction of the index fund investors in determining the price boom and bust observed during the period 2006-2009.

The objective of this contribution is to test whether the investing activity in the future market of different traders categories can be identified as a source of the increasing agricultural commodity prices. The result should show how much the speculative activities, in particular, might have been influential. The causality modelling approach proposed by Irwin and Sanders (2010, 2011, 2013), with some modifications and extensions, will be implemented to test their achievements using an up-to-date time series dataset on the same commodity markets. Granger's causality is, hence, modelled market by market and simultaneously by adopting a Seemingly Unrelated Regression (SUR) model.

2. INVESTORS AND THE COMMODITY FUTURES MARKETS

Generally speaking speculation provides that an individual performs a transaction with the prospect of obtaining an uncertain income assuming the risk of a corresponding economic loss. Therefore financial speculation involves the buying, holding, selling and also the short selling of stocks, bonds, commodity futures contracts to profit from fluctuations in their prices.

The association between money inflows from index funds and commodity futures prices developed several results but in literature is still controversial. Many organizations, such as IFPRI (Robles et al., 2009) and OXFAM (Herman et al., 2011), strongly supported the "Masters Hypothesis" and some studies reported evidence of a relationship between CIT positions and returns (Gilbert, 2010). Some studies test for the

existence of price bubbles with mixed results (Gutierrez, 2012). Several other studies does not find evidence of a significant causal link between speculative activity and changes in agricultural futures price movements (Irwin e Sanders, 2010; Irwin, 2013).
It's a fact that during the last decade there has been an increase in commodity prices and in their volatility and at the same time there has been a great flow of liquidity that financial investors have allocated to the agricultural commodity futures markets. Investors have begun to consider the derivatives on agricultural commodities as an asset class to their portfolios. This change in their negotiations and in their choice of investments is, however, a direct consequence of the search for greater profitability in a period characterized by low levels of interest rates. Operators have moved away from equity and bond markets toward other assets such as real estate and commodities.
The commodity derivatives include futures and options traded on regulated markets as well as forwards and options traded over-the-counter. Regulated markets (Futures Exchanges proper) monitor the contract negotiations and require margin and guarantee deposits which compel investors to protect themselves against counterparty risk (protecting, in this way, the integrity of the regulated market).
Over-the-counter (OTC) derivatives contracts are bilateral exchanges, exclusive and customized by the parties according to their needs. In these cases margins are not required and there is no monitoring of trade. While the futures markets, being regulated, provide a pre- and post-trade transparency, OTC negotiations are completely opaque and allow the big players to assume very high levels of risk through financial instruments, far more complicated than traditional futures and options usually traded in the Futures Exchanges.
Investors, as mentioned, when consider commodity futures a useful component to diversify their portfolios, can trade directly on the Futures Exchange by purchasing futures contracts. Normally, the investors prefer, rather than a specific commodity, the purchase of a package (i.e. Commodity Pool) offered and managed by a Commodity Pool Operator (CPO). Sometimes the investor does not buy directly into the Exchange, but turns to index providers or swap dealers. It is only banks or financial institutions that offer OTC index-based investments[1] that have the commodity as underlying and which provide returns linked to the performance of commodity's price. The swap dealers, after taking short positions against their clients who wanted to invest in commodity indices, can mitigate the risk exposure of their position in the index hedging all commodities (oil, wheat, copper, etc.) on the corresponding Futures Exchange.
The hedging transaction on regulated markets for the swap dealer is, obviously, discretionary and therefore can be carried out selectively, across the different commodities involved. It depends on the market perspectives and the vision that the swap dealer has for each commodity. Swap dealers actually are hedgers, but in a different way: they're not commercials, but financial intermediaries which implement an hedging strategy that is, as mentioned, not directed to the risk inherent in the spot price, but to a financial one.

3. AGRICULTURAL COMMODITY TRADE INFORMATION

After the investors choices and strategies have been clarified we can now devote to the topic under discussion. The verification of a causal link between the behaviour of speculators and price trends requires an appropriate approach and also the availability of specific statistics.
The data needed entail indicators about trading activities and on the behaviour of prices: this information allow for the selection of a wide number of proxies. The set of variables chosen agrees substantially with that adopted by many recent contributions (Irwin and Sanders, 2010; Gilbert, 2010).
The price behaviour is described with three major indicators (called market factors): (1) returns of nearby futures prices, (2) realized volatility and (3) implied volatility.
The returns (R) are calculated on the series of the nearby futures prices as the weekly average of the five daily returns, transformed with natural logarithms, which were recorded in the trading days ranging from Wednesday to the Tuesday of the following week.
The realized volatility (RV) is computed as the standard deviation of the last 20 first differences of natural logarithm on the nearby time series: the resulting volatility is expressed as an annualized percent using the correction factor $\sqrt{240}$. Instead the implied volatility (IV) is provided by Thompson-Reuters online service

[1] Commodity indices follow the broad movement of commodity prices: S&P-GSCI and DJ-UBS are the most widely tracked. While every index is diversified in terms of sectors and markets, oil represents about 40 percent of the entire commodity indices composition since constitutes the largest share of total commodity production. Traditional livestock and agricultural markets play a much smaller weight.

which calculates the "Implied Volatility 'At the Money' Interpolated[2]" distinguishing the value for the call option from the one for the put. The weekly value for IV is the average of five pairs of daily data; the resulting forward looking volatility measure is converted in annual terms.

On the other side, to capture the size and the changes in trading activity we analyse (1) net long positions, (2) percent of long positions held by trading categories, (3) Working's Index, and (4) the ratio of volume to open interest in futures contracts.

The main sources of data on traders positions are two reports released weekly by the U.S. Commodity Futures Trading Commission (CFTC): the Supplemental Commitment of Traders Report (SCOT) and the Disaggregated Commitments of Traders Report (DCOT)[3]. Both reflect combined futures and options positions and provide a breakdown of each Tuesday's open interest (OI) according to different categories of traders. OI is an indicator that measures the total number of contracts to buy (long) and sell (short) that are outstanding at the end of the daily trading session.

The first disaggregation proposed by the two reports is between the reportable and the non-reportable positions. In essence there is a threshold for the size of the open position of any trader; if the trader exceeds the threshold then falls under the category reportable and is required to submit additional documentation on its business.

Then SCOT and DCOT differs in the way the reportable positions are split. The distinctive trait of SCOT is to break down the open interest of Commodity Index Traders (CIT), which is a category that includes all individuals who prefer the investment in commodity indices, regardless of their institutional nature. The OI held by reportable positions different from the CIT is divided between commercials and non-commercials (see Table 1).

A trader is classified as commercial if he (or her) is engaged in business activities hedged by the use of the derivatives traded in the Exchange; otherwise gets classified as a "non-commercial" entity. The CIT category includes operators who are generally replicating a commodity index by establishing long positions in futures and rolling them forward using a fixed methodology. All of these traders come from the non-commercial or commercial categories, but they are put together because index trading represent a substantial part of their overall trading activity.

Table 1

The following relation (adapted from Sanders et al., 2008) explains how the market's total open interest for the futures contracts traded is disaggregated by the SCOT:

$$\begin{aligned}&\left[SPE2LG + SPE2SH + 2\,SPESP\right] + \left[COM2LG + COM2SH\right]\\&\left[CITLG + CITSH\right] + \left[NRPLG + NRPSH\right] = 2\,COI\end{aligned} \qquad (1)$$

The characteristics of the SCOT dataset limit the length of the period and the frequency of information considered: data are weekly and are available only since June 2006. The markets for which the SCOT data are broken down are only twelve (see Table 3).

In September 2009 the CFTC began publishing the Disaggregated Commitments of Traders Report (DCOT)[4] in which the reportable and non-reportable positions are separated into categories of traders as set forth in Table 2. The taxonomy of traders adopted by the DCOT is based on the economic rationale that guides them in transactions on Futures Exchanges. Entities intending to reduce exposure to price risk are classified as hedgers and, therefore, they transfer the risk to speculators who, instead, accept it.

Table 2

[2] The Implied Volatility 'At the Money' Interpolated is calculated using the nearest two options series at-the-money, one above and one below the underlying price (Datastream, 2008).

[3] The CFTC is the U.S. agency committed to the supervision of futures and options markets. This organization has, among others, the task of producing weekly reports on the size of trader positions in the regulated markets of the U.S.. These reports, unfortunately, do not have a match in Europe with regard to the active futures markets in the EU.

[4] During year 2010 the CFTC published the historical DCOT data back to June 2006.

The equation (2) draws the traders codes listed in Table 2 and summarizes how the total open interest of the market (OI) is broken down by DCOT categories:

$$\begin{aligned} &\left[PMPULG + PMPUSH\right] + \left[SWAPLG + SWAPSH + 2\left(SWAPSP\right)\right] \\ &+ \left[MONLG + MONSH + 2\left(MONSP\right)\right] + \left[OTHLG + OTHSH + 2\left(OTHSP\right)\right] \\ &+ \left[NRPLG + NRPSH\right] = 2\left(OI\right) \end{aligned} \tag{2}$$

in which the total of long positions is equal, of course, to the open interest of all the short positions.
In the DCOT report the reportable positions are separated into two main categories: hedgers and speculators. Speculators have distinguished between Managed money and Other reportables, the Swap Dealers and Producer / Merchant / Processor / User, on the other side, perfectly decompose the category of hedgers. While the breakdown of speculators distinguishes individuals who are the same in the strategy, but essentially differing only in the dimensional scale, the separation made for hedgers highlights two types of operators with strategies and different business. The Producer / Merchant / Processor / User are commercial hedgers, entities mainly involved in transactions in the physical commodity market because they produce it or transform it or move it in time and space. The Swap Dealer, on the other hand, turns to futures market to manage or hedge the risk associated with swap transactions.
The CIT positions monitored by the SCOT have a certain relationship with the Swap Dealer's category reported by DCOT although the correspondence, however, is not and could not be filled. In fact, in order to classify in the CIT category, are not taken into account the motives of the trader, but only the instruments he (or she) trades. In most cases, the CIT are banks that negotiate swaps, but it is also a matter of pension funds or hedge funds that DCOT ranks, as appropriate, such as Managed money or as Other reportables.
The recent sharp increase of their positions suggests that the evolution of open interest held by the Swap Dealer category (or, alternatively, by CIT) is best able to represent the behaviour of the speculation on the commodity markets. Nevertheless we will evaluate the dynamics of the other categories of trader such as Managed money and commercial hedgers.
The changes in traders positions are described with four indicators (causal variables): the net long positions, the percent of long positions, the ratio of volume to open interest and, endly, the Working Index .
The first indicator is the net long position by category (NL) and corresponds to the difference between the number of long positions and the short one. When the difference is positive we have a net long position while a negative number is a net short position. The net position should capture the size of the negotiations and the direction they will influence the prices: upward if the net long positions increase, downward if they decrease (or become net short).
The percent of long positions (PL) shows the portion of the total long positions held by each trader category. It is not surprising that CIT and swap dealers represent as much as 40% of the long positions within some markets.
The daily ratio of volume to open interest (VOIR) in futures contracts should describe the changes in the trading activity under the assumption that the majority of speculators trades begin and are completed, i.e. taking opposite positions, intraday. Buying and selling contracts within the day increases the daily trading volume, but does not affect the open interest at the end of the day. Hence the changes in the ratio would potentially capture the short-term component of the speculative activity.
Finally the Working's speculative index (TW) is calculated for each commodity market using the SCOT trader categories:

$$TW = 1 + \frac{SS}{HL + HS} \quad if \ \left(HS \geq HL\right) \tag{3}$$

or

$$TW = 1 + \frac{SS}{HL + HS} \quad if \ \left(HS < HL\right) \tag{4}$$

where SS, SL, HS and HL denote OI held by speculators short, speculators long, hedgers short and hedgers long respectively[5]. The TW has been introduced (Working, 1960) and used to evaluate the adequacy of speculative activity relative to the demand for hedging in the market place. The TW index varies only when speculators trade with other speculators, not when they are the counterpart in hedging strategies.

Table 3 shows the complete list of ag-commodities covered by the SCOT and the DCOT reports; the analysis of the role of financial speculation has been restricted to a subset of eleven of them which are negotiated on three futures markets (CME-CBOT, CME and ICUS-NYBT). The eleven agricultural (or soft) commodities under analysis are highlighted in bold.

Table 3

4. THE APPROACH TO THE CAUSAL RELATIONSHIP

According to the Irwin and Sanders' approach, we evaluated the causal relationship between market factor and causal variables, using the Granger causality test for the same markets considered by the two Authors (Irwin and Sanders, 2010). Only the implied volatility of the HRW in KCBT has been excluded from the analysis because the information was not available. The series, at least for the first elaborations described, are used on a weekly basis.However, when available,he information were collected at their original frequency, usually daily, which will prove useful for a second group of elaborations.
More specifically, the model adopted in the study can be analytically described as follow:

$$y_{t,k} = \alpha_k + \sum_{i=1}^{4} \gamma_{i,k} y_{t-i,k} + \sum_{i=1}^{4} \beta_{i,k} x_{t-i,k} + \varepsilon_{t,k} \tag{5}$$

Where the market factors $y_{t,k}$ for each market k in each year t is explained by an intercept α_k, an autoregressive component $\sum_{i=1}^{4} \gamma_{i,k} y_{t-i,k}$, a causal component $\sum_{i=1}^{4} \beta_{i,k} x_{t-i,k}$ and a residual term $\varepsilon_{t,k}$. The autoregressive component is composed by a market factor coefficient $\gamma_{i,k}$, where i identifies the lag, and the lagged market factor $y_{t-i,k}$; the causal variable is formed by a causal coefficient $\beta_{i,k}$ and the causal variable $x_{t-i,k}$. According to the Irwin and Sanders' contribution, the number of lags was limited to four. The estimation problem was solved using an OLS approach minimizing the residual terms $\varepsilon_{i,k}$ for identifying the level of $\alpha_{i,k}$, $\gamma_{i,k}$ and $\beta_{i,k}$. This latter can provide the causality relationship between market factors and trading activity (as causal variables). The hypothesis test can clarify the strength of this relation.
To increase the power of the estimation process and to investigate the role of causality variables to determine the evolution of all the market factors, we tested the estimates obtained by seemingly unrelated regression (SUR), where all the markets were modelled as unique system of equations. As the SUR approach suggests, the common component for each market is the residual term. In other words, following the idea of Irwin and Sanders, we want to assess the total effect of the speculator behaviour on the market dynamics. For the 12 markets considered, the associated SUR system is:

[5] Referring to symbols and categories listed in Table 1 the parameters for the Working index are calculated as follows:

$$SS = SPE2SH + CITSH + \left[NRPSH \cdot (SPE2SH + CITSH) / (SPE2SH + CITSH + COM2SH) \right]$$

$$SL = SPE2LG + CITLG + \left[NRPLG \cdot (SPE2LG + CITLG) / (SPE2LG + CITLG + COM2LG) \right]$$

$$HS = COM2SH + \left[NRPSH \cdot COM2SH / (SPE2SH + CITSH + COM2SH) \right]$$

$$HL = COM2LG + \left[NRPLG \cdot COM2LG / (SPE2LG + CITLG + COM2LG) \right]$$

$$
\begin{array}{lllllllll}
y_{t,1} & = & \alpha_1 & + & \sum_{i=1}^{4}\gamma_{i,1}y_{t-i,1} & + & \sum_{i=1}^{4}\beta_{i,1}x_{t-i,1} & + & \varepsilon_t \\
y_{t,2} & = & \alpha_2 & + & \sum_{i=1}^{4}\gamma_{i,2}y_{t-i,2} & + & \sum_{i=1}^{4}\beta_{i,2}x_{t-i,2} & + & \varepsilon_t \\
y_{t,3} & = & \alpha_3 & + & \sum_{i=1}^{4}\gamma_{i,3}y_{t-i,3} & + & \sum_{i=1}^{4}\beta_{i,3}x_{t-i,3} & + & \varepsilon_t \\
\vdots & & & & \vdots & & \vdots & & \vdots \\
y_{t,12} & = & \alpha_{12} & + & \sum_{i=1}^{4}\gamma_{i,12}y_{t-i,12} & + & \sum_{i=1}^{4}\beta_{i,12}x_{t-i,12} & + & \varepsilon_t
\end{array}
\qquad (6)
$$

where the residual term is the same for every equation.

Some relevant innovations was introduced in the model such as the obvious extension of the time series from January 2006 to February 2014 that allows doubling the number of observations in respect to the Irwin and Sanders' work. Nevertheless the extension of the period observed did not affect the results already illustrated by Irwin and Sanders and, indeed, would not even confirm the existence of a contribution, by the trading activity, to the reduction of market volatility that these Authors had detected.

It is now widely recognized that the presence of outliers can affect the results of any statistical analysis. The second innovation of this paper consists in the outlier check in data series for excluding the effect of anomalous observation on the causality relationship of the SUR system in (6). Each time series has been preliminarily analysed using the forward search (FS) approach (Atkinson and Riani, 2000; Atkinson Riani and Cerioli, 2004). The FS is a powerful general method for detecting anomalies in structured data, whose diagnostic power has been shown in many statistical contexts. A recent general review of forward search methods is Atkinson et al. (2010). A comparison with other robust estimators can be found in Riani *et al.* (2014), while for the theoretical properties of this approach we refer to Cerioli *et al.* (2014). The idea behind the FS is simple and attractive. Given a sample of n observations and a generating model for them, the method starts from a subset of cardinality $m \ll n$, which is robustly chosen to contain observations coming from the postulated model. This subset is used for fitting the model and the residuals, or other deviance measures, are computed. The subsequent fitting subset is then obtained by taking the m+1 observations with the smallest deviance measures. A major advantage of the FS is that it provides clear evidence of the impact that each unit, or block of units, exerts on the fitting process, with outliers and other peculiar observations entering in the last steps of the search. More in detail, in our context, the robust initial subset of size m=p=9 in each of the 12 regression equations in (6) has been found using Least trimmed squares or Least median of squares (Rousseeuw, 1984). This subset has been updated ordering at each step the n squared residuals using an estimate of the regression coefficients based on a subset of size m.

The automatic algorithm for outlier detection, as the subset increases is based on that of Riani, Atkinson and Cerioli (2009) who used scaled Mahalanobis distances to detect outliers in multivariate normal data. For regression, we replace these distances by deletion residuals. In order to test the stability of the results, in what follows, the findings of the Granger causality tests have been examined including or excluding the observations detected as outliers.

The third innovation is represented by the evaluation of the inverse relationships between market factors and causal variables. The market factors have been tested also as causal variables, avoiding giving priority to only one sense of the relationship according to the Granger's causality. This extension, however, has not led to detect the existence of any Granger-causality relationship.

Furthermore, in our study we do not limit the analysis to the Commodity Index Traders (CIT), the typology usually investigated, but we include all the other market actors, as indicated by Table 2. Unfortunately, even the widening of the spectrum of the categories of operators considered does not reveal statistically significant relationships and seems to justify the lack of attention that the literature has so far devoted to these cases.

The fifth innovation concerns the estimation of the equation parameters by implementing the SUR system approach in two versions. The first one is the standard approach, where the independent variable is estimated only in relation to its lags, as the Granger's causality approach foresees; while, the second version considers the current value for the causal variable. We call the first version the "not-contemporaneous" model and the second the "contemporaneous" model.

Even though it is difficult to find a Granger's causality relationship inside the models, it is important to remark that the benefit of a SUR model is always verified: the agricultural commodity markets shows a high residual correlation significance and therefore they are adapt to be constrained in a unique equation system. The high residual correlation demonstrates that all the markets keep the same behaviour reacting to the same exogenous changes with clear homogeneity. The level of fitness of the SUR system for the agricultural market was investigated by adopting the Lagrange multiplier statistic developed by Breusch and Pagan (1980).
The poor evidence of significance in Granger's causality relationships might rely on the inappropriateness of the information in terms of time frequency. As we previously highlighted, the available information are published each Friday and are referred to the Tuesday of the previous week. Even though the trading activity has a daily dynamic, it is recorded with a weekly frequency. Therefore, the information might neglect some important phenomena that exhaust their effect in a range of few observations (days).
Finally, concluding the attempts described above, we tried to test if the weekly frequency of the most part of the information is the reason of the low or null level of causality. For this purpose, we applied the above methodology to daily data starting since January 3, 1995.
Among the market factors the returns and the realized daily volatility (RV) are available at a daily frequency. RV has been calculated as the absolute value of the daily returns. Instead the unique indicator of the trading activity at daily level is the VOIR. This option impedes to distinguish the behaviour of the different market operators, but guarantees a daily information detail.

5. Granger-causality approach (the Not-Contemporaneous Model)

For the variables I(0) (our case), the causality model corresponds to the following systems of equations:

$$y_{t,k} = \alpha_k + \sum_{i=1}^{4} \gamma_{i,k} y_{t-i,k} + \sum_{i=1}^{4} \beta_{i,k} x_{t-i,k} + \varepsilon_t \quad \forall t,k \tag{7}$$

$$x_{t,k} = \alpha_k + \sum_{i=1}^{4} \gamma_{i,k} x_{t-i,k} + \sum_{i=1}^{4} \beta_{i,k} y_{t-i,k} + \varepsilon_t \quad \forall t,k \tag{8}$$

Where the model (7) identifies the system of equations for the not-contemporaneous model where for each market $y_t = f(\gamma_1 y_{t-1},...,\gamma_4 y_{t-4}, \beta_1 x_{t-1},...,\beta_4 x_{t-4}) + \varepsilon_t$, and an inverse model version (8), where the market factors become causal variables, i.e. $x_t = f(\gamma_1 x_{t-1},...,\gamma_4 x_{t-4}, \beta_1 y_{t-1},...,\beta_4 y_{t-4}) + \varepsilon_t$.
Before implementing the Granger's causality approach, the FS algorithm was applied to the original time series to detect the outliers with respect to the relationship between the volatility and the trading activity and the inverse one. The outlier detection routine was applied for each market operating a horizontal cut interesting all the markets in correspondence to the date of the outlier and its previous four lags.
Both the basic and inverse relationships show the same outliers for non-contemporaneous and contemporaneous model. For the basic relationships, the FS algorithm detected 1.270 outliers corresponding to about 26% of the total observations, while the inverse model identified 550 outliers, i.e. 11% of the total observations.
The results of these models can be read in a predicting view, because they are estimated using information expressed in its lags and available at the time *t-1*.
As trading activity indicator (TA) we have adopted the VOIR as predictor of the market factors. The unique significant causal effect has been identified in respect to RV. Tables 4 and 5 provide the estimation results for the unique significant relationship between VOIR and volatility. All the variables adopted in the model have been standardized to make comparable the estimates for the different markets.
In the equation *RV= fa(TA)*, described by the Table 4 and Figure 1, the autoregressive coefficients are very significant for all the markets, while the causal coefficients are significant just for few occurrences.
The inverse equation *TA= fb(RV)* presents more satisfying results in terms of estimates significance. Table 5 and Figure 2 show a very high significance in the autoregressive coefficients and also for the causal coefficients. This means that the prior volatility affects negatively (inversely) the current level of trading activity. Already the significance of individual coefficients makes sense that the Wald test applied to $\sum \beta$ is highly significant.

An important remark is related to the degree of homogeneity of the estimates related to different commodity: all the coefficients values are very close and the proportions between *β* and *γ* is kept for each market.

Table 4

Table 5

Figure 1

Figure 2

6. THE IMPACT OF CURRENT VARIABLES (THE CONTEMPORANEOUS MODEL)

The contemporaneous model has the objective to clarify the ex-post incidence of the independent variable. To achieve this purpose, the equations (7) and (8) have been integrated by contemporaneous series of data estimating the following models:

$$y_{t,k} = \alpha_k + \sum_{i=1}^{4} \gamma_{i,k} y_{t-i,k} + \sum_{i=0}^{4} \beta_{i,k} x_{t-i,k} + \varepsilon_t \;\; \forall t,k \tag{9}$$

$$x_{t,k} = \alpha_k + \sum_{i=1}^{4} \gamma_{i,k} x_{t-i,k} + \sum_{i=0}^{4} \beta_{i,k} y_{t-i,k} + \varepsilon_t \;\; \forall t,k \tag{10}$$

The coefficients $\beta_{i,k}$ related to the lags have been estimated considering the influence of the independent series at the time *t* and are thus purified from their influence.

The equations (9) and (10) do not correspond to a Granger's causal relation and, thus, it is not possible to use the results for predictive purposes. Furthermore, it is not possible to state if the contemporaneous causality is from *x* to *y* or from *y* to *x*. However the inclusion of such a variable contributes to improve the significance and to better interpret the dynamics and the impact of lagged variables.

Also for these models all the variables have been standardized for allowing the comparison among markets.

Table 6

Table 7

From the Tables 6 and 7, emerges the positive contribution of the current variables to the estimation significance. The role of the autoregressive coefficients is confirmed. The contemporaneous independent variable is highly significant and contribute to improve the statistical significance of its lags too. The impact of lagged variables in *RV= ga(TA)* is different from the case *TA= gb (RV)*: the lags *t-1* and *t-2* of the trading activity are more significant, while for the realized volatility the most significant lags are *t-2*, *t-3* and *t-4*.

Figure 3

Figure 4

The degree of homogeneity in the results for the different markets is evident both in the level and in the sign of the corresponding coefficients.

The main positive effect is provided by the contemporaneous variables for both the equations (9) and (10). Specifically, the linkage between the realized volatility and the trading activity is positive (Figure 3): if the trading activity observed in the past was high, then it is likely that the current realized volatility is lower. In the inverse relation (10), the past dynamic for the trading activity has a strong effect on the current trading activity level, but this effect tend to disappear within few days (one or two).

The explanation of the role of the contemporaneous variables is more articulated. First of all, it is difficult to establish if a causal relationship between the two variables exists or, on the contrary, if they are both affected by a third unobservable variable.
An attempt to isolate the effect of a variable at time t with respect to the other has been done through the use of methods based on instrumental variables, where the instruments are vectors of lagged, or contemporaneous - but exogenous - series (*z*) pinched from the entire information set available at time *t*. The equations (9) and (10) are ri-estimated by GMM as well LIML.

Table 8

Table 9

The theory entails that price of financial activities reflects the whole information available when trade is made: according to that the set of instruments included a group of variables common to both functions – (9) and (10) – and also some instruments specific for one or for the other relationship. The common group presents realized volatilities and VOIRs for all the markets at time *t-1*, absolute changes in the log GSCI and DJ-UBS price index[6], the difference (in absolute value) between traded volumes at time *t-1* and *t-2* for market *k* and, finally, still for the market *k*, the open interest at time *t-1* and the complete set of lagged realized volatilities and VOIRs (time *t-2*, *t-3* and *t-4*).
The set of instruments specific for estimation of equation (9) - RV= ga(TA) – included the difference (always in absolute value) between open interests at time *t-1* and *t-2* for market *k*, the traded volume at time *t-1* for market *k* , the turnover change, in absolute value of shares, of the Dow Jones Industrial Average and the index CVEQ[7] at time *t*. On the other side, the set of instruments specific for estimation of equation (10) - TA= gb(RV) – included the absolute value of change, for market *k* , between the opening price at time *t* and the settlement price at time *t-1* (called NIGHT) and the VIX[8] at time *t* . The utility of the instrument set depends on there being no relation with the residuals of each equation. The assumption has been checked for the variable NIGHT, the only one not clearly exogenous and contemporaneous, at least partially; NIGHT was found to be orthogonal in 6 cases over 12.
Tables 8 and 9 show the result of the contemporaneous test: the relation that emerges confirms the qualitative indications already reached with the Granger-causality approach and adds information on the existence and on the sign of the relationships linking trading activity and volatility at time t. The relation that is more definite is the one that considers the influence of the volatility on the trading activity (Table 9), nevertheless it is significant, from a statistical point of view, also the opposite relationship.
At time t each variation, which is an increase or a decrease in volatility, generates a corresponding increase or decrease of trading activity. Greater volatility foreshadows profit opportunities and calls for a higher number of transactions.
As the Table 8 shows, a structural causality occurs in the opposite direction too. From increasing transactions at time *t* flow even greater price volatilities. Investors, at time t, in contemporary time, have not yet developed a shared vision about the future price dynamics and, therefore, they individually take different (opposite) positions. This initial uncertainty is resolved quickly during the very next days as evidenced by the sign of the coefficients referred to lagged variable.
It can be assumed that the origin of the changes in trading activity and volatility is the arrival of news regarding exogenous macroeconomic developments and key market developments for individual

[6] The index adopted as instruments correspond widely to the ones used by Gilbert and Pfuderer (2014). The Dow Jones-UBS commodity price index (DJ-UBS) and the S&P Goldman Sachs Commodity Index (=GSCI) are the two index more relevant to investors in agricultural futures.
[7] The CVEQ index is quite similar to the one introduced by Gilbert and Pfuderer (2014, p.316): it is formed as the daily weighted sum of traded volumes (and not of the reported positions) for the 12 contracts. The sum is converted in a number of equivalent wheat SRW contracts using as denominator the average value of one wheat SRW contract during year 2013.
[8] VIX is the volatility index regarded as a measure of perceived riskiness of the entire range of financial markets, calculated with the implied volatility of the Standard &Poor 500 index of US equities prices (Gilbert and Pfuderer, 2014).

commodities. Volatility and trading activity react to news individually and, subsequently, influence one another, even at time t, according to the mechanism described above. In the following days the initial stress is absorbed rapidly running out. In fact, the signs of the coefficients for the four delays considered are negative and their sum cancels (from an algebraic point of view) the positive coefficient that the independent variable shows in contemporary.
The variables used as instruments have proved effective, and this conclusion is documented by Tables 8 and 9. The Weak Instrument Diagnostics provides information on the instruments used during estimation. This information includes the Cragg-Donald statistic and the associated Stock and Yugo critical values. The Cragg-Donald statistic has been proposed by Stock and Yugo as a measure of the validity of the instruments in a regression. Instruments that are only marginally valid, known as weak instruments, can lead to biased inferences; thus testing for the presence of weak instruments is important.
Figure 5 shows the complete set of relationships found between trading activity and volatility. The transactions, at time t, are likely to be influenced by news that cause a reaction in the market. As it happens in the stock markets, there could be an upstream cause for both the variables associated to the unexpected information arising from the market at the time *t*.

Figure 5

If in period *t* a lot of unexpected information arrives to the market, the effect is to produce either a change of expectations, which leads to adjustment of equilibrium prices and in the number of transactions (trading activity), and greater heterogeneity of views and feelings among the traders, which leads to greater volatility. At time *t*, between trading activity and volatility there is a causal relationship and their relationship is added to that which already binds them depending on the cause they have in common, based on the information that has been spread onto the market.
The Figure shows that past values of volatility contribute to increase it: the coefficients are low but significant, uniform among the markets and almost the same for all the lags considered. The past values of the trading activity also exert a positive influence on the level of this parameter at time *t*. The value of the coefficient at time *t-1* is, in this case, much more important than those of the previous periods. In general, the past values of the trading activity weigh a little more than their corresponding series do in the volatility case. Above all the contour of lagged variables coefficients is quite different in the two cases.
Cross effects between lagged *RV* and *TA* are present and are statistically significant (as shown by the Wald tests). The sign of the relationship is negative in both cases and shows, first, that an earlier increase in trading activity helps to reduce the volatility of the market and, secondly, that an increase of past volatility cools investors activity reducing market transactions and exchanges. The previous volatility affects the trading activity of the time t with coefficients uniform and persistent, but low; the impact of trading activity on the volatility is much more relevant and focused and, in fact, runs out in two consecutive trading days.
The direct effect exerted by a change in trading activity (volatility) on the volatility (trading activity) runs out on day t since, during the very next days, the negative sign of the coefficients compensates and cancels the (positive) effect early registered.

7. CONCLUDING REMARKS

The paper examines the causal link between trading activity and market factors (returns and volatility). In spite of the extension of the period observed, when we used weekly data, the results endorse those already illustrated by IRWIN and SANDERS (2010) and, indeed, would not even confirm the existence of a contribution, by the trading activity, to the reduction of market volatility that the two Authors had detected.
The market factors have been tested also as causal variables, avoiding giving priority to only one sense of the relationship according to the Granger's causality. This extension, however, has not led to detect the existence of any Granger-causality relationship. Furthermore, in our study we do not limit the analysis to the Commodity Index Traders (CIT), the typology usually investigated, but we include all the other market actors. Unfortunately, even the widening of the spectrum of the categories of operators considered does not reveal statistically significant relationships and seems to justify the lack of attention that the literature has so far devoted to these cases.
The null significance in Granger's causality relationships might rely on the inappropriateness of the information in terms of time frequency. Even though the trading activity has a daily dynamic, it is recorded

with a weekly frequency. Therefore, the information might neglect some important phenomena that exhaust their effect in a range of few observations (days).

For this reason we applied the Granger's causality approach to daily data adopting the VOIR as unique indicator of the trading activity at daily level. The models tested were two. The first one ("not-contemporaneous" model) is the standard approach, where the independent variable is estimated only in relation to its lags, as the Granger's causality approach foresees. Conversely the second model considers also the current value for the causal variable ("contemporaneous" model).

The ratio of volume to open interest in futures contracts performs better than other parameters extensively adopted in literature.

The characteristic of the estimates obtained using the contemporaneous model is that all the coefficients, included the coefficient referred to the independent variable at time t, are very significant. When the equations are estimated according to the conventional model the factors identified, while similar, do not show, almost never, the adequate statistical significance showed by the contemporaneous model.

Even when it is impossible to find a Granger's causality relationship inside the models, it is important to remark that the benefit of a SUR model is always verified: the agricultural commodity markets shows a high residual correlation significance and therefore they are adapt to be constrained in a unique equation system. The high residual correlation demonstrates that all the markets keep the same behaviour reacting to the same exogenous changes with clear homogeneity.

The contemporaneous model do not correspond to the Granger's causal relation and, thus, it is not possible to use the results for predictive purposes. However the inclusion of the independent series at the time *t* contributes to improve the significance and to better interpret the dynamics and the impact of lagged variables. In order to better evaluate the relationship between trading activity and volatility at time *t*, a set of instruments has been introduced to ri-estimate the equations by GMM and LIML.

From these contemporaneous tests we conclude that there is strong evidence of a causal relationship between the two variables in both directions. The direct effect exerted by a change in trading activity (volatility) on the volatility (trading activity) runs out on day t since, during the very next days, the negative sign of the coefficients compensates and cancels the (positive) effect early registered.

Only drawing upon higher frequency data (e.g. daily) has made it possible to reveal dynamics and relationships between variables that you might have not identified if lower frequency data (e.g. monthly or weekly) were used.

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Table 1: Traders categories provided by the Supplemental Commitments of Traders Report and corresponding codes

		LONG	SHORT	SPREADING
Reportable Positions	Non-Commercial	SPE2LG	SPE2SH	SPESP
	Commercial	COM2LG	COM2SH	
	Index Traders	CITLG	CITSH	
Nonreportable Positions		NRPLG	NRPSH	

Table 2: Traders categories provided by the Disaggregated Commitments of Traders Report and corresponding codes

		LONG	SHORT	SPREADING
Reportable Positions	Commercial hedgers (*)	PMPULG	PMPUSH	
	Swap dealers	SWAPLG	SWAPSH	SWAPSP
	Managed money	MONLG	MONSH	MONSP
	Other reportables	OTHLG	OTHSH	OTHSP
Nonreportable Positions		NRPLG	NRPSH	

(*) The COT Reports indicate this traders category as Producer/Merchant/Processor/User.

Table 3: List of ag-commodities and markets covered by SCOT and DCOT reports

Symbol	Commodity	Market	Supplemental COT Report (since January 3, 2006)	Disaggregated COT Report (since June 13, 2006)
CC	**Corn**	CME-CBOT	Y	Y
WC	**Wheat SRW**	CME-CBOT	Y	Y
DK	Wheat HRW	CME-CBOT	Y	Y
DG	Wheat HRS	MGE		Y
SC	**Soybeans**	CME-CBOT	Y	Y
OC	**Soybean Oil**	CME-CBOT	Y	Y
FC	Soybean meal	CME-CBOT	Y (since April 5, 2013)	Y
RC	Rice	CME-CBOT		Y
IC	Oats	CME-CBOT		Y
DG	Wheat	MGE		Y
EC	**Feeder Cattle**	CME	Y	Y
GC	**Lean Hogs**	CME	Y	Y
LC	**Live Cattle**	CME	Y	Y
HN	**Coffee C**	ICUS (NYBOT)	Y	Y
JN	Juice	ICUS (NYBOT)		Y
NN	**Cotton**	ICUS (NYBOT)	Y	Y
AN	**Cocoa**	ICUS (NYBOT)	Y	Y (since April 28, 2010)
ZN	**Sugar N.11**	ICUS (NYBOT)	Y	Y

Notes: “Y” indicates the COT report publish information on the commodity.

Table 4: Coefficient estimates for the not-contemporaneous model – Granger-causality relationship between trading activity and realized volatility [*RV= fa (TA)*], January 3,1995 to February 27, 2014

Market	**Autoregressive variables**				**Independent variables: Trading activity**			
	γ_{a1}	γ_{a2}	γ_{a3}	γ_{a4}	β_{a1}	β_{a2}	β_{a3}	β_{a4}
COCOA	0.0615	0.0217***	0.0790*	0.0307**	-0.0524	0.0164	-0.0122	0.0172
CORN	0.0461***	0.0737***	0.0613***	0.0905	0.0200	-0.0154	0.0085	0.0131
WHEAT HRW	0.0541***	0.0672***	0.0511***	0.0800*	0.0262***	-0.0464**	0.0350	0.0132
FEEDER CATTLE	0.0058***	0.0595**	0.0389***	0.0642***	0.0526**	-0.0398	0.0220	0.0232**
LEAN HOGS	0.0517***	0.0760***	0.0585***	0.0692	0.0065	-0.0320	0.0280	0.0122
COFFEE	0.0450***	0.0508*	0.0305**	0.0427***	0.0662	-0.0295	0.0373	0.0398***
LIVE CATTLE	0.0139***	0.0598***	0.0619***	0.0481**	0.0390***	-0.0711	-0.0146***	0.0503
COTTON	0.1364***	0.0960***	0.0636***	0.1034	-0.0167	-0.0288	-0.0174**	0.0472
SOYBEAN OIL	0.0532***	0.0461***	0.0541***	0.0449	-0.0155	0.0219	-0.0252	-0.0021
SOYBEANS	0.0594***	0.0457**	0.0323***	0.0603	-0.0315*	0.0435	-0.0148	0.0089
WHEAT SRW	0.0406***	0.0512***	0.0538***	0.0782	-0.0047	-0.0220	-0.0074***	0.0400
SUGAR	0.0867***	0.0692***	0.0836***	0.0714	0.0161	-0.0160	-0.0332***	0.0670

*** Significance < 1%
** Significance < 5%
* Significance < 10%

Table 5: Coefficient estimates for the not-contemporaneous model – Granger-causality relationship between realized volatility and trading activity [*TA= fb (RV)*], January 3,1995 to February 27, 2014

Market	**Autoregressive variables**				**Independent variables: Realized volatility**			
	γ_{b1}	γ_{b2}	γ_{b3}	γ_{b4}	β_{b1}	β_{b2}	β_{b3}	β_{b4}
COCOA	0.4637***	0.1405***	0.0634	0.0246**	-0.0253***	-0.0860***	-0.0388*	-0.0237***
CORN	0.4591***	0.1513***	0.0988***	0.1215***	0.0313***	-0.0436***	-0.0289***	-0.0279***
WHEAT HRW	0.4496***	0.1436***	0.0725***	0.0933	0.0109***	-0.0591**	-0.0267***	-0.0272***
FEEDER CATTLE	0.4174***	0.1052***	0.0659***	0.0876***	0.0737***	-0.0435**	-0.0245	-0.0167
LEAN HOGS	0.4969***	0.1001***	0.0694***	0.0648	0.0086**	-0.0260**	-0.0279	-0.0035**
COFFEE	0.4900***	0.1292***	0.0750***	0.1316*	-0.0218***	-0.0635***	-0.0314**	-0.0252***
LIVE CATTLE	0.4560***	0.0898***	0.0568***	0.0746	0.0067***	-0.0325	-0.0032	-0.0064
COTTON	0.4624***	0.0707***	0.1131***	0.0648***	0.0350***	-0.0745***	-0.0620**	-0.0258***
SOYBEAN OIL	0.4618***	0.1691***	0.1150***	0.1090	0.0137***	-0.0479***	-0.0506***	-0.0345***
SOYBEANS	0.4390***	0.1983***	0.0842***	0.1124	0.0022***	-0.0453*	-0.0166***	-0.0352***
WHEAT SRW	0.4303***	0.1608***	0.1069***	0.1012	0.0139***	-0.0618***	-0.0370***	-0.0483***
SUGAR	0.4525***	0.0899***	0.0798***	0.0908	-0.0136***	-0.0763	-0.0106**	-0.0312***

*** Significance < 1%
** Significance < 5%
* Significance < 10%

Table 6: Coefficient estimates for the contemporaneous model – Relationship between trading activity and realized volatility [*RV= ga (TA)*], January 3,1995 to February 27, 2014

Market	**Autoregressive variables**				**Independent variables: Trading activity**				
	γ_{c1}	γ_{c2}	γ_{c3}	γ_{c4}	β_{c0}	β_{c1}	β_{c2}	β_{c3}	β_{c4}
COCOA	0.0801***	0.0572***	0.0955***	0.0468***	0.4835***	-0.2682***	-0.0539**	-0.0391*	-0.0013
CORN	0.0432***	0.0952***	0.0773***	0.1034***	0.5069***	-0.2071***	-0.0964***	-0.0482**	-0.0417**
WHEAT HRW	0.0434***	0.0779***	0.0570***	0.0904***	0.2662***	-0.0853***	-0.0808***	0.0079	-0.0142
FEEDER CATTLE	-0.0337**	0.0879***	0.065***	0.0760***	0.5019***	-0.1376***	-0.0957***	-0.0197	-0.0198
LEAN HOGS	0.0413***	0.0988***	0.088***	0.0720***	0.5099***	-0.2489***	-0.0857***	-0.0014	-0.0234
COFFEE	0.0744***	0.0953***	0.0600***	0.0531***	0.6605***	-0.2691***	-0.1044***	-0.0241	-0.0328
LIVE CATTLE	0.0184	0.0817***	0.0750***	0.0616***	0.4992***	-0.1928***	-0.1139***	-0.0482**	0.0092
COTTON	0.1151***	0.1331***	0.0907***	0.1131***	0.4790***	-0.2306***	-0.0778***	-0.0510**	0.0101
SOYBEAN OIL	0.0541***	0.0710***	0.0806***	0.0645***	0.4992***	-0.2343***	-0.0703***	-0.0935***	-0.0497**
SOYBEANS	0.0625***	0.0762***	0.0439***	0.0820***	0.5228***	-0.2598***	-0.0674***	-0.0515**	-0.0460**
WHEAT SRW	0.0345***	0.0691***	0.0661***	0.0973***	0.3180***	-0.1398***	-0.0648***	-0.0495***	0.0079
SUGAR	0.0829***	0.1209***	0.1000***	0.0944***	0.5879***	-0.2108***	-0.0923***	-0.0997***	0.0101

*** Significance < 1%
** Significance < 5%
* Significance < 10%

Table 7: Coefficient estimates for the contemporaneous model – Relationship between realized volatility and trading activity [*TA= gb (RV)*], January 3,1995 to February 27, 2014

Market	**Autoregressive variables**				**Independent variables: Realized volatility**				
	γ_{d1}	γ_{d2}	γ_{d3}	γ_{d4}	β_{d0}	β_{d1}	β_{d2}	β_{d3}	β_{d4}
COCOA	0.4655***	0.1372***	0.0629***	0.0268*	0.3254***	-0.0500***	-0.0984***	-0.0642***	-0.0383***
CORN	0.4543***	0.1461***	0.1002***	0.1195***	0.1981***	0.0161**	-0.0569***	-0.0390***	-0.0407***
WHEAT HRW	0.4449***	0.1477***	0.0736***	0.0895***	0.2126***	-0.0029	-0.0719***	-0.0410***	-0.0419***
FEEDER CATTLE	0.4042***	0.1077***	0.0640***	0.0746***	0.2952***	0.0659***	-0.0596***	-0.0370***	-0.0328***
LEAN HOGS	0.4906***	0.1031***	0.0674***	0.0635***	0.2094***	0.0074	-0.0332***	-0.0331***	-0.0107
COFFEE	0.4706***	0.1324***	0.0590***	0.1260***	0.3595***	-0.0524***	-0.0827***	-0.0457***	-0.0495***
LIVE CATTLE	0.4535***	0.0978***	0.0556***	0.0658***	0.2690***	0.0027	-0.0417***	-0.0151	-0.0173
COTTON	0.4604***	0.0752***	0.1183***	0.0514***	0.2479***	0.0128	-0.0912***	-0.0806***	-0.0457***
SOYBEAN OIL	0.4649***	0.1679***	0.1228***	0.1019***	0.1895***	0.0037	-0.0599***	-0.0636***	-0.0452***
SOYBEANS	0.4389***	0.1949***	0.0889***	0.1070***	0.2261***	-0.0088	-0.0604***	-0.0325***	-0.0494***
WHEAT SRW	0.4339***	0.1598***	0.1083***	0.0981***	0.2314***	-0.0001	-0.0792***	-0.0494***	-0.0637***
SUGAR	0.4410***	0.0795***	0.0908***	0.0700***	0.3252***	-0.0487***	-0.0863***	-0.0373***	-0.0548***

*** Significance < 1%
** Significance < 5%
* Significance < 10%

Table 8: Contemporaneous test results, January 3,1995 to February 27, 2014

Market	Trading activity at time t Coefficient		Weak Instrument Diagnostics		
	GMM	LIML	Test	GMM	LIML
COCOA	0.2080***	0.2366***	7.81	< 20%	< 5%
CORN	0.3110***	0.2904***	73.89	< 5%	< 5%
WHEAT HRW	0.3228***	0.5535***	16.19	< 10%	< 5%
FEEDER CATTLE	0.0138	0.0302*	7.80	< 20%	< 5%
LEAN HOGS	0.2172***	0.2503***	9.08	< 20%	< 5%
COFFEE	0.2533***	0.2120***	10.84	< 20%	< 5%
LIVE CATTLE	0.0139	0.0150	8.43	< 20%	< 5%
COTTON	0.2005***	0.0173	8.97	< 20%	< 5%
SOYBEAN OIL	0.3347***	0.3706***	47.14	< 5%	< 5%
SOYBEANS	0.0782***	0.0580***	79.44	< 5%	< 5%
WHEAT SRW	0.2664***	0.2930***	37.25	< 5%	< 5%
SUGAR	0.2667***	-0.0450	6.13	< 20%	< 5%

*** Significance < 1%
** Significance < 5%
* Significance < 10%

Table 9: Contemporaneous test results, January 3,1995 to February 27, 2014

Market	Realized volatility at time t Coefficient		Weak Instrument Diagnostics			Orthogonality test
	GMM	LIML	Test	GMM	LIML	p
COCOA	0.4177***	0.4129***	30.74	< 5%	< 5%	0.07
CORN	0.4187***	0.3507***	123.80	< 5%	< 5%	0.28
WHEAT HRW	0.2554***	0.1971***	54.77	< 5%	< 5%	0.71
FEEDER CATTLE	0.4650***	0.5012***	51.02	< 5%	< 5%	0.00
LEAN HOGS	0.1269***	0.1173***	299.96	< 5%	< 5%	0.00
COFFEE	0.4581***	0.4205***	29.85	< 5%	< 5%	0.00
LIVE CATTLE	0.2284***	0.2015***	111.55	< 5%	< 5%	0.00
COTTON	0.2459***	0.1616***	60.81	< 5%	< 5%	0.05
SOYBEAN OIL	0.4052***	0.3905***	56.07	< 5%	< 5%	0.25
SOYBEANS	0.5039***	0.4802***	91.90	< 5%	< 5%	0.00
WHEAT SRW	0.3463***	0.3884***	52.65	< 5%	< 5%	0.08
SUGAR	0.1200**	0.0081	40.47	< 5%	< 5%	0.00

*** Significance < 1%
** Significance < 5%
* Significance < 10%
Note: The orthogonality test has been applied to the variable NIGHT

Figure 1: γ and β estimates for the not-contemporaneous model - *RV= fa (TA)*

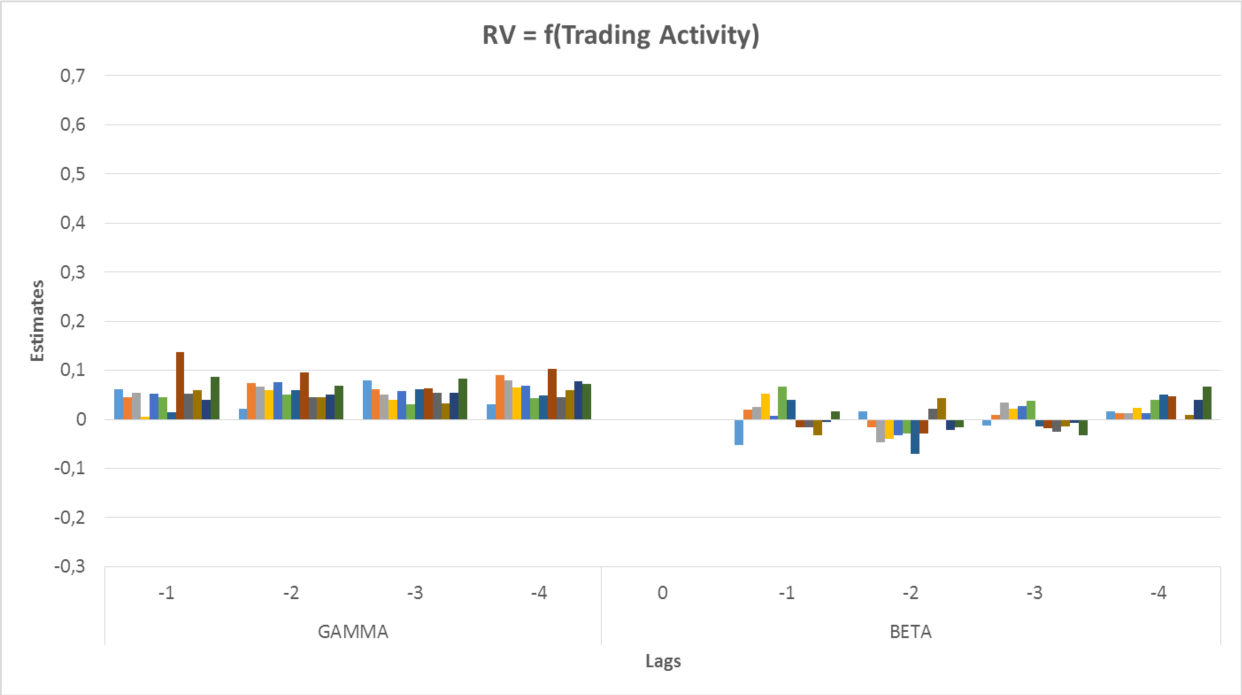


Figure 2: γ and β estimates for the for the not-contemporaneous model - *TA= fb (RV)*

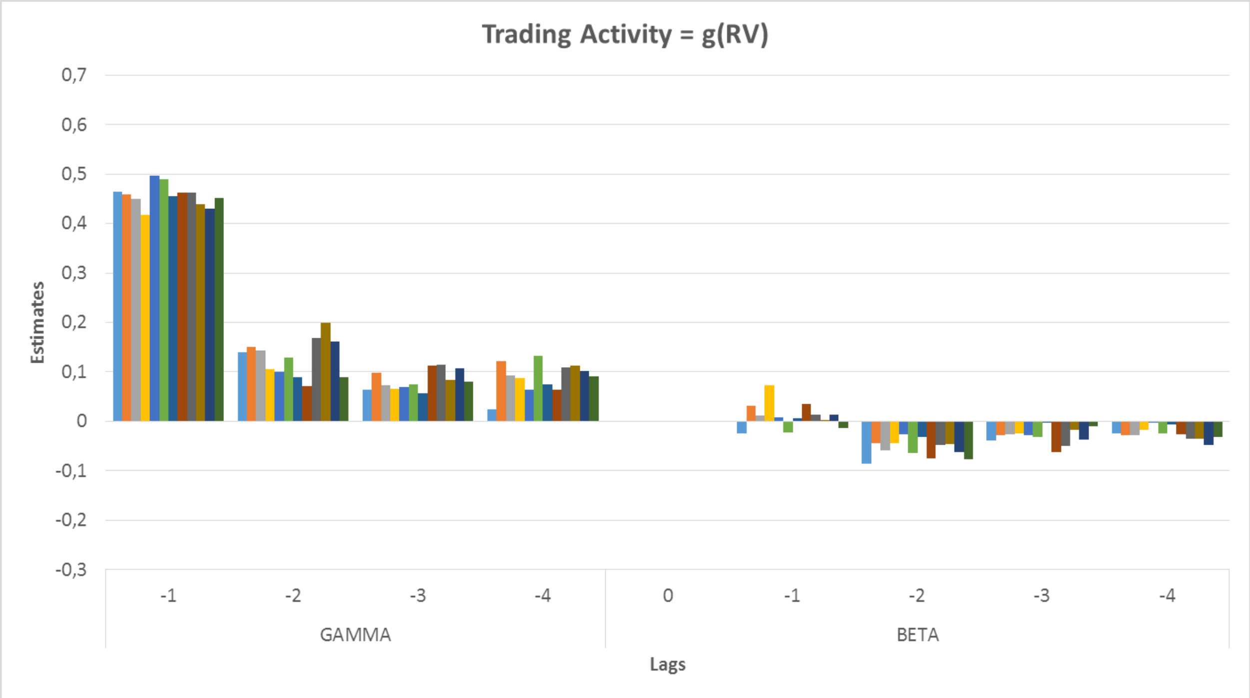


Figure 3: γ and β estimates for the contemporaneous model - *RV= ga(TA)*

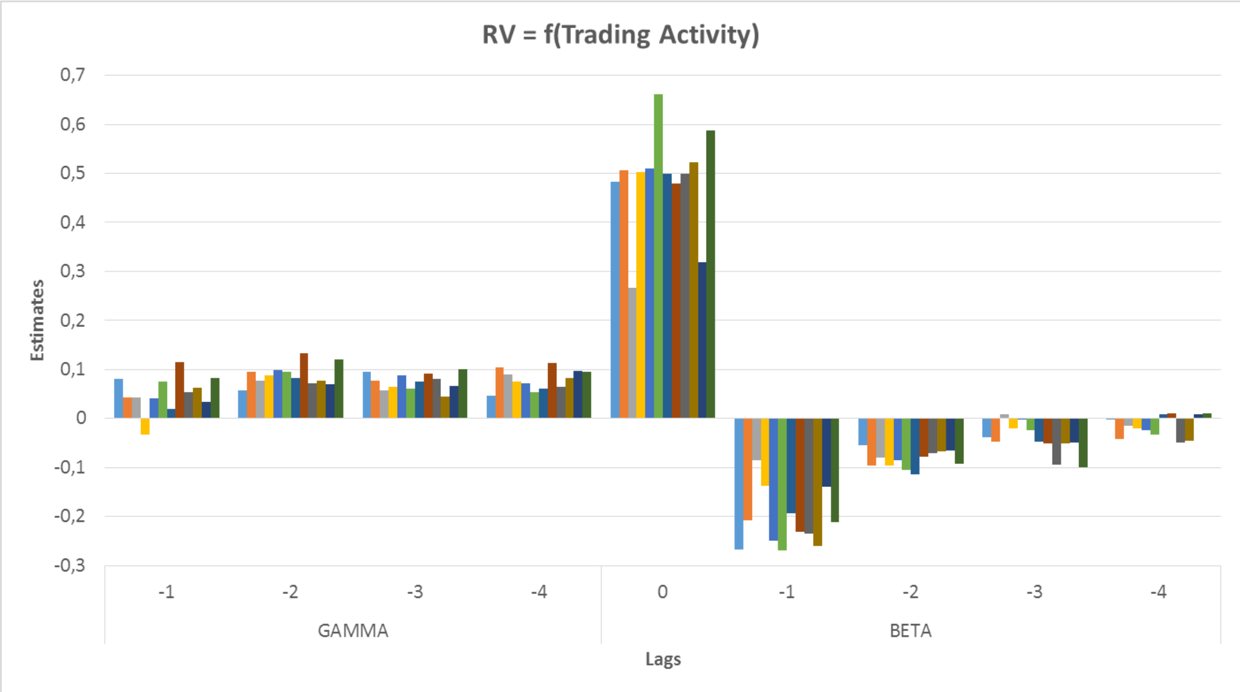


Figure 4: γ and β estimates for the contemporaneous model - *TA= gb(RV)*

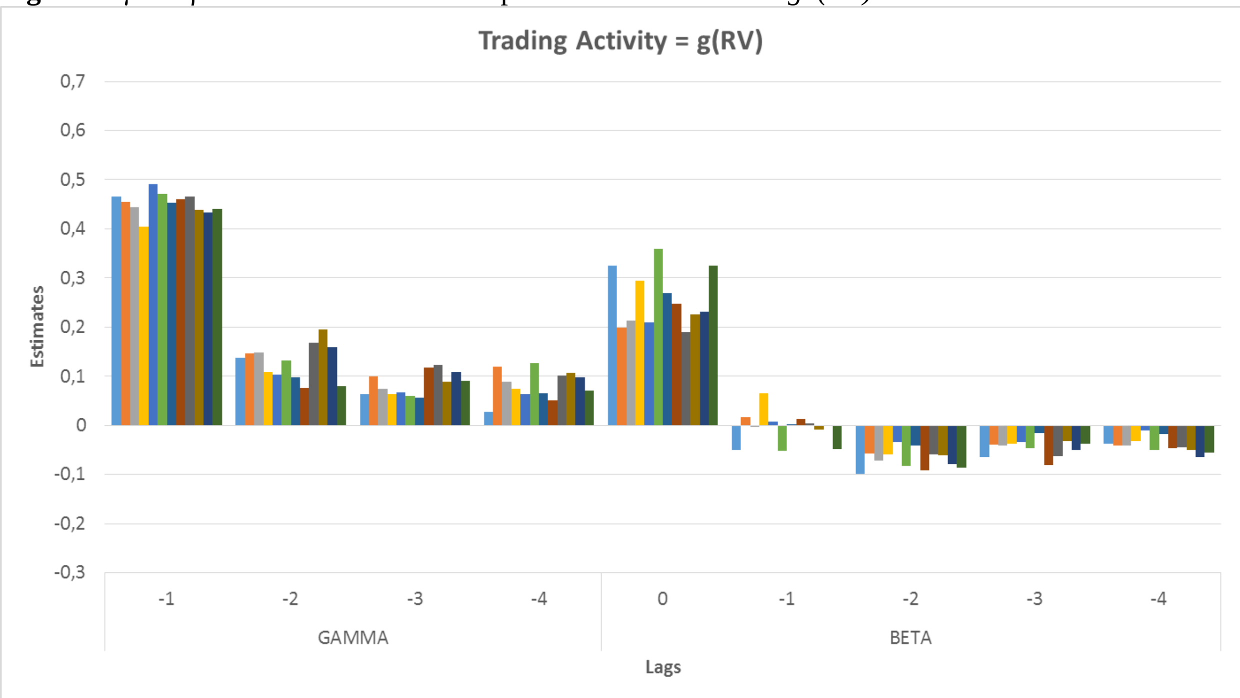
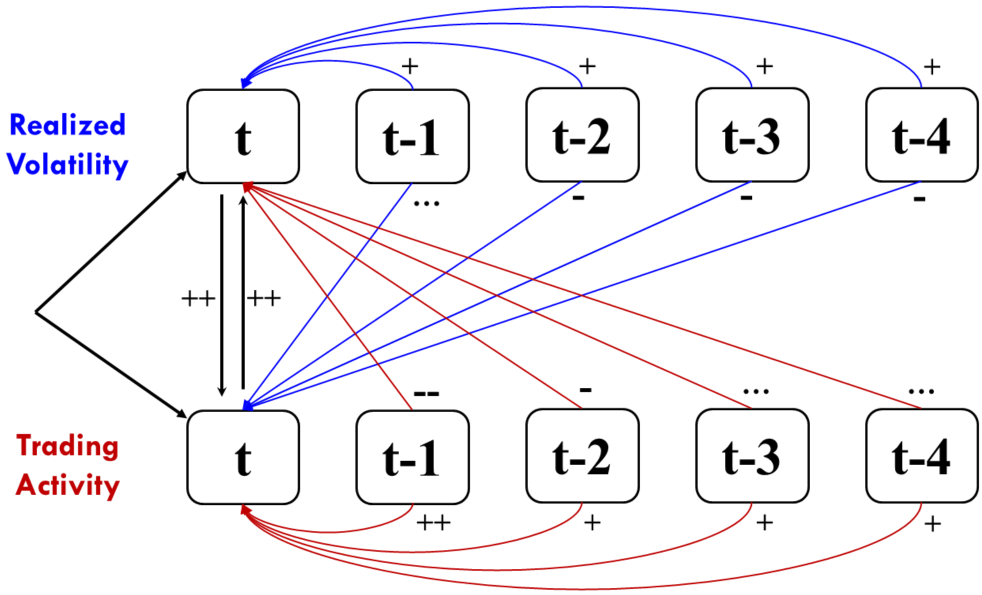


Fig. 5: Relationship between realized volatility and daily trading activity



+	positive correlation
++	strong positive correlation
-	negative correlation
--	strong negative correlation
…	no evidence of correlation