Università degli Studi di Udine

CORSO DI DOTTORATO DI RICERCA IN

ECONOMIA ECOLOGIA E TUTELA DEI SISTEMI AGRICOLI E PAESISTICO-AMBIENTALI

CICLO XXV

TESI DI DOTTORATO DI RICERCA

Market efficiency and price transmission: the case of Italian and US agricultural prices

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ANNO ACCADEMICO
2012/2013

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Abstract

The increasing co-movements between the world oil and food prices in the 2000s has prompted interest in the information transmission mechanism between the two markets. This research investigates the market integration and price transmission of some important agricultural commodities traded in a market area that includes United States and Italy for the period January 1999 to May 2012. The hypothesis of market integration is verified for crude oil and three agri-commodities, selected for their market relevance: corn and soybean, because their growingly demand diversified in food, feed and fuel; wheat because its higher accounting for much of the world food consumption. US and Italy agricultural markets are connected by a consistent volume of trading and by the recognized influence of the CBT price signals on the Italian agri-commodity markets.

This study extends the knowledge on the oil–agricultural commodity prices nexus (particularly for the Italian case) and on the price transmission dynamics from international (US) to domestic market (Italy). For this purpose, a multiple approach is applied starting from detecting structural breaks in the time series, proceeding with cointegration and price transmission analysis, to end with a causality approach.

The results suggest that there is quite evidence of market integration between crude oil and US food prices with non linear causality direction going from oil to agri-commodity prices; cointegration and price transmission between US and Italian food prices suggest to accept the hypothesis of a unique price; there is no clear evidence of causality between oil and Italian agri-commodities, but evidence of linear causality from US to Italian agricultural markets, suggesting the oil price volatility is transmitted directly to the US agri-market and indirectly to the Italian one.

Understanding the dynamics of the economy leads to better economic policies. Thus, this topic is important for investors and policy makers interested in price shocks and transmission.

1. Introduction

Prices of oil and agricultural commodities rose sharply in 2007, peaking in the second half of this year for some products and in the first half of 2008 for others. The '07-'08 price spike seems to have been caused by different factors: a macroeconomic instability influencing the world commodity markets as the rapid growth of food demand by the BRIC countries, due to rising GDP, the international financial crisis, and the growing influence of the oil price volatility on the other commodity markets (Piot-Lepetit and M'Barek, 2011). The agro-fuel commodities deserve an additional so-called knock-on effect due to the expanding U.S. corn production for ethanol use, reducing the oilseed acreage, such that the oilseed prices tended to increase for the expected tightening supplies. The upward price trend is enhanced by the rising demand for meals being the cereal feedstock substitutes and for vegetable oils used for bio-diesel production (OECD, 2008). Most agricultural commodity markets seems to manifest in recent times a higher volatility; however, a physiological price fluctuation is accepted for the changes of agricultural output from period to period caused by natural shocks such as weather ad pests. Another reason is the rigidity of demand due to the length of time for the production to adjust to market changes.

It is widely acknowledged the growing exchanges and integration among the world market with price transmission affecting the condition of market efficiency and speed of adjustment to market level in response to leading price signals (Rapsomanikis *et al.*, 2006). The market theory, suggests that the spatial price transmission is an essential condition for the existence of the market efficiency condition based on the "Law of one price"[1]: the price transmission is complete if the prices generated in two competitive markets, converted in a unique currency, will differ only by the transaction costs. The spatial arbitrage will reduce these price differences to the level of transport cost (Ardeni, 1989; Baulch, 1997; Barrett and Li, 2002). The rational expectation based on the competitive storage theory support this

[1] The law of one price states that the price changes in one market caused by variation in demand and supply are instantaneously transmitted to other markets so that the price variation in related markets will uniquely reflect the local changes in market equilibrium. In this sense the markets are integrated and price changes are due to spatial arbitrage (Enke, 1951, Samuelson, 1952, Takayama-Judge, 1971). A distinction is needed between short and long run equilibrium: beside price transmissions can be incomplete in short run they are complete in long run because the efficient arbitrage will fade out the differences. In this case price changes are not passed instantaneously from one market to another and delay in price changes can be imputed to policy intervention, number of stages in marketing and corresponding contractual arrangement, transport condition, rapidity of the operators to adapt to new market conditions, inventory holdings, financial speculation. These causes of market inefficiencies will affect the price adjustment either in rapidity of change and asymmetric response.

condition: the commodity stocks, expected prices and hauling costs drive the commodity prices to an equilibrium prices for the presence of competitive speculators who trade their stocks according with price expectation and carrying costs. Their unwillingness to hold negative inventories generate asymmetry in storage causing non linear price components (Deaton and Laroque, 1995). The absence of market integration or of a complete pass-through of price changes from one to another market, has important implications for the welfare distribution (Sharma, 2002). Market integration and price transmission, both spatially and vertically, are supported by theories and quantitative techniques apt to test the degree of market efficiency and has highlighted several factors interfering with the complete pass-through of the price signals. An important cause of market inefficiency is the government action either in the form of policies at the border or as price support mechanisms, that alter the market equilibrium by weakening the flows of products between the international and domestic markets (Gardner, 1975; Mundlak and Larson, 1992).

The biofuel policies, encouraging farmers to produce biofuel feed-stocks, have increased the dependency of the agricultural prices to the energy prices (Shagaian, 2010; Gohin and Chantret, 2010). Trade limitation as import tariffs, quotas and export subsidies or taxes, trade barriers, exchange rate policies, have caused inefficient arbitrage by insulating the domestic markets and hinder the full transmission of price signals. They are responsible of excess demand or supply schedules of domestic commodity markets possibly inducing asymmetric price response reflected in a non linear adjustment between prices (Kinnucan and Forker, 1987; Quiroz and Soto, 1996; Abdulai, 2000; Sharma, 2002, Rapsomanikis *et al*, 2006). Over the past decades, the world-wide integration has led to a significant increase in global trade; since late 2002, the major grains and oilseeds world markets have experienced a period of tight supplies and severe contraction in world trade; in addition the production of biofuels (ethanol and biodiesel from agricultural feedstock) and growing use of chemical and petroleum derived inputs has experienced a remarkable growth over the last decade, causing a growing dependence among oil and agri-commodity prices (Harri *et al.*, 2009)[2].

[2] The US Energy Information Agency indicate that the total world production of biofuel increased nearly six times over the 2000-2010 period from 315 thousand barrels/day to 1,856 barrels/day.

Three countries are the main integrated areas today: United States, Europe and Brazil. The ethanol is the main biofuel for US and Brazil while biodiesel is the most produced biofuel in the EU[3]. Ethanol is the most attractive in the Northern countries for the higher energy balance compared to biodiesel, and is now accounting for the three–fourth of the world biofuel output.

With the higher price volatility of agricultural commodities, the possibility of incurring losses (or realizing gains) on future transactions (sales or purchases) of those commodities becomes more real. Moreover, the uncertainty reduces the opportunities to access credit markets and drives farmers to adopt lower risk production techniques (John, 2007; Rosa, 2009). Studies directed to test the market integration and influence of the oil on agri-commodities have moved in two directions: econometric studies based on traditional demand and supply models adapted to capture the demand diversification in the world relied upon partial and computable general equilibrium models (Lapan and Moschini, 2012; de Gorter and Just, 2009; Hertel *et al*., 2010). These models could suffer from arbitrarily determined or calibrated price elasticity used in stimulating the long-run sensitivity of agricultural commodity prices to oil shock prices. The second approach is based on time series analysis addressed to capture the price transmission and causal nexus among markets. Cointegration methods have been very popular tools in applied economic work since their introduction about twenty years ago, this approach is relatively more recent compared to the first one, there are some critics regard the limited number of information used to predict structural adjustment in agri-markets. However the growing sophistication of analytical tools has made possible to understand better the nature of market interferences, as the price volatility and transmission in short periods, and price adjustment in longer period, improved forecasting price that are complementary market information to improve the production and market decisions.

In recent years, in particular, the turmoil observed in many agricultural markets has increased the attention of researchers and policy makers on the increasing volatility of prices and on the need for explicitly modeling the change of volatility over time (time-varying volatility) in price transmission analysis. It is natural to

[3] Ethanol growth is impressive in US, with 57.1% of the world production in 2010, in future the 2nd generation ethanol produced from the most performing non-food cellulosic feedstock (*Arundo, Panicum, Sorghum*), is the most promising biofuel source estimated to reach in **optimal** conditions 10-15,000 liters per hectare (EIA, 2012).

analyze volatility by looking at the variance of the error term of the stochastic process generating the price series under observation.

The typical tool of such analysis is the specification of GARCH (Generalized Autoregressive Conditional Heteroskedasticity) effects, that is, the specification of a price generating stochastic process whose error term follows itself a stochastic (ARMA) process. In multivariate stochastic processes, as in price transmission models, these GARCH effects can also arise across individual series, consequently allowing the time-varying variance of one series to affect that of another series. These are also called Multiple GARCH (MGARCH) effects (Bollerslev, 1990) and are appropriate tools to analyze volatility spillovers. Gardebroek and Hernandez (2012) paper follows a multivariate GARCH (MGARCH) approach to examine the dynamics and cross-dynamics of price volatility in oil, ethanol and corn markets in the United States between 1997 and 2011. They want to evaluate the magnitude and source of interrelation (whether direct or indirect) between markets and, in particular, whether price volatility in energy markets stimulate price volatility in grain markets. Results indicate a higher interaction between ethanol and corn markets in recent years, particularly after 2006. We only observe, however, significant volatility spillovers from corn to ethanol prices but not the converse. They also do not find major cross-volatility effects from oil to corn markets. The results do not provide evidence of volatility in energy markets stimulating price volatility in grain markets.

The analysis of the time-varying volatility in price transmission models and the change in volatility itself transmitted across markets (volatility spillovers or contagion) is beyond the scope of this thesis. Therefore, we deal with our research without using such econometric tools.

This research is aimed to analyze the agricultural markets linkages, with spatial integration and price transmission that have become the most influential effects on agri-market equilibrium induced by external factors as the oil price volatility. The above observations suggest to test the hypothesis that the oil price working as an exogenous price signal, is leading the agricultural markets, transmitting volatility especially in the last years. This hypothesis will be plausible assuming the market integration as a consequence of the spatial equilibrium model.

The results of this study may have important implications for both policy makers and global investors who need to follow the price shocks and transmission mechanisms between alternative investment areas closely. Therefore, research results will be beneficial in forecasting prices, establishing strategies.

The remaining of the thesis evolves as follows. Next section discusses the relevant literature. Third section introduces methodology and fourth section presents data characteristics and preliminary descriptive analysis. Fifth section discusses relevant tests and empirical findings and the last section concludes.

2. Literature review

The sharp increase in agricultural commodity prices in the recent years has increased interest on the determinants of this price surge. Different motivations are provided in the literature. As all prices, prices on food are determined by the interaction of demand and supply forces and the recent increases have been driven by a combination of factors, supply and demand related.

The **demand-side** factors are thought to be the main driving forces of increasing agricultural commodity prices. Rising world demand for agricultural commodities based on increasing population, change in diet of households in the emerging economies driven by rapid economic growth and improvement in the standards of living determining rising per capita meat consumption (Headey and Fan, 2008); expansion in the biofuels production causing the raise in corn and oilseed prices and the acreage invested in biofuel crops and feeding the “fuel vs. food” debate (Gilbert, 2010; Mitchell, 2008; Rosegrant *et al*., 2008; Zhang *et al*, 2010); the weakening of dollar (Trostle, 2008); and the speculation stemming from increased activity in futures markets (Robles *et al.*, 2009) are also considered as demand-driven factors that contribute to agricultural commodity prices[4].

On the supply side, several factors have had an effect. Among others, slow growth in agricultural production, increases in energy prices rising farm production costs like transportation fertilizer, pesticide (Tyner and Taheripour, 2008; Sumner, 2009; von Braun *et al*., 2008), and droughts (Trostle, 2008) are more pronounced supply-side explanations.

[4] The price surges caused by speculation could determinate turbulence to the global grain markets affecting the market’s efficiency in responding to fundamental changes in supply, demand, and costs of production (Spears, 2011)

Given the number of factors at work, it is difficult to establish which ones have been the most prominent in influencing food price increases

According to the OECD (2008), oil prices and feedstock demand for biofuel production seem to keep their importance in determining the recent behaviour of agricultural commodity prices and appear to be permanent factors of demand for agricultural products and of agricultural prices. Others authors attribute the link between agricultural and oil prices to the rising production of biofuels (Zhang *et al.*, 2010; Ciaian and d'Artis, 2011a,b;)

Existing literature on the effect of crude oil on agricultural commodities is relatively new; almost all studies connected to this topic began after the 2008 food crises, although even previously the same issues was somehow highlighted. Some studies have examined the relationship and the long-run relationship among soft commodities prices and in some cases among selected soft commodities prices and crude oil price.

Campiche *et al.* (2007) examine the relationship between crude oil prices and corn, sorghum, sugar, soybeans, soybean oil, and palm oil prices during the 2003-2007 time period using a vector error correction model. Results reveal no cointegrating relationships during the 2003-2005 period whereas corn prices and soybean prices are cointegrated with petroleum prices for the 2006-2007 time frame. The authors conclude from their analysis that soybean prices seems to be more correlated to crude oil prices than corn prices.

These conclusion confirm Arshad and Hameed's (2009) results who address one specific question: is there a long-term relationship between crude oil and cereal prices? Their results support the hypothesis that there is evidence of a long-run equilibrium relationship between the oil prices and cereal prices and that changes in petroleum prices play an important role in agricultural price formation.

Yu *et al.* (2006) investigates the long-run interdependence between major edible oil prices oils prices, including soybean, sunflower, rapeseed and palm oils, and examines the dynamic relationship between vegetable and crude oil prices. They conclude that shocks in crude oil prices do not have a significant influence on the variation of edible oil prices, which appears to reflect the results in Campiche (2007).

Zhang and Reed (2008) examined the impact of the crude oil price on China's agricultural commodity prices focalizing their attention on feed grain (corn and soybeans) and pork. The results from time series techniques determine nonsignificance of crude oil price fluctuation over the study period (2000-2007). Similar results are found by Nazlioglu and Soytas (2011) for Turkey.

Tyner and Taheripour (2008) emphasized that rise in oil prices have an influence on the increasing corn prices. Rosegrant *et al*. (2008) states that allocation of land for food crops resulted in a volatility spillover between food and oil prices. In this study it is estimated that increased demand in biofuel causes 39% of the increase in corn prices and 30% of increase in grain prices. Gilbert (2010) indicates that all agricultural markets are affected by the change in oil prices. Oil prices have an influence on food prices either by increasing cost of food production or by using food an input for biofuel production. The author also emphasizes cost of food production has increased because of the transportation cost and the fertilizer cost.

Saghaian (2010) utilizes cointegration test, vector error correction model, and Granger causality test to examine the link between corn prices, soybean prices, wheat prices, crude oil prices and ethanol prices The results show a strong correlation among oil and commodity prices, but also that the evidence for a causal link from oil to commodity prices is mixed

Nazlioglu (2011) concentrates on relationships between the world oil and corn, soybeans, and wheat. He finds evidence from nonlinear causality between of world oil and agricultural commodity prices. Along the same line Nazlioglu and Soytas (2012) find strong evidence of the impact of world oil price changes on agricultural commodity prices employing panel cointegration and Granger causality methods.

Moving to the relation oil – biofuel - crops, Serra *et al.* (2010a) find the prices of oil, ethanol and corn for the US to be positively correlated, and the existence of a long term equilibrium relationship between these prices, with ethanol. In the Serra *et al*. (2010b) study of Brazil, the relevant feedstock is sugar cane. They find sugar and oil prices exogenously determined, and focus their attention on the response of ethanol prices to changes in these two exogenous drivers. The authors conclude that ethanol prices respond relatively quickly to sugar price changes, but more slowly to oil prices.

Hertel and Beckman (2011) indicate that the rapid biofuel production strengthened the transmission of energy price volatility into agricultural commodity price variation. They estimate that if biofuel policy are implemented imposing aggressive mandates on biofuel use in domestic refining, the impacts from energy price volatility are small (about one-quarter), while the impacts from corn supply volatility are magnified (nearly one-half).

Serra and Gil, (2012), explain price volatility considering the influence of energy prices, corn stocks and global economic conditions. Their findings support evidence of price volatility transmission between ethanol and corn markets. While the impacts of stocks in the very short-run are very high relative to the effects of energy price and macroeconomic instability, in the long-run the ethanol price and interest rate volatility are found to have the strongest impacts.

Considering now the role of trade policy intervention, Esposti and Listorti (2013) investigate on national and international markets; trade policy regime has an important role in price transmission mechanisms and the trade policy intervention put forward to mitigate the impact of price exuberance is considered. The authors analyze agricultural price transmission during price bubbles, in particular, considering Italian and international weekly spot (cash) price data over years 2006–2010. Their results suggest that the bubble had only a slight impact on the price spread and the temporary trade-policy measure, when effective, has limited this impact.

On the same matter, Mela and Canali (2012), use cointegration techniques allowing for structural breaks to assess the extent to which the Fischler reform of the CAP increases price transmission elasticity (PTE) between the world and European corn, wheat, and soybean markets. The Fischler reform of the Common Agricultural Policy (CAP) was agreed between Member States in 2003 and started to be implemented in 2005-07. The main characteristic of the reform was the progressive introduction of fully decoupled payments to farmers, in order to mitigate trade and market distorting effects of EU policies and re-align European prices to world ones. However, a greater integration of EU markets to the world ones means also a greater exposure of European farmers to price volatility, which can in turn substantially change agriculture's profitability and trigger deep changes in the structure of European agriculture. Results show that the reform increased the transmission elasticity in the case of corn and wheat, while its impact was negligible for soybeans. However, the long-term relationship (cointegration) between world and European prices can be detected only taking into account – other than the Fischler reform's structural break – also the fact that world commodity markets were interested, in 2003-04 and 2007-08, by price bubbles. In particular the latter affected the world – European corn price relationship in the ascending phase, while the wheat and soybeans markets in the descending phase.

As world food markets are open to investors and speculators, just like the oil markets, the prices in both commodity markets may be governed by similar dynamics. Food, oil and energy prices have been studied extensively in the literature. There are many studies modeling spillovers between different food commodities, and also various papers concerning different crude oil prices. However, to the extent of our knowledge there aren't any studies that explicitly make a comparison between world agri-commodities, Italian corn, soybeans, wheat and oil prices. Next section introduces methodology

3. Methodology: time series analysis

Time series analysis is frequently used to study the agricultural markets (Tomek and Myers, 1993; Rosa, 1999; Thompson et al., 2002; Rapsomanikis et al., 2006; Gutierrez et al., 2007; Listorti, 2009; Esposti and Listorti, 2010; Carraro and Stefani, 2010; Nazlioglu, 2011). A time series is an ordered sequence of values of a variable at equally spaced time intervals and the usage of time series models is twofold: i) to obtain an understanding of the underlying forces and structure that produced the observed data; ii) to fit a model and proceed to forecasting, monitoring or even feedback and feedforward control (Hamilton, 1994)

Time series analysis comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data. Most of these studies analyze the co-movement of prices using cointegration relationship and error correction models, that is a common procedure for analyzing spatial market relationships and price transmission, replacing earlier empirical tools, such as the bivariate correlation coefficient or simpler regressions analyses. This approach is well suited to test market conditions such as completeness, speed and asymmetry of price relations and is appropriate to give evidences about market failures, direction, magnitude and distribution of welfare changes. Nevertheless, time series analysis has also been criticized as being unreliable (Blauch, 1997; Barrett and Li, 2002). However, recent researches are focusing on the switching regime models that incorporate data on prices, volumes traded and transactions costs and these objections become less relevant.

In our approach we utilize stationarity tests of the series using the traditional unit root tests and the Zivot Andrews one break test. Then, we perform a cointegration test to determine whether there exists a long-run relationship among the series in the system and we specify a vector error correction model to analyze the price transmission. This is followed by causality tests with the linear (Granger causality test) and the non linear approach suggested by Diks and Panchenko (2006)to examine the causal linkage among the variables. Finally, we analyze the impulse response function and dynamics of adjustment.

3.1. Unit root test

To understand the dynamics underlying the changes in prices, variables are exposed to various tests. In order to have robust estimation results, identification of the stationarity of the data has an utmost importance. Stationarity properties of the variables are determined by various unit root tests. Since some tests can give contradictory results, a variety of tests are conducted to check reliability. To continue with further econometric analysis, all series must be integrated of the same order.

Aforementioned tests are augmented Dickey-Fuller (1979) [ADF], Phillips-Perron (1988) [PP], Kwaitkowski-Phillips-Schmidt-Shin (1992) [KPSS]. The null hypothesis of the unit root tests, apart from KPSS, is that the series in concern has a unit root against an alternative of stationarity. On the other hand, stationarity of the variable is the null for KPSS.

As a standard procedure to test the non stationarity of a series, the ADF test is based on the regression:

$$y_t = \mu + \beta t + \alpha y_{t\text{-}1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \varepsilon_t \qquad (1)$$

where μ is a constant, β the coefficient on a time trend and k the lag order of the autoregressive process. The unit root test is then carried out under the null hypothesis $\alpha = 0$ against the alternative hypothesis of $\alpha < 0$. Non stationarity is refused when the test suggests that α is different from 1.

However, if a structural break is present in the data generating process, the conventional ADF test is biased toward the acceptance of the null resulting in a dramatic loss of power.

A common problem with conventional unit root tests, is that they do not allow for any break in the data generation process. If there is a structural break, running the conventional unit root test may result in misleading inferences. Assuming the time of the break as an exogenous phenomenon, Perron (1989) has demonstrated that the power to reject a unit root decreases when the stationary alternative is true and a structural break is ignored.

This is why we compare the results of conventional tests with those obtained with the Zivot and Andrews (1992)[ZA] unit root test; it is an endogenous structural break test with unknown timing in the individual series utilizing the full sample and different dummy variable for each possible break date. The break time is selected where the t-statistic from the ADF test of unit root is at a minimum (most negative), then a break date is chosen where the evidence is least favorable for the unit root null.

The null hypothesis is that the series is integrated without an exogenous structural break against the alternative that the series can be represented by a trend-stationary process with a once only break point occurring at some unknown time. ZA test is a variation of Perron's original test with the endogenous implementation of structural breaks in the analysis: the date of the break is determined on the basis of t-statistics test of the unit root, with respect to the criteria of minimum values.

Following Perron's characterization of the form of structural break, ZA formulate three different characterizations of the trend break to test for a unit root: i) model A, "*the crash model*", that allows the break in the intercept; ii) model B, "*the changing growth model*", which allows for a one-time change in the slope of the trend function with the two segments joined at the break point; iii) model C, "*the mixed model*", which combines simultaneously the one-time changes in the level with the slope of the trend function of the series[5]. The aim of the procedure is to sequentially test the breakpoints candidates and select that which gives most weight to the trend stationary alternative. Hence, to test for a unit root against the alternative of a one-

[5] For the three models, Zivot and Andrews estimate the testing equation by allowing the break to take place beginning successively in the second, third, fourth, and so on, observation, up to observation T - l, where T stands for the total sample size used in the estimation and l are the lags. The alternative specifications are estimated by OLS, and the length of the lag (k) for the difference terms is determined by starting at k = 8, and working backwards until significant values are identified. The estimate of the breakpoint is that particular observation corresponding to the minimum t-value for the one period lagged term, for each model A, B, and C. In order to test the unit root hypothesis, this minimum t-value is compared with a set of asymptotic critical values from the work of Zivot and Andrews (1992).

time structural break, Zivot and Andrews propose the following regression equations (derived from equation 1)corresponding to the above three situations.

$$y_t = \mu + \beta t + \alpha y_{t-1} + \gamma DU_t + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \varepsilon_t \qquad \text{(Model A)}$$

$$y_t = \mu + \beta t + \alpha y_{t-1} + \theta DT_t + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \varepsilon_t \qquad \text{(Model B)}$$

$$y_t = \mu + \beta t + \alpha y_{t-1} + \theta DT_t + \gamma DU_t + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \varepsilon_t \qquad \text{(Model C)}$$

where DU_t is an indicator dummy variable for a mean shift occurring at each possible break-date while DT_t is corresponding trend shift variable. The null hypothesis in all the three models is $\alpha = 0$, which implies that the series y_t contains a unit root with a drift that excludes any structural break, while the alternative hypothesis $\alpha < 0$ implies that the series is a trend-stationary process with a one-time break occurring at an unknown point in time. The Zivot and Andrews test regards every point as a potential break-date and runs a regression for every possible break-date sequentially.

3.2. Cointegration analysis

Johansen (1991, 1995) and Johansen and Juselius (1990) procedure, is used to determine the absence or presence of cointegrating relationship among variables. Although there are other tests like Engle and Granger (1987), Johansen's cointegration test has superiority of considering all variables as endogenous and its capability of testing more than one cointegrating relationship. The main goal of a co-integration test is to examine if two or more series are linked to form an equilibrium relationship. The concept of cointegration means that the two price series cannot wander off in opposite directions for very long without coming back to a mean distance eventually.

Let us consider a static regression between $I(1)$ variables:

$$y_t = \mu + \alpha x_t + \varepsilon_t \qquad (2)$$

where x_t is a vector of independent variables. The system is cointegrated if the errors ε_t are $I(0)$. In this case the relation (2) may be interpreted as a long run equilibrium toward which the process *yt* tends.

Assuming x_t and y_t are integrated processes, if there is a linear combination which is integrated of a lower order, both variables are cointegrated. Failure to reject the null of no cointegration implies that two price series drift apart in the long run driven by non proportional stochastic trends (Rapsomanikis *et al*., 2006).

Johansen cointegration test starts considering a vector autoregressive (VAR) model with k lags under the consideration that variables are I (1): written in error-correction form

$$\Delta p_t = \alpha + \Pi p_{t-1} + \sum_{k=1}^{t} \Gamma_k \Delta_{t-k} + \varepsilon_t \tag{3}$$

where $\boldsymbol{p_t}$ is an n x 1 vector of n price variables, $\boldsymbol{\Delta}$ is the differencing operator such that $\Delta p_t = p_t - p_{t-1}$, $\boldsymbol{\alpha}$ is an n x 1 vector of estimated parameters that describe the trend component, $\boldsymbol{\Pi}$ is an n x n matrix of estimated parameters that describe the long-term relationship and the error correction adjustment, $\boldsymbol{\Gamma_k}$ is a set of n x n matrices of estimated parameters that describe the short-run relationship between prices, one for each of q lags included in the model, and $\boldsymbol{\varepsilon_t}$ is an n x 1 vector of error terms.

The rank of matrix Π is of interest with regard to the long-run cointegrating relationships between variables in the model. That is if $\Pi = 0$, all variables are non-stationary and model (3) reduces to a differenced vector time series model implying that no cointegration relationships exist among variables and there are no cointegrating vectors and for $\Pi = 1$, there is one cointegrating vector. If $\Pi > 1$, there is more than 1 cointegrating vectors. If the rank of Π equals zero, (Johansen and Juselius, 1990).

The Johansen procedure uses Trace and Eingenvalue tests. The trace statistic reports the null hypothesis of r cointegrated relations against the alternative of k cointegrating relations, where k is the number of endogenous variables. The maximum eigenvalue test, on the other hand, tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of $r + 1$ cointegrating vectors. The rank r is calculated with the eigenvalues of a matrix. If all the eigenvalues are significantly different from zero, all processes are stationary. On the contrary, if there is at least one eigenvalue equal to zero, the process x_t is integrated. On the other side, if none eigenvalue is significantly different from zero, not only the process x_t is non stationary but this is for all the linear combinations. In other words there is no evidence of cointegration.

It has been found that the trace test is the better test, since it appears to be more robust to skewness and excess kurtosis (Sjö, 2009).

Following Johansen (1992), to determine if cointegration relationships exist between the variables, first the lag length (k) is determined and then cointegration rank (r) is determined. To determine the lag length the Schwarz Bayesian Criterion (SBC) (Schwarz, 1978) (also known as BIC) is used.

Finally, Gregory and Hansen (1996) apply a test that is an extension of the Engel - Granger residual based cointegration analysis. This approach is an extension of the endogenous univariate test of Zivot and Andrew (1992) unit root tests with structural breaks: Gregory and Hansen propose the cointegration tests which accommodates a single endogenous break in an underlying cointegrating relationship.

The null hypothesis of cointegration is tested against the alternative of cointegration with a break in cointegrating relationship. Gregory and Hansen extend the residual test to take into account a possible break in the long-run relationship of unknown date.

They examine tests for cointegration which allow the possibility of regime shift and develop ADF*, Z_t^* and Z_α^* type tests designed to test the null of no cointegration against the alternative of cointegration in the presence of a possible structural break. The authors consider three modified version of equation (2) that includes dummies for the structural change :

Model C: Level Shift

$$y_t = \mu + \theta DU_t + \alpha x_t + \varepsilon_t \tag{4a}$$

Model C/T: Level Shift with Trend

$$y_t = \mu + \theta DU_t + \beta t + \alpha x_t + \varepsilon_t \tag{4a}$$

Model C/S: Regime Shift (Intercept and Slope coefficients change)

$$y_t = \mu + \theta DU_t + \alpha_1 x_t + \alpha_2 DU_t x_t + \varepsilon_t \tag{4c}$$

where *y* is the dependent and *x* is the independent variable, *t* is time subscript, ε is an error term and *DU* is a dummy variable.

Model C entails a level shift in the equilibrium relationship, model C/T adds a trend to the previous model whilst model C/S deals with regime shift by adding a change in the slope coefficients. The structural change is endogenously determined by the smallest value (the largest negative value) of the cointegration test statistics across all possible break point.

Next step will be testing for Granger causality which plays an important part in many vector error correction models. The cointegration implies causality in the Granger sense defined in terms of predictions of future values of Y improved by using present and past values of X.

3.3. Granger causality

The Granger test (1969) is to see how much of the current *y* can be explained by a past value of *x* and then to see whether adding lagged value can improve the explanation. *y* is said to be 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.

In this step the examining of the relationship by the traditional Granger causality test is simply to give an indicator of the direction relationship. The Granger causality test has to be run on *I*(0) series, and it is done by a simple F-test. The causality relationship can be evaluated by estimating the following:

$$\Delta X_t = \sum_{j=1}^{m} \alpha_{1j} \Delta X_{t-j} + \sum_{j=1}^{m} \beta_{1j} \Delta Y_{t-j} + \varepsilon_{1t} \tag{5a}$$

and

$$\Delta Y_t = \sum_{j=1}^{m} \alpha_{2j} \Delta X_{t-j} + \sum_{j=1}^{m} \beta_{2j} \Delta Y_{t-j} + \varepsilon_{2t} \tag{5b}$$

where X_t and Y_t are the prices of time series to test for causality. In this specific case, the null hypothesis to be tested are:

- oil price does not Granger-cause US food commodity price and US food commodity price does not Granger-cause crude oil price i.e. H_0:β_{1j}=0, j=1,2,...m and H_0:α_{2j}=0,j=1,2,...m.
- oil price does not Granger-cause Italian food commodity price and Italian food commodity price does not Granger-cause crude oil price

- US food commodity price does not Granger-cause Italian food commodity price and Italian food commodity price does not Granger-cause US food commodity price

As a complementary analysis, nonparametric Granger causality tests are performed to uncover potential nonlinear dynamic relations between oil and agri-commodities. Traditional linear Granger causality tests have high power in identifying linear causal relations, but some authors argue that the linear Granger causality is ineffective in capturing nonlinear causal relations, and recommend to test for nonlinear Granger causality (Baek and Brock,1992; Hiemstra and Jones,1994).

An increasing number of studies report evidence for causality between time series on the basis of the Hiemstra and Jones (1994) test which has become quite diffused in this type of analysis (Bai *et al.*, 2009; Chen *et al.*, 2004).

Assuming that linear causality tests might overlook nonlinear dynamic relations between oil and agri-commodities, we verify the hypothesis of non linear Granger causality performing the nonparametric causality test proposed by Diks and Panchenko, (2006) [DP] which avoids the over-rejection observed in the test proposed by Hiemstra and Jones (1994).

Considering that the null hypothesis of Granger non-causality can be rephrased in terms of conditional independence of two vectors X and Z given a third vector Y, Diks and Panchenko (2006) show that the Hiemstra and Jones test is sensitive to variations in the conditional distributions of X and Z that may be present under the null hypothesis. To overcome this problem, they replace the global test statistic by an average of local conditional dependence measures.

Dicks and Panchenko's nonparametric causality test can be summarized as follows. Consider two stationary series, X_t and Y_t, such as the oil and each single agricultural price defined previously. When testing for Granger causality, the aim is to detect evidence against the null hypothesis H_0: X_t does not Granger-cause Y_t. In a nonparametric setting, this null hypothesis is equivalent to testing for the conditional independence of Y_t on X_{t-1},…… X_{t-lx}, given Y_{t-1},…… Y_{t-ly}[6].

[6] For details in the methodology refer to Diks and Panchenko (2006)

4. Data characteristics

For the empirical analysis, weekly spot prices[7] of major agri-commodities and of oil are taken into consideration in this thesis. The high frequency of observation has been chosen to capture the dynamic market linkages and causal nexus among prices (Nazlioglu, 2010). The data are the average of daily quotations of US and Italian agri-commodity prices. Soft wheat, maize and soybeans were selected because their high importance for food, feeds and fuel. Wheat is more energy intensive and the key product for food, corn and soybean are the most important biofuel feedstock; wheat, corn and soybean are still used in crop rotation for sustainable reasons. Table 1 presents the variables used in analyzing both markets, along with the sources.

Table 1. List of variables

Variable		Description	Source
Italian	corn price	Weekly average of spot prices in €/ton of national hybrid corn-market at the origin (**cit**)	DATIMA provided by ISMEA[8]
	soybean price	Weekly average of spot prices in €/ton of soybeans with 14% of moisture--market at the origin (**sit**)	DATIMA provided by ISMEA
	wheat price	Weekly average of spot prices in €/ton of good mercantile wheat--market at the origin (**wit**)	DATIMA provided by ISMEA
US	corn price	Weekly average of spot prices converted in €/ton of US yellow no. 2 corn at the Gulf of Mexico (**cus**)	FAO International Commodity Price Database
	soybean price	Weekly average of spot prices converted in €/ton of US no. 1 yellow soybean at the Gulf of Mexico (**sus**)	FAO International Commodity Price Database
	wheat price	Weekly average of spot prices converted in €/ton of US no. 2 soft red winter wheat at the Gulf of Mexico (**wus**)	FAO International Commodity Price Database
Oil price		Weekly spot prices of Brent crude oil converted in €/barrel (**oil**)	US Energy Information Administration

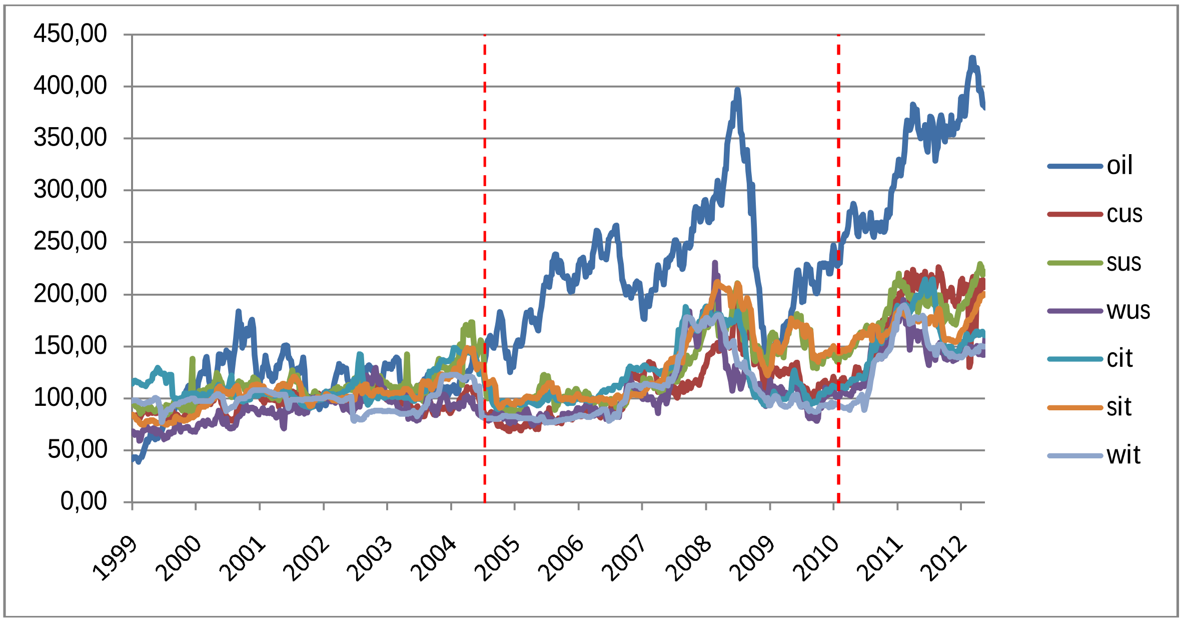
The weekly price series have been monitored for a period spanning from January 1999 to May 2012, a total of 699 observations. The prices of US agri-commodities and oil, originally expressed in US dollar, are converted in euro by using the official $/€ exchange rate[9] considering the weekly averages of daily quotations.

Line graphs of spot market prices presented in Figure 2 indicate non-stationary trend in the data. Also it can be stated that there is high volatility in oil spot market

[7] Spot prices are used because most of the transactions in Italy are made in these markets.
[8] DATIMA is a collection of statistical databases including Italian agricultural market data and foreign trade; ISMEA is the Italian agri-food market Institute
[9] Available at http://www.statistics.dnb.nl/index.cgi?lang=uk&todo=Koersen

by going through the graphic. A visual inspection of the price series (above all of the oil prices) suggests to divide the all sample in more sub-samples with different characteristics: a relatively quiet period till 2004, considerable wide fluctuations in the following period (till the end of 2008), due to turmoil in financial and energy markets transmitted to the agricultural markets, and finally an instable period with relative increment of all commodities prices.

Figure 1. Index of current prices of some agri commodities and oil (Jan 04, 2002= 100)



Source: own elaborations. cit, wit, sit, cus, wus, sus: €/ton; for oil: €/barrel

4.1. Testing for stationarity and structural break

To check for the order of integration of the time series and to better identified the subdivision of the samples, I first perform the stationary tests. A stationary process has the property that the mean, variance and autocorrelation structure do not change over time. These tests are usually incorporated as first in all the time series econometric analysis since the stationary condition must be achieved before further proceeding with other analysis. In this thesis I prefer to study such condition even before the description of the price series characteristics to better define the split-periods of investigation.

The results of the conventional unit root tests for levels and first differences are presented below. According to Table 2, it can be concluded that all the variables are integrated of order 1, even though there are slight differences between the results of different tests.

Table 2. Unit root test results

		levels			first differences		
		ADF	PP	KPSS	ADF	PP	KPSS
Intercept	cus	-0.31	-1.28	1.93*	-13.84*	-33.22*	0.14
	sus	-1.42	-1.35	2.20*	-30.21*	-30.99*	0.08
	wus	-2.23	-2.15	1.79*	-28.81*	-28.75*	0.03
	cit	-1.77	-2.08	1.18*	-16.35*	-16.41*	0.05
	sit	-1.28	-1.02	2.22*	-14.74*	-21.10*	0.06
	wit	-1.48	-1.77	1.03*	-18.51*	-19.42*	0.06
	oil	-1.23	-1.17	2.48*	-21.42*	-21.42*	0.04
Trend & intercept	cus	-1.59	-2.91	0.44*	-13.88*	-33.66*	0.05
	sus	-3.06	-3.08	0.36*	-30.20*	-31.02*	0.03
	wus	-3.36	-3.29^	0.12^	-28.80*	-28.73*	0.02
	cit	-2.47	-2.76	0.12^	-16.35*	-16.37*	0.03
	sit	-2.73	-2.46	0.17°	-14.73*	-21.09*	0.04
	wit	-2.07	-2.36	0.16°	-18.50*	-19.41*	0.04
	oil	-2.78	-2.71	0.14^	-21.41*	-21.41*	0.04

Schwarz Information Criterion is used to determine the optimal lags for ADF test; the bandwidth for PP and KPSS tests is selected with Newey-West using Bartlett kernel (by default). */°/^ denote statistical significance at 1, 5 and 10% respectively

Table 3 reports the results of Zivot-Andrews one break test. Minimum ZA t-statistics for the levels of the variables show similar results with those obtained from the unit root tests without accounting for structural breaks with the exception for oil and sus: once a break in the deterministic trend is allowed for, the null hypothesis of a unit root process is rejected. We run the test in the three versions illustrated in section 3, that includes a deterministic trend and allowing a shift either in the intercept or in the slope of the trend or in both. A structural break was found in the US soybeans series.

The estimated date is July 2004 (2004: week 29) with a model fitted in the drift (model A) and a change in the trend slope and drift (model C). Oil series appears to be stationary with a break in October 2008 (2008: week 40) with change in trend slope and drift. As underlined by Piehl *et al*., (1999), the knowledge of break time is a central point in the accurate evaluation of any program intended to bring about structural changes; such as the climate shocks, market disruption, regime shifts and others.

Table 3. Zivot Andrews one break test

	Model A change in drift	Model B change in trend	Model C change in drift and trend
cus	-3.63	-3.10	-3.42
sus	-4.98**(2004: w29)	-4.15	-5.48*** (2004: w29)
wus	-3.78	-3.50	-3.87
cit	-3.20	-2.83	-3.82
sit	-4.03	-3.02	-4.03
wit	-3.18	-2.81	-3.26
oil	-3.27	-3.30	-5.16** (2008: w40)

***/** denote statistical significance at 1% and 5% respectively; break date in brackets

	Critical value		
	1%	5%	10%
Model A	-5.34	-4.80	-4.58
Model B	-4.93	-4.42	-4.11
Model C	-5.57	-5.08	-4.82

The asymptotic critical value for Zivot and Andrews (1992) test at different levels of significance

All the other price series are found to be $I(1)$ confirming the traditional unit root tests. Even though sus and oil price series are stationary in model C, this condition does not appears with the same evidence in model A neither in model B. For this reason we conservatively assume that all the variables are integrated of order one I*(1)*.

4.2. Descriptive statistics

Table 4 reports descriptive statistics of the price in each market: mean of price changes, minimum and maximum value, standard deviation and asymmetric distribution around the mean value. The skewness is particularly important for the investment theory: a positive value (long RHS tail) means frequent small price drops and few extreme price run up, while a negative value (long LHS tail) means frequent small gains and few extreme losses. Positive skewness implies larger price increase while negative skewness implies large price drops

Table 4. Summary statistics (entire period)

	oil	cus	sus	wus	cit	sit	wit
Mean	44.15	116.77	246.83	139.64	156.75	283.85	168.15
Median	39.73	104.00	219.86	127.65	140.50	252.00	152.97
Maximum	96.30	229.35	434.00	307.81	273.80	475.67	292.13
Minimum	8.75	69.44	157.65	78.98	113.85	166.30	118.00
Std. Dev.	20.30	38.86	67.21	40.31	37.71	77.50	43.64
Skewness	0.62	1.40	0.83	1.18	1.15	0.62	1.20
Kurtosis	2.48	4.05	2.56	3.85	3.24	2.26	3.42
Jarque-Bera	52.77	261.23	85.00	183.94	155.69	60.74	171.94
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: own elaboration

All price series follow a non-normal distribution. *Jarque-Bera* test statistics are significant implying a deviation from normality[10]. According to Table 4, *kurtosis*[11], indicating the flatness of the curve, exceeds 3 pointing out the presence of fat tails in cus, wus, cit and wit; this suggests a leptokurtic distribution with value concentration

[10]The **Jarque–Bera** test is a goodness-of-fit measure of departure from normality, based on the sample kurtosis and skewness. The test statistic *JB* is defined as

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}K^2\right)$$

where n is the number of observations (or degrees of freedom in general); S is the measure of skewness (third moment), and K is the kurtosis (fourth moment) of the data. The statistic *JB* has an asymptotic chi-square distribution with two degrees of freedom and can be used to test the null hypothesis that the data are from a normal distribution.

[11] **Kurtosis** is a measure of whether the data are peaked or flat relative to a normal distribution. The value 3 signals a normal distribution, value above 3 signals a peaked curve near the mean declining rather rapidly and having heavy tails. With kurtosis value below 3 the curve tend to have a flat top near the mean; value 0 suggest that the curve is horizontal.

around the mean. *Skewness* measures the symmetry of the curve: for perfect symmetric normal distribution, the skewness value is zero, the negative skewness indicates that the mean is inferior to the median, the asymmetric distribution will show a long left tail with the mass of the distribution concentrated on the right side of the figure. At these conditions the market activity is higher, because operators have positive expectation about price increase. The reverse RHS tail implies higher risk for operators and minor willingness for producers to enter the market. The commodities observed, show long right tail and leptokurtic distribution meaning that there is a lower frequency of values with positive small deviation and a higher risk of losses.

4.3. Price variability

Food price instability refers to variation over time in the price of food. To analyze price variation of the data sets, a rather intuitive approach is considered: the coefficient of variation, defined as follows:

$$CV = \sigma/\mu \qquad (6)$$

where σ is the standard deviation of the variable of interest over a given time period and μ is the mean value over that period.

It is a common measure to estimate price volatility of a given price series, which expresses a variability of the series as a ratio to its average value. This permits comparison across commodities with different average prices. A traditional measure of variability used in this calculation is the standard deviation of observed prices. This measure refers to *ex post* observations of actual prices. But it implicitly considers all price variability to be unexpected.

Clearly, some variability can be predicted (*e.g.* seasonal variation, business cycles, or other trending behavior) such that results from using the simple standard deviation may overstate the degree of volatility or uncertainty (for more discussion see Moledina *et al.*, 2004). Therefore, in order to have a better measure of the unpredictability or uncertainty faced by the market, it is common to take into account only movements of the series that cannot be predicted on the basis of its previous values.

Coefficient of variation, as defined in equation (6), is a useful measure because independent of the unit in which the measurement has been taken: it is a dimensionless number. The higher the coefficient of variation is, the larger the dispersion of series and greater the volatility.

Table 5. Coefficient of variation

	total sample	sub-samples		
	1999:w1-2012:w25	1999:w1-2004:w29	2004:w30-2008:w40	2008:w40-2012:w25
oil	0,460	0,229	0,247	0,287
cus	0,333	0,090	0,285	0,269
sus	0,272	0,151	0,263	0,151
wus	0,289	0,154	0,312	0,214
cit	0,241	0,127	0,254	0,255
sit	0,273	0,156	0,301	0,101
wit	0,260	0,106	0,313	0,254
# obs	699	289	220	190

Source: own elaboration

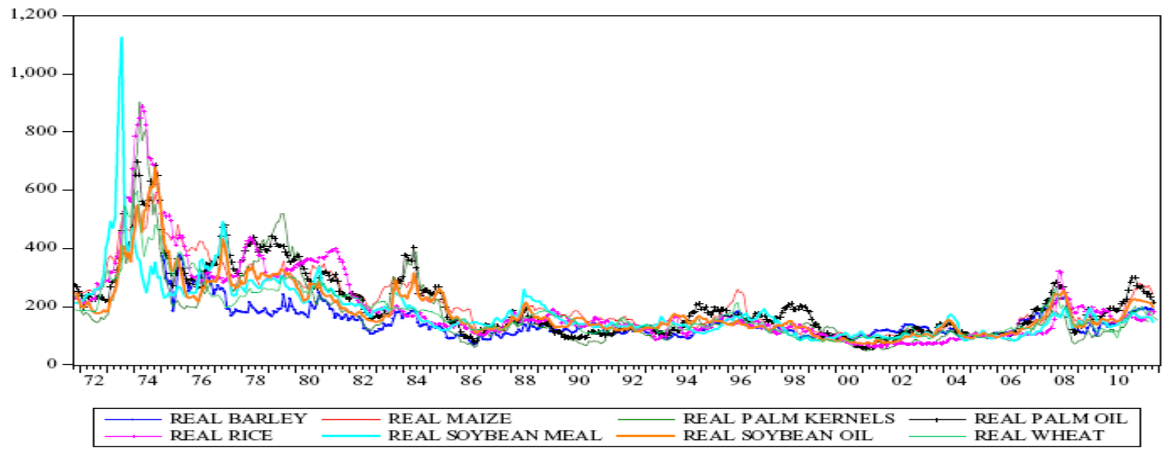
Table 5 reports the coefficient of variation for the whole period and the sub-periods as individuated by ZA one break test. Considering the total sample, January 1999 to May 2012, oil and US commodity markets generally experienced more volatility than Italian markets. Coefficient of variation increased both on the oil and agricultural commodity markets between 2004-2008 and 2008-2012, with the oil recording more dramatic increases. However, comparing the three sub-periods, dispersion of prices in 2004–08 measured by coefficient of variation is higher than the other two sub-period; note that 2004-08 time period includes price peaks, significantly shifting the means of the time series. In absolute terms the coefficient of variation remains higher on the US than on the IT markets during 2004-2008 and 2008-2012 for all products but wheat where the levels are comparable. During the last sub-period, however, comparing the agri-commodity prices, volatility of soybeans is relatively low.

4.4. Descriptive analysis of price correlation

This preliminary analysis is addressed to provide “ex ante“ information about price dynamics but doesn’t support any hypothesis about market integration or efficiency. The general presumption is that crude oil prices and agricultural product prices should be related through production costs for high energy intensive agriculture and more recently as a result of increasing use of agricultural feedstock (cereals, oilseeds and sugar crops) for biofuel production (Houchet-Bourdon, 2010).

The visual inspection of the historical price series (Figure 3) suggests a closer co-movement with moderate unvaried pattern, cyclical long run movements, non-linear trend components and random fluctuation in shorter period. Observing the long run, considerable wide fluctuations were observed in the periods 1973, 78, 84 corresponding to the oil shocks, followed by a relatively quiet period, A surge of volatility appears in the 2007-08 period due to turmoil in financial and energy markets transmitted to the agricultural markets followed, then, by decline and rising again in summer 2010 (Algieri, 2012).

Figure 2. Real commodity price indexes



Source: Algieri, 2012

Oil price patterns could have affected the efficiency of agricultural market in the last period (1999-2012) with substitution of price signals generated by market fundamentals (demand-supply-stock) with other reference signals (Headey and Fan, 2008; OECD, 2008). The integration among agricultural, energy and financial markets is the relevant topic to frame the policies to prevent the agri-commodity destabilization in the long term (Tyner and Taheripour, 2008).

The most familiar measure of correlation is the Pearson correlation coefficient (r) used to measure the linear relationship between two variables here represented by the prices of commodities X and Y. The coefficient r is the ratio between covariance and square root of product variance between X and Y, as follows (6):

$$r = \frac{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)\left(Y_i - \bar{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2} \cdot \sqrt{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2}} \tag{7}$$

The interpretation of the correlation coefficient beside all such criteria are in some ways arbitrary: the extreme values +/-1 indicate a perfect linear correlation (positive/negative) between the pairwise variables X and Y; values between 0 and 0.3 (0 and -0.3) indicate a weak positive (negative) linear relationship; values between 0.3 and 0.7 (0.3 and -0.7) indicate a moderate positive (negative) linear relationship; finally, values between 0.7 and 1.0 (-0.7 and -1.0) indicate a strong positive (negative) linear relationship.

The correlations between the oil price and each of the agricultural price series are computed over the whole sample and within the split samples (identified by the visual inspection) and results are reported in Table 6. The Pearson correlation values for the whole period of observation (Table 6 a) suggest the following considerations: the pairwise correlation coefficient between oil and most of the commodities is generally high (>.70), attesting the close co-movements among the prices. Some values deserve more attention: the lower values of correlation between oil and respectively the corn and wheat prices in Italy suggest that the agri-markets are not strictly influenced by the oil price movements, while the higher correlation between sus and sit suggests a stronger link, probably due to the high quantity of soybean imported by Italy and quoted in US market.

Table 6. Pearson correlation coefficients

	1999:w1-2012:w25 (a)							1999:w1-2004:w29 (b)						
	oil	cus	sus	wus	cit	sit	wit	oil	cus	sus	wus	cit	sit	wit
oil	1.00	0.80	0.77	0.74	0.68	0.80	0.66	1.00	0.39	0.43	0.39	-0.17	0.57	0.10
cus		1.00	0.89	0.79	0.77	0.80	0.78		1.00	0.50	0.75	-0.08	0.51	0.11
sus			1.00	0.79	0.76	0.93	0.75			1.00	0.50	0.53	0.87	0.46
wus				1.00	0.81	0.81	0.88				1.00	-0.03	0.58	0.10
cit					1.00	0.75	0.92					1.00	0.43	0.50
sit						1.00	0.76						1.00	0.47
wit							1.00							1.00
# obs							699							289
	2004:w39-2008:w40 (c)							200:w41-2012:w25 (d)						
	oil	cus	sus	wus	cit	sit	wit	oil	cus	sus	wus	cit	sit	wit
oil	1.00	0.79	0.83	0.56	0.71	0.81	0.64	1.00	0.84	0.79	0.74	0.81	0.72	0.78
cus		1.00	0.89	0.67	0.81	0.86	0.77		1.00	0.85	0.85	0.89	0.70	0.91
sus			1.00	0.76	0.84	0.96	0.81			1.00	0.83	0.84	0.90	0.84
wus				1.00	0.89	0.80	0.95				1.00	0.89	0.69	0.94
cit					1.00	0.87	0.97					1.00	0.75	0.93
sit						1.00	0.86						1.00	0.71
wit							1.00							1.00
# obs							220							190

Source: own elaboration

The correlation coefficients for sub-periods reported in sections b, c and d of Table 6, indicates that energy and agricultural prices co-movement are stronger in the more recent years with the signs as they were expected. The period 99-04, characterized by lower price volatility, presents a pairwise correlation (oil/agri-commodities) with lower values and negative in one case; Figure 1 helps to explain this result by showing a great oil price variability not followed by the same fluctuation of the agricultural prices. Examining correlations among the food prices, values are in general positive but lower, meaning a low co-movement except for the soybean market that confirms the previous observation.

A comparison across periods, indicates that energy and agricultural markets became more and more interconnected in the recent period of observation with positive correlation for all markets. Even considering the results between international and Italian agri-commodities, we can notice that starting from 2004 there is a strong positive linear correlation. Anyhow, higher (or lower) values of linear correlation coefficients do not necessarily imply existence (or not existence) of causal nexus between two variables

5. Econometric analysis results

Usually, checking for stationary condition of price series is the first test in any econometric analysis. In order to have robust estimation results, identification of the stationarity of the data has an utmost importance. Anyhow, in this thesis, it has already been done at the beginning of the data analysis to delineate the break point in order to divide the sample into sub-samples. From results of section 4.1., the time series under investigation are all integrated of first order so, I can continue with the cointegration and VEC analyses based on Johansen (1991, 1995) and Johansen and Juselius (1990) procedure.

5.1. Cointegration analysis

The increasing co-movements between oil and agri-commodity prices during the recent years suggest to consider the cointegration relationship among the variables under investigation.

Although some of the series we checked for unit roots were found to be stationary with a breaking trend, we conservatively run tests of cointegration for all possible couple of series.

We first run the conventional test of Johansen and then Gregory and Hansen (GH) test that accounts for a break in the cointegration relationship as described in section 3.

Table 7. Matrix of Cointegration Test: trace test results (1999:w1-2012:w25)

	cus	sus	wus	cit	sit	wit	oil	
r=0 r≤1	NA	18,87 4,61	27,79 6,03	26,60 7,24	12,74 4,56	23,93 7,44	15,36 3,83	**cus**
r=0 r≤1	18,87 4,61	NA	26,44 9,23	27,15 8,04	25,91 7,04	29,33 6,59	17,73 7,33	**sus**
r=0 r≤1	27,79 6,03	26,44 9,23	NA	30,74 5,54	32,52 10,36	42,17 6,13	21,16 6,69	**wus**
r=0 r≤1	26,60 7,24	27,15 8,04	30,74 5,54	NA	29,56 10,60	31,24 4,91	23,11 7,02	**cit**
r=0 r≤1	12,74 4,56	25,91 7,04	32,52 10,36	29,56 10,60	NA	28,69 7,44	16,38 7,68	**sit**
r=0 r≤1	23,93 7,44	29,33 6,59	42,17 6,13	31,24 4,91	28,69 7,44	NA	19,50 4,78	**wit**
r=0 r≤1	15,36 3,83	17,73 7,33	21,16 6,69	23,11 7,02	16,38 7,68	19,50 4,78	NA	**oil**

H_0 no cointegration. Red indicates rejection of Ho

Critical value			
	1%	5%	10%
r=0	31,15	25,87	23,34
r≤1	16,55	12,52	10,67

MacKinnon-Haug-Michelis (1999) critical values;

Table 7 reports the results of the cointegration test for all possible couple of series. The trace test indicates that all food prices are cointegrated in bivariate pairs with the exception of US and IT soybeans that have no cointegration with US corn. This support the idea that Italian markets are integrated with the US agri-markets and consequently the price changes in the two markets are quite interdependent. This hypothesis is supported by the Law of One Price

No agri-commodity prices are found to be cointegrated with Brent Blend price. We found very weak evidence for IT corn and oil and cannot reject the null of no cointegration at 10% level.

Again I run the test for the single sub-periods as highlighted by the structural break test.

Table 8. Matrix of Cointegration Test: trace test results (1999_w1-2004:w29)

	cus	sus	wus	cit	sit	wit	oil	
r=0	NA	26.10	30.80	21.47	17.32	17.24	21.37	**cus**
r≤1		8.73	9.70	8.12	6.97	4.97	7.84	
r=0	26.10	NA	25.95	34.33	39.44	34.24	30.75	**sus**
r≤1	8.73		7.82	8.85	6.88	6.60	8.95	
r=0	30.80	25.95	NA	20.40	15.48	17.60	18.89	**wus**
r≤1	9.70	7.82		7.43	6.21	6.79	7.67	
r=0	21.47	34.33	20.40	NA	18.18	23.18	22.44	**cit**
r≤1	8.12	8.85	7.43		7.83	5.89	11.02	
r=0	17.32	39.44	15.48	18.18	NA	17.75	24.10	**sit**
r≤1	6.97	6.88	6.21	7.83		5.59	5.63	
r=0	17.24	34.24	17.60	23.18	17.75	NA	17.03	**wit**
r≤1	4.97	6.60	6.79	5.89	5.59		6.59	
r=0	21.37	30.75	18.89	22.44	24.10	17.03	NA	**oil**
r≤1	7.84	8.95	7.67	11.02	5.63	6.59		

H_0 no cointegration. Red indicates rejection of Ho

Table 8 shows results of the cointegration test in the first sub-period among all the variables. The null hypothesis of no cointegration relation is rejected in few cases: there is a reduction of cointegration relationships among food prices. US soybeans is cointegrated with all the other agricultural commodities and with oil; besides, wheat and corn are cointegrated only in the US market. The Italian market doesn't experiment any cointegration relationship a part from soybeans cointegrated with the US corresponding commodity and with oil prices.

Table 9. Matrix of Cointegration Test: trace test results (2004:w30-2008:w40)

	cus	sus	wus	cit	sit	wit	oil	
r=0	NA	15.60	19.70	21.70	13.71	23.95	15.32	**cus**
r≤1		5.26	5.61	3.60	3.25	3.17	4.47	
r=0	15.60	NA	12.93	23.18	24.74	24.37	19.03	**sus**
r≤1	5.26		4.40	3.81	3.00	3.51	5.55	
r=0	19.70	12.93	NA	12.69	34.77	30.09	12.66	**wus**
r≤1	5.61	4.40		1.45	4.83	2.57	5.23	
r=0	21.70	23.18	12.69	NA	31.06	16.53	10.85	**cit**
r≤1	3.60	3.81	1.45		5.12	1.13	3.79	
r=0	13.71	24.74	34.77	31.06	NA	30.44	15.24	**sit**
r≤1	3.25	3.00	4.83	5.12		4.80	6.17	
r=0	23.95	24.37	30.09	16.53	30.44	NA	17.36	**wit**
r≤1	3.17	3.51	2.57	1.13	4.80		4.14	
r=0	15.32	19.03	12.66	10.85	15.24	17.36	NA	**oil**
r≤1	4.47	5.55	5.23	3.79	6.17	4.14		

H_0 no cointegration. Red indicates rejection of Ho

Next period (2004-2008) presents a different situation. Table 9 results show that there isn't cointegration between oil and food prices but Italian soybeans and wheat prices show a cointegration linkage with almost all the other agricultural prices.

In the last sub-period the situation is radically changed especially with regard to the relation to the linkage between oil and food prices. In this case the null hypothesis of no cointegration relation is rejected for all the combination of prices. This finding is in fact consistent with increasing importance of corn and soybeans as a consequence of the significant expansion of biofuels in the last years and the fact that wheat production process is becoming more and more energy intensive.

Table 10. Matrix of Cointegration Test: trace test results (2008:w41-2012:w25)

	cus	sus	wus	cit	sit	wit	oil	
r=0	NA	27.75	29.53	24.50	18.05	42.80	28.80	**cus**
r≤1		6.45	6.67	3.63	3.35	2.79	10.04	
r=0	27.75	NA	16.70	9.51	47.26	19.27	36.68	**sus**
r≤1	6.45		4.65	3.00	6.15	2.86	7.48	
r=0	29.53	16.70	NA	14.86	11.59	62.59	36.22	**wus**
r≤1	6.67	4.65		3.24	5.37	3.12	6.88	
r=0	24.50	9.51	14.86	NA	9.20	13.35	20.46	**cit**
r≤1	3.63	3.00	3.24		2.84	2.43	3.37	
r=0	18.05	47.26	11.59	9.20	NA	9.62	32.39	**sit**
r≤1	3.35	6.15	5.37	2.84		3.86	3.23	
r=0	42.80	19.27	62.59	13.35	9.62	NA	35.91	**wit**
r≤1	2.79	2.86	3.12	2.43	3.86		1.38	
r=0	28.80	36.68	36.22	32.39	32.39	35.91	NA	**oil**
r≤1	10.04	7.48	6.88	3.23	3.23	1.38		

H_0 no cointegration. Red indicates rejection of Ho

Quite similar results are reported in literature. Campiche *et al.* (2007) examine the co-movements between world crude oil prices and corn, sorghum, sugar, soybeans, soybean oil, and palm oil prices during the period 2003–2007 based on weekly data. The empirical analysis with the Johansen cointegration test shows that while there is no cointegrating relation among the variables in concern for the period 2003–2005, corn and soybean prices are cointegrated with crude oil prices during the period 2006–2007. Harri *et al.* (2009) report a consistent cointegrating relationship between crude oil and corn, soybeans starting in April 2006. Nazlioglu (2011) considers the cointegration between oil and the three key agri-commodity prices (corn, soybeans and wheat) and reports that corn and soybeans are cointegrated with the oil prices during the period 2008-2010. If our results differ from those found in literature is mostly because samples length is different.

To be sure to give a good interpretation of the results from Johansen's testing framework, since the structural break dates were determined *a priori* instead of finding them endogenously in the cointegration model, the relationship between brent and agri-commodity prices is also analyzed by running the Gregory-Hansen test with structural break.

Table 11. Cointegration test with structural break[12] between US agri commodities and oil

		cus-oil	sus-oil	wus-oil
ADF*	C	-3.45	-4.21	-4.23
	C/T	-3.84	-5.38** (2004: w34)	-4.26
	C/S	-4.06	-4.94* (2008: w10)	-4.65
Z_t*	C	-4.69** (2010: w19)	-4.44* (2007: w39)	-3.81
	C/T	-5.52*** (2004: w22)	-5.72*** (2004: w33)	-3.85
	C/S	-5.72*** (2004: w37)	-5.20** (2007: w39)	-4.03
Z_α*	C	-42.20** (2010: w19)	-40.26** (2007: w39)	-28.61
	C/T	-56.96** (2004: w22)	-61.15*** (2004: w33)	-28.91
	C/S	-62.39*** (2004: w37)	-52.52** (2007: w39)	-31.49

***/**/* denote statistical significance at 1%, 5% and 10% level of significance, respectively. Break dates in brackets

Table 11 reports results of cointegration of the Gregory Hansen test between oil and US agri-commodity prices. As far as brent and cus price relation is concerned, ADF* fails to reject the null hypothesis of no cointegration with model C, C/T and C/S whereas Z_t^* and Z_α^* type test results indicate the rejection of the null for all the three models; the significant breaking periods are in May and September 2004 (week 22 and 37) and May 2010 (week 19).

In the case of soybeans and brent, all these three tests do not reject the null hypothesis of cointegration presenting a structural break in August 2004 (week 33);

[12] Model C: Level shift, Model C/T: level shift with trend, Model C/S: Regime shift. Null hypothesis: no cointegration. For ADF* and Z_t* tests, critical values in Model C are: -5.13 at 1%, -4.61 at 5% and -4.34 at 10%; in Model C/T:-5.45 at 1%, -4.99 at 5% and -4.72 at 10%; in Model C/S: -5.47 at 1%, -4.95 at 5% and -4.68 at 10%. Critical values for Z_α* test are -50.07, 40.48, -36.19 respectively at 1, 5 and 10% in Model C; -57.28, -47.96 and –43.22 at 1, 5 and 10% in Model C/T; -57.17, -47.04 and -41.85 at 1, 5 and 10% in Model C/S. The optimal lag length for ADF* test was selected by Akaike information criterion (Akaike, 1974, 1987).

besides, Z_t^* and Z_α^* fail to reject the null in the regime shift model with a break in July 2007 (week 39).

For the long run relationship between wheat and brent prices, the tests do not support evidence on the existence of a cointegration relationship. In general, a possible explanation is the wheat prices were heavily influenced by weather events, that were reflected in the expectation about the stock levels overcoming the effect of the input prices more related to oil prices; in any case the results of Table 10 are not contrasting these last findings as they were related to a shorter period.

Table 12. Cointegration test with structural break between IT agri commodities and oil

		cit-oil	sit-oil	wit-oil
ADF*	C	-3.77	-4.11	-3.75
	C/T	-4.01	-4.13	-3.84
	C/S	-4.27	-4.20	-4.27
Z_t^*	C	-3.58	-3.69	-3.36
	C/T	-3.58	-3.71	-3.33
	C/S	-3.73	-3.84	-3.59
Z_α^*	C	-24.72	-27.95	-21.93
	C/T	-24.63	-28.21	-22.15
	C/S	-28.14	-29.42	-25.67

In table 12, the results of the Gregory Hansen tests do not support the evidence of cointegration among the brent and the Italian commodity prices confirming the result obtained with the Johansen test. This result is coherent with our hypothesis of market integration that give priority to the US market signals.

Table 13. Cointegration test with structural break between It and US agri commodities

		cit-cus	sit-sus	wit-wus
ADF*	C	-3.89	-4.83** (2010: w19)	-5.29** (2001: w34)
	C/T	-4.21	-4.96* (2010: w19)	-5.26** (2001: w14)
	C/S	-4.43	-6.11*** (2008: w29)	-5.56*** (2004: w28)
Z_t^*	C	-4.81** (2008: w31)	-7.11*** (2010: w19)	-5.70*** (2001: w19)
	C/T	-5.10** (2003: w27)	-7.04*** (2010: w19)	-5.71*** (2001: w19)
	C/S	-4.86** (2008: w26)	-7.63*** (2010: w19)	-5.98*** (2004: w29)
Z_α^*	C	-45.21** (2008: w31)	-90.15*** (2010: w19)	-61.46*** (2001: w19)
	C/T	-50.52** (2003: w27)	-88.94*** (2010: w19)	-61.49*** (2001: w19)
	C/S	-46.00* (2008: w26)	-103.52*** (2010: w19)	-67.48*** (2004: w29)

***/**/* denote statistical significance at 1%, 5% and 10% level of significance, respectively. Break dates in brackets

The test statistics reported in table 13 confirm the existence of cointegration between the Italian and the US agri-commodity markets; it appears to be more robust for wheat and soybeans. These results confirmed those obtained by running the cointegration test without structural breaks; anyway, in the case of corn, the evidence of cointegration is supported by Z_t^* and Z_α^* tests.

5.2. Price transmission

After dealing with price cointegration, I focused my attention on price transmission between Italian food prices (considered domestic) and US prices that can represent the world prices. Research on price transmission has been motivated largely by the belief that co-movement of prices in different markets can be interpreted as a sign of efficient, competitive markets, while lack of co-movement is an indication of market failures, including lack of information, poor infrastructure, or uncompetitive markets. Early studies of price transmission used simple correlation coefficients of contemporaneous prices. A high correlation coefficient is evidence of co-movement and was often interpreted as a sign of an efficient market. Another early approach was to use regression analysis on contemporaneous prices, with the regression coefficient being a measure of the co-movement of prices. For example, Mundlak and Larson (1992) estimated the transmission of world food prices to domestic prices in 58 countries using annual price data from the FAO. They found very high rates of price transmission. Following the price transmission testing framework suggested by Rapsomanikis *et al.* (2006) and the model proposed by Minot (2011), I carried out an econometric test of the impact of US food prices on Italian food prices. The Minot model makes a series of rather stringent assumptions, i.e. homogeneous cereal products, competition among numerous small traders, perfect information, no trade taxes or other policy barriers to trade, and no transportation and transaction costs. In the above mentioned analysis,

I considered the vector error correction model (VECM) which assumes that the domestic food price is affected by the world price and examined three relationships: one for corn, one for soybeans and one for wheat. The VECM is appropriate if two conditions are met:

- Each variable is nonstationary and integrated to degree 1, written as $I(1)$. This means that the variable follows a random walk, but the first difference (X_t - X_{t-1}) is stationary, written as $I(0)$.
- The variables are cointegrated, meaning that there is a linear combination of the variables that is stationary. As two prices at a time are analyzed, the cointegrating equation would take the form of:

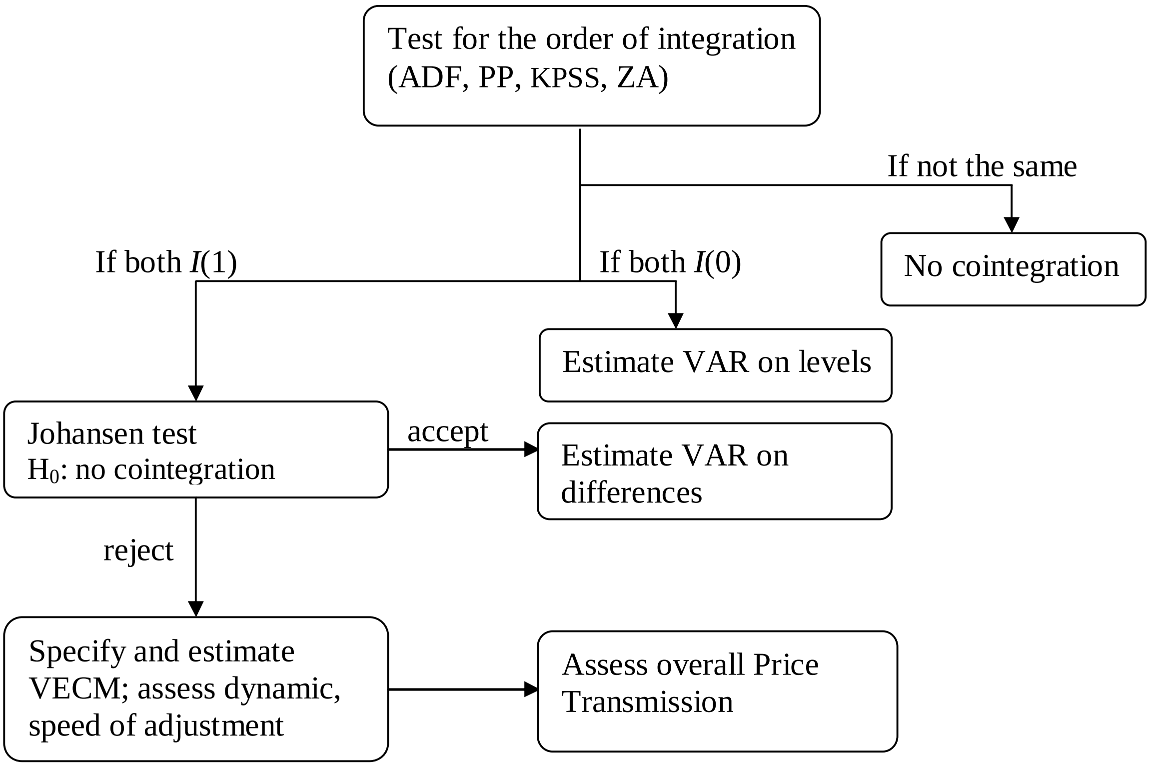
$$P_1 = \alpha + \beta P_2 + \varepsilon \qquad (7)$$

where the error term ε is stationary and the equation is comparable to eq (2) of the previous section.

For each pair of domestic and international prices, the analysis consists of more steps (partially investigated previously) outlined in Figure 1.

The first one is to determine whether the individual variables are nonstationary or *I*(1). If the prices are not both *I*(1), they cannot be cointegrated. If they are both stationary or *I*(0) they can be studied with the vector autoregressive (VAR) model that is a general framework used to describe the dynamic interrelationship among stationary variables. If the series are both *I*(1), the null hypothesis that they are not cointegrated is tested using cointegration test (in our case the Johansen procedure). Finally, if the Johansen test indicates that there is a long-run relationship between the two variables, the vector error correction model (VECM) can be estimated. If the results of the test indicate that there is not cointegration between the two variables, then they can be studied with a VAR on differences.

Figure 3. Basic empirical strategy for estimating price transmission



Source: Own elaboration based on Rapsomanikis et al. (2006)

The VECM tests for the effect of each variable on each other variable. In the context of this study, the two-variable VECM tests the effect of world prices on domestic prices as well as the effect of domestic prices on world prices. Since Italy may be considered "small country" in the staple foodcrop markets, there is little value in testing the effect of domestic prices on world prices. In addition, tests indicate that one lagged term is generally sufficient. For our purposes, then, we are interested in only one portion of the VECM. This portion can be simplified as follows:

$$\Delta p_t^d = \alpha + \theta\left(p_{t-1}^d - \beta p_{t-1}^w\right) + \delta \Delta p_{t-1}^w + \rho \Delta p_{t-1}^d + \varepsilon_t \quad (8)$$

where p_t^d is the natural logarithm of the Italian (domestic) price of corn, soybeans and wheat respectively, p_t^w is the natural logarithm of the US (world) price of the same Italian commodities, $\alpha, \theta, \beta, \delta$, and ρ are parameters to be estimated and ε_t is the error term.

In equation (8) the term in parenthesis (p^d_{t-1}- β p^w_{t-1}) represents the long term transmission of international prices on Italian prices. The following two terms measure the short term impact of the lagged increments (Δ) of the natural logarithm of international and domestic prices. As β is unknown we first develop the equation (7), then estimate relation (8).

The coefficients in the error correction model can be interpreted as follows:

- The cointegration factor (β) describes how one price reacts to changes in the other in the long run[13]. The expected value for imported commodities is $0 < \beta < 1$, but for exports, it may be greater than 1. Thus, if $\beta = 0.5$, this implies that 50% of the proportional change in the international price will be transmitted to the domestic price in the long run (Minot, 2011).
- The error correction coefficient (θ) reflects the speed of adjustment. We expect it to fall in the range of $-1 < \theta < 0$. If the lagged error correction term (the term in parentheses) is positive (the domestic price is too high given the long-term relationship), then the negative value of θ "corrects" the error by making it more likely that the Δp_t^d is negative. The larger θ is in absolute value (that is, the closer to -1), the more quickly the domestic price (p^d) will return to the value consistent with its long-run relationship to the world price (p^w).
- The coefficient on change in the world price (δ) is the short-run elasticity of the Italian price relative to the US price. In this case, it represents the percentage

[13] Since prices are expressed in logarithms, β can be interpreted as the long-run elasticity of the domestic price with respect to the international price; it is the long-run elasticity of price transmission.

adjustment of domestic price one period after a one percent shock in international price. The expected value is $0 < \delta < \beta$.

- The coefficient on the lagged change in the domestic price (ρ) is the autoregressive term, reflecting the effect of each change in the Italian price on the change in the same price during the next period. The expected value is $-1 < \rho < 1$.

Table 14 provides a summary of the results for the transmission of US prices to Italian ones. The unit root tests [results in section 4.1.] indicate all that domestic prices are not stationary. This result enables us to proceed with the Johansen cointegration test to see if there is a long-run relationship between each Italian price and the corresponding international price [results in section 5.1.]. The cointegration test indicates that all the local prices have a long-run relationship with international corresponding prices.

The long-run elasticity of price transmission is statistically significant and high for all the commodities especially for soybeans (0.96) and wheat (0.74) meaning that a high percentage of the proportional change in the US price is transmitted to the Italian price in the long run.

The speed of adjustment coefficient (θ) is negative as expected for sit and wit and also statistically significant at 1% level. Corn has got a slightly positive θ.

The coefficient of short run adjustment (δ) is in the expected range but it hasn't got significance for all the pair of commodities.

The auto-regressive term is statistically significant for all the variables and is higher for corn.

Table 14. Transmission of US food prices (world) to Italian food prices (domestic)

	Unit root in Italian prices?	Long run relationship?	Error correction model			
Commodity	ADF PP KPSS ZA	Johansen test	Long run adjustment β	Speed of adjustment θ	Short-run adjustment δ	Auto-regressive term ρ
cit	yes	yes	0.569*	0.002	0.015	0.416*
sit	yes	yes	0.963*	-0.038*	0.013	0.202*
wit	yes	yes	0.738*	-0.017*	0.026	0.296*

* statistically significant at 1% level

Summarizing the result obtained from the transmission model we can say that the long run relationship prevails on the short run transmission for all the commodities in terms of value and significance. An important role takes also the autoregressive term meaning that approximately 42% of the change of the Italian corn price will be transmitted to the domestic price of the commodity in the subsequent period (20% for soybeans and almost 30% for wheat). Italian soybeans and soft wheat seem more connected to the international market than corn in the long run due to the high quantity of import[14].

The following steps will be performed for testing the existence and direction of causality with the Granger causality test and the speed of adjustment providing evidence of the price influence using the Vector auroregressive (VAR).

5.3. Granger causality

5.3.1. Linear approach

After having demonstrated the existence of cointegration, the next step consists to infer into causality using the vector autoregressive VAR to know how prices are spatially transmitted along the markets. For this reason the linear causality tests is performed over the entire sample period, as well as on sample subperiods, to analyze whether the dynamic relationships between oil and ag-commodities prices are changed through time.

Table 15 reports the results of the Granger causality-test using the Durbin Watson diagnostic test (1950, 1951, 1971) to detect the presence of autocorrelation in the residuals from the regression analysis. The residuals of most of the estimated model confirm that they are free from autocorrelation (except the models obtained from the regression between oil and Italian agri commodities whose DW statistic results are substantially less than 2, with clear evidence of positive serial correlation).

The Ramsey Regression Equation Specification Error Test (RESET test; Ramsey, 1969), a general specification test for the linear regression model, clearly shows that the functional forms for the models are appropriately specified (with some exception in the comparison between oil and Italian commodities). Results about the linear Granger causality are reported in the following table.

[14] During the 2009-10 commercial campaign, Italy imported 60% of soft wheat, 87% of soybeans and 20% of maize (Associazione Nazionale Cerealisti, 2011)

Table 15. Linear Granger causality test

Upper section	1999w1-2012w21		1999w1-2004w29		2004w30-2008w40		2008w41-2012w21	
	F-test	Probability	F-test	Probability	F-test	Probability	F-test	Probability
oil →cus	0.71	0.55	1.76	0.18	2.65*	0.07	0.25	0.61
cus →oil	0.92	0.43	1.05	0.35	0.35	0.71	1.01	0.32
Durbin-Watson	2.22		2.15		2.11		2.28	
RESET test	0.08	0.78	1.47	0.23	1.13	0.29	0.12	0.73
oil →sus	0.18	0.67	1.24	0.27	0.69	0.50	3.42**	0.03
sus →oil	0.38	0.53	0.83	0.36	0.17	0.84	1.46	0.23
Durbin-Watson	2.27		2.54		1.88		2.25	
RESET test	0.24	0.63	0.00	0.97	0.99	0.32	0.00	0.99
oil →wus	1.45	0.23	0.77	0.38	0.08	0.78	5.03***	0.01
wus →oil	0.77	0.38	1.29	0.26	0.61	0.44	0.51	0.60
Durbin-Watson	2.14		2.04		1.97		2.12	
RESET test	0.90	0.34	0.80	0.37	0.09	0.76	0.50	0.48

Mid section	1999w1-2012w21		1999w1-2004w29		2004w30-2008w40		2008w41-2012w21	
	F-test	Probability	F-test	Probability	F-test	Probability	F-test	Probability
oil →cit	2.08	0.15	0.17	0.68	0.00	0.97	0.24	0.79
cit →oil	0.34	0.56	1.71	0.19	1.19	0.28	0.07	0.93
Durbin-Watson	1.14		1.43		1.32		1.07	
RESET test	4.50	0.03	0.66	0.42	0.22	0.64	2.00	0.16
oil →sit	2.13	0.14	0.14	0.71	0.01	0.93	0.64	0.53
sit →oil	1.15	0.28	0.66	0.42	0.08	0.77	1.02	0.36
Durbin-Watson	1.61		1.43		1.67		1.75	
RESET test	11.15	0.00	0.30	0.59	0.48	0.49	3.11	0.08
oil →wit	0.45	0.64	0.32	0.57	2.36	0.13	0.83	0.43
wit →oil	0.02	0.98	0.03	0.86	1.61	0.21	1.19	0.31
Durbin-Watson	1.33		1.54		1.19		1.57	
RESET test	2.57	0.11	1.25	0.27	0.21	0.66	3.05	0.08

Lower section	1999w1-2012w21		1999w1-2004w29		2004w30-2008w40		2008w41-2012w21	
	F-test	Probability	F-test	Probability	F-test	Probability	F-test	Probability
cus → cit	2.36**	0.04	0.88	0.45	3.72**	0.03	1.77*	0.07
cit → cus	0.56	0.72	1.10	0.35	0.64	0.53	0.55	0.85
Durbin-Watson	1.14		1.40		2.08		2.34	
RESET test	0.01	0.92	0.89	0.45	2.51	0.12	1.01	0.32
sus →sit	4.49***	0.00	4.82**	0.03	14.89***	0.00	16.54***	0.00
sit →sus	0.19	0.31	3.34*	0.07	0.83	0.44	1.99	0.14
Durbin-Watson	1.76		1.46		1.90		2.01	
RESET test	0.30	0.58	0.52	0.47	0.14	0.71	0.71	0.67
wus → wit	14.10***	0.00	0.44	0.51	4.61***	0.00	7.44***	0.01
wit →wus	8.64***	0.00	0.01	0.93	1.86	0.12	1.68	0.20
Durbin-Watson	1.42		1.52		1.35		1.62	
RESET test	1.92	0.17	0.05	0.82	2.41	0.12	0.01	0.92

→ means non Granger causality hypothesis; ***/**/* denote statistical significance at 1%, 5% and 10% level, respectively. The optimal lag length was selected by Schwarz information criterion.

In the upper section of the table 15, values of F-statistic are reported at different probability levels for the null hypothesis of no causality between brent and the US agricultural prices (and *vice versa*). Results suggest the absence of causality from the oil prices to the agricultural prices, and the neutrality hypothesis in the entire period of observation; for the sub-samples analysis, these results are consistent with those found by Nazlioglu (2011).

The middle section reports the results for the Granger Causality analysis between oil and the Italian commodities. In general it is observed the absence of linear Granger causality between oil and agri-commodity prices consistent with Zhang and Reed (2008) findings for local agri-commodities.

The lower section of the table reports the interaction between US and Italy markets: there is evidence of linear Granger causality with direction from US to Italy except for wheat where there is feedback. In all three cases the US ag-commodities do Granger-cause the Italian prices for the entire sample period and sub-samples.

5.3.2. Non linear approach

The test is carried out in two steps: first it is applied to stationary series, and then, and second is applied to the estimated residual series to remove any linear dependence, using the VAR model applied to the pairwise variables of interest. “By removing linear predictive power with a linear VAR model, any remaining incremental predictive power of one residual series for another, can be assumed as non linear predictive power” (Hiemstra and Jones, 1994).

The tests are performed for different lag values depending on the length of the sample, and the data are normalized to unit variance before running the test; the bandwidth value that plays an important role on the detection of non linear causality, is set to 1, as it is one time the standard deviation (Dicks and Panchenko, 2006). Because nonparametric tests rely on asymptotic theory, causality tests on sample subperiods are not performed in this case. Table 16 reports the t values for Diks and Panchenko’s test statistic applied to the variables and to residuals in both directions and for different lag lengths (1–2 lags) to give evidence of non linear Granger causality.

Table 16. Nonlinear Granger causality (Diks –Panchenko test)

		Raw data		Residuals	
	lags	**1**	**2**	**1**	**2**
oil-us_commodities	brent →corn_us	2.019**	2.788**	1.434*	2.282**
	corn_us →brent	0.210	0.812	0.450	0.144
	brent →soybeans_us	1.686**	1.826**	1.570*	1.796**
	soybeans_us →brent	0.395	0.172	0.311	0.250
	brent →wheat_us	1.290*	1.282*	0.968	1.329*
	wheat_us →brent	1.969**	1.829**	2.140**	2.135**
oil-it_commodities	brent →corn_it	1.491 *	0.844	1.133	1.238
	corn_it →brent	0.765	0.435	0.674	0.732
	brent→soybeans_it	0.546	0.633	1.702 **	1.166
	soybeans_it →brent	0.446	1.670 **	0.360	1.284 *
	brent →wheat_it	2.627 ***	2.473 ***	1.133	1.238
	wheat_it →brent	1.061	1.724 **	0.674	0.732
us-it commodities	corn_us →corn_it	3.574 ***	3.596 ***	3.585 ***	3.578 ***
	corn_it →corn_us	2.682 ***	2.716 ***	3.076 ***	3.079 ***
	sus →sit	2.704 ***	2.697 ***	3.081 ***	3.065 ***
	soybeans_it →soybeans_us	2.011 **	1.983 **	1.746 **	1.732 **
	wheat_us →wheat_it	2.547 ***	2.537***	2.252 **	2.221 **
	wheat_it →wheat_us	1.613 *	1.596 *	2.236 **	2.202 **

→ means non Granger causality hypothesys. ***/**/* denote statistical significance at 1%, 5% and 10% levels of significance, respectively.

Looking at the first part of the table, there is evidence of unidirectional causality going from **oil to corn** and **soybean** for raw data, at one and two lags, confirmed after filtering the series with VAR model and testing the residuals. This condition persist in the long period. The economic meaning is that the oil price volatility is transmitted to corn and soybean commodity prices and these findings confirm those obtained by Nazlioglu (2011). Until early 2007, corn prices were not affected by crude oil prices; since then, corn prices have been growingly responsive to changes in crude oil prices; the main justification is the growing amount of US corn used for fuel ethanol now around 40% of corn is used for biofuel production. With rapid growth of the ethanol industry in the last few years, corn has become very much an energy crop as well as the world's most important source of feed grains for production of livestock, poultry, and dairy products

The causality between **oil and wheat**, tested with raw data shows a weak statistical evidence of causality going from oil to wheat and stronger evidence for the reverse direction. Further investigation with the VAR residuals confirm these results at lag one and two. These findings emphasize the market differences between wheat and the other two commodities by giving evidence of less dependence of this cereal from the oil market probably justified by the prevailing use in the food industry. Apart from oil influence, there are other exogenous factors determining the price volatility of wheat. The weather is the most important factor of influence on the supply situation for agricultural products. Weather uncertainty as long periods of droughtness, becoming more frequent in last years could have great impacts on supplies and prices, as well as extremely wet periods, and wide range of temperature fluctuations.

The second section of table 16 reports the results for the nonlinear causality analysis between *brent* and the *Italian commodities*. In general there is no linkage between brent and agri-commodity prices. In the case of corn_it and wheat_it, the non parametric results after removing the linear dependence support the neutrality hypothesis; with respect to the non linear causal linkages between brent and soybeans_it prices, results denote a fluctuating relationship.

Finally, last section of the table suggests the non linear causality between the US and the Italian commodity prices. Raw data provide a feed-back evidence in the relationship between the variables prices and the same findings are presented after filtering the series. Such misleading results could be explained with the fact that there is a one way strictly *linear causality* among the examined variables (see Table 15), whereas a unidirectional non linear causality from the American to the Italian commodity prices does not appear.

5.4. Vector Autoregression model

As presented in Table 7 there are no cointegrating vectors for oil and agricultural commodities. On account of the absence of cointegration, we can perform a VAR model in first differences (see Figure 3) estimating a system of equations that captures the inter-relationships among variables and describes the evolution of a set of k variables (called endogenous variables) over the same sample period (t = 1, ..., T) as a linear function of only their past evolution. All the variables in a VAR are treated symmetrically by including for each variable an equation explaining its evolution based on its own lags and the lags of all the other variables in the model. Based on this feature, Christopher Sims (1980) advocates the use of VAR models as a method to estimate economic relationships.

In our study, the VAR model is built to highlight the following trivariate relationship:

$z = (P_{us}, P_{it}, P_o)$ where z is the endogenous variable, P_{us} is the price of US commodities (corn, soybeans and wheat), P_{it} is the corresponding prices of the Italian commodities and P_o is the price of oil.

Let $Y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})$ indicate an (n×1) vector of time series variables. The basic p-lag vector autoregressive model has the form:

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_p Y_{t-p} + \varepsilon_t,$$

where c represents a vector of constant terms, Π_i for i = 1...p are (n×n) coefficient matrices and ε_t is a vector of error.

In our case, the trivariate VAR(3) model equation has the following form:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} + \begin{pmatrix} \pi_{11}^1 & \pi_{12}^1 & \pi_{13}^1 \\ \pi_{21}^1 & \pi_{22}^1 & \pi_{23}^1 \\ \pi_{31}^1 & \pi_{32}^1 & \pi_{33}^1 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{pmatrix} + \begin{pmatrix} \pi_{11}^2 & \pi_{12}^2 & \pi_{13}^2 \\ \pi_{21}^2 & \pi_{22}^2 & \pi_{23}^2 \\ \pi_{31}^2 & \pi_{32}^2 & \pi_{33}^2 \end{pmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \\ y_{3t-2} \end{pmatrix} + \begin{pmatrix} \pi_{11}^3 & \pi_{12}^3 & \pi_{13}^3 \\ \pi_{21}^3 & \pi_{22}^3 & \pi_{23}^3 \\ \pi_{31}^3 & \pi_{32}^3 & \pi_{33}^3 \end{pmatrix} \begin{pmatrix} y_{1t-3} \\ y_{2t-3} \\ y_{3t-3} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix}$$

Significant estimates in the Π matrix indicates strong interrelationships among the three variables.

Once the model has been chosen, the Schwartz Info Criterion (SIC) test is used to choose the optimal lag of the model. The specification that minimizes the information criteria gives the optimal selection of lags: the smaller the values are the better the model performance is. The SIC test, suggests to select one lag. The Vector Autoregression model results are shown in the following tables. Numbers in parentheses [ ] represent the t-statistics and in ( ) are standard errors. They tell whether there is a significant relationship between the respective variables.

Assuming a 5% critical value interval, and considering a sample size larger than 200 observations, the t-critical values are +1.96 and -1.96. Tables below reports the coefficient estimates for the main variables. These coefficients suggest the positive or negative link of the coupled variables, and the size of the change. In Table 17 the relationship between corn (US and Italian) and oil prices is considered.

Table 17. VAR corn_oil

Sample (adjusted): 1999:w3-2012:w21
Included observations: 697 after adjustments

	d_cit	d_cus	d_oil
d_cit(-1)	0.433	0.101	-0.007
	(0.034)	(0.065)	(0.016)
	[12.59]	[1.1554]	[-0.479]
d_cus (-1)	0.146	-0.124	-0.010
	(0.071)	(0.038)	(0.009)
	[2.063]	[-3.224]	[-1.039]
d_oil (-1)	0.101	0.004	0.215
	(0.080)	(0.152)	(0.038)
	[1.263]	[0.027]	[5.636]

The only significant relationships it has been found is between the U.S. corn price (-1) and the IT corn price, whose value 0.146 implies that if the U.S. corn price in period t-1 goes up by one unit, the IT corn price in period t would move up by 0.146. In other words, the two corn prices are positively linked, as it was expected considering the other evidences of the research and confirming the condition of market efficiency (LOP). The US corn market (global) leads the Italian one (local).

For soybeans, our findings support a strong relationship between sus and sit; oil does not appear to influence the prices of the agricultural commodities.

Results of the VAR model are reported in the table below. Similarly to the relationship between cus price and cit price, the model suggests that the US soybean price in period t-1 and the IT soybean price in period t are positively linked. If sus prices increase by one unit in period t-1, sit prices are expected to increase by 0.174 in period t. the model suggests also a reverse relationships between sus and sit. It seems that also the increment of one unit in the price of sit in the period t-1 will shift sus up.

Table 18. VAR soybeans_oil

Sample (adjusted): 1999:w3-2012:w21
Included observations: 697 after adjustments

	d_sit	d_sus	d_oil
d_sit(-1)	0.140	0.170	0.009
	(0.037)	(0.067)	(0.009)
	[3.787]	[2.534]	[0.960]
d_sus (-1)	0.174	-0.187	0.002
	(0.022)	(0.067)	(0.005)
	[8.062]	[-4.867]	[0.396]
d_oil (-1)	0.017	-0.217	0.193
	(0.143)	(0.260)	(0.038)
	[0120]	[-0.834]	[5.018]

In Table 18, results of the VAR model showing the trivariate relationship between US_wheat, IT_wheat and oil are reported. As expected there is a significant positive influence of wus on the Italian corresponding commodity. According to the findings, when US wheat price goes up by one unit in this period, the IT wheat prices increase in the next period by 0.073; besides, an increase in the Italian price shift US wheat price up.

Table 19. VAR wheat_oil

Sample (adjusted): 1999:w3-2012:w21
Included observations: 697 after adjustments

	d_wit	d_wus	d_oil
d_wit(-1)	0.319	0.249	0.0001
	(0.036)	(0.068)	(0.017)
	[8.851]	[3.640]	[0.010]
d_wus(-1)	0.073	-0.110	-0.008
	(0.020)	(0.039)	(0.009)
	[3.540]	[-2.811]	[-0.868]
d_oil(-1)	-0.131	-0.209	0.211
	(0.082)	(0.156)	(0.038)
	[-1.602]	[-1.341]	[5.563]

Finally, in the all three models, it was found that each variable in this period is affected by its own value in the past period (lag 1). In other words, the corn price today is affected by the corn price one week before in both markets.

Similarly, the soybean price one week later affects the soybean price today either in the US than for the Italian case, the wheat price yesterday affects wheat price today as well as the oil price in period t-1 affects the oil price in period t. These findings are commonly observed in many time-series data where the past behavior of a variable influences its future behavior.

5.4.1. Impulse Response Function

After analyzing the VAR models, the Impulse Response Functions is computed from the coefficients of vector regression in order to show how a shock in one variable would persist in future periods. Generally, an impulse response refers to the reaction of any dynamic system in response to some external change and traces the effect of one standard deviation shock to one of the innovations on current and future values of each of the endogenous variables in the system[15]. The forecast is made

[15] For details in the methodology refer to Lin (2006)

considering a ten-week period and the shock corresponds to one standard deviation innovation.

As illustrated in Figure 4, impulse response curves for oil price short run effects on corn prices indicate a rapid increasing in the corn both for the US and the Italian price with different lags. After a sudden increase in oil prices, both US and Italian corn prices will increase. Corn price then starts decreasing to the starting point within a seven/eight-week period, which proves to be a temporary response. This response of the corn price can be easily explained by the strong linkage between oil and biofuel, and between biofuel and corn. A positive oil shock should trigger an increase in the demand for ethanol which should translate into an higher demand for corn with the resulting higher corn prices. As the price of oil raises, there is a higher demand of biofuel that determines a sudden increase in the maize price. Even a sudden increase in the US corn price would affect the behavior of the corresponding Italian commodity. Corn prices are positively linked each other and this result supports the condition of market efficiency (LOP). The global market leads the local one by imposing its own price.

The other cases are as one can expect: Italian corn price doesn't affect the US one and a rising in both maize price levels do not change positively the oil price.

Figure 4. Impulse Responses of cit, cus and oil

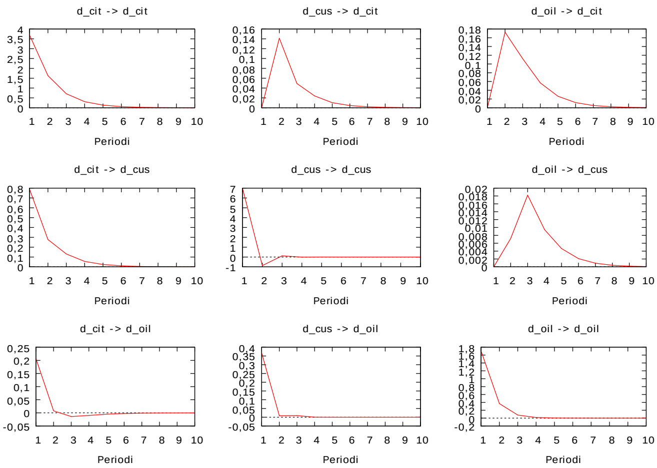
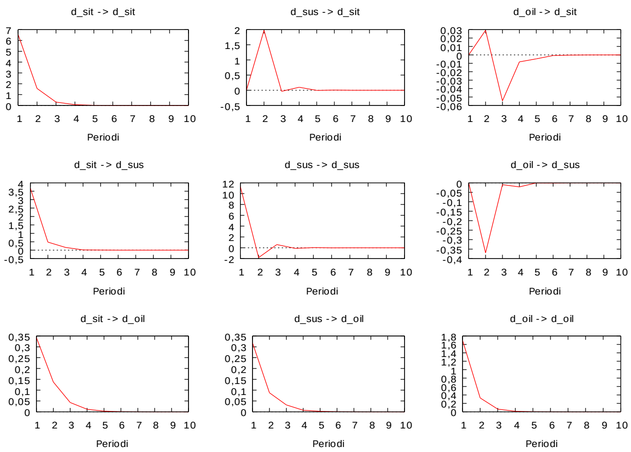


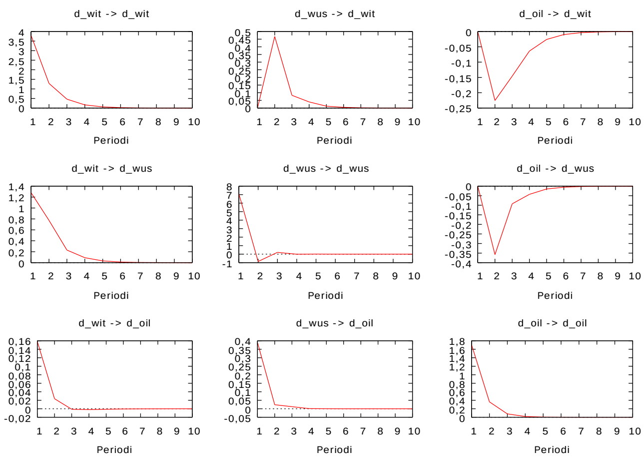
Figure 5 shows that after a positive shock (increase) of one S.D. in world oil prices, US soybean prices seem to drop to a lower level. However, this will be also a temporary response. After a two-week period, sus prices start to increase again, and it eventually goes back to its initial point. The explanation here is again linked to the biofuel sector: when oil prices increase, the U.S. corn demand is likely to increase with resulting of higher corn prices. This leads to a decrease in soybeans prices. As farmers would be profiting more with corn production than with soybean production. A decrease in soybean production would lead to a decrease in soybean prices. Anyway, the effect of oil prices on US soybeans die out in less than five weeks. The reaction of Italian soybean prices to sudden change of oil prices is an initial increase of that quickly wanes and to become comparable to the US soybeans reaction.

Figure 5. Impulse Responses of sit, sus and oil



A similar response is found for wheat, as Figure 6 illustrates. Anyway, in this case , within the sixth and the seventh period the fluctuations tend to die out. The lack of agricultural commodity price persistence to an oil price shock indicates a rapid market response mitigating oil-price effects

Figure 6. Impulse Responses of wit, wus and oil



On the contrary, the IRF generated from the VAR model using linear specification of US agri commodity price shocks to the corresponding Italian variable prices is positive in all three cases. These findings support those found with the cointegration analysis and the Granger causality and confirm the condition of market efficiency (LOP).

6. Conclusion

Starting with the evidence that the world-wide market volatility has generally increased in the last years with prices hiking in 07-08, the main objective of this research was to give empirical evidence that the fluctuation in crude oil prices, caused by oil declining supply, higher extraction costs and great speculation, was transmitted to US and Italian agricultural commodity markets and that crude oil was the leading indicator for the agricultural market.

The relationship between food and oil prices has attracted much attention lately because of the spectacular increases in commodity prices observed in the first part of 2008 and in the second part of 2010. Oil is an important direct input in the production of agricultural outputs, but also in the manufacturing of key agricultural inputs. Another possible cause of higher price fluctuation could have been induced by biofuel policies that stimulated the production of agri-commodities for biofuel industry increasing the demand against a quite rigid supply affected also by weather uncertainty.

These policies may or may not hinder the market integration depending if they are directed to protect domestic markets, however this do not seems the case as a lot of feedstock is currently traded around the world and only in few cases Argentina and Russia have applied for security purposes protectionist policies. Trading is considered quite fluid between US and Italy with higher volume of biofuel and feedstock used for producing biofuel.

Time series analysis has been used to test the hypothesis of market integration, and transmission of price and to verify the inherent dynamic market relationships due to other factors as discontinuity or non linearity arising from market inefficiencies in arbitrage. In order to find the cause-effect relations, the research has tested the existence of cointegration, price transmission and Granger causality among the prices. The results of the linear Granger causality analysis suggest to accept the presence of neutrality hypothesis in the US markets which means that the prices of oil and the US agricultural commodities do not cause each other in a strictly linear sense. Similar results are evident for oil and the Italian market; anyhow, Italian prices are co-integrated with US corresponding prices of agri-commodities and there is also evidence of linear unidirectional Granger causality going from US to Italian markets suggesting a transmission from global to local agri-commodity markets. These results confirm the Law of One Prices for that the US and Italian ag-commodity markets are working efficiently.

Non linear components of price trends are observed for oil, particularly evident in the period of hike in price. The Diks Panchenko test confirm the existence of non linear relationship between oil and the agri-commodities. For US the crude oil is confirmed to be a representative *leading indicator* exogenous to the formation of agri-commodity prices.

The oil price is a destabilizing factor for corn and soybeans markets because these markets are now closely linked to the biofuel prices. The case of wheat prices is completely different: the world has consumed more wheat than has been produced in the last six or seven years. The resulting drawdown in wheat stocks is responsible for the increase in wheat prices. This perception of food insecurity, due to the diminishing supply of flours, has brought wheat prices to surge upwards dramatically for the financial speculation prevailing on market fundamentals.

With the current large size of the ethanol industry, corn prices have become closely related to crude petroleum prices because corn is now the major energy crop in the northern hemisphere as well as the world's most important source of feed grains for production of livestock, poultry, and dairy products. This market evolution has strengthen the relationship between corn prices, crude oil and ethanol. This relationship has fluctuated in a moderate range in the past few years.

Volatility becomes an important issue for policy analysis when it induces risk averse behavior that leads to inefficient investment decisions and when it creates problems that are beyond the capacity of producers, consumers or nations to cope with. To be effective, the market policies need to have unbiased information about the agri-food supply chain, producers, consumers and traders to reduce the risk of market volatility. It is necessary to focus on the policy options designed to prevent or reduce price volatility and mitigate its consequences: some would help to avert a threat, others are in the nature of contingency plans to improve readiness, while still others address long-term issues of resilience.

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