INTERNATIONAL CONFERENCE OF AGRICULTURAL ECONOMISTS

ICAE

29th | Milan Italy 2015

UNIVERSITÀ DEGLI STUDI DI MILANO AUGUST 8 - 14

AGRICULTURE IN AN INTERCONNECTED WORLD

Climate Variability and Agricultural Price volatility: the case of corn and soybeans

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Abstract

Many studies have analysed agricultural market instability under different perspectives, but little attention has been given to the effect of climate oscillations on agricultural price volatility. Climate variability, and in particular the extreme events, can alter agricultural yields and stocks, causing relevant effects on prices. In this paper we used a Volatility Impulse Response Function (VIRF) from a multivariate GARCH model (Hafner and Herwartz, 2006) to investigate the effects of climate shocks variability (El Niño/Southern Oscillation - ENSO) on corn and soybeans prices volatility from 1960 to 2014. Results highlighted how extreme ENSO events influence price volatility with different dynamic between corn and soybeans.

Keywords: El Niño/Southern Oscillation (ENSO), Corn, Soybeans, MGARCH, VIRF

JEL codes: Q02, Q54, G15, C58

1. Introduction

The recent global food crisis has caused an increase in agricultural market volatility, raising important questions on the determinants of this instability. Many studies have analyzed this issue focusing on price volatility, including past volatility and trend, transmission across prices, oil price volatility, export concentration, stock levels and yields (Balcombe, 2010). Until now little attention has been given to the effect of climate oscillation on agricultural price volatility. Climate variability, and in particular the extreme events, can alter agricultural yields and stocks, causing relevant effects on prices. Our work focused on this issue, particularly we investigated the effects of climate variability on agricultural price volatility using El Niño/Southern Oscillation (ENSO) index.

The Southern Oscillation as the main phenomenon related to global climate variability was first described by Walker and Bliss (1932). In 1969, Bjerknes recognized a close connection between El Niño and the Southern Oscillation and lately Philander (1990) documented a relationship between Southern Oscillation and La Niña.

Even if El Niño/Southern Oscillation events take place in tropical Pacific, they have been found to have a significant impact on global weather influencing seasonal temperature and precipitation and thus crop yields in many regions.

The relationship between ENSO events and agricultural commodity supply has been largely documented within the economic literature in respect both to production (e.g. Handler, 1983; Adams *et al.*, 1995; Keppenne, 1995; Dilley, 1997; Solow *et al.*, 1998; Chen and McCarl, 2000; Naylor *et al.*, 2001; Letson and McCullough, 2001; Chen *et al.*, 2001, 2002; Toshichika *et al.*, 2014) and pricing (e.g. Brunner, 2002; Ubilava, 2012a, 2012b, 2014; Ubilava and Holt, 2013; Tack and Ubilava, 2013).

This large body of literature highlights as ENSO events, especially El Niño, adversely affects crop yields and lead to an increase in prices. However many studies in the last years have pointed out that historically food markets have had to deal with high volatility (Chavas *et al.*, 2014). Considering that after the 2008 financial crisis food price volatility has become a relevant argument within economic and political debate (FAO, 2011) and that one of the factors influencing price dynamics is linked to climate variability, in this paper we investigated the historical ENSO events effects on commodities price volatility. No previous study has empirically investigated the relationship between climate variability and agricultural price volatility and such an analysis is reasons. Firstly, this study provided a further contribution in that part of literature that seeks to identify and quantify the causes of price volatility, taking into account one variable that has never been considered before. The understanding of this relationship is relevant, since there is the possibility that regulators overreact to global food crises and higher volatility introducing market reforms that actually may reduce the overall efficiency of markets (Minot, 2014). Moreover a better knowledge of these aspects could be useful for the economic literature related to climate change. Even if was out of the aim of this paper analyzing ENSO variability in a climate change perspective, detecting a nexus between ENSO and agricultural price volatility could be useful for the adaptation strategy to climate change like, for example, the use of scarce water resources or the developing of drought-tolerant crops.

Within this framework, we focused the analysis on corn and soybeans, which are two key commodities for food security and two of the most relevant commodities traded on the world market. As far as ENSO index is concerned we used the Southern Oscillation Index (SOI) anomalies which measure the deviations between air-pressure differentials in the Pacific Ocean and their historical averages. From a methodological point of view to analyze the effects of ENSO anomalies on commodities price volatility we followed the approach of Hafner and Herwartz (2006). This approach allows researchers to visually examine volatility impulse response functions (VIRF) for multivariate GARCH models highlighting as a shock in volatility in one variable influences the dynamic adjustment of volatility of the other variable in the system. We also analyzed the volatility impulse response function considering the different effect relate to positive (El Niño) and negative (La Niña) shocks. More than half a century is covered in this study with data that start from the early sixties.

The implications of our analysis could be useful for policy makers, in respect to mitigation and adaptation strategy for global change and, as a consequence, for farmers, consumers and traders. The paper is organized as follows: Section 2 reviews existing research about commodity price volatility and ENSO events impact on production and prices, Section 3 focuses on the GARCH model and VIRF, section 4 presents the data and the results, Section 5 discusses main conclusions.

2. Agricultural price volatility and ENSO events: a brief overview

Historically, agricultural markets have always been unstable (Chavas *et al.*, 2014) even if bouts of extreme volatility have been rare (Prakash, 2011). According to FAO (2011) analysis, it is reported that historical cereal and oilseed price volatility has been rising over the past 50 years; a characteristic not shared by most of others commodities. Although some recent academic literature shows some doubts on the evidences of increasing volatility (Minot, 2014; Gilbert and Morgan, 2010) it is widely believed that agricultural price volatility has a history and its characteristics (magnitude), its causes, and the solutions imagined to deal with it have changed over time (Gerard *et al.*, 2011). Price volatility makes anticipating future price patterns difficult and creates significant price risk for market participants (Chavas *et al*., 2014). Episodes of strong volatility are a major peril to food security in developing countries. The impact of volatility in agricultural price on consumers is clearly negative: their impact falls heaviest on the poor, who may spend over 80 percent of their income on food. Variable real income leads not only to malnutrition but also reinforces poverty traps since physical and human capital is eroded. Volatility causes economic uncertainty and may result in lower investment, especially in small businesses lacking access to credit (Tadesse *et al.*, 2014). For farmers, who are highly dependent on commodities for their livelihoods, volatility can result in large income fluctuations for which they have little or no recourse to the mechanisms that assure safeguards, such as savings and insurance. Therefore price volatility discourages investment and innovation having a more uncertain return (Subervie, 2008). In summary, volatility generates risk and asymmetry of impact, impeding growth, accentuating poverty, leading to malnutrition and increasing political insecurity and the risk of internal conflict (Prakash, 2011).

Past experience suggests that direct intervention in food market to stabilize prices was sometimes problematic, above all the policy responses of individual countries should make international prices even more volatile. Increasing information on global market dynamics also by the estimation of the effects of ENSO events could reduce the incidence of panic-driven prices and prevent the negative effects of higher volatility.

Even if the relationship between ENSO events and agricultural commodity has been largely documented within the economic literature, so far the analysis of the relationship between ENSO and commodity price volatility has not been carried out. Indeed, researchers have focused the attention on both production and pricing effects of climate variability. Specifically, a stream of researcher have analyzed the impact of ENSO events on U.S. crop production highlighting the economic impact and the subsequent relevance of an accurate and more detailed ENSO phase definition and forecast (Handler, 1983; Adams *et al.*, 1995; Solow *et al.*, 1998; Chen and McCarl, 2000; Chen *et al.*, 2001, Chen *et al.*, 2002). Keppenne (1995) and Letson & McCullough (2001) paying attention on the socioeconomic relationship between ENSO and soybean price, reaching different conclusions. While the first author identifies the influence of ENSO events on soybean future prices, the latter authors do not discover a direct link between them. Other authors focused the attention on the economic damages of ENSO events in local production for maize-yield variation in Mexico (Dilley, 1997) and for Indonesian rice and corn production (Naylor *et al.*, 2001). Brunner (2002) extends the study of the ENSO events impact to world commodity prices and economic activity, studying the effect on G-7 consumer price inflation and GDP growth, highlighting as El Niño has some explanatory power in those variables.

Recently, a body of literature focused the attention on the study of nonlinearities between agricultural commodity price and ENSO events using a smooth transition vector error correction model. Specifically, these studies have analyzed coffee, soybean-to-corn price ratio, fishmeal–soybean meal price ratio and vegetable oil prices (Ubilava, 2012a; Ubilava, 2012b; Ubilava, 2014 and Ubilava and Holt, 2013) so as the spatial heterogeneity of ENSO effects at the U.S. county-level (Tack and Ubilava, 2013). Finally, in a recent article Iizumi et al. (2014) have highlighted as at global level the response of crop yield production is different from the two ENSO events and between rice, maize, soybeans and wheat.

3. The model

To analyze the dynamic effect of ENSO shock on commodity price volatility we employed Hafner and Herwartz (2006) methodology. Conceptually, this approach allows researchers to visually examine volatility impulse response functions (VIRF) for multivariate GARCH models highlighting as a shock in volatility in one variable influences the dynamic adjustment and persistence of volatility of the other variable in the system.

To this end we firstly defined a bivariate GARCH model with the mean equation modelled as bivariate ARMA(1,1) model, as follow:

$$z_t = \phi + \Gamma z_{t-1} + \Theta \varepsilon_{t-1} + \varepsilon_t \qquad (1)$$

$$\varepsilon_t | \Omega_{t-1} \sim (0, \mathrm{H}_t) \qquad (2)$$

where vector z_t includes two variables and, Γ and Θ are respectively coefficients of the AR(1) and MA(1) matrices, Ω_{t-1} represents the whole information set at time t – 1 and earlier. To model the conditional variance H_t we used a BEKK specification (Engle and Kroner, 1995):

$$\mathrm{H}_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \qquad (3)$$

where $A'A, B'B$, in our bivariate specification is a *2* x *2* matrices and C is a lower triangular matrix to ensure positive definiteness of H. The diagonal elements of matrix A (a_{11} and a_{22}) represent the ARCH effect, that is the effect of lagged shocks, while the off-diagonal elements (a_{12}, a_{21}) represent the cross-spillover effects. The diagonal elements of matrix B (b_{11} and b_{22}) measure the GARCH effect, that is the lagged volatility effect, and the off-diagonal (b_{12} and b_{21}) the cross-volatility spillover effects. Hence, we refer to the off-diagonal elements of matrices A and B respectively for shocks spillover effects and for volatility spillover effects.

Accordingly with Hafner and Herwartz (2006) the above BEKK model is then transformed in its *Vech* representation so as to generate volatility impulse response functions defined as the expectation of volatility conditional on initial shock and history, minus the expectation conditional only upon history:

$$\begin{aligned} vech(V_{t+1}) &= A\, vech(u_t u_t' - H_t) \\ vech(V_{t+k}) &= (A+B)\, vech(V_{t+k-1}) \end{aligned} \tag{4}$$

where H_t is the covariance matrix, previously estimated by the (3), at time t. The shock to the conditional variance is the amount by which $u_t u_t'$ differs from its expected value. In a bivariate framework the Hafner and Herwartz (2006) methodology allows to analyse the impulse response of the conditional variance separately for the two variables of interest, as well as the response of the conditional covariance. In the VIRF estimate we take k=36 months.

Several approaches can be used to select the date of the shocks for the VIRF analysis. Some authors select some historical shocks (Le Pen and Sévi, 2010; Jin et al. 2012;) whereas others compare two relevant periods (Panopoulou and Pantedlidis, 2009; Olson et al 2014) while Hafner and Herwartz (2006) tests both the approaches.

In this paper in selecting the date of shock we ordered the Enso index and recorded that dates corresponding to the 5^{th} percentile, 50^{th}, and 95^{th} percentile of the distribution. We then implemented a bivariate VARMA-GARCH and VIRF methodology for both SOI index-soybeans and for SOI index-corn for each of the dates within the 5^{th} percentile, 50^{th}, and 95^{th} percentile of the distribution. Then, for the three percentiles of the distribution, following Hafner and Herwartz (2006) we calculated the average value of estimated volatility impulse responses functions. Thus, we are able to compare average VIRF that correspond to La Niña (5^{th} percentile) and El Niño (95^{th} percentile) shocks for both soybeans and corn having as a benchmark the neutral phases (50^{th} percentile).

4. Data and results

The analysis presented in this paper use monthly data spanning from January 1960 to June 2014. Within climate science several indexes are performed to track ENSO events, among them the most popular are the Southern Oscillation Index – SOI (Troup, 1965), the See Surface Temperature - SST

(Barnston *et al*., 1997) and the Multivariate ENSO Index - MEI (Wolter and Timlin, 1993, 1998). Overall a visual inspection of data highlights as the three indexes show very similar pattern (Figure 1) with period of high volatility followed by others of relatively low volatility, suggesting that the use of homoskedastic residuals is inappropriate[1] to model this behavior.

[insert figure 1]

A large body of literature, spanning across different fields of research, has analyzed the efficiency of these indicators for ENSO behavior and forecast. However, at the moment no unanimous consensus has been reached about the index that should be used to measure the changes in climate in a worldwide perspective. Indeed existing literature is mostly focused on the study of suitable indexes in relation to geographical areas investigated and/or season considered (Piechota *et al*. 1998; Nicholson *et al*. 2001; Murphy and Ribbe, 2004; Kirono *et al*. 2010; Walter and Timelin, 2011; Zeldis, 2013).

Descriptive statistics of the main three indexes (Table 1) show that in the analyzed period SOI index has the greater standard deviation and Kurtosis leading us to conclude that such an index presents the greater variability. Since we are moving in a heteroskedastic framework focusing the attention on volatility issue we decided to use SOI index for our analysis[2].

[insert table 1]

Specifically, the Southern Oscillation Index (SOI), collected from U.S. Climate Prediction Centre (CPC)[3], is a standardized index based on the anomalies of observed sea level pressure differences between Tahiti and Darwin, Australia[4]. The negative phase of the SOI represents below-normal air pressure at Tahiti and above-normal air pressure at Darwin. Prolonged periods of negative (positive) SOI values coincide with abnormally warm (cold) ocean waters across the eastern tropical Pacific typical of El Niño (La Niña) episodes.

As far as the commodity prices series are concerned we collect data from the World Bank data set[5]: for corn we used maize number 2 yellow (f.o.b. U.S. Gulf ports) and for oilseed we used soybeans U.S. (c.i.f. Rotterdam), both are expressed in U.S. dollars per ton.

Unit roots test have been calculated to determine the appropriate variable transformations. Table 2 reports results of the Dickey and Fuller test, where the null hypothesis is unit root against the alternative of stationary. Results indicate that the SOI index is stationary at 1% significant level,

[1] To be comparable with the others index and for a reading convenience in respect to the economic literature related to ENSO event and agricultural commodity prices in Figure 1 and in the empirical application we have multiplied the SOI index for -1, hence positive variation in the index correspond to El Niño events, while negative shock to La Niña.

[2] To verify the robustness of results we also estimate the model with the SST index obtaining similar results in the sign of estimated coefficient and in the VIRF pattern.

[3] http://www.cpc.ncep.noaa.gov/data/indices/soi

[4] Anomalies are calculated in respect to base period 1981-2010

[5] http://databank.worldbank.org/data

while prices series are unit roots in levels and stationary at 1% in first differences. Therefore, in the implementation of the model corn and soybeans price series were used in logarithmic first differences while the SOI index in level[6] (Figure 2).

[insert figure 2 and table 2]

As previously described within the methodology section the approach used to analyze VIRF is a bivariate GARCH model with the mean equation modeled as a VARMA(1,1)[7]. The model was estimated with a BEKK(1,1) specification using quasi-Maximum Likelihood with a Simplex preliminary estimation method to refine initial parameter for the BFGS estimation algorithm, *t*-Student distribution was assumed for the error process. Rats software was used to perform the analysis.

The estimates are reported in Tab. 3 for Enso index - Corn returns and in Table 4 for Enso index - Soybeans returns. Panel A and Panel B of tables 3 and 4 respectively report the mean equation and the variance equation results, in Panel C residual diagnostic are reported and in Panel D the Hafner and Herwartz (2008) tests for causality in variance are shown. All the residual diagnostics confirmed the validity of model specification for both corn and soybeans models, as demonstrated by the multivariate Ljung-Box test (*Q*-statistics) and by the multivariate ARCH test (Panel C of table 3 and 4).

[insert tables 3 and 4]

As previously outlined, the primary interest of this analysis is to investigate the VIRF of soybeans and corn prices returns as a consequence of an Enso shock/s. The Hafner and Herwartz (2006) methodology estimated with an unrestricted BEKK model produces the impulse response of the conditional variance for both the first (Enso) and the second (Soybeans; Corn) variables of the system, so as the conditional covariance. Hence, as a first step we checked if the estimated parameters of matrices A and B of equation 3) (Panel B and C of table 3 and 4) are in line with expectations: i.e. Enso events influence commodities prices volatility but not *viceversa* since, obviously, the opposite effect is meaningless[8]. As expected for both the commodities in matrices A and B of equation (3) the coefficients a_{21} and b_{21} (the cross effect from commodities to Enso index) were not significant while we found significant ARCH effect for corn to Enso index (a_{12}) and GARCH effect for soybeans to Enso index (b_{12}). Moreover the Hafner and Herwartz (2008) test for causality in variances confirmed expectations. Indeed it confirmed the hypothesis that there is a

[6] Specifically, for commodity prices we used the following specification: $100 \times \log (P_t/P_{t-1})$.

[7] In the empirical application we also test the GARCH model with the mean equation modeled as an AR(1), obtaining very similar results in the covariance matrices, but with residual diagnostic not significative.

[8] We also tested a restricted version of the model with $a_{21}=b_{21}=0$ and $a_{12}\neq0$ and $b_{12}\neq0$ (i.e. a triangular BEKK) obtaining analogous results.

significant causality direction effects from Enso events to corn and from Enso events to soybeans, but not the opposite (Panel D of table 3 and 4).

Figure 3 and 4 respectively display the volatility impulse response functions (36-month horizon) of corn and soybeans related to shocks associated with La Niña, El Niño and the neutral phase. If we consider that ENSO events occur only when the SOI index is over (under) a certain threshold (out of the so called neutral band), we can isolate this set of observations from the whole sample to quantify the impact of El Niño (La Niña) events on price volatility. As a threshold we considered the percentile distributions of the SOI index. Specifically, La Niña lines are averages of VIRF over a set of forty dates representing the 0 to 5th percentile of the SOI index value, i.e. all the dates of the sample period where the value of SOI index is <-2.8. Likewise El Niño lines correspond to an average VIRF of thirty-two dates representing the 95th to 100th percentile of the distribution, i.e. with a SOI index >2.4. In Figures 3 and 4 are also displayed lines of a neutral phase, that we use as a benchmark for El Niño and La Niña phases. The VIRF of the neutral phases is an average of the Hafner and Herwartz (2006) methodology applied on that set of dates where the SOI index is included within the 50th percentile of the distribution (twenty dates with SOI index =0.2). This approach allowed us to produce a benchmark to analyse the additional impact of El Niño and La Niña events on prices volatility.

[insert figure 3]

VIRF analysis highlighted as, in respect to neutral phases, both El Niño and La Niña increase corn volatility, with El Niño that has stronger effect in respect to La Niña (Figure 3). These results are in line with Iizumi et al. (2014) and Prakash, (2011). Indeed the former authors, in a relevant publication, provided evidence that at a global level extreme Enso event decreases corn yields and, as a consequence, for the law of supply and demand, prices tend to increase. The latter author demonstrated that typically, when prices are high they are also volatile (Prakash, 2011).

Figure 4 reports soybeans VIRF. Contrary to corn, soybeans VIRF showed different dynamic with El Niño and la Niña events. Specifically, in respect to the neutral phase, La Niña strongly decreased volatility while El Niño slowly increased it, even if the latter value remained negative. As for corn these results are in line with Iizumi et al. (2014) that in their article have highlighted as La Niña events globally increased soybeans yields while El Niño decreased it.

[insert figure 4]

5. Concluding remarks

Considering a very wide time horizon, more than half a century, in this paper we focused the attention on two relevant issues regarding agricultural economics debate: agricultural price volatility and climate behavior. A rich body of literature has already analyzed these two issues within different frameworks, but no previous study has investigated the effects of climate variability on agricultural price volatility. In this paper we have analyzed volatility impulse response function from a multivariate GARCH model (Hafner and Herwartz, 2006). The SOI index is used to model teleconnection, while corn and soybean prices as a agricultural prices.

Results highlighted as price volatility of both the commodities are affected by extreme ENSO events. In respect to neutral phase both La Niña and El Niño tend to increase corn volatility, while soybeans prices volatility tend to decrease with La Niña and to increase with El Niño. All the actors involved in the ongoing debate on agricultural price volatility and climate-change issues could benefit from these results by adopting adequate policy and action to mitigate such effect like for example, the use of scarce water resources or the developing of drought-tolerant crops. This is a first effort in this topic, to strengthen these results additional investigations are necessary, like a different methodological approach, different commodities investigated or time span to be considered.

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Figure 1 – ENSO indexes dynamics: MEI, SSST and SOI.

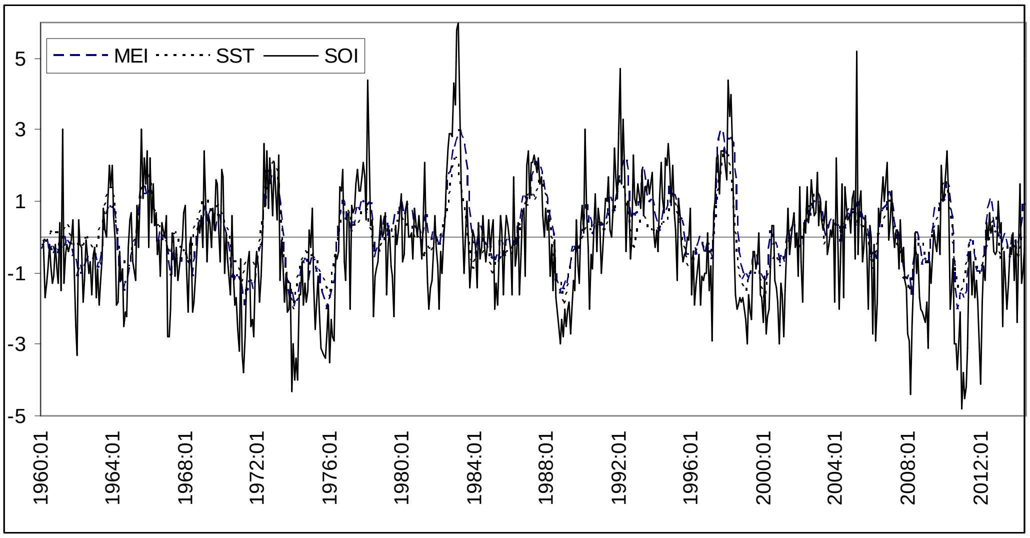


Table 1 – Descriptive statistics of ENSO indexes (MEI, SOI and SST), maize and soybeans

	Obs.	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	JB	Prob.
MEI	654	0.084	0.014	3.038	-2.031	0.967	0.386	3.175	17.039	0.000
SOI	654	-0.231	-0.250	6.000	-4.800	1.599	0.220	3.629	16.087	0.000
SST	654	-0.002	-0.100	2.400	-2.000	0.808	0.304	3.080	10.272	0.006
ΔMAIZE	653	0.230	0.000	29.751	-24.484	5.514	-0.035	6.248	287.249	0.000
ΔSOYBEANS	653	0.261	0.245	31.985	-35.364	5.817	0.057	9.245	1061.379	0.000

Note: Sample period, monthly data: 1960:01-2014:06.

Table 2 – Unit root test

Variables	Level	First-Difference
SOI	-7.995	
MAIZE	-2.173	-20.213
SOYBEANS	-2.180	-20.841

Note: Sample period, monthly data: 1960:01-2014:06.

1% critical values: -3.440

Tab. 3 – Estimate of bivariate VARMA-GARCH Bekk model for ENSO index and Corn

Panel A - Mean equation

$$\Phi = \begin{bmatrix} -0.03\,(\mathit{0.29}) \\ 0.22(\mathit{0.29}) \end{bmatrix};\ \Gamma = \begin{bmatrix} 0.86\,(\mathit{0.00}) & -0.01(0.63) \\ 0.33(\mathit{0.05}) & 0.22(\mathit{0.05}) \end{bmatrix}; \Theta = \begin{bmatrix} -0.37\,(\mathit{0.00}) & 0.00\,(\mathit{1.00}) \\ -0.51\,(\mathit{0.02}) & 0.03(\mathit{0.76}) \end{bmatrix}$$

Panel B - Variance equation

$$C = \begin{bmatrix} 0.96(\mathit{0.00}) & \\ 0.28(\mathit{0.43}) & 0.00(\mathit{1.00}) \end{bmatrix}; A = \begin{bmatrix} 0.30\,(\mathit{0.00}) & -0.49(\mathit{0.01}) \\ 0.00\,(\mathit{0.83}) & 0.20(\mathit{0.00}) \end{bmatrix}; B = \begin{bmatrix} 0.55\,(\mathit{0.01}) & -0.23(\mathit{0.33}) \\ 0.00\,(\mathit{0.91}) & 0.97(\mathit{0.00}) \end{bmatrix}$$

Panel C - Residual diagnostics

Multivariate

Q (8) = 23.21 (0.87); *Q* (20) = 79.89 (0.48); ARCH = 14.36 (0.70)

Panel D - Test for causality in variance *

ENSO → Maize: yes	Chi-Squared(2) = 15.04 (0.00)
Maize → Enso: no	Chi-Squared(2) = 0.05 (0.97)

* Hafner and Herwartz (2008). *P-value* are in parenthesis.

Tab. 4 - Estimate of bivariate VARMA-GARCH Bekk model for ENSO index and Soybeans

Panel A - Mean equation

$$\Phi = \begin{bmatrix} -0.03\,(\mathit{0.25}) \\ 0.28(\mathit{0.09}) \end{bmatrix};\ \Gamma = \begin{bmatrix} 0.87\,(\mathit{0.00}) & -0.01(0.59) \\ 0.16(\mathit{0.33}) & 0.13(\mathit{0.20}) \end{bmatrix}; \Theta = \begin{bmatrix} -0.38\,(\mathit{0.00}) & 0.01\,(\mathit{0.79}) \\ -0.15\,(\mathit{0.46}) & 0.16(\mathit{0.12}) \end{bmatrix}$$

Panel B - Variance equation

$$C = \begin{bmatrix} 1.09(\mathit{0.00}) & \\ -0.90\,(\mathit{0.00}) & 0.00(\mathit{1.00}) \end{bmatrix}; A = \begin{bmatrix} 0.20\,(\mathit{0.03}) & -0.13(\mathit{0.61}) \\ 0.00\,(\mathit{0.93}) & 0.44(\mathit{0.00}) \end{bmatrix}; B = \begin{bmatrix} 0.40\,(\mathit{0.00}) & 1.42(\mathit{0.00}) \\ 0.00\,(\mathit{0.80}) & 0.82(\mathit{0.00}) \end{bmatrix}$$

Panel C - Residual diagnostics

Multivariate

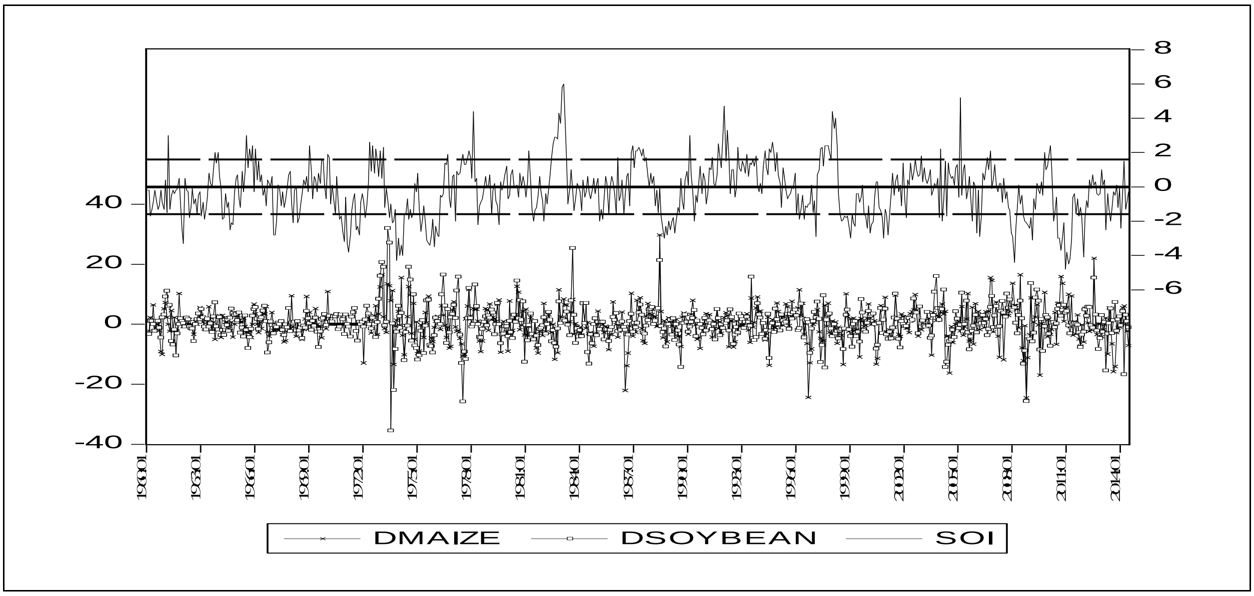
Q(8) = 24.85 (0.81); Q(20) = 68.98 (0.80); ARCH 19.45 (0.36)

Panel D - Test for causality in variance *

ENSO → Soybeans; yes	Chi-Squared(2)= 73.83 (0.00)
Soybeans → Enso; No	Chi-Squared(2)= 0.07 (0.97)

* Hafner and Herwartz (2008). *P-value* are in parenthesis.

Figure 2 - First-differences of corn and soybeans prices series, SOI index and its standard deviation (neutral band).



Note: Left axis: first-differences of maize and soybeans prices series. Right axis: inverted SOI index with standard deviation.

Figure 3 - Volatility impulse response function of corn to Enso shocks.

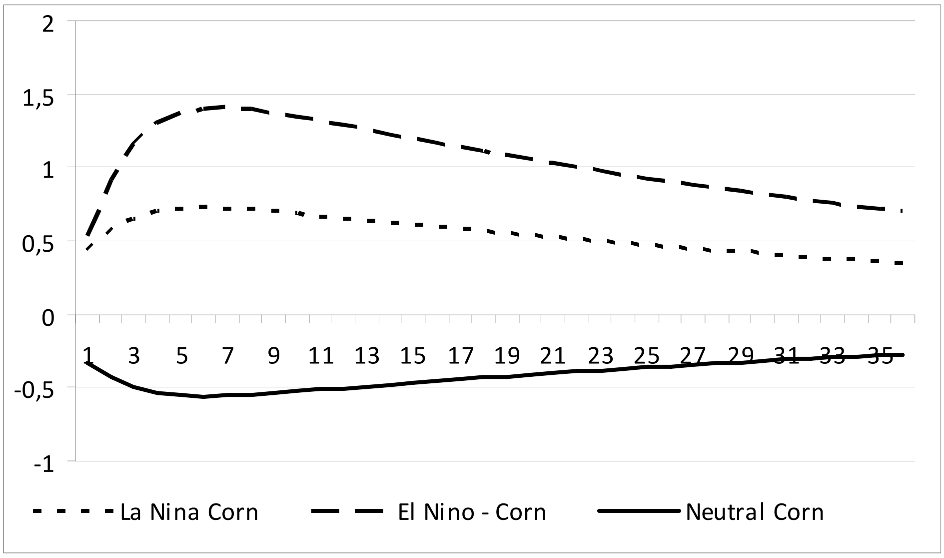


Figure 4 - Volatility impulse response function of soybeans to Enso shocks.