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Felipe Grimaldi Avileis and Mindy Mallory

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**THE IMPACT OF BRAZIL ON GLOBAL GRAIN DYNAMICS:
A STUDY ON CROSS-MARKET VOLATILITY SPILLOVERS**

Felipe Grimaldi Avileis and Mindy Mallory¹

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¹ Felipe Grimaldi Avileis is a Masters Student and Mindy Mallory is an associate professor in the Department of
Agricultural and Consumer Economics at the University of Illinois at Urbana-Champaign

The Impact of Brazil on Global Grain Dynamics: A study on cross-market volatility spillovers

We will investigate the evolution of the relationship between Brazilian and Global grain markets. Through a three step approach, we will test the series for cointegration, proceed with the adequate modeling (VAR or VECM) and use the residuals of these models to estimate a BEKK GARCH and relative volatility spillovers across two time periods, before and after Brazil started double-cropping. Our results indicate no significant cointegration between corn and soybeans markets before Brazil started double-cropping and significant cointegration after, for both markets. Volatility spillovers dynamics also changes, from no spillovers to spillovers from and to Brazil on corn, and from the US spilling over Brazil to Brazil spilling over to the US on soybeans. Our results are important because they show that the importance of Brazil to global grain price formation is substantial and risk managers must be aware of it in order to perform well.

Key words: volatility spillovers, soybeans and corn, multivariate GARCH, market integration.

INTRODUCTION

Over the past 15 years Brazil's farm sector went through several structural changes. The biggest one of them is the development of more adapted soybean and corn varieties, allowing farmers to double-crop in the same year. Farmers in Brazil are able now to grow soybeans and then corn on the same land. That fact by itself almost doubled production for these crops.

As Brazil's production increased, so did its importance in global grain dynamics. Brazil jumped from a negligible exporter in corn to being the second largest exporter and is now the largest soybean producer and exporter in the world. While global grain prices have historically been prices on the Chicago Mercantile Exchange (CME), through futures contracts, grain handlers are more and more looking to Brazil for fundamental price information.

In this paper, we will analyze how double-cropping changed Brazilian grain price relations with global prices. Our methodology incorporates the seasonal nature in volatility spillovers between Brazilian and US markets. Through a three step approach, we will define if markets were cointegrated or not and proceed to estimate the existence and magnitude of volatility spillovers between Brazilian prices and US (Global) prices.

The first step involves defining whether or not the series are cointegrated. Using Johansen's cointegration test, we will test the series divided in two periods, pre (2004-2009) and post (2010-2019) the double-crop. The results obtained in step one will be used on step two, as they will define which type of model we will use to model the series.

The second step consists of using either a Vector Autoregressive (VAR) or Vector-Error Correction Model (VECM). If the series are not cointegrated, we proceed with a VAR and in case they are we proceed with a VECM. From this step, we will use the residuals obtained to run a BEKK GARCH.

The third step consists of estimating a BEKK GARCH and extracting the target coefficients to calculate the volatility spillovers. The target coefficients are the ones that bring the isolated cross-market effects from one market to the other, on that market conditional

volatility equation. This measure will allow us to describe the magnitude and type of spillover the pairs are showing. It is also important because it will allow us to see if there is any seasonality on the spillovers. By calculating a daily spillover ratio, we will be able to show that during Brazil's planting and harvesting months, the spillover from Brazil to the US is around 35%, on average, and the spillover for corn is twice the size of the spillover from the US to Brazil.

BACKGROUND

GLOBAL GRAIN PRODUCTION

Global grain consumption per capita significantly grew from 2000-2017. Estimates from the USDA shows that soybeans and corn consumption 64% and 42% increases, respectively. Taking into consideration that the world population jumped from around 5 billion to 6.5 billion, demand for corn and soybeans has never been higher.

The United States, China, and Brazil are giants in corn production, representing approximately 60% of total production. However, China used to be a big exporter in the early 2000s, but is now a net importer of corn, due to its growth in demand over the past 20 years. That change in China's dynamic, moving from net exporter to importer, created a gap in supply that was filled mainly by two things: a global trend in increasing yields and Brazil entering world markets and becoming the second largest exporter of the grain.

When it comes to soybeans, the three biggest producers are Brazil, the United States, and Argentina, with the three countries representing close to 80% of total production. On the demand side, China accounts for more than 60% of global imports. Asia as a continent accounts for 80%. The big shift in soybeans is that, on a 10-year span, Brazil surpassed the US as the largest producer and exporter of soybeans. Brazil, therefore, was one of the main countries responsible for the growth in production that kept global corn and soybean supply on pace with global demand.

BRAZILIAN PRODUCTION

As noticed above, Brazil was fundamental to keep global grain stocks in good conditions. Without the country's significant growth in production, it is unlikely that grain production would have been able to keep up with rising demand. The "discovery" of the *Cerrado* region (or Center-West) as a viable location for area expansion in the early '70s and its subsequent development were fundamental factors allowing the transformation in production cycles that the country saw in the early/mid-2000's. Figure 1 highlights the Cerrado region, in light green. It accounts for the states of Goias, Mato Grosso and Mato Grosso do Sul, leading states in grain production in Brazil.



Figure 1 - Map of Brazil and Cerrado

Source: Associação Brasileira de Desenvolvimento Sustentável (ABIDES)

Due to its privileged location in the country, right under the Amazonic basin, the area receives good amounts of rain through the crops growing season, and government efforts to develop corn and soybeans cultivars better adjusted to the region climate, yields in the region are growing year after year, almost doubling over the past 10 years.

The development of this region as a big producer of grain is key for the surge of Brazil as a top grain producer and, most important, exporter. The importance of this region is even bigger now, as in the early 2000's researchers and farmers discovered the possibility of double cropping, planting soybeans and corn in the same year, that, in theory, doubled the available area for planting (as now farmers could grow both grains on the same space). Double cropping is only possible because of the hydric privileged region that the Cerrado is in.

As Figure 2 shows, there is plenty of available water on the soil until the end of May. That means that, on average, a farmer in that region should be able to have enough water for a crop to develop until that period.

Poxoréo/MT | Maximum Retentive Capacity | AWC = 125 mm

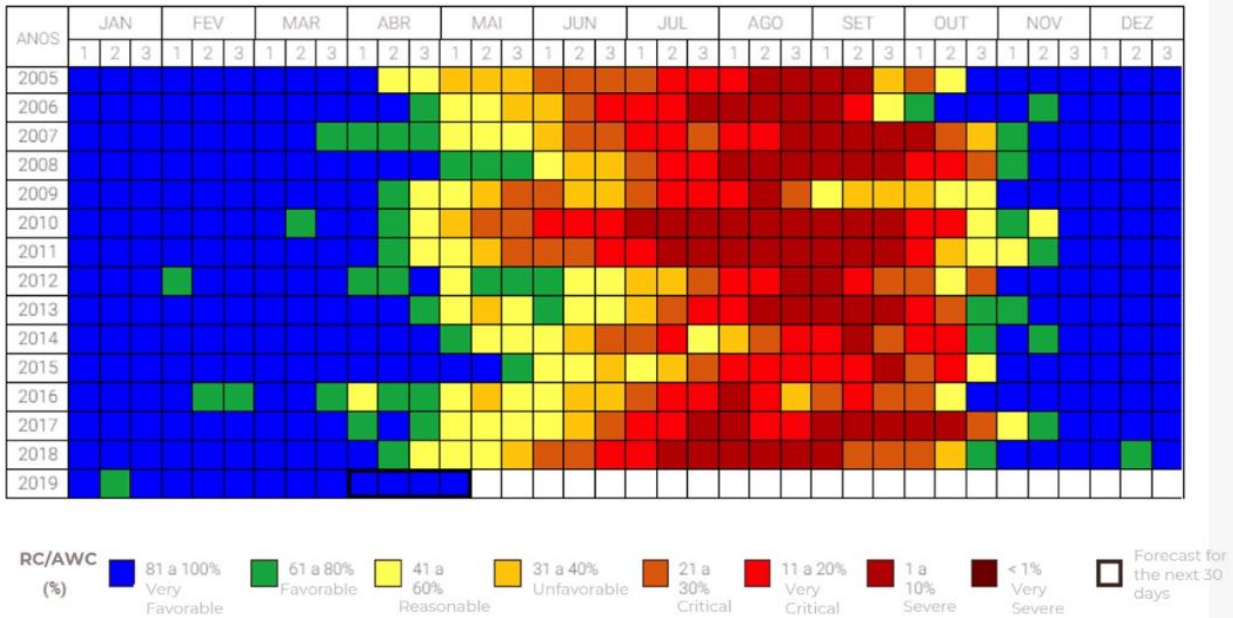


Figure 2- Available Water on Soil

Source: Agrymet (2019)

With an average cycle of 120 days for soybeans and 150 days for corn, 270 day total, farmers started planting beans as early as possible, usually starting in October, and planting corn right after harvesting beans. This allows the same area to be used for both crops, increasing production for both. Figure 3 illustrates soybeans and corn planting and harvesting months.

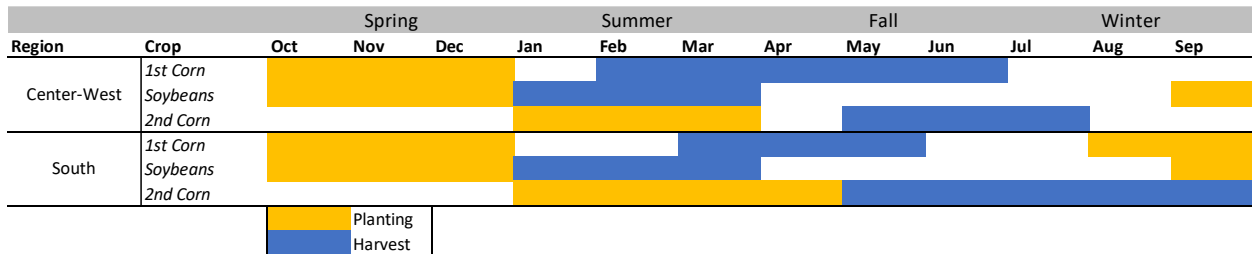


Figure 3- Crop Calendar

Source: Conab (2019) – built by the author

One important factor is that, if the farmer chooses to plant Corn as a first crop, he loses the opportunity to double-crop, as corn takes longer to mature when compared to beans (30 day difference). This feature existent in Brazil pushed the country to the top exporters list in both commodities, increasing yields and area planted.

Another structural change that the second crop brought was a change in price responsiveness of Brazilian farmers. Before Brazil was able to double-crop, Brazilian farmers had similar planting decision as US farmers. Corn and soybeans would act like perfect substitutes and, in order to maximize the utility of the land, farmers should select the most

profitable crop in that year to plant.² Land allocation, then, would bring prices to equilibrium³. That behavior kept Brazilian and US farmers with similar levels of price responsiveness, and, by default, similar reactions to price shocks.

However, Brazilian farmers that have the ability of double-cropping react differently. Instead of having to select which crop to plant, these farmers will (most likely) plant both. Considering that the only combination for double-cropping is Soybeans then Corn, farmers will plant soybeans and then corn, regardless of the price ratio between both. This smaller reaction to price shocks is important when understanding the change in dynamics and volatility transmission on global markets.

Soybeans

Brazil is currently the largest soybeans producer in the world, recently passing the United States. Soybean production is spread out across the country, with the biggest producing states being Mato Grosso, Parana, Rio Grande do Sul, Goias and Mato Grosso do Sul, as shown in Figure 4 - Soybean Production Map 4.

² We acknowledge that other factors affect a farmers decision on what to plant. However, several studies similar to Miao, Khanna and Huang (2015) point that price is the main driver.

³ Varies every year. In general, a 2.5 soybeans/corn ratio is considered the “trigger” ratio for planting.

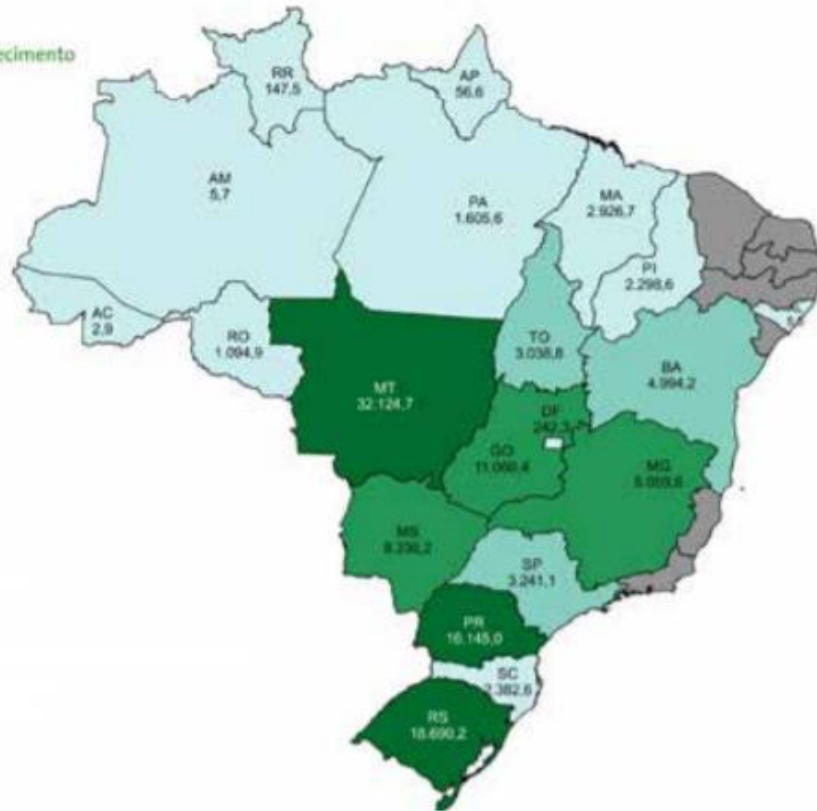


Figure 4 - Soybean Production Map

Source: Conab (2019)

From the top 5 producers, 4 of them (north of Parana) allow the farmer to double crop. The fact that an area that, before the second crop, used to be destined for corn (or other crop) is now destined for beans allowed productions to significantly increase, as shown in Figure 5, going from 40 million tons to 120 million tons (300% increase) in less than 20 years and only doubling planted area.

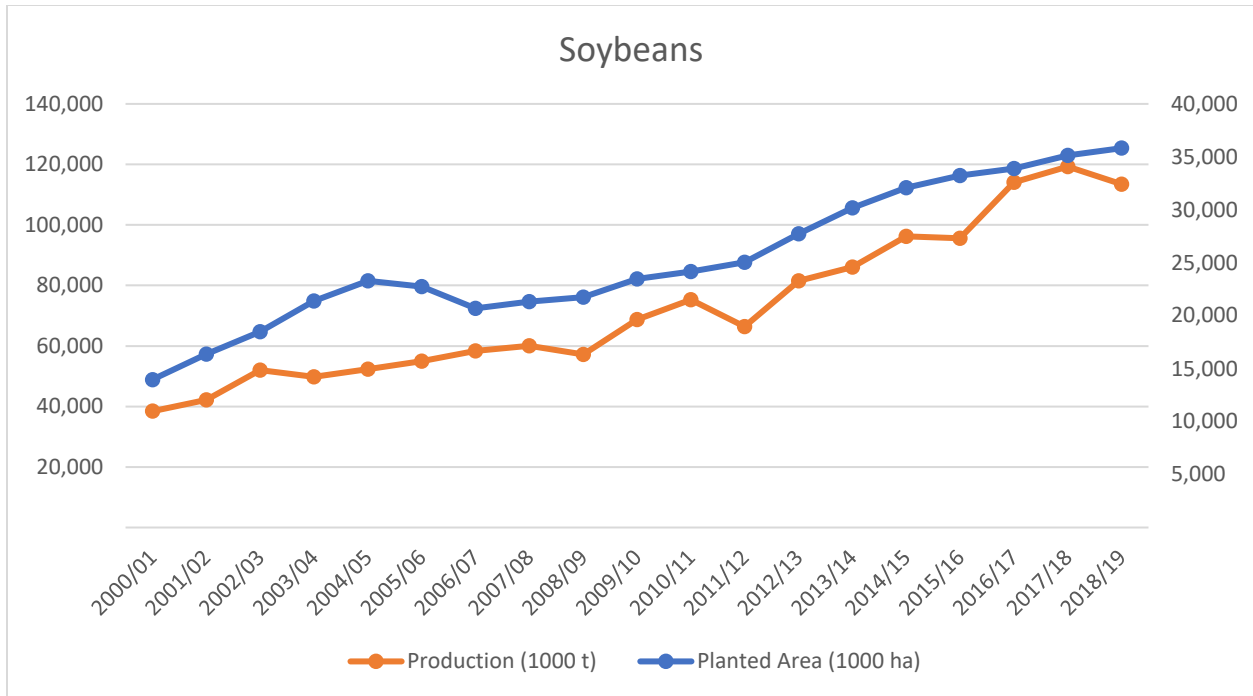


Figure 5 - Soybeans Production and Planted Area
 Source: Conab (2019) – Built by the author.

This big increase in production allowed Brazil to fulfil increases in global demand. This transformed Brazil in the main exporter of the commodity in the world, surpassing the U.S., as it's possible to compare in Figure 6 and Figure 7.



Figure 6 - Global Soybeans Exports Shares in 2003
 Source: UN COMTRADE (2019) – built by Atlas Media.

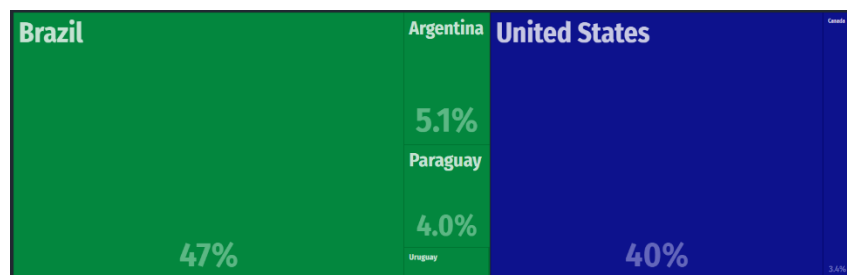


Figure 7 - Global Soybeans Exports Share in 2017
 Source: UN COMTRADE (2019) – built by Atlas Media.

Corn

The ability to double crop and use the land available in Cerrado transformed Brazil into a soybean giant, and the same effect can be seen in Corn. While corn can be planted across the entire country, there is a difference between the biggest production regions between first and second crop. The first crop is produced mostly in southern states, as seen in Figure 8, such as Rio Grande do Sul, and in parts of the Southeast, as in these regions double-cropping is not feasible due to colder weather. The second crop, on the other hand, resembles the soybean production map, as the biggest producing states (Mato Grosso, Parana, and Goias) are the ones that get enough rain to double crop, as seen in Figure 9.

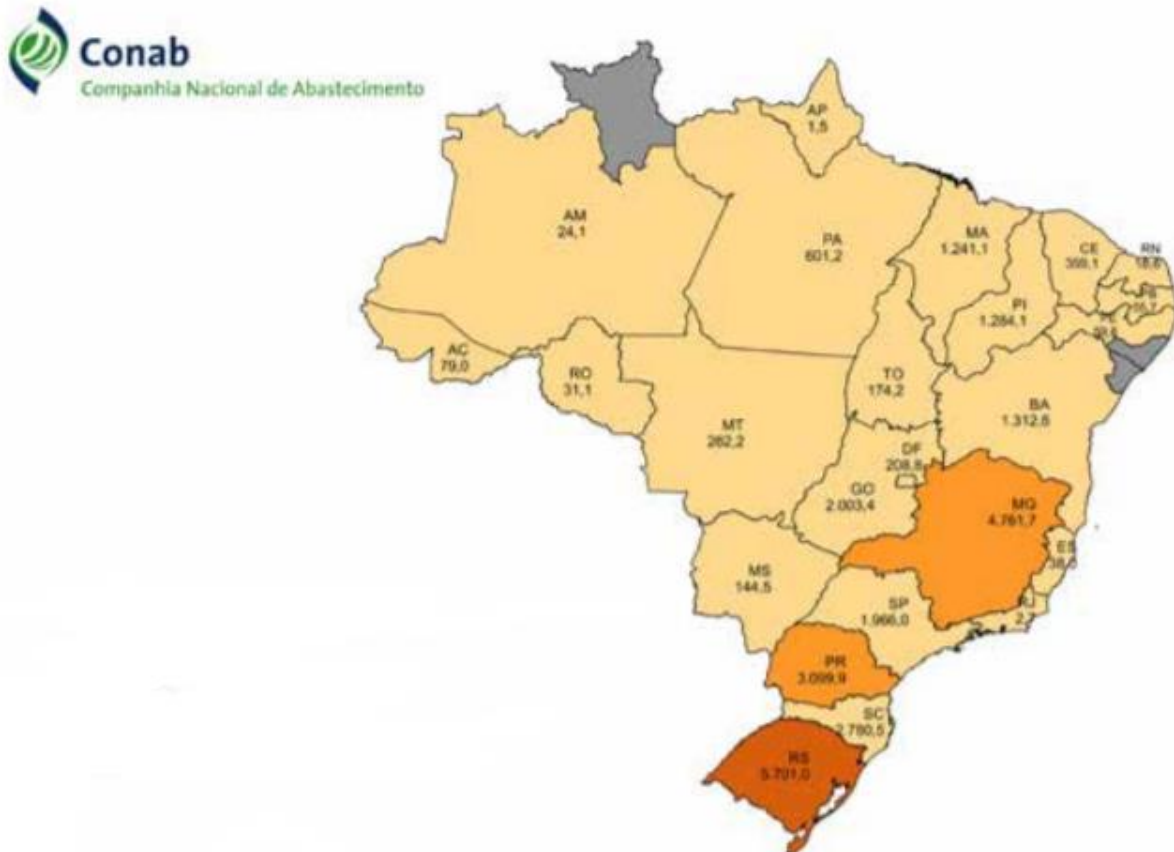


Figure 8 - 1st Corn Crop Production Map
Source: Conab (2019)



Figure 9 - 2nd Corn Crop Production Map
Source: Conab (2019)

Over the period, corn production more than doubled in the country, but with an interesting dynamic. As seen in Figure 10, 1st crop production decreased in the period, from almost 40 million tons to less than 30 million tons (mostly due to area being switched to soybeans), while 2nd crop production had a tremendous increase, going from less than 10 million tons to nearly 70 million tons, a 700% increase.

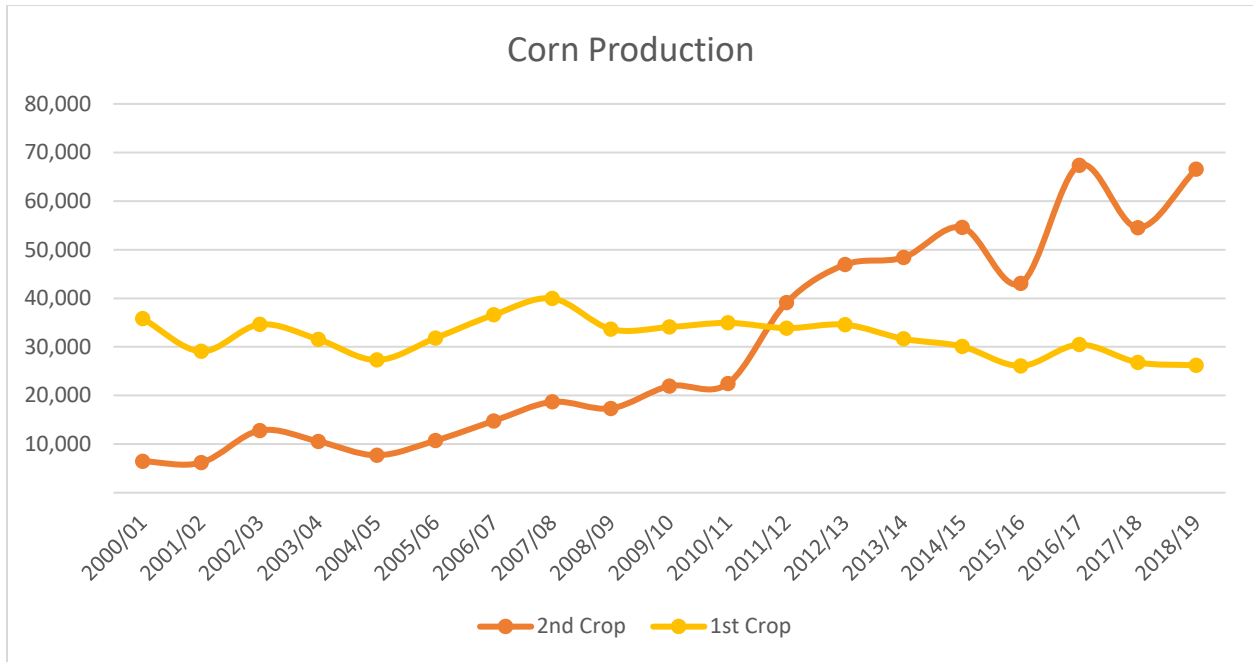


Figure 10 - Corn Production
Source: Conab (2019)

This change was the main reason why Brazil moved from representing less than 5% of global exports in 2003 (Figure 11) and became the second largest exporter in the world 15 years later (Figure 12).

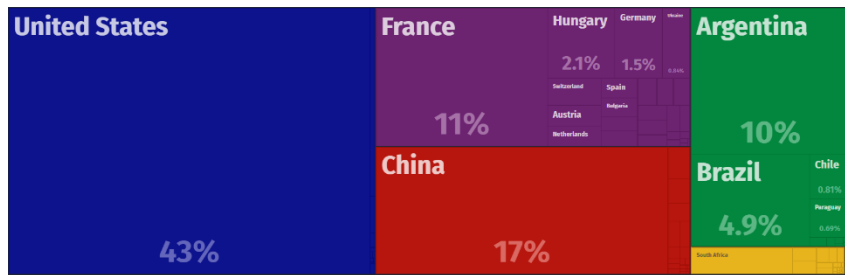


Figure 11 - Global Corn Export Shares in 2003
Source: UN COMTRADE (2019) – built by Atlas Media.

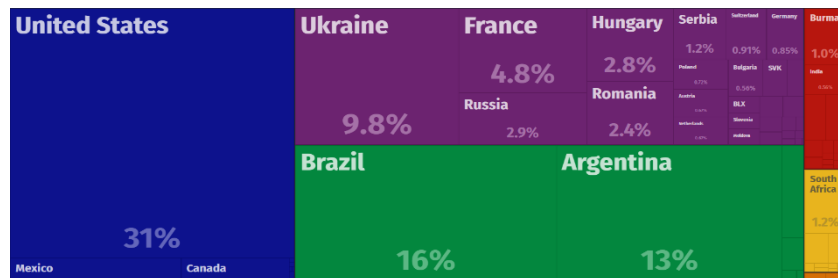


Figure 12 - Global Corn Export Shares in 2017
Source: UN COMTRADE (2019) – built by Atlas Media.

MARKETS

International Markets

As previously discussed, Brazil plays a leading role both in corn and soybeans exports markets. However, buyers for these grains are very different.

On the soybeans side, Brazilian shipments are mostly directed to China, which imports 75% of the total volume, as shown in Figure 13, while the rest is mainly exported to European Union countries.

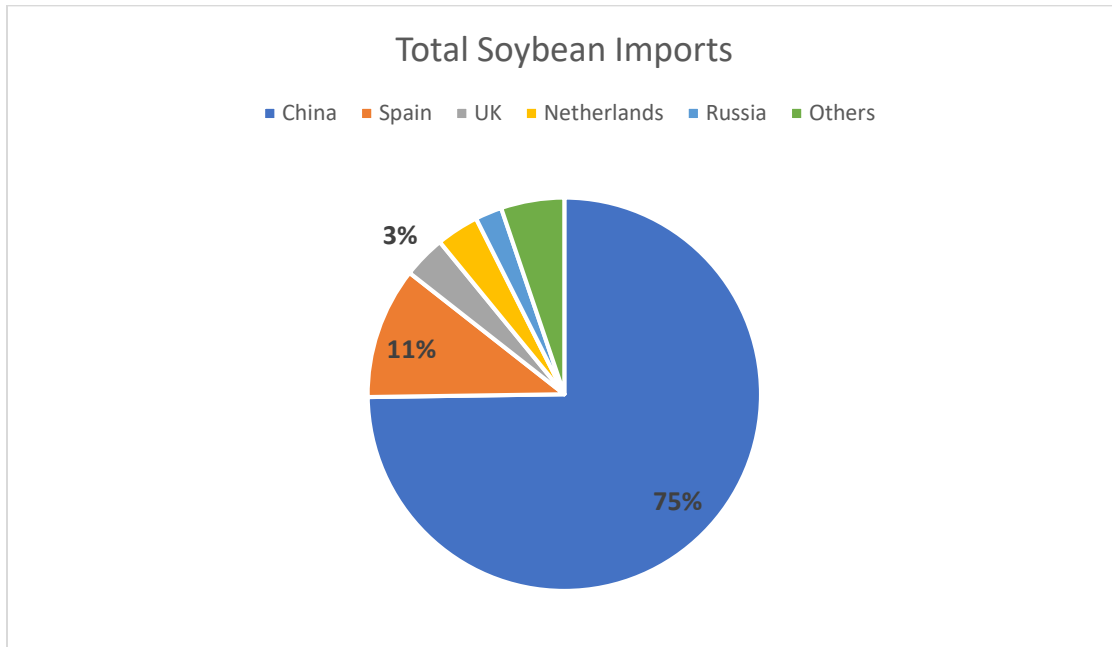


Figure 13 - Brazilian Soybeans Exports Destination

Source: MDIC (2019), built by the author.

It is also worth mentioning that China is the largest importer of soybeans in the world, as seen in Figure 14, and is also the biggest destination for U.S. beans. Because of that, Brazilian and US soybeans are big price competitor in international markets.



Figure 14 - Global Soybeans Import Shares

Source: UN COMTRADE (2019) – built by Atlas Media.

Corn buyers are very different from soybeans buyers. While China is the biggest player in soybeans, importing more than everyone else together, corn destinations are more scattered. As Figure 15 shows, most of the Brazilian corn is destined towards the Middle East and Asia, with Vietnam and Iran being the biggest buyers.

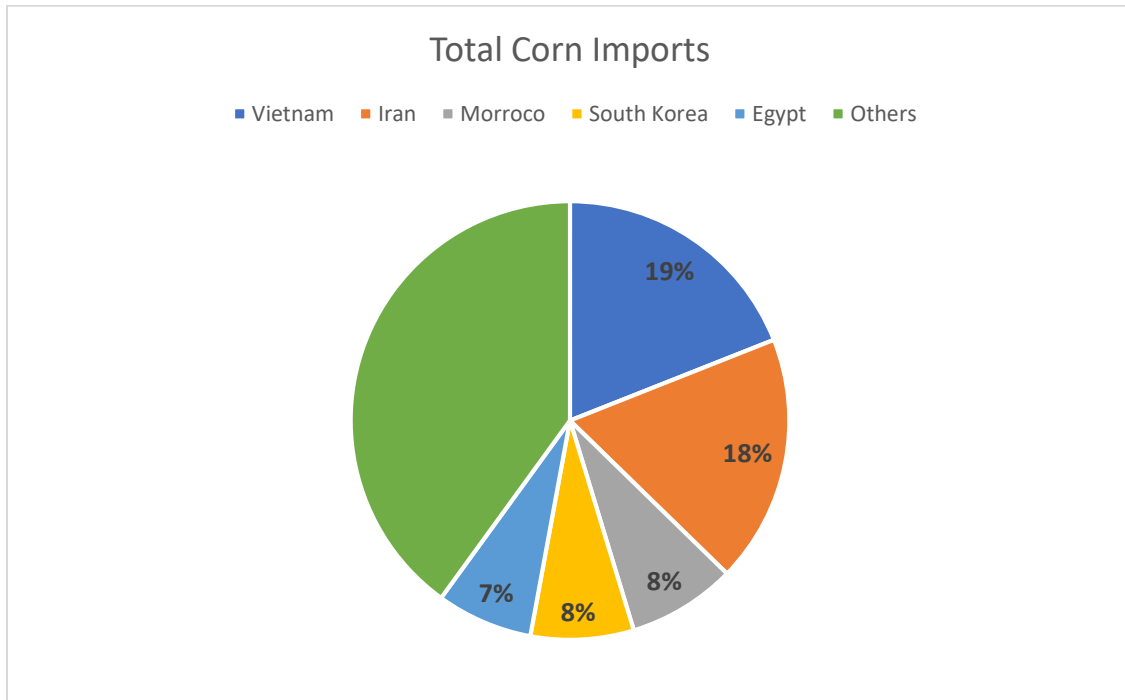


Figure 15 - Brazilian Corn Exports Destination
Source: MDIC (2019), built by the author.

In contrast to soybeans, in which Brazil and the US compete for the Chinese market, corn destination for the two biggest exporters do not overlap. US biggest buyers are Japan, Mexico, and the European Union. As we can see in Figure 16, there is no clear hub destination for corn.

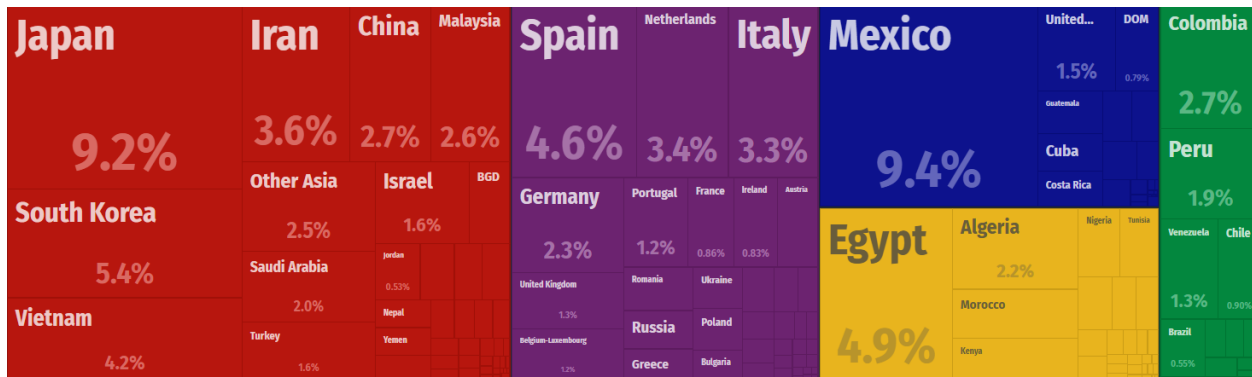


Figure 16 - Global Corn Import Shares
Source: UN COMTRADE (2019) – built by Atlas Media.

Domestic Market

While a big participant in international markets for soybeans and corn, Brazil is also a big consumer of grain. The country has not only the largest commercial cattle herd in the world, but also is a leader in pork and the second-largest poultry producer in the world. As Figure 17 shows, more than 50% of the corn produced in the country stays is consumed in the country.

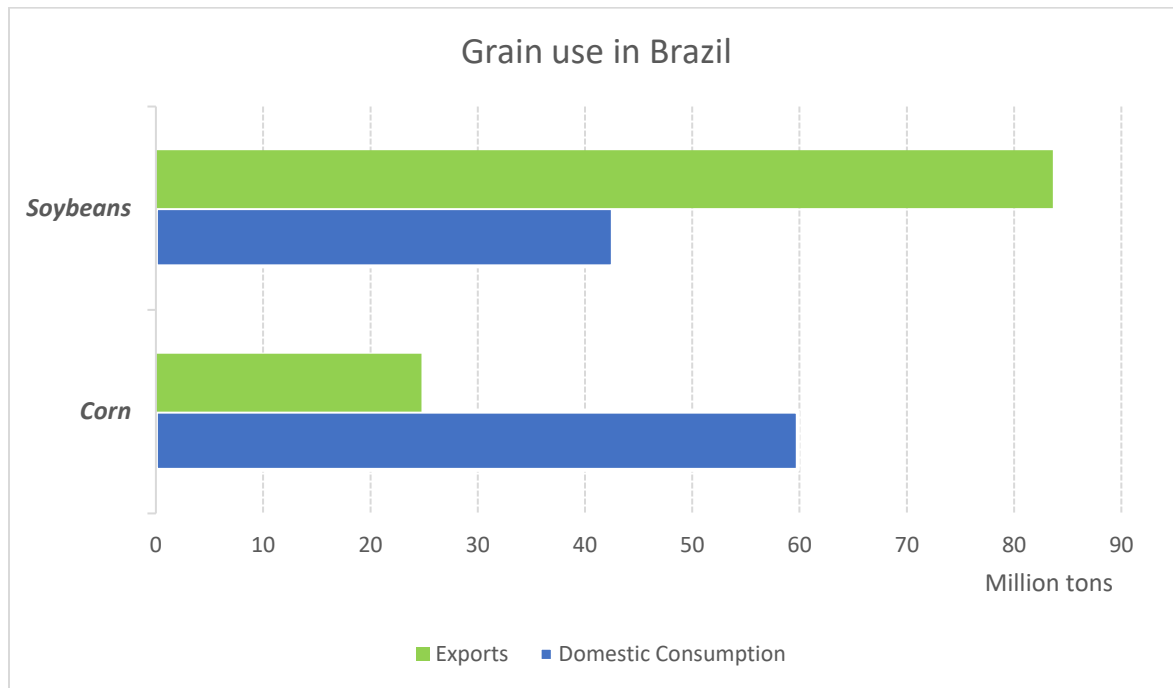


Figure 17 - Grain use in Brazil

Source: CONAB (2019), built by the author.

Most of this corn is destined to pork and poultry production, whose main hubs are in Parana, Santa Catarina and Rio Grande do Sul, all southern states that produce most of the 1st corn crop. Because of that, the first crop is considered a domestic crop, supplying this demand, and the second corn crop is usually used to fill the rest of the demand gap and exports.

Another important reason why second corn crop is exported is that, as it is planted after the soybean harvest, it does not compete for space in the ports. Brazil's infrastructure for exports is limited, even though several ongoing expansion projects will help alleviate some of the pressure. Having the soybeans exported and then switching to corn makes logistical sense. As Figure 17 illustrates, soybeans exports volume is more than three times the actual volume of corn, so beans have priority during peak harvest months for the summer crops.

Soybeans are exported because China's biggest demand is for the raw grain, not for the processed products, meal, and oil. Because of that, and Brazil not having a very large crushing industry, the country exports two-thirds of its production, being very close to maximum processing capacity usage.

Due to these reasons, soybeans are, in general, more exposed to global prices, while shifts in domestic production and demand in Brazil can have big impacts in domestic prices, that will not necessarily follow global market prices.

LITERATURE REVIEW

Understanding the relationships between cash and futures prices is fundamental for risk managing purposes. The understanding of cointegration was introduced by Engle and Granger (1987) and states that two variables are cointegrated because of the presence of a long-run equilibrium between them. Several studies, like Lai and Lai (1991), present strong evidence of cointegration between a future and its cash market. Ghosh (1993) points out that, when the presence of cointegration is not considered, a smaller than optimal hedge position will likely take place. Lien (1996) adds to that, saying that if cointegration is not taken into account, hedge performance will be worse and will likely cost more for the errant hedger. Lien (1996) also adds that, while GARCH effects will not affect the under/over hedge derived from the cointegration relationship, they play an imported role in allowing for a time-varying minimum risk hedge ratio. Understanding GARCH effects between two prices, then, is also important.

Modeling volatility spillovers through GARCH models linking different futures markets or futures and cash markets can be done in several different ways. Ng (2000) proposes a two-factor model that allows for an external shock to spillover over the studied markets utilizing univariate and multivariate GARCH models for stock indexes. Other authors investigate these relationships across energy and agricultural markets.

Utilizing the BEKK specification, proposed by Engle and Kroner (1995), Zhang et al. (2009) examined how food prices were affected by US energy markets. Serra et al. (2011) use the BEKK to analyze volatility spillovers between crude oil, ethanol, and Brazilian sugarcane prices. Wu, Guan, and Myers (2010) use a similar approach Ng (2000) but allowing for a time-varying volatility spillover coefficient and analyze how spillover effects coming from crude oil to corn were enough to utilize crude oil as a cross-hedge tool to hedge corn. Trujillo-Barrera, Mallory, and Garcia (2012) use a two-step approach to calculate volatility spillovers between crude oil, corn and ethanol, finding that crude oil and corn spillover ethanol.

Another set of studies focuses on impulse response to price shocks. Among them, Garderbroek and Hernandez (2013) derive impulse response functions from a tri-variate T-BEKK model and a DCC-GARCH for crude oil, corn, and ethanol. Most of these studies, however, are focused on the relationship between energy and agricultural markets.

Studies that focus on grain and oilseed markets include Booth and Ciner (1997), who study corn markets and spillovers for different regions, Goychuk and Meyers (2001) that focus on wheat and Fossati, Lorenzo and Rodriguez (2009) that study cattle markets and grains. Global market relations are also studied by Yang et al. (2003), who look at wheat futures among North America and Europe.

Brazilian markets were also topics of different studies. Balcombe et al. (2007) analyzed how Brazilian, Argentine and US grain markets were related, investigating possible threshold effects. They approach it using Eq-TAR and Band-TAR models with a Bayesian approach. Utilizing data up to 2006, their study finds that threshold effects exist, and transmission was bigger for corn markets and US and Argentine markets, with Brazil not affecting at all.

Mattos and Silveira (2015) measure the impacts of the second corn crop in Brazil on seasonality, basis behavior and integration to international markets. They find that, after the double crop, Brazilian markets became more integrated into international markets. Cruz Jr. et al. (2016) builds on this and, utilizing futures and cash prices for soybeans and corn, using causality tests find that the level of market integration increased and price sensibility to global markets has also increased.

This study will contribute to the literature in three forms. We test for market cointegration only using Brazilian cash prices and US futures prices, as Brazilian Futures markets for soybeans and corn were found to be inefficient for hedging purposes by Rodrigues and Martines Filho (2015). This is important as studies that considered Brazilian futures could have distorted results deriving from the inefficiency present in these markets.

Our second contribution is that we are the first ones measuring volatility spillovers seasonal changes, only possible through our calculation of time-varying spillover ratios obtained through the BEKK conditional variances. Finally, we also contribute by analyzing the effects, or lack of, on global grain prices after the trade war between the US and China on cointegration and volatility spillovers.

DATA

Data used is for daily closing futures log prices for Soybeans (S) and Corn (C) from CME, using most active contract prices rolled on a per volume basis, ranging from September 10th, 2003 to March 26th, 2019 as our benchmark for US Futures prices. Brazilian prices are the daily average price at the Port of Paranaguá, for soybeans, and daily average prices from Chapecó and Sorriso for corn. These prices are from CEPEA and are converted to US\$/bu using daily foreign exchange rates from the Federal Reserve Economic Data (FRED – St Louis Fed). Figure 18 illustrates the selected cash prices locations.



Figure 18 - Cash Prices Location in Brazil

Source: Departamento Nacional de Infraestrutura de Transportes (DNIT) (2019), adapted by the author.

The yellow dot indicates the Port of Paranaguá region. Data from COMEXSTAT (2019) points that the Port of Paranaguá exported approximately 15 million tons of soybeans, only behind the Port of Santos (20 million tons). The difference between the two ports is that, while

Santos only exports grain coming from the Center-West and Southeast, Paranagua exports grains from these regions and also grain originated in the South, so it will serve as our Brazilian proxy for soybeans prices.

On the corn side, we have the green and red dots. The red dot represents Chapeco, our proxy for first crop supply and demand, as farmers around this area do not double-crop and most poultry and pork feedlots are in this area, meaning that domestic consumption is mainly there. The green dot represents Sorriso, the biggest producer of grain in the country and one of the largest areas for double-cropping. Most of the corn produced there is second crop, as Figure 9 shows, and because of that it will serve as our proxy for second crop. Figure 19 and Figure 20 shows the prices across the time studied. Red lines indicate where we are separating our sample in two distinct periods (Pre and Post Second Crop).

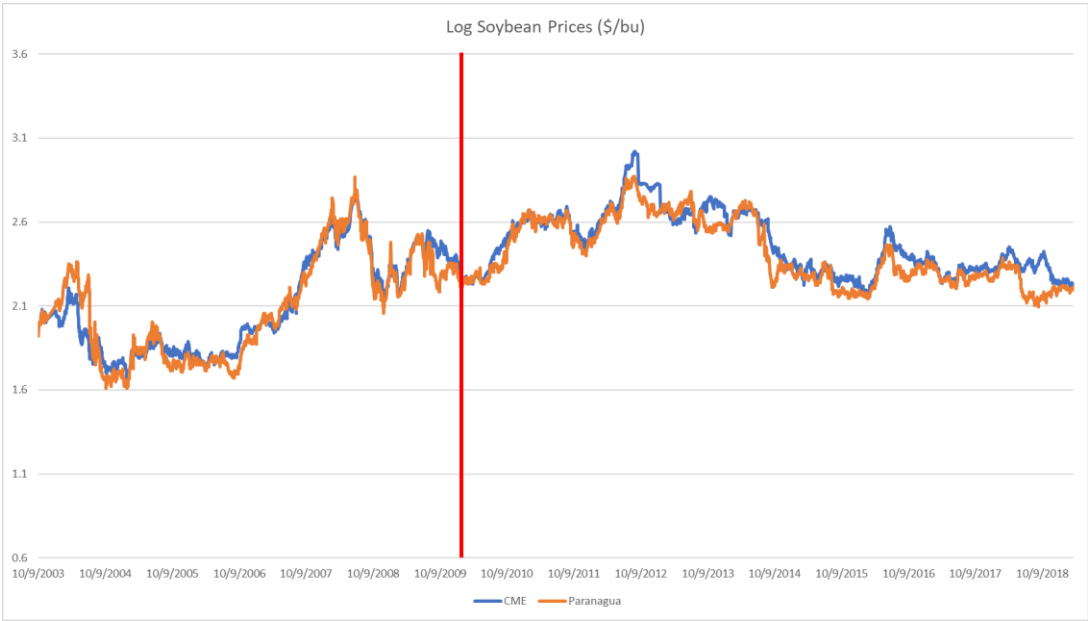


Figure 19 - Log Soybean Prices
Source: CME and CEPEA, built by the author. (2019)

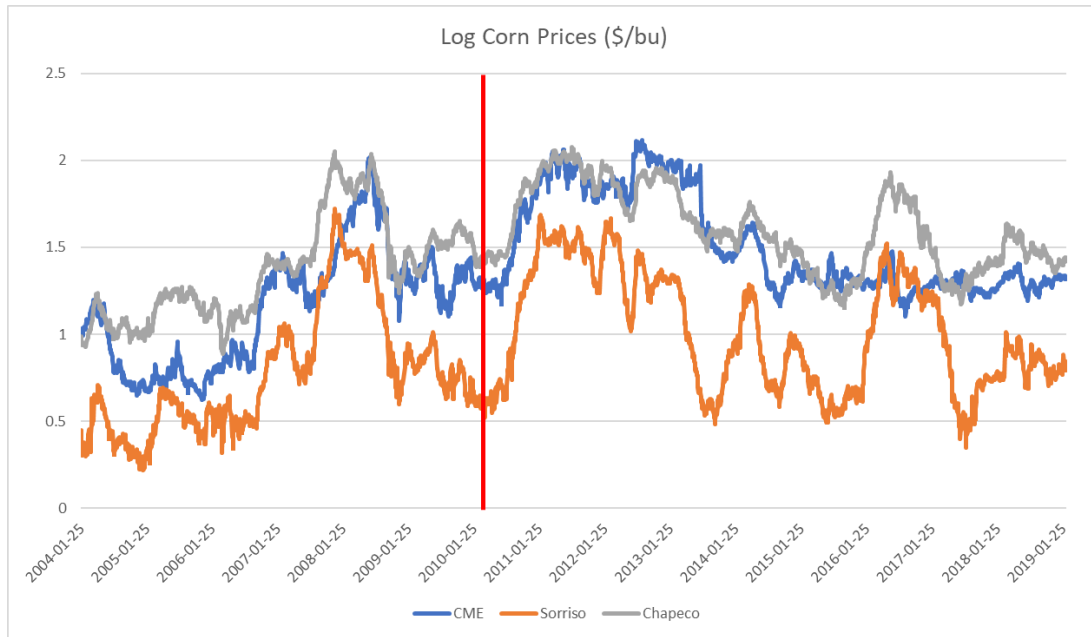


Figure 20 - Log Corn Prices
 Source: CME and CEPEA, built by the author. (2019)

Correlations for the sample are shown in Table 1 . It is noticeable how log prices correlation is higher than returns correlation in all cases.

Table 1 - Correlations

| Correlations | | Corn CME | Corn Sorriso | Corn Chapeco | Soybeans CME | Soybeans Paranagua |
|--------------|--------------------|----------|--------------|--------------|--------------|--------------------|
| Log Prices | Corn CME | 1.00 | 0.76 | 0.85 | - | - |
| | Corn Sorriso | 0.76 | 1.00 | 0.93 | - | - |
| | Corn Chapeco | 0.85 | 0.93 | 1.00 | - | - |
| | Soybeans CME | - | - | - | 1.00 | 0.96 |
| | Soybeans Paranagua | - | - | - | 0.96 | 1.00 |
| Returns | Corn CME | 1.00 | 0.14 | 0.13 | - | - |
| | Corn Sorriso | 0.14 | 1.00 | 0.24 | - | - |
| | Corn Chapeco | 0.13 | 0.24 | 1.00 | - | - |
| | Soybeans CME | - | - | - | 1.00 | 0.53 |
| | Soybeans Paranagua | - | - | - | 0.53 | 1.00 |

Table 2 presents the summary statistics for the data used. Stationarity tests using the Augmented Dickey Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) are performed. Both indicate that our sample and sub-samples are non-stationary and stationary of order 1. We also perform the Zivot-Andrews test to make sure that the unit-root processes are not due to structural breaks, which the test indicate that is not the case. Because of that, we will proceed with a VAR in first differences and a VECM in price levels.

Table 2 - Summary Statistics

| Statistics | Minimum | Maximum | 1st Quartile | 3rd Quartile | Mean | Median |
|--------------------|----------------|----------------|---------------------|---------------------|-------------|---------------|
| Corn CME | 1.86 | 8.31 | 3.42 | 4.89 | 4.17 | 3.74 |
| Corn Sorriso | 1.24 | 5.59 | 1.87 | 3.43 | 2.66 | 2.31 |
| Corn Chapeco | 2.43 | 7.97 | 3.69 | 5.73 | 4.72 | 4.42 |
| Soybeans CME | 5.18 | 20.50 | 8.67 | 12.75 | 10.57 | 10.41 |
| Soybeans Paranagua | 5.00 | 17.69 | 8.63 | 12.44 | 10.18 | 9.81 |
| Corn CME | -0.11 | 0.13 | -0.01 | 0.01 | 0.00 | 0.00 |
| Corn Sorriso | -0.16 | 0.26 | -0.01 | 0.01 | 0.00 | 0.00 |
| Corn Chapeco | -0.11 | 0.14 | -0.01 | 0.01 | 0.00 | 0.00 |
| Soybeans CME | -0.09 | 0.11 | 0.00 | 0.00 | 0.00 | 0.00 |
| Soybeans Paranagua | -0.26 | 0.18 | 0.00 | 0.01 | 0.00 | 0.00 |

| Statistics | Variance | SD | Skewness | Excess kurtosis |
|--------------------|-----------------|-----------|-----------------|------------------------|
| Corn CME | 2.30 | 1.52 | 0.80 | -0.13 |
| Corn Sorriso | 1.02 | 1.01 | 0.83 | -0.46 |
| Corn Chapeco | 1.78 | 1.33 | 0.50 | -0.75 |
| Soybeans CME | 8.99 | 3.00 | 0.27 | -0.25 |
| Soybeans Paranagua | 8.02 | 2.83 | 0.21 | -0.62 |
| Corn CME | 0.00 | 0.02 | 0.04 | 2.87 |
| Corn Sorriso | 0.00 | 0.03 | 0.37 | 5.77 |
| Corn Chapeco | 0.00 | 0.02 | -0.19 | 4.96 |
| Soybeans CME | 0.00 | 0.01 | -0.55 | 9.80 |
| Soybeans Paranagua | 0.00 | 0.02 | -1.70 | 37.09 |

RESEARCH METHOD

Our empirical analysis will be done using a three-step approach. The first step is to determine the presence, or not, of unit-roots and/or structural breaks in the series. This is a crucial step as it will allow us to better determine on to approach our data. The second step of our analysis is determining the existence of cointegration between the studied pairs, to model our series either through a Vector Autoregressive (VAR) process or through a Vector Error Correction Model (VECM). Lastly, our third step consists of extracting the residuals from the VAR/VECM and utilizing a BEKK model, a multivariate GARCH, that will allow us to model conditional volatilities and the spillover ratios.

Unit-Root Tests

In this section, we will present all the methods to define whether there is a unit-root in our sample. The first thing we need to do is define the number of lags we will utilize for our sample. Due to the high number of data points in our sample, our lag selection method will be the Hannan-Quinn Information Criterion (Hannan and Quinn, 1979), an alternative to the Akaike Information Criterion (AIC). The main difference between the two methods is that while AIC selects a true model that overfits (larger than the true model), so we opt to use HQ, that selects the smallest true model. The test proposed by them is in Equation 1:

Equation 1- Hannan-Quin Information Criteria

$$HQC = -2LMAX + 2k \ln(\ln(n))$$

Lmax = log likelihood, k= number of parameters, and n= number of observations

We tested our data for stationarity using two different methods: Augmented Dickey-Fuller and KPSS. Even though they are testing stationarity, these tests have some differences.

The ADF test was introduced by Dickey and Fuller (1979) and tests with its null hypothesis being that the process has unit-root or is “difference stationary”. The alternative hypothesis is that the process does not have unit-root (in our test, rejecting the null means that the process is stationary). On the other hand, the KPSS’ null hypothesis is that the process is stationary, while the alternative hypothesis is that the process has unit-root, as proposed by its authors in 1992.

In addition, we will perform the Zivot-Andrews (Z-A)(1992) test for Structural Breaks. We run the Z-A test after the stationary tests because we want to make sure that the unit-root process that we found in the ADF and KPSS tests are not due to a structural break in the series. The Z-A test must be run after we perform the stationarity tests, and after we find a unit-root in those tests, otherwise it is misspecified.

Cointegration Test and Model Selection

We proceed in this second step by breaking our corn and soybeans series in two series, one pre-double cropping and one post double cropping. Figure 5 and Figure 10 indicate an increased growth in production starting in the crop year of 2009/10, so we will separate our data in these points.

After separating our data, we will use Johansen's (1991) Cointegration Test. This well-known multivariate test will allow us to determine whether there is a long-run equilibrium relationship between tested pairs or not. If we find that there is one cointegration relationship, we will assume the markets are integrated.

Determining the existence of cointegration is important as it will direct us to our first model selection. In case the test points for no cointegration, we proceed using a VAR. If the series are integrated, we proceed using a VECM.

Vector Autoregressive (VAR)

A generalization of the univariate autoregressive model (AR model), VAR models captures the linear interdependencies intertemporally between two or more variables. The model is shown in Equation 2, as each variable has its own equation, affected by its own lagged term, the lagged term of the other(s) variable(s) and an error term. A simple VAR with one lag and two variables interacting can be described as:

Equation 2 - VAR

$$\begin{aligned} br_t &= a_{10} + a_{11}br_{t-1} + a_{12}us_{t-1} + e_{1t} \\ us_t &= a_{20} + a_{21}br_{t-1} + a_{22}us_{t-1} + e_{2t} \end{aligned}$$

The significance of the lagged coefficients helps to determine the linear relationships between the two variables. For our next step, we will extract the residuals from this system, defined in Equation 3 - VAR Residuals Matrix as:

Equation 3 - VAR Residuals Matrix

$$\varepsilon_t = [e_{1t}, e_{2t}]$$

Vector Error Correction Model (VECM)

The Vector Error Correction Model is, stated intuitively, a VAR with an added term. This added term represents the cointegration relationship, or the long-run equilibrium between the studied variables called the Error Correction Term. As we are studying pairs, we can only find no-cointegration (VAR) or one cointegration relationship, therefore adding one ECT per equation, as in

Equation 4 - VECM Equations:.

Equation 4 - VECM Equations:

$$\begin{aligned} \Delta br_t &= \delta_{10} + \alpha_1(\beta_0 + \beta_1 br_{t-1} + \beta_2 us_{t-1}) + \delta_{11} br_{t-1} + \delta_{12} us_{t-1} + e_{1t} \\ \Delta us_t &= \delta_{20} + \alpha_2(\beta_0 + \beta_1 br_{t-1} + \beta_2 us_{t-1}) + \delta_{21} br_{t-1} + \delta_{22} us_{t-1} + e_{2t} \end{aligned}$$

While the δ 's are the same as the regression coefficients in the VAR equations, the error correction term part introduces new terms, the α 's and the β 's. The ECT is a combination of the equilibrium relationship, determined by $\beta_0 + \beta_1 br_{t-1} + \beta_2 us_{t-1}$, and the speed of adjustment terms, α_1 and α_2 .

That means that the β 's indicate how one variable relates to the other one in the long-run,. The α 's, on the other hand, indicate how the two series will adjust to a disequilibrium. That means that, for example, if US deviates from BR "disrespecting" the long-run equilibrium, the

α 's will bring the relationship back. One important thing is that the α 's also indicate who responds faster to a disequilibrium, having its applications for price discovery and other metrics.

Similar to how we handle the VAR model, we extract the residuals vector, similar to Equation 3, and use those to calculate market interactions.

BEKK GARCH and Spillover Ratio Estimation

GARCH models are useful to model volatility within a series. When dealing with more than one variable, one should use a multivariate GARCH (MGARCH) to properly model the volatilities and interactions between the series evaluated. While several different specifications for MGARCH exist, this paper will utilize the BEKK-GARCH, defined by Baba, Engle, Kraft, and Kroner (1990).

Using the BEKK model specification guarantees some important benefits against other MGARCH, like the VEC and the Dynamic Conditional Correlation (DCC) specifications. The BEKK, that is a restricted VEC in a way, is positive definite, an important definition for the volatility studied in this paper. As Equation 5 shows, the model decomposes the constants term into a product of two triangular matrices makes sure that H_t , that is the conditional variance-covariance matrix, is positive semi-definite.

Equation 5 - BEKK Specification

$$H_t = C'C + \sum_{j=1}^q \sum_{k=1}^K A'_{kj} e_{t-j} e'_{t-j} A_{kj} + \sum_{j=1}^q \sum_{k=1}^K B_{kj}' H_{t-j} B_{kj}$$

Positive definiteness is plus compared to VEC, it also will apply better to our modeling over the DCC-GARCH as, even with the DCC having fewer parameters than the BEKK, its conditional correlations follow the same dynamic structure. The BEKK, on the other hand, allow them to change.

As mentioned in section 4.2, we will utilize the residuals matrices extracted from the pair studied to estimate the BEKK. Considering a two-variable system (br and us), Equation 5 yields:

$$\begin{bmatrix} h_{brbr,t} & h_{brus,t} \\ h_{brus,t} & h_{usus,t} \end{bmatrix} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}' + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} e_{br,t-1}^2 & e_{br,t-1} e_{us,t-1} \\ e_{br,t-1} e_{us,t-1} & e_{us,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{brbr,t-1} & h_{brus,t-1} \\ h_{brus,t-1} & h_{usus,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

This defines the conditional volatilities of br and us to be:

Equation 6 - Variable br conditional volatility

$$h_{brbr,t} = c_{11}^2 + a_{11}^2 e_{br,t-1}^2 + 2a_{11} a_{21} e_{br,t-1} e_{us,t-1} + a_{21}^2 e_{us,t-1}^2 + b_{11}^2 h_{brbr,t-1}^2 + 2b_{11} b_{21} h_{brus,t-1} + b_{21}^2 h_{usus,t-1}^2$$

Equation 7- Variable us conditional volatility

$$h_{usus,t} = c_{12}^2 c_{22}^2 + a_{12}^2 e_{br,t-1}^2 + 2a_{12}a_{22}e_{br,t-1}e_{us,t-1} + a_{22}^2 e_{us,t-1}^2 + b_{12}^2 h_{brbr,t-1}^2 + 2b_{12}b_{22}h_{brus,t-1} + b_{22}^2 h_{usus,t-1}^2$$

After defining the conditional volatilities and the terms that calculate them, we will proceed to separate and evaluate the isolated cross-market effects. We define isolated cross-market effects as the effects caused on the target market (i.e. *br*) by, and solely by, the other market (i.e. *us*). Table 3 shows the price shock isolated coefficients and the price volatility isolated coefficients that affect the other market.

| Effect | Conditional Volatilities | |
|------------------|--------------------------|-------------------------|
| | $h_{aa,t}$ | $h_{bb,t}$ |
| Price Shocks | $a_{21}^2 e_{b,t-1}^2$ | $a_{12}^2 e_{a,t-1}^2$ |
| Price Volatility | $b_{21}^2 h_{bb,t-1}^2$ | $b_{12}^2 h_{aa,t-1}^2$ |

Albeit these coefficients are not the only ones that represent market effects, these are the only ones that represent purely information coming from the other market. Subsequently, to isolating these coefficients, we measure a Spillover Ratio at time t . As Equation 8 shows, the sum of the price shock effect and the volatility effect are divided by the total conditional volatility of the other market.

Equation 8 - Spillover Ratio

$$SR_{br \rightarrow us} = \frac{(a_{21}^2 e_{us,t-1}^2 + b_{21}^2 h_{usus,t-1})}{h_{brbr}}$$

As the BEKK defines conditional volatility as always positive and the fact that price shock effects are squared, the ratio automatically assumes a positive or zero value. Another interesting assumption is that the SR can be higher than 100%. Although the cross-market coefficients will always be positive, by definition, the other coefficients in the calculation are not necessarily positive. The interaction coefficients (i.e. $2a_{11}a_{21}e_{br,t-1}e_{us,t-1}$) from Equation 6 and Equation 7 not only can, but will, assume negative values (for example when a shock is negative and the coefficient is positive, or vice versa).

This definition derived from the BEKK conditional volatilities equation will allow the calculated Spillover Ratio from Equation 8 to be bigger than 100%. There are two interpretations of this phenomenon:

- Volatility at t is way lower than at $t-1$, so the volatility and price shocks effects from $t-1$ are representing most of the volatility at t ;
- The interaction coefficients are assuming high negative values, implying that our Ratio is overestimating the cross-market effects.

Although not a perfect measure, this approach to calculating the cross-market effects, or spillovers, allow this study to calculate varying t -to- $t+1$ ratios. This is key to evaluate seasonal effects between markets, a key aspect of this study.

RESULTS AND DISCUSSION

We will separate the results and discussion section in two parts, one for corn and the other one for soybeans.

CORN

Following our procedures, we divide our corn series in two sub-samples, with the breaking point in the 09/10 crop year. This is an important moment because, as it can be seen in Figure 10, that is the moment that the “safrinha” or second crop started to gain momentum.

The first test that we run is the Johansen test for cointegration. For simplicity, we will present the results for Sorriso, the second crop corn⁴. Table 4 and Table 5 show the results obtained for the two sub-samples.

Table 4 - Cointegration Test for Corn from 2004-2009

| 2004-2009 | <i>US Futures x Sorriso Spot</i> | | |
|---------------------------|---|-----------------------|-------|
| | | <i>Critical Value</i> | |
| <i>Cointegration Rank</i> | λ_{max} | 95% | 99% |
| r=0 | 9.15 | 15.67 | 20.20 |
| $r \leq 1$ | 1.97 | 9.24 | 12.97 |

It is possible to observe a clear change. While we cannot reject the null of no cointegration ($r=0$) for the first period, we are able to reject the null at the 1% level for the second period.

Table 5- Cointegration Tests for Corn from 2010-2019

| 2010-2019 | <i>US Futures x Sorriso Spot</i> | | |
|---------------------------|---|-----------------------|-------|
| | | <i>Critical Value</i> | |
| <i>Cointegration Rank</i> | λ_{max} | 95% | 99% |
| r=0 | 25.70** | 15.67 | 20.20 |
| $r \leq 1$ | 2.86 | 9.24 | 12.97 |

The indication the test gives us is that, on the second period, there seems to be one cointegration relationship ($r < 1$ cannot be rejected) between the two price series. From what was previously discussed, these results go along with the increased participation Brazil has had on global corn markets after the country started double-cropping. It also indicates that, before double-cropping, Brazilian corn did not participate in a long-run equilibrium with global prices.

⁴ Results for the US Futures/Chapeco pair are the same, only with slightly magnitudes differences, and are available on

This is also important, because indicates the country moving from a domestic based pricing to a more globalized price discovery.

After defining the presence of cointegration or not, we proceed with modeling our series. For the first period, then, we will use a VAR in first differences. The second period will be modeled through a VECM in levels. The estimation results⁵ can be found in Table 6 and Table 7.

Table 6 provides important takeovers from the VAR. The VAR indicates that US (or Global) markets had effects over Brazilian corn changes. In the meantime, Brazilian corn prices changes are not significant on the US equation, pointing to the South American corn not affecting US/Global markets.

Table 6 – Corn VAR parameters - 2004/2009

| VAR Lagged Parameters - 2004-2009 | | | | |
|--|------------------|-----------------|-------------------|--|
| <i>Equation</i> | <i>Parameter</i> | <i>Estimate</i> | <i>Std. Error</i> | |
| Sorriso Spot | Sor L1 | -0.16054** | 0.027 | |
| | US L1 | 0.09176** | 0.035 | |
| | Sor L2 | -0.05391** | 0.027 | |
| US Futures | US L2 | 0.02824 | 0.035 | |
| | Sor L1 | 0.01240 | 0.021 | |
| | US L1 | 0.02668 | 0.027 | |
| | Sor L2 | 0.01275 | 0.021 | |
| | US L2 | 0.01306 | 0.027 | |

**(*) Denotes significance at 1% (5%) level

Table 7 – Corn VECM Coefficients - 2009/2019

| VECM Parameters - 2009-2019 | | | | |
|------------------------------------|------------------|-----------------|-------------------|--|
| <i>Equation</i> | <i>Parameter</i> | <i>Estimate</i> | <i>Std. Error</i> | |
| | β_{sor} | 1 | | |
| | β_{us} | -1.0028** | | |
| Sorriso Spot | α_{sor} | -0.010214** | 0.003 | |
| | 2016 Dummy | 0.007967** | 0.002 | |
| US Futures | α_{us} | 0.005648** | 0.002 | |
| | 2016 Dummy | -0.003408** | 0.002 | |

**(*) Denotes significance at 1% (5%) level

The VECM coefficients also provide interesting results. After adding a dummy variable for 2016⁶, we find highly significant α and β . The sum of the β is very close to zero, expected when we are pricing the same commodity and assuming no constant arbitrage relationship. The α also provides insight on the relationship. In absolute terms, the α for Sorriso is two times bigger

⁵ Results for Sorriso. Chapeco results can be found in Appendix A.

⁶ In 2016 a big drought affected Brazilian producers, on both corn crops. As stocks were already low, the country had to import corn and there were several interventions by CONAB through federal auctions to contain prices.

than the US, indicating that Brazilian prices respond faster and with more intensity to a disequilibrium.

After extracting the residuals from the VAR and from the VECM, the BEKK GARCH coefficients estimation can be seen in Table 8 and Table 9.

Table 8 – Corn BEKK Coefficients - 2004/2009

| BEKK GARCH - 2004-2009 | | |
|-------------------------------|--------------------|--------------------|
| <i>Variable</i> | <i>Coefficient</i> | <i>t-Statistic</i> |
| C(sor,sor) | 0.004** | 6.98 |
| C(us,sor) | 0.000 | -0.43 |
| C(us,us) | 0.002** | 2.89 |
| A(sor,sor) | 0.269** | 11.74 |
| A(sor,us) | 0.016 | 1.00 |
| A(us,sor) | 0.007 | 0.02 |
| A(us,us) | 0.179** | 6.82 |
| B(sor,sor) | 0.951** | 131.71 |
| B(sor,us) | -0.005 | -0.82 |
| B(us,sor) | 0.007 | 0.86 |
| B(us,us) | 0.978** | 116.48 |

**(*) Denotes significance at 1% (5%) level

Table 9 – Corn BEKK Coefficients - 2010/2019

| BEKK GARCH - 2010-2019 | | |
|-------------------------------|--------------------|--------------------|
| <i>Variable</i> | <i>Coefficient</i> | <i>t-Statistic</i> |
| C(sor,sor) | 0.006** | 6.07 |
| C(us,sor) | 0.000 | 0.17 |
| C(us,us) | 0.001** | 2.94 |
| A(sor,sor) | 0.196** | 6.58 |
| A(sor,us) | -0.052** | -3.41 |
| A(us,sor) | 0.059** | 2.74 |
| A(us,us) | 0.244** | 10.80 |
| B(sor,sor) | 0.941** | 53.64 |
| B(sor,us) | 0.008 | 1.10 |
| B(us,sor) | -0.002 | -0.42 |
| B(us,us) | 0.966** | 167.62 |

**(*) Denotes significance at 1% (5%) level

The red boxes highlight the cross-market coefficients that will be used to calculate the spillover ratios. The biggest takeaway from these tables is that on the first period not a single cross-market coefficient is significant, when in the second period the A matrix is significant (price shocks matrix). This indicates that in the pre second crop period there were no clear signs of volatility spillovers from one market to the other. That dynamic changes after the markets become cointegrated, as we find that not only the US is spilling over in Brazil, but Brazil is also spilling over the US. Figure 21⁷ shows the spillover ratios for US/Sorriso and US/Chapeco⁸.

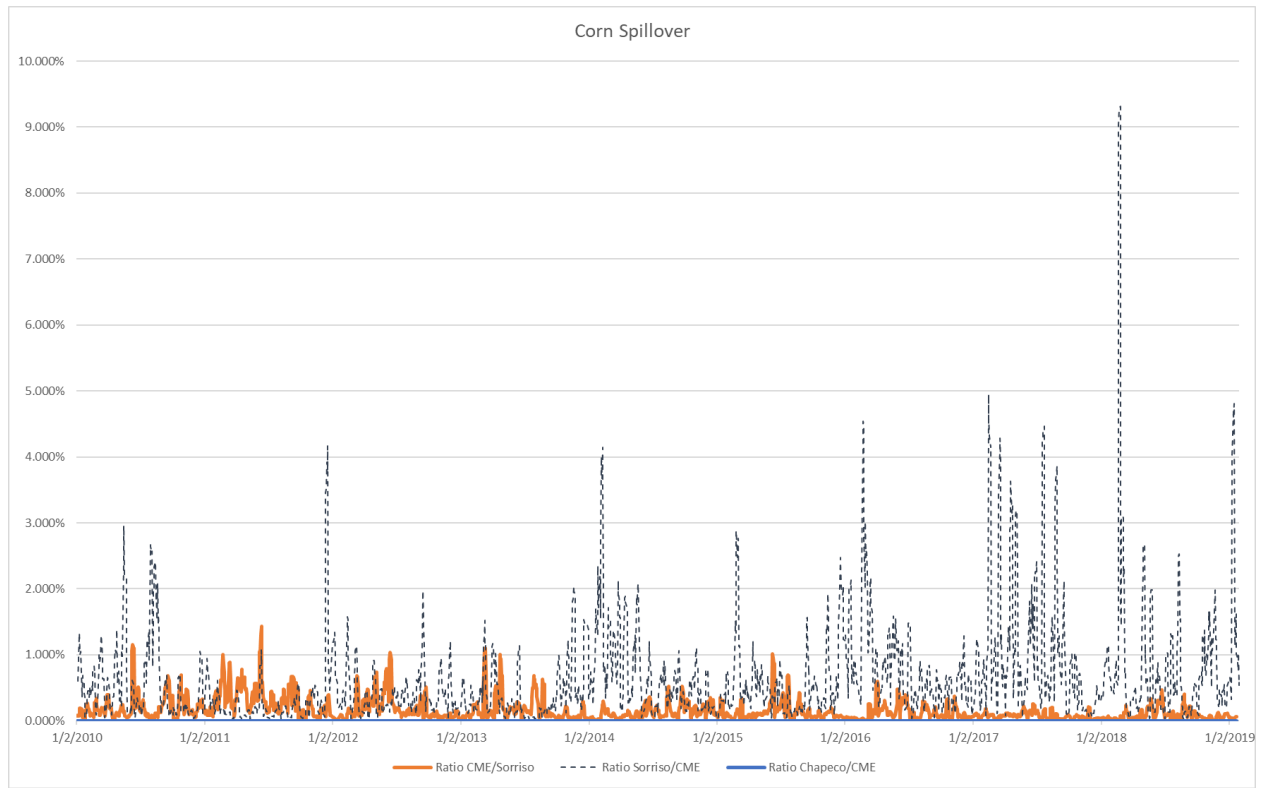


Figure 21 - Spillover Ratios for Corn

The figure shows a clear pattern in spillover season. When Brazil is harvesting its first crop and planting its second (Jan – April), spillovers are higher. When US season is happening, Brazil’s spillovers tend to go down. There is also a trend of increased spillovers from Brazil into the US.

The main reason for that is that US corn volatilities have been low for the past 4 years, consistent with a high stocks and low price scenario. Brazil, however, has had big droughts and general uncertainty over the country that caused Brazilian volatility for corn to be almost double the US corn volatility over our sample. Also, with markets more and more integrated every year, volatility relations should be higher.

⁷ Spillovers for the first period are not plotted, as they are all non-significant.

⁸ Although significant, US/Chapeco spillovers are very close to 0%.

SOYBEANS

Similar to our corn procedures, we divide our soybeans series in the 09/10 crop year. The results for the Johansen cointegration test can be found in Table 10 and Table 11.

Table 10 - Cointegration Tests for Soybeans from 2004-2009

| 2004-2009 | <i>US Futures x Parangua Spot</i> | | |
|---------------------------|--|-----------------------|-------|
| | | <i>Critical Value</i> | |
| <i>Cointegration Rank</i> | λ_{max} | 95% | 99% |
| r=0 | 7.67 | 15.67 | 20.20 |
| $r \leq 1$ | 1.18 | 9.24 | 12.97 |

Table 11 - Cointegration Tests for Soybeans from 2010-2019

| 2010-2019 | <i>US Futures x Parangua Spot</i> | | |
|---------------------------|--|-----------------------|-------|
| | | <i>Critical Value</i> | |
| <i>Cointegration Rank</i> | λ_{max} | 95% | 99% |
| r=0 | 23.18** | 15.67 | 20.20 |
| $r \leq 1$ | 2.48 | 9.24 | 12.97 |

The results point out to the same conclusions as corn. Even though Brazil was already a big player in soybeans markets before the second crop, its prices were not cointegrated with global prices until 2010. After that, like in corn, prices become cointegrated at the 1% level of significance. Because of this pattern, soybeans modeling will be the same as corn: VAR for the first period and VECM for the second. The results for that are in Table 12 and Table 13.

Table 12 – Soybeans VAR Parameters - 2004/2009

| VAR Lagged Parameters - 2004-2009 | | | |
|--|------------------|-----------------|-------------------|
| <i>Equation</i> | <i>Parameter</i> | <i>Estimate</i> | <i>Std. Error</i> |
| Paranagua Spot | Paranagua L1 | -0.14421** | 0.033 |
| | US L1 | 0.20469** | 0.048 |
| | Paranagua L2 | -0.15786** | 0.034 |
| | US L2 | 0.15603** | 0.049 |
| | Paranagua L3 | -0.08385** | 0.033 |
| | US L3 | 0.11181** | 0.048 |
| US Futures | Paranagua L1 | 0.1184527** | 0.023 |
| | US L1 | -0.1030326** | 0.033 |
| | Paranagua L2 | 0.02498 | 0.024 |
| | US L2 | 0.00559 | 0.034 |
| | Paranagua L3 | -0.00084 | 0.023 |

**(*) Denotes significance at 1% (5%) level

Table 13 – Soybeans VECM Parameters - 2010/2019

| VECM Parameters - 2009-2019 | | | |
|------------------------------------|------------------|-----------------|-------------------|
| <i>Equation</i> | <i>Parameter</i> | <i>Estimate</i> | <i>Std. Error</i> |
| | β_{par} | 1 | |
| | β_{us} | -1.034** | |
| US Futures | α_{us} | 0.018** | 0.004 |
| Paranagua Spot | α_{par} | -0.005 | 0.005 |

**(*) Denotes significance at 1% (5%) level

Unlike corn, soybeans coefficients in the VAR regression are all significant for one lag (and lags two and three are significant in the Brazilian prices equation). That goes along with Brazil already being a big player in the oilseed market, not only getting affected, but also affecting global price changes.

However, after Brazil started double-cropping, with a big increase in production, the α for Brazil in the VECM is, in absolute terms, four times smaller than the α for the US. It is also worth noticing that the α for Brazil is not significant, indicating that Brazilian bean prices are not being affected by CME. This is an important indication of the behavior of the volatilities' transmission.

Table 14 and Table 15 present the results of the BEKK GARCH for both periods. Unlike corn, in which cross-markets coefficients are not significant and then significant, soybeans present a different pattern.

The first period, Table 14, shows that only the cross-markets coefficients related to the US spilling over Brazil are significant, in line considering that the US was the biggest producer and exporter at the time. However, moving to the second period (Table 15), only the coefficients related to Brazil spilling over the US are significant, indicating a complete change of dynamic between the markets.

Table 14 – Soybeans BEKK Coefficients - 2004/2009

| BEKK GARCH - 2004-2009 | | |
|-------------------------------|--------------------|--------------------|
| <i>Variable</i> | <i>Coefficient</i> | <i>t-Statistic</i> |
| C(par,par) | 0.002** | 6.53 |
| C(us,par) | 0.000 | 0.42 |
| C(us,us) | -0.001** | -5.32 |
| A(par,par) | 0.607** | 11.25 |
| A(par,us) | 0.032 | 1.29 |
| A(us,par) | -0.413** | -7.74 |
| A(us,us) | 0.184** | 6.04 |
| B(par,par) | 0.803** | 23.04 |

| | | |
|-----------|---------|-------|
| B(par,us) | 0.003 | 0.40 |
| B(us,par) | 0.142** | 4.24 |
| B(us,us) | 0.970** | 93.73 |

**(*) Denotes significance at 1% (5%) level

Table 15- BEKK Coefficients - 2010/2019

| BEKK GARCH - 2010-2019 | | |
|-------------------------------|--------------------|--------------------|
| <i>Variable</i> | <i>Coefficient</i> | <i>t-Statistic</i> |
| C(par,par) | 0.001** | 4.59 |
| C(us,par) | 0.004** | 23.55 |
| C(us,us) | 0.000 | 0.00 |
| A(par,par) | 0.156** | 3.55 |
| A(par,us) | -0.548** | -13.68 |
| A(us,par) | 0.003 | 0.11 |
| A(us,us) | 0.381** | 8.53 |
| B(par,par) | 0.976** | 81.91 |
| B(par,us) | 0.138** | 3.95 |
| B(us,par) | -0.078 | -1.32 |
| B(us,us) | 0.200** | 2.16 |

**(*) Denotes significance at 1% (5%) level

As Figure 22 shows, US was spilling over in Brazil before Brazil started double-cropping. After that, the dynamic switches, and Brazil moves on to spillover in the US. Another difference is in the magnitude of spillovers. The first period has an average spillover of around 10% (meaning that 10% of the volatility in Brazil was explained by the US). The second period, on the other hand, shows an average spillover ratio of about 30% (meaning that 30% of the volatility in the US/CME was due to volatility coming from Brazilian spot). Going in the same line as the VECM, the BEKK GARCH indicates that Brazilian prices are not suffering from volatility spillovers generated in the US.

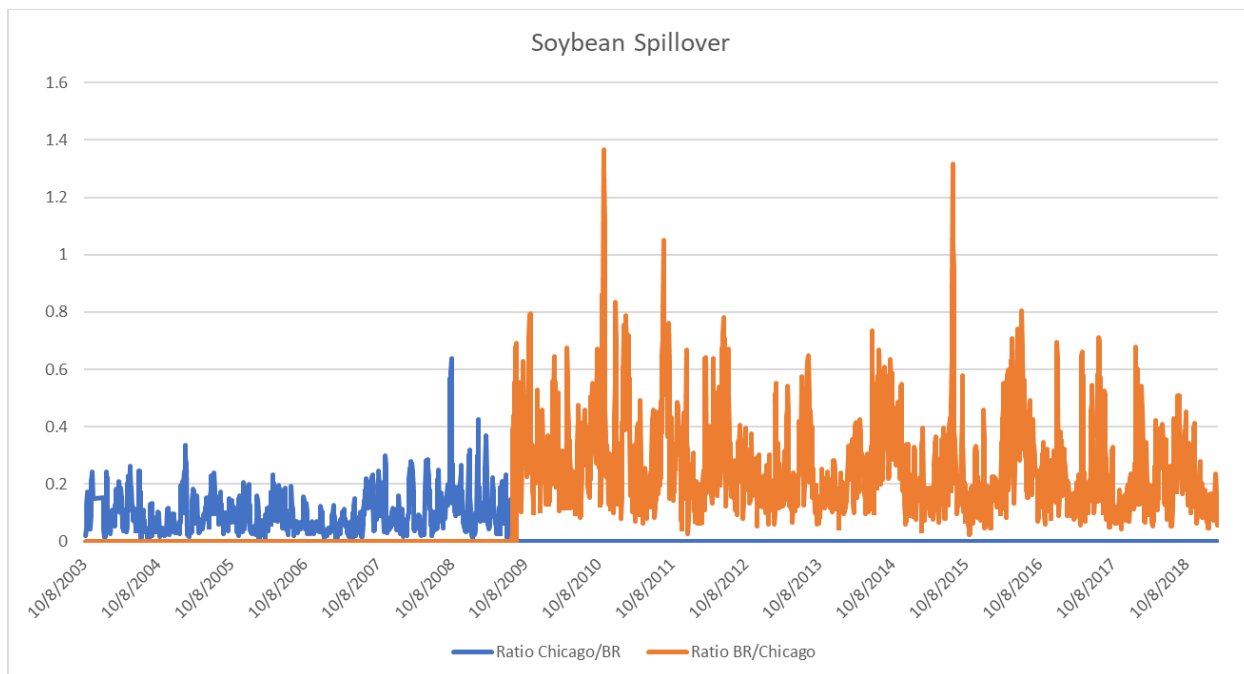


Figure 22 - Spillover Ratio for Soybeans

FINAL REMARKS

This study uses cointegration analysis and GARCH models in order to evaluate the change in dynamics in grain markets after Brazil started to double-crop beans and corn. The first change in dynamic captured by our analysis goes against what was found in Cruz Jr. et al (2016). While analyzing different prices sources, our study uses cash prices instead of the inefficient Brazilian corn futures contract, their findings point to the existence of cointegration before and after Brazil's second corn crop. Our results indicate that, for both soybeans and corn, Brazilian markets were not cointegrated with US futures prices before the second crop, but then, soybean and corn prices in Brazil become cointegrated with US Futures. That finding is important as it leads us to understanding that the increase in production in Brazil, highlighted in Figure 5 and Figure 10, led the country towards being an important part of global prices.

After proceeding our analysis using a VAR for the first period and a VECM for the second, the coefficients from the equations also provide interesting insights. For the first period, the VAR for corn, regardless of the cash price location, indicate that Brazilian prices were affected by changes in global corn prices (US Futures), while not affecting US Futures. For soybeans, however, our VAR indicates that Brazilian beans were affecting and getting affected by US Soybean Futures, as the lagged coefficients were significant both ways.

On the second period the scenario changes. The VECM for corn markets indicate that a long-run equilibrium now exists and that both prices are correcting to it (alphas are significant), as shown in Table 7. On the other hand, while the autoregressive coefficients for soybeans show the same behavior as in the pre second-crop period, soybean long-run equilibrium is defined by only one significant alpha, the one for US Futures. Even though the betas are significant, indicating the long-run relationship, the alpha for Brazil is not significant. That indicates that Brazilian cash prices are not correcting for the long-run equilibrium, even though they are

affected by US prices on the AR part of the model. These results anticipate what the BEKK GARCH and the volatility spillovers look like.

Our last step is to evaluate the presence, or not, of volatility spillovers between the markets. As Equation 8 discusses, we can measure the spillovers between the markets by isolation the cross markets terms from the conditional volatility equation. On the pre second crop period, the BEKK for corn does not show any significant cross-market coefficients, indicating that there were no volatility spillovers between the corn markets. On the second period, however, there are significant volatility spillovers from Brazil to the US and vice-versa.

Unlike the results we found on corn, soybean markets present a complete change in volatility spillover direction. The first period is marked by volatility spillovers from the US into Brazil, but not the inverse. After moving to the double-crop era, the spillover gets bigger, mostly due to the increase in cointegration between the markets and is only coming from Brazil to the US. This was anticipated by the VECM results that showed an “exogenous” Brazil on the second period.

Our metrics also allow us to analyze seasonality of the volatility spillovers. Both grain markets present similar behavior, with Brazil spilling over more during its crop cycle, first semester, and the US during the remaining part of the year. This is a big innovation that this paper introduces, as our approach to calculating the spillovers allow us to check for seasonality in the spillovers.

The results are important for risk managers (hedgers), speculators and market regulators. Understanding what is affecting market volatility is fundamental when placing hedges or trading strategies. Our study shows that grain futures markets changed a lot over the last 15 years, with Brazil playing a bigger role in price determination and volatility year after year. Our metrics will help traders better prepare for innovations coming from South American markets, and also allow them to know during what periods effects from Brazil cause the bigger impacts, thanks to our volatility spillover seasonality analysis. As for market regulators, discussions over a new futures contracts for Brazilian Soybeans, for example, can use this study to show that Brazilian beans have an exogenous behavior on the equilibrium relationship and are bringing around 30% of extra volatility to the traditional US Soybeans Futures, which can be a problem.

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APPENDIX A

Table 16 - Cointegration Tests for Corn - Chapeco x US Futures from 2004 to 2009

| 2004-2009 | | US Futures x Chapeco Spot | | |
|---------------|-----------------|---------------------------|-------|--|
| | | Critical Value | | |
| Cointegration | | | | |
| Rank | λ_{max} | 95% | 99% | |
| r=0 | 9.54 | 15.67 | 20.20 | |
| r ≤ 1 | 2.47 | 9.24 | 12.97 | |

Table 17 - Cointegration Tests for Corn - Chapeco x US Futures from 2010 to 2019

| 2010-2019 | | US Futures x Chapeco Spot | | |
|---------------|-----------------|---------------------------|-------|--|
| | | Critical Value | | |
| Cointegration | | | | |
| Rank | λ_{max} | 95% | 99% | |
| r=0 | 22.50** | 15.67 | 20.20 | |
| r ≤ 1 | 1.87 | 9.24 | 12.97 | |

Table 18 - Corn Chapeco VAR Lagged Parameters - 2004-2009

| VAR Lagged Parameters - 2004-2009 | | | |
|-----------------------------------|-----------|------------|------------|
| Equation | Parameter | Estimate | Std. Error |
| Chapeco Spot | Chap L1 | -0.11407** | 0.027 |
| | US L1 | 0.05097** | 0.022 |
| | Chap L2 | 0.02761 | 0.027 |
| | US L2 | 0.03086 | 0.022 |
| US Futures | Chap L1 | 0.00721 | 0.034 |
| | US L1 | 0.02856 | 0.027 |
| | Chap L2 | -0.01920 | 0.034 |
| | US L2 | 0.01882 | 0.027 |

**(*) Denotes significance at 1% (5%) level

Table 19 - Corn Chapeco VECM Lagged Parameters - 2010-2019

| VECM Parameters - 2009-2019 | | | |
|------------------------------------|------------------|-----------------|-------------------|
| <i>Equation</i> | <i>Parameter</i> | <i>Estimate</i> | <i>Std. Error</i> |
| | β_{chap} | 1 | |
| | β_{us} | -0.8134** | |
| Chapeco Spot | α_{chap} | -0.011443** | 0.002 |
| | 2016 Dummy | 0.005189** | 0.001 |
| US Futures | α_{us} | 0.007546** | 0.003 |
| | 2016 Dummy | -0.002785* | 0.001 |

**(*) Denotes significance at 1% (5%) level

Table 20 - Corn Chapeco BEKK GARCH Coefficients - 2004-2009

| BEKK GARCH - 2004-2009 | | |
|-------------------------------|--------------------|--------------------|
| <i>Variable</i> | <i>Coefficient</i> | <i>t-Statistic</i> |
| C(chap,chap) | 0.003** | 18.18 |
| C(us,chap) | 0.000 | -1.03 |
| C(us,us) | 0.002** | 7.92 |
| A(chap,chap) | 0.323** | 11.41 |
| A(chap,us) | 0.017 | 0.75 |
| A(us,chap) | -0.005 | -0.23 |
| A(us,us) | 0.168** | 8.29 |
| B(chap,chap) | 0.915** | 93.11 |
| B(chap,us) | -0.005 | -0.67 |
| B(us,chap) | 0.010 | 1.95 |
| B(us,us) | 0.9802** | 217.58 |

**(*) Denotes significance at 1% (5%) level

Table 21 - Corn Chapeco BEKK GARCH Coefficients - 2010-2019

| BEKK GARCH - 2010-2019 | | |
|-------------------------------|--------------------|--------------------|
| <i>Variable</i> | <i>Coefficient</i> | <i>t-Statistic</i> |
| C(chap,chap) | -0.011** | -3.63 |
| C(us,chap) | 0.000 | 0.01 |
| C(us,us) | 0.002** | 5.05 |
| A(chap,chap) | 0.111** | 8.72 |
| A(chap,us) | -0.064** | -3.56 |
| A(us,chap) | 0.037** | 2.25 |
| A(us,us) | 0.307** | 10.58 |
| B(chap,chap) | 0.990** | 413.50 |
| B(chap,us) | 0.007 | 1.39 |
| B(us,chap) | -0.008 | -1.51 |
| B(us,us) | 0.946** | 91.26 |

**(*) Denotes significance at 1% (5%) level