Research article

Dynamic connectedness and volatility spillover in the Brazilian agricultural market in the context of the Covid-19 pandemic♦

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Abstract

Agricultural commodities price volatilities experienced an increase in the period of 2006-2008 and since then, the shocks from the global crises have been affecting these markets, as the Covid-19 pandemic period. Many studies have evaluated volatility spillovers around agricultural markets by focusing on crises cycles. However, few of these studies focus on emerging markets. This study examines the impacts of the Covid-19 pandemic on Brazilian agricultural price volatility. This study also considers the USD/BRL exchange rate and crude oil prices. We examine the volatility spillover effects and dynamic connectedness among the markets. A TVP-VAR model was applied, considering the specifications proposed by Antonakakis et al. (2020). The results indicate an increase in volatility connectedness after the Covid-19 outbreak, where volatility transmission affected all markets domestically. These effects were still significant after the Russia-Ukraine conflict and dissipated from mid-2022 onwards. Overall, the exchange rate and soybean were the largest net transmitters during the pre- and post-Covid-19 pandemic, and corn was a net receiver. Crude oil had a significant transmission effect after a short period after the Covid-19 outbreak and the Russia-Ukraine war. Additionally, wheat was a significant volatility receiver after the Russia-Ukraine conflict and rice was a net transmitter during the Covid-19 pandemic. These findings corroborate that the crises cycles also affect Brazil but highlight that in the context of an emerging market, the exchange rate is more important in explaining agricultural price dynamics than crude oil.

Keywords

Commodities market, Dynamic connectedness, Volatility spillover, Covid-19 pandemic, Brazil.

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♦ Grant # 2023/13145-9, São Paulo Research Foundation (FAPESP).

Recebido: 02/01/2024.

Revisado: 31/05/2024.

Aceito: 04/07/2024.

DOI: https://doi.org/10.1590/1980-53575446dclg

Conectividades dinâmicas e transbordamento de volatilidade entre os mercados agrícolas brasileiros após a pandemia da Covid-19

Resumo

As volatilidades dos preços agrícolas aumentaram a partir do período 2006-2008 e, desde então, crises internacionais têm intensificado estes choques, como a pandemia da Covid-19. Diversos estudos têm buscado compreender as dinâmicas destes choques globalmente, porém, poucos analisaram os impactos em mercados emergentes. Neste sentido, este artigo propõe avaliar os impactos da pandemia da Covid-19 nas volatilidades dos preços agrícolas no Brasil, como foco nas conectividades dinâmicas e transbordamento de volatilidades entre os mercados agropecuários. Também são considerados o mercado de petróleo Brent e a taxa de câmbio US$/R$. Para isso, aplica-se o modelo TVP-VAR, considerando as especificações propostas por Antonakakis *et al.* (2020). Os resultados apontam para um aumento nas conectividades e transmissão de volatilidade após o início da pandemia. Os efeitos se perpetuam até o posterior conflito entre Rússia e Ucrânia, se dissipando a partir do segundo semestre de 2022. Em geral, a taxa de câmbio e a soja apresentaram-se como os maiores transmissores de volatilidade, tanto no período pré, quanto pós-pandemia. O petróleo foi significativamente transmissor de volatilidade em um curto período após o início da pandemia e do conflito entre Rússia-Ucrânia. O conflito também aumentou os efeitos de transmissão do trigo, enquanto a pandemia levou o arroz a ser um transmissor líquido de volatilidade. Tais apontamentos corroboram que os mercados agrícolas no Brasil também são afetados pelos efeitos de crise. No entanto, evidenciam que a taxa de câmbio possui uma relevância ainda maior que os preços do petróleo na explicação dos choques de volatilidade no país, destacando a importância de se considerar seus efeitos em mercados emergentes.

Palavras-chave

Mercados de commodities agrícolas, Conectividade dinâmica, Transbordamento de volatilidade, Pandemia da Covid-19, Brasil.

Classificação JEL

C22, Q02, Q11.

1. Introduction

Agricultural price volatilities have received much attention since the period – 2006-2008, where global prices have reached their highest level so far (Serra 2011; Tyner 2010; Trujillo-Barreras *et al.* 2013; Vacha *et al.* 2013; Saghaian *et al.* 2018). Previous studies have found several factors that contributed to this change in price dynamics, ranging from US monetary policy to harvest losses (Irwin and Good 2009; Tyner 2010; Trujillo-Barreras *et al.* 2012; Serra and Zilberman 2013; Siami-Namini *et al.* 2019).

Among these factors, we highlight the following: (i) the exchange rate, which has an impact on agricultural price volatility for some markets, including the emerging economies (Shahrestani and Rafei 2020; Jeong and Gopinath 2022; Yildirim *et al*. 2022); and (ii) an increase in the linkages between energy and agricultural markets (Zhang *et al*. 2010; Serra 2011; Tyner 2010; Vacha *et al*. 2013; Kristoufek *et al*. 2014; Cabrera and Schulz 2016; Saghaian *et al*. 2018).

In addition, a branch of the literature has also highlighted the importance of the price dynamics volatility of agricultural commodities beyond the primary industry. A generalized escalation in commodity prices can potentially affect domestic social indicators and raise concerns about food security (Acemoglu *et al*. 2003; Huchet-Bourdon 2011; Kumar *et al*. 2022). In addition, the abnormal volatility in these prices is often derived from international crises, which, in turn, contribute to worsening economic effects, especially in vulnerable developing countries (Frenk and Turbeville 2011).

Recently, with the Covid-19 pandemic, the world experienced impacts that were as intense as in the previous 2006-2008 period, where different production chains were involved as long as countries imposed lockdowns (Beckman and Countryman 2021; Dmytrów *et al*. 2021). The negative effects include global-scale disruptions in production chains and, consequently, negative supply shocks for goods and services (De Vijlder 2020; Rajput *et al*. 2021; Beckman and Countryman 2021).

Initially, there was a decline in crude oil prices, followed by a fall in commodity prices. Preliminary spillover effects occurred with a drop of more than 50% in crude oil prices, significant falls in metal prices, and a slight reduction in agricultural commodity prices (World Bank 2020). As long as the global economy was recovering its activities, crude oil and mineral commodities prices increased. Thus, the increase in price volatility in these markets impacted agricultural prices (Dmytrów *et al*. 2021; Beckman and Contryman 2021). Subsequently, in early 2022, volatility peaks in international agricultural markets were observed after the Russia-Ukraine conflict began (Fang and Shao 2022; Just and Echaust 2022; Wang *et al*. 2022; Gaio and Capitani 2023).

The pandemic's impacts were even greater in emerging economies, especially in countries with a large share of participation in international trade (FAO 2022, UNCTAD 2022). These major effects change the rate of domestic price indices, which increases concerns related to food security

(Huchet-Bourdon 2011; Frenk and Turbeville 2011; Thanh *et al.* 2021; Kumar *et al.* 2022). Considering Brazil, for example, beyond the country's agriculture production and share in the international market, corn, soybean, and rice prices rose to thresholds close to 80%, 100%, and 120%, respectively, in an interval between 9 and 15 months after the start of the Covid-19 pandemic (CEPEA 2023). Consequently, the consumer price index (IPCA) was greater than 10% by 2021 (IBGE 2022). In addition, the average USD/BRL exchange rate devaluated close to 35% between pre- and post- Covid-19 periods (IBGE 2022).

Thus, this study examines the effects of the crisis environment after the Covid-19 pandemic on the price returns of agricultural commodities in Brazil. We analyze the spillover effects among the major agricultural markets in Brazil. We will also consider in the analysis crude oil price returns, aiming to explore the connections between commodities and energy markets, and exchange rates, once Brazil is a large commodity exporter.

The period consists of January 2018 to July 2023, and four time samples are considered: full sample, pre-pandemic period, critical pandemic period, and post-critical pandemic period. Additionally, we test the effects of Russia-Ukraine conflict. The spillover effects and market dynamic connectedness are estimated using a TVP-VAR model with the specifications proposed by Antonakakis *et al.* (2020).

This analysis can shed light on the recent discussion of the net effects of the Covid-19 pandemic on commodity price volatilities. In addition, it introduces an analysis of an emerging economy and a large commodity exporter such as Brazil. The inclusion of the exchange rate can bring new elements to understanding the possible additional impacts on developing countries. Further, the study provides a better illustration of the connections between the energy and commodities markets, especially in an emerging economy.

This study was divided into different sections. In addition to the introduction, in the following section, we discuss the literature on volatility transmission in the agricultural market to address the impact of global crises. Subsequently, we present the data used in the empirical investigation and fit the model. In another section, we present the results and discuss the findings on the connections between markets at different times. Finally, we conclude with limitations, implications, and suggestions for future research.

2. Volatility transmission in agricultural markets

Since the commodity boom of 2006-2008, many reasons for the increase in agricultural price volatility have been pointed out, such as: (i) increased demand from China and other emerging markets; (ii) crop failures worldwide; (iii) US dollar devaluation; (iv) linkages between inventories and agricultural prices (Wright 2011; Serra, 2011; Lahiani *et al*. 2013); and (v) the increase in biofuel production, especially in the North American market, with the use of corn as an ethanol feedstock (Irwin and Goodman 2009; Trujillo-Barreras *et al*. 2012; Serra and Zilberman 2013).

In this sense, although previous literature pointed to different possible reasons for the commodity boom and the consequences in regional markets, most subsequent studies suggest a direct (and strong) relationship between energy and agricultural markets, especially between crude oil and crop markets such as corn, wheat, soybeans, rice, and oats, which in turn have a strong relationship with animal protein markets (Zhang *et al*. 2010; Serra 2011; Vacha *et al*. 2013; Kristoufek *et al*. 2014; Cabrera and Schulz 2016; Saghaian *et al*. 2018).

Trujillo-Barreras *et al*. (2013) also pointed out that the relationship between energy and agricultural markets (from 2006-2008 to 2012) has become closer because of the increased use of biomass, grains, and oilseeds to produce biofuels. Tyner (2010) also suggests that the increase in ethanol consumption in the US market gave an additional boost to changes in the prices of agricultural commodities, which followed changes in crude oil prices. However, Serra and Zilberman (2013) indicate that these findings are not the same and depend on the analyzed market (region) as well as on the economic model applied in each study. Thus, they suggest caution when comprehending them.

Recent literature has explored the effects of the Covid-19 pandemic on commodity price prices and volatility, dividing the effects of the pandemic into two periods. First, due to the rapid drop in the mineral commodities and energy prices at the beginning of the Covid-19 pandemic, as economies went into lockdown. Second, because of the strong rise in commodity prices, economies returned to previous levels. During this phase, most agricultural markets renewed their price records (De Vijlder 2020; Elleby *et al*. 2020; Wang *et al*. 2020; Borgdards *et al.* 2021; Kamdem *et al.* 2020; Hung 2021; Dmytrów *et al.* 2021; Farid *et al.* 2022; Just and Echaust 2022; Rajput *et al.* 2021; Wang *et al.* 2022; Mishra *et al.* 2023; Quintino *et al.* 2023).

Most of these studies have focused on analyzing the volatility spillover between agricultural markets by comparing the periods before and during the Covid-19 pandemic (Borgdards *et al.* 2021; Kamdem *et al.* 2020; Hung 2021; Just and Echaust 2022; Wang *et al.* 2022). Other studies have examined the linkages between energy commodities, especially crude-oil, and agricultural commodities, especially grains (Wang *et al.* 2020; Dmytrów *et al.* 2021; Farid *et al.* 2022; Babar *et al.* 2023; Quintino *et al.* 2023; Palazzi *et al.* 2024).

Overall, such studies have observed a significant increase in the volatility transmission between these markets after the Covid-19 pandemic. Specifically, Borgdards *et al.* (2021) note an increase in volatility spillover among all commodities. However, the linkages between crude oil and agricultural markets exhibit a greater intensity. Similarly, Farid *et al.* (2022) point out strong spillover effects on commodity price returns. Strong connections are noted between energy, mineral, and grain markets and less intense effects on animal protein, sugar, coffee, and cocoa markets. Hung (2021) also demonstrates this strong relationship between crude oil and agricultural commodities markets, as well as a greater effect on grain markets, especially corn, soybeans, and wheat. These grain markets became net volatility transmitters after the pandemic, whereas sugar and oats increased their levels as volatility receivers. Just and Echaust (2022) point to strong volatility spillovers in grain markets during this period. This effect reached a new record after the Russia-Ukraine conflict.

It is important to note that such studies have used different methodological approaches to examine the connection between commodity price volatilities. These approaches consider time-series models to assess volatility spillovers through agricultural markets, such as GARCH-DCC and Diebold-Yilmaz methods (Borgdards *et al.* 2021; Dmytrów *et al.* 2021; Kamdem *et al.* 2021; Hung 2021; Farid *et al.* 2022; Just and Echaust 2022; Babar *et al.* 2023; Mishra *et al.* 2023; Palazzi *et al.* 2024). In addition, other studies have applied cross-correlation analysis through multifractal models (Wang *et al.* 2020; Quintino *et al.* 2023), or wavelets coherence (Kamdem *et al.* 2020). As for the analyzed time horizon, there are studies that considered a period from the 2006-2008 crisis (Farid *et al.* 2022; Quintino *et al.* 2023), while others adopted short intervals, most of them before and after the Covid-19 pandemic (Wang *et al.* 2020; Hung 2021; Kamdem *et al.* 2020; Borgdards *et al.* 2021; Dmytrów *et al.* 2021; Just and Echaust 2022). Overall, most studies have used daily price returns. However, Quintino *et al.* (2023) used weekly prices, and Borgdards *et al.* (2021) intraday price returns.

However, few studies have examined the impact of the Covid-19 pandemic on the volatility of commodity prices and their connections in Brazil. Palazzi *et al.* (2024) evaluated the dynamic connectedness between energy markets and Brazilian commodity markets, and used a TVP-VAR, using the Diebold-Yilmaz (2012) method. The dataset comprises the period from 2007 to 2022, including the global commodities crisis cycles and the Covid-19 outbreak. However, their study considered several global energy commodities. Ethanol, soybean, sugar, and corn were the agricultural markets evaluated in Brazil. They then focused on the connection between global energy and agricultural futures markets and Brazilian agricultural spot markets. Capitani and Gaio (2023) focused their analysis in the volatility transmission between global and Brazilian agricultural markets. However, they considered the period after the Russia-Ukraine conflict, and applied a DCC-GARCH model to examine volatility transmission.

Thus, there is a gap that needs to be addressed. First, our analysis focuses on the dynamic connectedness among Brazilian agricultural markets, including other important markets, such as coffee, cattle, rice, and wheat. Second, the inclusion of the exchange rate is important when examining its impact on local agricultural markets. Third, the dataset is extended and comprises the period of the Russian-Ukraine conflict.

3. Methods and data

3.1. Data

The dataset consists of the daily spot prices of corn, soybean, rice, wheat, live cattle, sugar, and coffee in Brazil. We consider the major production regions of each agricultural market in Brazil available by Cepea (2023). To capture potential exogenous effects on these markets, Brent crude oil futures prices and the USD/BRL exchange rate (Ptax) are used. Brent crude oil prices are considered to capture linkages with the global energy markets (Kristoufek *et al*. 2014; Saghaian *et al*. 2018; Quintino *et al*. 2023; Palazzi *et al*. 2024). The exchange rate is used to capture the potential influence of international trade on the dynamics of volatilities of domestic agricultural commodities, given Brazil's importance in global food trade, following the propositions made by Yildirim *et al.* (2022).

The full sample adopted in this study was from January 2, 2018, to July 10, 2023. As long as this manuscript proposes to examine the Covid-19 impacts on agricultural commodities prices, we also consider four other subsamples beyond the full period. First, the pre-pandemic period was from January 2, 2018, to January 30, 2020. The second is the pandemic period, from February 1, 2020, to June 30, 2021, considering the most critical period of the Covid-19 pandemic. The third sub-sample comprises the most critical period of the Russia-Ukraine conflict, from February 1, 2022, to July 31, 2022. Finally, the fourth sub-sample comprises the least critical period of the conflict (where the economic shocks from military conflicts seem to be lower), from August 1, 2022, to July 10, 2023. This last period is called as the post-conflict.

Note that we consider the Covid-19 pandemic beginning as the WHO announced the dissemination of the coronavirus worldwide. We also consider the end of the most critical period of Covid-19 pandemic in the mid-2021, where global economy activity was basically recovered. This period also coincides with the end of 2020-21 crop-year in Brazil (CONAB, 2024), as well as commodity price series and the exchange rate have received positive shocks since 2020. This period followed Quintino *et al.* (2023). In addition, we consider the beginning of the military conflict between Russia and Ukraine a couple of weeks sooner due to military movements around the frontiers of these countries. The definition of the critical period of conflict follows Gaio *et al.* (2023) and Gaio and Capitani (2023).[1]

The returns of commodities prices and exchange rate (r_t) were used for estimations according to expression 1 below.

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \times 100 \quad (1)$$

where P_t is the current price collected in the followed data, and P_{t-1} is the price in the previous day than the collected data.

Figure 1 shows the behavior of the returns on the seven agricultural commodities in Brazil, Brent crude oil, and the USD/BRL exchange rate (USD_r).

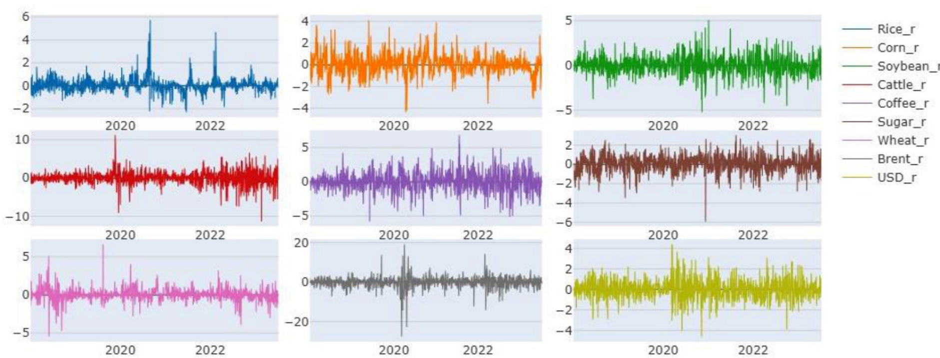

Figure 1 – Commodities prices return and exchange rate return

Table 1 summarizes the descriptive statistics of series returns for the different periods considered in the analysis.

[1] Additionally, to overcome the undesired features of small TVP-VAR, a natural idea is to consider large samples (Zheng *et al.* 2023), e.g., the period considered to the critical period of the Russian-Ukraine comprises a minimum number of observations to attend to the model restrictions.

Table 1 - Price returns descriptive statistics

	Rice	Corn	Soybean	Cattle	Coffee	Sugar	Wheat	Brent	USD
Full sample (1,376 observations)									
Mean	0.057	0.036	0.05	0.04	0.043	0.053	0.05	0.011	0.029
Variance	0.363	0.849	1.108	2.816	1.861	0.802	0.69	7.703	0.924
Skewness	1.98***	0.077	-0.055	-0.42***	0.135**	-0.47***	0.20***	-0.991***	0.038
Kurtosis	14.95***	2.11***	2.16***	5.65***	2.15***	2.01***	8.09***	15.26***	1.771***
JB test	13730***	255.91***	268***	1874***	270***	282.7***	3768***	13587***	180.12***
Q(10)	619.98***	475.33***	17.13***	160.77***	29.53***	45.05***	83.80***	8.0	13.05**
Q2(10)	476.98***	126.45***	93.17***	79.17***	117.32***	50.89***	82.34***	181.63***	145.80***
Pre-COVID-19 (519 observations)									
Mean	0.06	0.08	0.033	0.052	0.006	0.024	0.071	-0.026	0.051
Variance	0.222	1.054	0.66	1.778	1.18	0.807	0.869	3.645	0.604
Skewness	0.389***	0.33***	0.044	0.333***	-0.104	-0.41***	0.42***	0.024	-0.31***
Kurtosis	0.682***	0.95***	1.48***	15.25***	2.76***	0.75***	10.77***	6.20***	1.15***
JB test	23.13***	29.02***	47.84***	5041.77***	165.41***	27.06***	2523***	832.0***	37.42***
Q(10)	36.81***	90.31***	14.74***	48.02***	13.36**	53.92***	19.92***	6.69	7.079
Q2(10)	6.034	21.89***	6.83	38.23***	31.59***	32.54***	30.38***	8.94	28.50***
COVID-19 pandemic (351 observations)									
Mean	0.087	0.159	0.174	0.146	0.167	0.113	0.127	0.072	0.046
Variance	0.706	0.973	1.624	1.596	1.775	0.805	0.575	15.036	1.52
Skewness	2.02***	-0.33**	-0.168	-0.27**	-0.069	-1.16***	0.382***	-1.24***	0.066
Kurtosis	10.83***	2.72***	2.00***	2.66***	1.38***	5.41***	2.972***	12.95***	1.33***
JB test	1955.42***	114.54***	60.37***	107.78***	28.07***	508.2***	137.7***	2544***	26.20***
Q(10)	295.88***	182.67***	7.461	42.58***	17.64***	11.38**	56.52***	8.47	3.957
Q2(10)	175.69***	35.58***	37.63***	20.49***	6.78	10.92**	12.82**	45.77***	35.42***
Russia-Ukraine conflict (103 observations)									
Mean	0.146	-0.149	0.055	-0.069	-0.078	-0.142	0.246	0.223	-0.022
Variance	0.531	0.615	1.598	4.573	2.389	0.897	0.618	12.976	0.974
Skewness	2.85***	-0.44*	-0.137	-0.45*	0.47**	-0.145	0.76***	-0.105	0.56**
Kurtosis	15.92***	3.74***	0.689	1.70***	0.99*	0.528	1.33**	3.27***	0.446
JB test	1227.18***	63.31***	2.361	15.92***	8.13**	1.559	17.79***	46.22***	6.33**
Q(10)	24.89***	30.16***	6.193	27.12***	5.01	7.541	7.727	5.769	12.71**
Q2(10)	2.389	8.556	7.282	20.61***	4.21	35.832***	12.56**	14.14***	12.55**
Post-Conflict (235 observations)									
Mean	0.025	-0.169	-0.133	-0.105	-0.195	0.024	-0.193	-0.148	-0.027
Variance	0.161	0.523	1.002	6.49	2.403	0.702	0.671	5.226	0.882
Skewness	0.21	-0.81***	-0.227	-0.51***	-0.17	-0.015	-0.70***	-0.41***	0.106
Kurtosis	2.54***	3.34***	1.82***	1.57***	0.49	1.22***	3.24***	0.535	1.289***
JB test	64.97***	134.80***	34.65***	34.26***	3.62	14.78***	122.73***	9.56***	16.716***
Q(10)	82.74***	148.61***	9.95*	35.78***	7.13	14.17***	16.29***	5.736	9.663*
Q2(10)	20.07***	90.94***	7.30	1.43	2.071	7.918	33.173***	1.857	9.324*

We observe significant variations in the means and variances of the returns for all periods under consideration. During the pandemic and Russia-Ukraine conflict, several series showed an increase in both means and variances. In particular, corn and soybeans showed a considerable increase during the pandemic. These results suggest that these markets were more affected by these crisis events, increasing price volatility and uncertainty.

Overall, the pandemic seems to cause the greatest variance in the returns of the series in the analysis, mainly in exchange rates and crude oil. This means that during the Covid-19 outbreak, there was greater volatility and instability in the markets.

3.2 Methods

To investigate the connections between markets, we used the positive and negative absolute returns of agricultural commodities, Brent crude oil, and the US dollar (USD/BRL). The investigation employed the TVP-VAR-related connectedness technique to adjust for the volatility transmissions involved. For this purpose, a bivariate approach to the TVP-VAR model was used.

The TVP-VAR approach is an adapted version of the traditional VAR approach, which is frequently used in financial literature. The linear version of the VAR model is described as equation 01:

$$y_t = c + B_1 y_{t-1} + \cdots + B_2 y_{t-p} + \varepsilon_t \tag{1}$$

where $\boldsymbol{y}$ is a K × 1 dimensional vectors with K variables at time t and order p. $\boldsymbol{B}$ represents the K × K matrices of the coefficients.

TVP-VAR methodology was used for the analysis. This method combines the Diebold and Yilmaz (2012) and Koop and Korobilis (2014) propositions, with the approach proposed by Antonakakis *et al.* (2020). This technique, known as the Time-Varying Parameter Vector Autoregressive Model (TVP-VAR), aims to overcome some of the limitations of the original approach by Diebold and Yilmaz (2012). Studies by Mishra *et al.* (2023) and Balcilar *et al.* (2021) are examples of TVP-VAR applications for the commodity financial market.

The TVP-VAR model proposed by Antonakakis *et al.* (2020) is an econometric model that allows the estimation of parameters that vary over time in a system of vector autoregressive equations (VAR). Unlike traditional VAR, in which the parameters are fixed over time, TVP-VAR recognizes that the relationships between variables can be subject to structural changes over time. TVP-VAR allows the analysis of connectedness between commodity markets in crisis periods.

The TVP-VAR model with a lag order of one is estimated following the Bayesian Information Criterion (BIC), as per equation 2:

$$\boldsymbol{y}_t = c + \boldsymbol{B}_t y_{t-1} + \varepsilon_t \varepsilon_t \sim N(0, \Sigma_t) \tag{2}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + v_t v_t \sim N(0, R_t) \tag{3}$$

where $\boldsymbol{y}_t$, $\boldsymbol{y}_{t-1}$ and ε_t are K × 1 dimensional vectors, and $\boldsymbol{B}_t$ and Σ_t are K × K dimensional matrices. $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v_t}$ are $K^2 \times 1$ dimensional vectors, and $\boldsymbol{R_t}$ is a $K^2 \times K^2$ dimensional matrix. This model allows the parameters $\boldsymbol{B}_t$ to be time-varying, which also allows the assessment of the relationship between commodity series over time. The disturbance terms are assumed to have equal variance and follow a normal distribution with a mean of zero and time-varying covariance matrix Σ_t, which, according to Mishra *et al.* (2023), results in market fluctuations and investment risk.

According to Helmi *et al.* (2023), to compute the dynamic interactions between variables, the variance-covariance matrix of the residuals $\boldsymbol{\Sigma_t}$ is decomposed as follows:

$$\Sigma_t = A_t^{-1} H_t (A_t^{-1}) \tag{4}$$

where $\boldsymbol{A_t}$ is the lower triangular matrix that externalizes the contemporaneous relationships and $\boldsymbol{H_t}$ is a matrix containing stochastic volatilities on the diagonals.

The model is based on the idea that commodity price series are interconnected, and that these interconnections can change over time. The TVP-VAR captures the changes in the interconnections between commodity markets and thus provides a better understanding of how they react to crisis events (Balcilar *et al.* 2021; Mishra *et al.* 2023).

According to Antonakakis *et al.* (2020), one of the main advantages of the TVP-VAR approach is its lower sensitivity to outliers, which contributes to a more accurate estimation of the model parameters. Furthermore, this technique does not require an arbitrary period window, which is a limitation of the original approach. Instead, we estimate the TVP-VAR model using the Bayesian Information Criterion (BIC) with a lag of one order. When estimating a TVP-VAR, Bayesian inference techniques or recursive filtering methods are commonly used to obtain estimates of time-varying parameters, such as the Kalman filter. These estimates allowed us to track structural changes and capture the dynamic effects that may occur during different periods.

Therefore, we apply the TVP-VAR methodology together with the expanded connectedness technique proposed by Balcilar *et al.* (2021). This allows us to overcome the limitations of the original approach by Diebold and Yilmaz (2012) by obtaining more accurate parameter estimates and a more comprehensive analysis of the interconnection between economic variables.

4. Results and discussion

4.1. Average connectedness

First, we present the average connectedness between market price returns and their volatilities. Table 2 shows the results for all the aforementioned sample periods. The average connectivity for the full sample (Scenario A) reveals that soybean and exchange rate are the greatest volatility transmitters (25.74 and 25.43%, respectively) and receivers (23.92 and 21.69%, respectively). The net return shock transmitters in the Brazilian market are exchange rate, soybean, crude oil, cattle, and sugar. The other series are net receivers of these shocks.

Table 2 - Average connectedness

	Rice	Corn	Soybean	Cattle	Coffee	Sugar	Wheat	Brent	USD	FROM
Scenario A: Full sample (1376 observations)										
Rice	92.55	1.42	0.54	0.56	0.83	1.41	0.91	0.91	0.87	7.45
Corn	1.48	84.58	6.08	1.53	1.2	1.31	1.05	0.51	2.26	15.42
Soybean	0.63	3.38	76.08	1.12	0.76	1.31	0.89	1.54	14.31	23.92
Cattle	0.46	1.32	0.62	93.31	1.23	0.5	0.92	0.97	0.66	6.69
Coffee	0.59	0.86	1.28	1.01	91.37	0.82	0.73	1.66	1.68	8.63
Sugar	1.24	1	0.89	0.83	0.72	92.28	0.68	1.41	0.95	7.72
Wheat	0.96	2.29	1.6	1.04	0.65	0.5	91.29	0.85	0.82	8.71
Brent	0.76	0.49	1.54	0.77	1.4	1.35	0.71	89.1	3.89	10.9
USD	0.72	0.85	13.21	0.73	1.22	0.71	0.47	3.78	78.31	21.69
TO	6.84	11.61	25.74	7.58	8.01	7.92	6.37	11.62	25.43	111.13
Inc.Own	99.4	96.19	101.82	100.9	99.38	100.2	97.66	100.71	103.74	cTCI/TCI
NET	-0.6	-3.81	1.82	0.9	-0.62	0.2	-2.34	0.71	3.74	13.89/12.35
NPT	3	1	3	6	3	4	2	7	7	
Scenario B: Pre-COVID-19 (519 observations)										
Rice	91.62	0.67	0.49	0.82	0.78	2.43	1.14	1.31	0.75	8.38
Corn	0.77	86.47	4.64	2.04	0.99	1.9	0.85	0.42	1.92	13.53
Soybean	0.51	1.89	75.29	1.63	0.91	0.85	0.27	1.56	17.09	24.71
Cattle	0.69	1.22	0.47	92.71	1.87	0.51	0.6	0.88	1.05	7.29
Coffee	0.48	0.63	0.98	1.75	91.19	1.08	0.37	1.37	2.15	8.81
Sugar	0.59	0.89	0.54	0.77	0.84	94.41	0.45	0.69	0.83	5.59
Wheat	0.65	1.02	0.34	0.6	0.41	0.51	94.83	1	0.65	5.17
Brent	1.12	0.41	0.96	0.96	1.33	0.77	0.36	91.71	2.38	8.29
USD	0.39	0.55	14.91	0.62	2.03	0.64	0.35	1.74	78.78	21.22
TO	5.2	7.29	23.32	9.19	9.15	8.69	4.37	8.97	26.81	102.99
Inc.Own	96.82	93.75	98.62	101.9	100.34	103.1	99.19	100.68	105.59	cTCI/TCI
NET	-3.18	-6.25	-1.38	1.9	0.34	3.1	-0.81	0.68	5.59	12.87/11.44
NPT	2	1	3	5	4	6	2	5	8	
Scenario C: COVID-19 pandemic (351 observations)										
Rice	95.43	1.05	0.26	0.69	0.53	0.41	0.51	0.27	0.84	4.57
Corn	0.83	84.34	5.98	1.26	2.63	0.53	0.98	0.23	3.24	15.66
Soybean	0.48	3.77	71.94	1.02	0.54	2.09	0.91	0.54	18.7	28.06
Cattle	0.23	1.38	1.36	91.54	2.8	0.81	0.57	0.6	0.72	8.46
Coffee	0.63	1.55	2.93	1.66	89.64	0.61	0.33	0.79	1.86	10.36
Sugar	1.18	1.57	1.38	0.8	0.78	86.99	0.77	5.12	1.42	13.01

Wheat	1.81	3.68	1.75	0.44	1.05	0.78	89.46	0.25	0.79	10.54
Brent	0.13	0.2	0.48	0.3	0.99	3.29	0.73	87.26	6.61	12.74
USD	0.95	1.94	17.44	1.27	0.34	0.88	0.65	5.73	70.79	29.21
TO	6.24	15.13	31.57	7.43	9.67	9.4	5.45	13.52	34.17	132.59
Inc.Own	101.7	99.48	103.52	98.97	99.32	96.39	94.91	100.79	104.96	cTCI/TCI
NET	1.67	-0.52	3.52	-1.03	-0.68	-3.61	-5.09	0.79	4.96	16.57/14.73
NPT	5	4	4	2	5	3	2	5	6	
Scenario D: Russia-Ukraine conflict (103 observations)										
Rice	87.29	2.98	1.15	0.83	1.46	1.84	1.3	0.87	2.27	12.71
Corn	3.04	73.4	8.26	0.3	3.48	0.78	2.85	3.24	4.66	26.6
Soybean	0.71	3.9	77.54	0.37	1.45	5.34	0.94	2.97	6.78	22.46
Cattle	2.35	0.12	0.16	88.61	0.59	0.26	1.95	3.41	2.55	11.39
Coffee	0.95	3.57	0.45	0.96	88.02	0.42	3.03	0.97	1.65	11.98
Sugar	6.66	1.56	2.32	4.56	0.61	76.47	2.9	0.72	4.2	23.53
Wheat	0.92	6.53	5.03	0.37	2.47	1.63	76.23	4.77	2.04	23.77
Brent	1.23	1.59	3.22	2.47	1.75	2.61	6.15	79.05	1.94	20.95
USD	0.9	0.59	7.54	4.47	0.47	2.98	0.88	3.87	78.32	21.68
TO	16.77	20.84	28.12	14.32	12.3	15.85	19.99	20.81	26.08	175.08
Inc.Own	104.1	94.24	105.66	102.93	100.31	92.33	96.22	99.86	104.39	cTCI/TCI
NET	4.06	-5.76	5.66	2.93	0.31	-7.67	-3.78	-0.14	4.39	21.88/19.45
NPT	4	3	5	5	4	2	5	3	5	
Scenario E: Post-Conflict (235 observations)										
Rice	88.15	2.26	0.33	1.09	2.58	2.16	2.17	0.33	0.93	11.85
Corn	3.1	86.08	3.09	1.37	0.38	2.04	0.74	1.22	1.98	13.92
Soybean	0.21	1.82	82.7	0.92	0.91	0.27	1.19	0.28	11.71	17.3
Cattle	0.18	0.29	1.55	91.47	2.34	0.14	0.95	2.58	0.49	8.53
Coffee	0.47	0.31	0.93	0.94	91.02	0.31	3.26	0.98	1.8	8.98
Sugar	3.11	1.06	0.94	0.83	0.53	88.91	0.36	2.39	1.86	11.09
Wheat	0.82	1.01	1.32	4.65	0.97	1.41	88.13	1.26	0.44	11.87
Brent	0.38	0.52	0.25	1.15	1.08	2.82	0.37	86.61	6.84	13.39
USD	0.25	0.31	11.61	0.37	0.93	1.65	0.68	3.74	80.46	19.54
TO	8.53	7.58	20.02	11.31	9.7	10.78	9.72	12.78	26.04	116.48
Inc.Own	96.67	93.67	102.72	102.79	100.72	99.69	97.85	99.39	106.5	cTCI/TCI
NET	-3.33	-6.33	2.72	2.79	0.72	-0.31	-2.15	-0.61	6.5	14.56/12.94
NPT	3	1	6	4	5	3	3	4	7	

Note: USD is the Exchange rate (USD/BRL); TO and FROM denote the total spillover transmitter and receiver to/from others, respectively; NET is the net directional spillover, e.g., the difference between TO and FROM.

Following Table 2, Scenario 2 points out that before the Covid-19 pandemic, the only strong connection observed was between soybean and the exchange rate. This finding corroborates the important role of Brazil as a major global soybean exporter. However, crude oil exhibited a weak connection with the Brazilian agricultural markets. Regarding spillover volatility, soybean and exchange rate were the highest transmitters, reinforcing the position of both markets in Brazilian agriculture dynamics. In contrast, corn, soybean, and exchange rates were the highest volatility receivers. However, the transmitter effects on the exchange rate and soybeans are more expressive, which in turn makes both markets net transmitters in this period. In addition, cattle, crude oil, and sugar are net transmitters, whereas corn, wheat, coffee, and rice are net receivers.

Considering the critical period of the Covid-19 pandemic (Scenario C), the results presented in Table 2 reinforce the strong connection between soybeans and the exchange rate. Further, the other markets exhibit an increase in volatility connectedness with each other in comparison with the period before the pandemic (Scenario B). These findings are in line with those of Borgdards *et al.* (2021) and Hung (2021) when examining international commodity markets. Additionally, soybeans and exchange rates are the highest volatility transmitters. During the pandemic period, crude oil and rice were also volatility transmitters in Brazil. There was also an increase in volatility receipt. Beyond soybean and the exchange rate, corn, sugar, crude oil, wheat, and coffee were volatility receivers. In the final balance, the exchange rate, soybean, and rice were net transmitters, while the other net receivers, especially wheat and sugar. Excluding appointments to crude oil, all other results are in line with those found by Farid *et al.* (2022) and Hung (2021) when analyzing global commodities markets.

Scenario D in Table 2 represents the period of the Russia-Ukraine conflict, where there was a substantial increase in connections around most of the assessed markets. However, there was a decrease in the linkages between soybean and the exchange rate, considering the other sample periods in the analysis. The connections between crude oil and agricultural markets exhibited a significant increase, especially for wheat and soybean. These movements were also observed by Fang and Shao (2022), Just and Echaust (2022) and Gaio and Capitani (2023) in the global commodities markets. All markets have improved their levels of volatility transmission and reception. Soybean, exchange rate, rice, cattle, and coffee were net volatility transmitters, while sugar, corn, wheat, and crude oil were net receivers.

The possible reason for the findings for corn and wheat (as net receivers) is that both markets were strongly affected by the military conflict because of the participation of Ukraine and Russia in these markets.

Finally, Scenario E (Table 2) shows the most recent period, after the critical period of the Russia-Ukraine and the Covid-19 pandemic. There was a significant drop in market connections. The results were closer to those observed during the pre-pandemic period (Scenario B). Such evidence was also pointed out by Quintino *et al.* (2023) when they examined global energy markets. The major difference from Scenario B is that soybean and the exchange rate were less connected. A possible reason for this is the instability of the exchange rate in Brazil in 2022/2023. The relevance of crude oil decreased in comparison to the previous period (Scenario D). Volatility transmissions are lower for all markets. In this recent period (Scenario E), we observe that the exchange rate, cattle, soybean, and coffee were net volatility transmitters, while corn, rice, wheat, crude oil, and sugar were net volatility receivers.

The results are better evidenced by the connectedness network among the commodities markets, as illustrated in Figure 2.

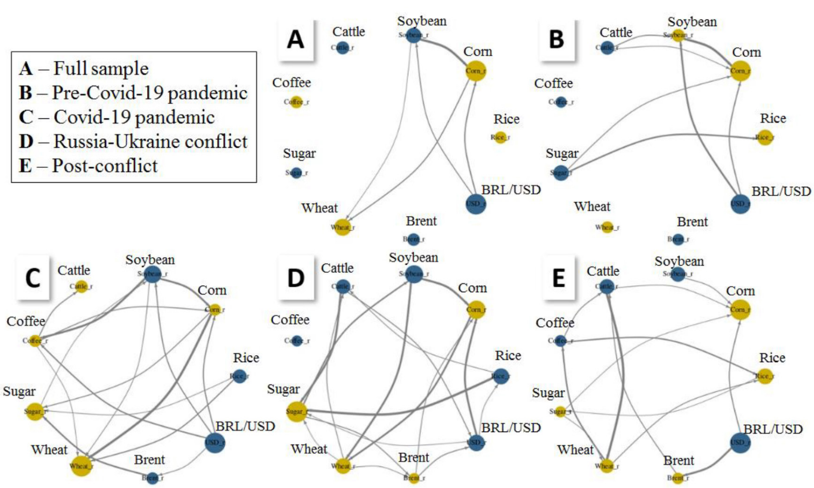

Figure 2 – Return connectedness network among commodities in all scenarios

Note: The yellow and blue spheres indicate the net market reception and transmission of shocks, respectively. Their size denotes weighted average net total directional connectedness. Lines are weighted by averaged net pairwise directional connectedness measures. The thicker the lines, the greater the connectedness between markets. The arrows indicate the connectedness direction.

Note that the critical period of the Covid-19 pandemic, as well as the Russia-Ukraine conflict period boosted market connectedness. It seems that this change had consequences even during the follow-up period (2022-2023), as the network was quite different from that observed in the period before the pandemic (2018-2020). The role of soybean and the exchange rate in shocks was also confirmed as transmitters of volatility in all periods. In addition, corn was frequently connected with soybeans, and the exchange rate was a volatility receiver. Wheat emerged as a receiver throughout crisis cycles. The appointments for sugar as a net receiver of shocks after the pandemic are in line with the findings of Palazzi *et al.* (2024). They also pointed out a major effect of volatility received for corn after the pandemic. However, despite observed similar findings, our study pointed out a major effect on this commodity after the Russian-Ukraine conflict.

4.2. Dynamic connectedness

Regarding the total connectedness for the entire period, Figure 3 shows a peak from the beginning of 2020, after the Covid-19 outbreak, which became a spillover cycle until the middle of 2021. Another significant peak is observed after the beginning of the Russia-Ukraine conflict, although within a short time window. Thus, it can be inferred that the period with the most significant (and longest) impact on agricultural market volatilities in Brazil was during the Covid-19 pandemic. A possible explanation for the higher impacts in comparison to the Russia-Ukraine conflict is the strong exchange rate devaluation experienced in Brazil after the Covid-19 outbreak, in association with the strong connection between the exchange rate and commodities prices.

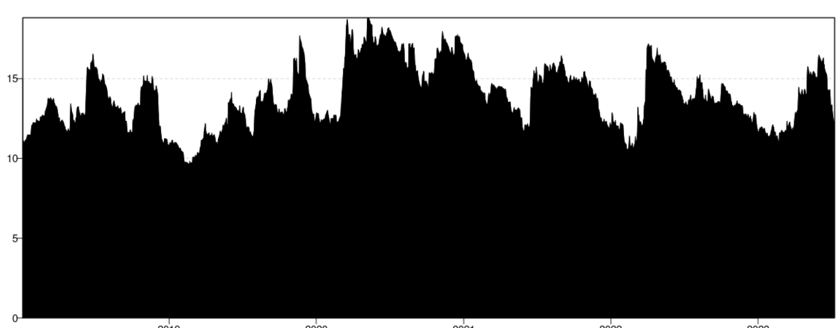

Figure 3 - Dynamic connectedness for all series – full period sample

When evaluating the dynamic connectedness for each of the analyzed markets, the results corroborated the greatest effects on soybeans, exchange rate, and corn. Soybean and exchange rates were mostly transmitters of shocks, whereas corn was predominantly a volatility receiver (Figure 4). For wheat, there was a late impact of the Covid-19 pandemic (receiver), with an increase after the Russia-Ukraine conflict. Rice behaved as a strong transmitter during the pandemic, reversing its role as a receiver. Crude oil had two brief transmission spikes at the beginning of the pandemic and the Russia-Ukraine conflict. The live cattle, coffee, and sugar series, on the other hand, fluctuated little in this period, except for sugar in the pre-pandemic period.

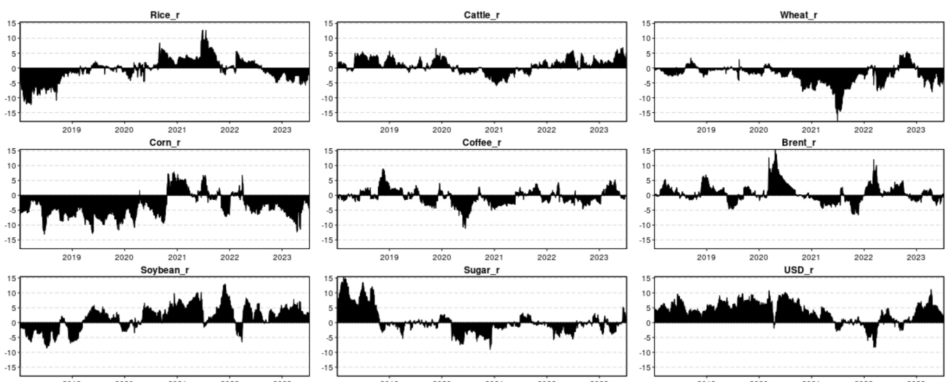

Figure 4 - Net total dynamic directional connectedness for each market – full period

For a better illustration, Figure 5 shows the total net results from the analysis of each pair of markets. Overall, it is observed that the greatest volatility connectedness occured (i) between the grain markets, such as soybean (transmitter) and corn (receiver), corn (transmitter) and wheat (receiver), soybean (transmitter), and wheat (receiver); (ii) in the connection between the exchange rate and some of the Brazilian export commodities, for example, exchange rate (transmitter) and soybean (receiver), exchange rate (transmitter) and corn (receiver), and exchange rate (transmitter) and coffee (receiver). Furthermore, some particular relationships were observed, such as between rice and sugar, with the relationship reversing after the Covid-19 pandemic. However, this case can be associated with dissonance between both markets and their opposing movements after the start of the pandemic. It is also observed that the Covid-19 pandemic was a driving factor for shocks in most connectedness.

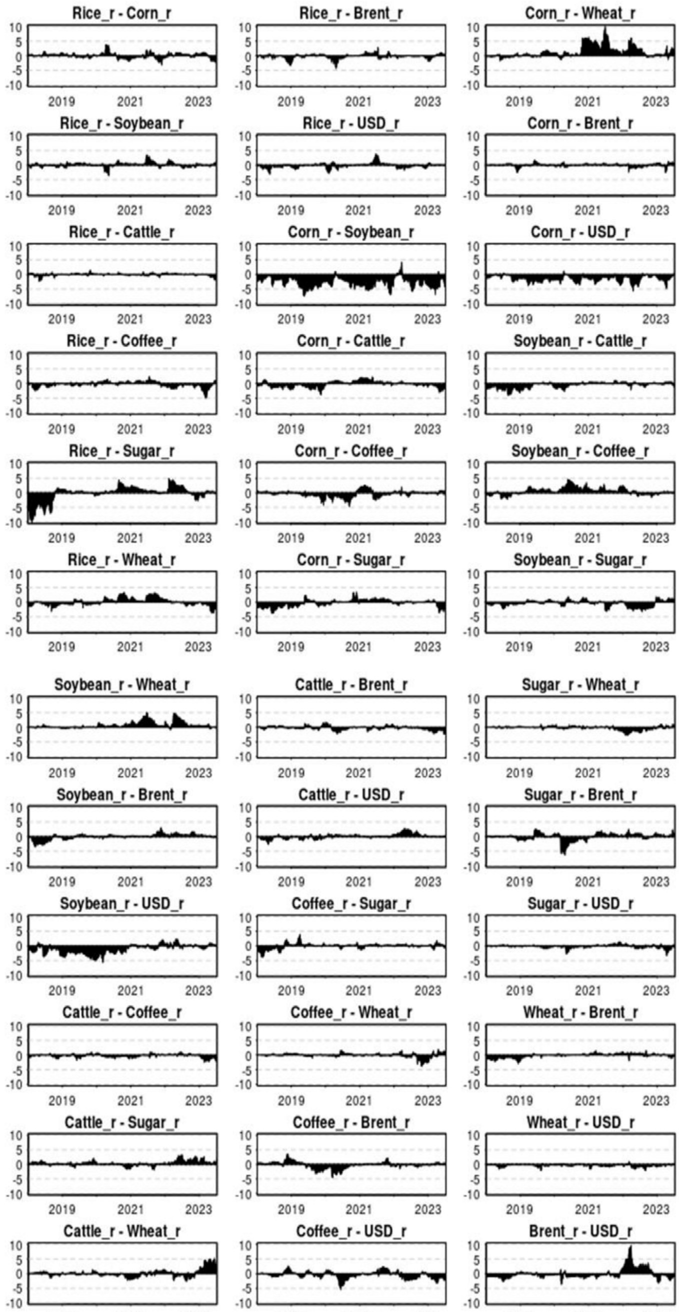

Figure 5 - Dynamic directional connectedness for each pair of markets – full period

5. Conclusions

This study estimated the volatility spillover and connectedness networks in Brazilian agricultural markets, focusing on the effects of the Covid-19 pandemic. Specifically, this study considered price returns in domestic markets for soybeans, corn, wheat, rice, coffee, sugar, and live cattle. In addition, we include the exchange rate and crude oil price (Brent).

A TVP-VAR model was applied, considering the specifications proposed by Antonakakis *et al.* (2020), which allow to examine the volatility spillover effects and the dynamic connectedness among the markets. The full sample covers the period from 2018 to 2023. The impacts were evaluated for different time periods, and four subsamples were evaluated. We then considered the pre- and post-pandemic period, with the second moment separated between the critical cycle of the pandemic, the Russia-Ukraine conflict, and the period of economic stabilization worldwide, with dissipation of the main effects of crisis cycles.

Overall, we observe that the connectedness network among the analyzed markets changed after the Covid-19 outbreak. The effects were maintained through the pandemic and Russia-Ukraine conflict. Specifically, the exchange rate showed a strong connection with most of the Brazilian agricultural markets and increased as a net volatility transmitter, especially through export commodities. Soybeans also exhibit strong connections with agricultural markets domestically, especially grains. In addition, soybeans are a net volatility transmitter for all periods, with significant effects during the pandemic. Both price return series (exchange rate and soybean) showed connectedness during the full period, especially during the pandemic, which can be explained by the BRL devaluation after the Covid-19 outbreak as well as the Brazilian position as the largest soybean exporter in the world.

Regarding other commodities, corn exhibited high connectedness with most markets in all periods, usually as a net volatility receiver. Wheat showed significant connectedness throughout the period of the Russia-Ukraine conflict as a net volatility receiver. This may be explained by the fact that Brazil is a wheat importer and that the conflict affected Russian exports. The Covid-19 pandemic influenced volatility connectedness in the rice market, which became a net transmitter during this period, especially in grain markets, as domestic prices increased by 120% between late 2020 and early 2021. Regarding coffee, sugar, and cattle, we did not observe any relevant movement, except for an increase in the connection during the pandemic period. Lastly, crude oil showed connectedness with Brazilian agricultural markets only in the beginning of Covid-19 pandemic and after the Russia-Ukraine conflict, which suggest that global energy markets are important volatility transmitters over crisis cycles.

The results converge with recent studies when there is a strong increase in spillover effects and connectedness between agricultural markets after the pandemic (Borgdards *et al.* 2021; Hung 2021; Farid *et al.* 2022; Palazzi *et al.* 2024) and at the beginning of the Russia-Ukraine conflict (Just and Echaust 2022; Fang and Shao 2022; Gaio and Capitani 2023). Furthermore, the results were consistent with the findings of Wang *et al.* (2020), Borgdards *et al.* (2021), Farid *et al.* (2022) and Palazzi *et al.* (2024) observed that soft commodities, such as sugar and coffee, in addition to animal protein markets, behaved as net volatility receivers after the Covid-19 pandemic. As for crude oil, markets show connectedness after crisis cycles, as Covid-19 outbreak and Russia-Ukraine conflicts, as pointed out by Kamdem *et al.* (2020), Dmytrów *et al.* (2021), Hung (2021), and Quintino *et al.* (2023) analyzed global markets. However, for Brazil, there was no linkage between crude oil and agricultural markets in the pre- and post-crisis cycles, which justifies the use of exchange rates to understand the influence of international trade.

This study has several practical, theoretical, and social implications. Practically, the results provide valuable insights for participants in the Brazilian agricultural market, assisting in decision-making and risk management. From a theoretical perspective, the findings contribute to the advancement of economic knowledge by applying the TVP-VAR methodology to agricultural markets and the exchange rate in an emergent country. Socially, it provides relevant information for policymakers, allowing for the development of strategies for economic policies and support for the Brazilian agricultural sector.

It should be noted, however, that a sample limitation requires a subsequent update of the information that can better capture how the connections take place in the long term in a less unstable market environment. An additional theme would be to explore the relationships between agricultural prices in Brazil and international markets to better understand such connectedness. Another future study could adopt new methodologies to analyze the frequency-time relationship, such as wavelet coherence models or even fractal models, to examine cross-correlations between markets.

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CONFLITO DE INTERESSE

Os autores declaram não terem quaisquer conflitos de interesse.

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