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VOLATILITY TRANSMISSION IN AGRICULTURAL MARKETS: EVIDENCE FROM THE RUSSIA-UKRAINE CONFLICT

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Abstract

This study investigates the impacts of the Russia-Ukraine conflict on agricultural commodities price volatilities. The analysis is conducted considering the movements in crude oil prices and their consequences in the global and Brazilian agricultural commodities markets. We employ a bivariate DCC-GARCH model to examine the volatility spillover and volatility contagion among the crude oil, wheat, corn, and soybean markets. Our results indicate an increase in volatility transmission after a military conflict. The increase in price cross-correlation in this period confirms the existence of contagious in crude oil and agricultural markets. The impacts seem to be greater at the international level, especially in the wheat and corn markets, highlighting the importance of Russia and Ukraine in grain production. Despite the participation of Brazil in global market, volatility transmission was similar to the pre-conflict period in local markets, indicating that emerging countries had also experienced other effects, as the exchange rate fluctuation.

Keywords: *Agricultural prices, Commodity markets, volatility transmission, Russia-Ukraine conflict, Brazil.*
JEL Codes: *Q02, Q14, G13*

1. Introduction

Ukraine and the Russian Federation are important players in global agricultural commodities markets, especially grains. Both countries have responded to 28.7% of wheat exports by 2020 (Comtrade, 2022). According to FAO (2022), nearly 50 countries imported more than 30% of wheat from Ukraine and Russia in this period. Ukraine is also a traditional corn exporter, responding to 15.1% of world exports by 2020 (Comtrade, 2022). In addition, both countries produced more than 50% of the world's sunflower seeds and approximately 20% of barley, from 2017-2021 (FAO, 2022).

Furthermore, Russia is a key exporter of fertilizers (nitrogen, potassium, and phosphorus), crude oil, and natural gas (FAO, 2022). As a consequence, any disruption in the Russian fertilizers and oil production chain can contribute to an increase in the cost of production of agricultural commodities.

Thus, the military conflict between Ukraine and the Russian Federation from February 24, 2022, has affected grain price dynamics, especially wheat, as well as crude oil prices (Umar et al., 2022; Wang et al., 2022). Indirectly, the disruption in local production chains affected fertilizer exports and promoted economic and financial instability worldwide (Adekoya et al. 2022; Umar et al., 2022; Adekoya et al., 2022; Bongou & Yatié, 2022). Additionally, crude oil price variations involve adjustments in agricultural and transportation costs (Su et al., 2019).

Global crisis consequences tend to be more significant in developing countries because of the simultaneous increase in food and energy prices as well as exchange rate volatility. This affects domestic price indices and, consequently, food security and poverty in the low-income population (Huchet-Bourdon, 2011; Saghaian et al., 2018; IFPRI, 2022). For economies in which agribusiness represents an important share of exports and GDP, agricultural commodities prices have significant welfare and policy implications (Melichar & Atems, 2019). Additionally, these countries are more vulnerable and tend to increase their political instability during these periods (Frenk & Turbeville, 2011; Wang et al., 2022).

This analysis is particularly interesting for Brazil. The country plays an important role in the global grain markets, as the largest soybean exporter, second corn exporter, fourth wheat importer, and second largest fertilizer importer (Comtrade, 2022; FAO, 2022). In addition, the country has experienced a combination of agricultural export records and a strong exchange rate devaluation since the Covid-19 pandemic outbreak in 2020. As consequence, Brazil exhibited the fourth highest price index in the World in 2021 and the first net reducing in the population income since 1990s (IMF, 2022). Thus, the possible impacts of the Russia-Ukraine conflict on Brazilian commodities and financial markets must be carefully examined.

Thus, this study proposes to evaluate the potential effects of the Russia-Ukraine conflict on agricultural commodities price volatilities. First, it considers the linkages between crude oil and agricultural prices in the global market. We then examine the relationship between Brazilian agricultural prices. Specifically, the analysis considers crude oil, wheat, corn, and soybean markets, considering the periods before and after the military conflict. For the volatility estimations, we use a Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity Model (DCC-GARCH).

This study contributes to the empirical literature on the evaluation of volatility connections in agricultural commodities markets, especially considering a crisis period (Wright, 2011; Trujillo-Barrera, Mallory, & Garcia, 2012) and the connections between energy and agricultural markets (Serra, 2011; Lahiani, Nguyen, & Vo, 2013; Vacha et al., 2013; Kristoufek, Janda, & Zilberman, 2014; Saghaian et al., 2018; Janda & Kristoufek, 2019). Further, the analysis considers the global impacts of Russia-Ukraine in agricultural commodities markets, and the association with an emergent and net agricultural exporter, such as Brazil, can shed light on new insights in the current literature.

2. Background

Agricultural commodities prices volatilities had experienced a significant increase over the period 2006-2008, where prices reached the highest level in history, so far (Wright, 2011; Trujillo-Barrera, Mallory & Garcia, 2012). Overall, the literature points out some reasons that contribute to these price movements. For example, demand growth from developing countries, production shortfalls, U.S. monetary policy, energy prices, and the increase in biofuel production (Irwin & Good, 2009; Zhang et al., 2010; Serra & Zilberman, 2013; Serra, 2011; Vacha et al., 2012; Kristoufek, Janda, & Zilberman, 2014; Cabrera & Schulz, 2016; Saghaian et al., 2018).

From the 2006-2008 period and following years, different studies proposed to examine prices and volatilities linkages over markets in local and global agricultural markets. Their conclusions usually suggest that energy prices mostly drive feedstock markets, especially crude oil prices affecting grain markets (Zhang et al., 2010; Serra et al., 2011; Kristoufek, Janda & Zilberman, 2014; Vacha et al., 2012; Saghaian et al., 2018).

According to Tyner (2010), agricultural commodities prices followed the up and downs on crude oil prices from 2006-2008. In addition, the impulse to ethanol consumption in the U.S.

domestic market led to an extra (and temporally) contribution to an increase in corn prices and related agricultural commodities production chain (Tyner, 2010; Trujillo-Barrera, Mallory, & Garcia, 2012). Thus, the increased price correlation between the agricultural and energy markets caused volatility spillovers between their prices and raised concerns about food security and, consequently, among consumers, producers, and policymakers (Tyner, 2010; Saghaian et al., 2018).

Similar connections were recently observed during the Covid-19 pandemic scenario, where agricultural commodity prices exhibited high volatility after global economic shocks. First, the pandemic effects led to a fall in commodity prices, especially in the crude oil and metal markets. A few months later, commodity prices have exhibited a rapid (and persistent) increase from 2020 to 2021. Most agricultural prices reached their historical levels during this period (World Bank, 2020; Rajput et al., 2020; Dmytrów, Landmesser & Bieszk-Stolorz, 2021; Beckman and Countryman, 2021). Overall, studies indicate a substantial increase in volatility spillover between crude oil and agricultural markets worldwide (Elleby, Domínguez & Adenauer, 2020; Borgdards, Czudaj & Van Hoang, 2021; Kamdem, Essomba & Berinyuy, 2020; Hung, 2021; Wang et al., 2022). Volatility transmission was even greater that those observed in 2006-2008 period (Dmytrów, Landmesser & Bieszk-Stolorz, 2021; Wang et al., 2022; Farid et al., 2022). The volatility spillover was more significant between energy and grain markets and less intense for livestock and soft commodities markets, such as coffee and cotton (Borgdards, Czudaj & Van Hoang, 2021; Farid et al., 2021).

Further, few studies have analyzed the volatility spillover in agricultural commodities markets after the conflict between Russia and Ukraine. Wang et al. (2022) observed that volatility increased from 35%-85% in global soybeans, corn, wheat and sugar markets after the conflict, where crude oil was a net volatility transmitter, and soybeans and wheat were net volatility receptors. Just & Echaust (2022) reported similar findings in their analysis of barley, corn, rice, soybeans, and wheat markets, considering a time series from 2000 to 37 days after the conflict. Other studies applied their analysis to many commodities markets, including agricultural (Fang & Shao, 2022) and financial markets (Umar et al., 2022). Their results also suggest a significant increase in volatility transmission, especially from the crude oil to corn and wheat markets.

3. Research Method

3.1 Volatility Transmission Method

To explore volatility spillover and contagion between agricultural commodities and crude oil markets, we used the approach proposed by Akhtaruzzaman, Boubaker & Sensoy (2021). The analysis was conducted in three steps as follows.

First, we summarize the descriptive statistics of the commodities' daily price returns. The return sample is divided into three subsamples. First, we consider the entire period from January 4, 2021, to June 15, 2022. Then, we consider the pre-conflict period from January 4, 2021, to February 23, 2022. Finally, we consider the post-conflict period from February 24 to June 15, 2022. The daily returns were estimated using Equation 1:

$$r_t = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

where r_t is the price return in day *t*; and P_t is the commodity price in day *t*.

In the second step, we estimate the conditional correlations between the commodities markets considered. We use the DCC-GARCH model proposed by Engle (2002). The general model follows Equations 2–5:

$$r_t = \phi + \varepsilon_t \tag{2}$$

$$\varepsilon_t = \sqrt{H_t} e_t \tag{3}$$

$$H_t = D_t R_t D_t \tag{4}$$

$$H_{i,t} = \alpha_{0i} + \sum_{q=1}^{Q_i} \alpha_{iq} \varepsilon_{i,t-q}^2 + \sum_{p=1}^{P_i} \beta_{ip} H_{i,t-p} \tag{5}$$

where ϕ is the constant vector, r_t corresponds to each commodity daily price return, ε_t is the conditional error, $\boldsymbol{H_t}$ is the conditional covariance (and variance) matrix (n × n) of ε_t, e_t is the independent and identically distributed random error, D_t is a diagonal matrix (n × n) of conditional errors ε_t, R_t is the matrix (n × n) of conditional correlations of ε_t in *t*, α corresponds to the volatility average (ARCH parameter), and β corresponds to the volatility transmission parameter (GARCH parameter).

For this study, we used the bivariated DCC-GARCH (1,1,) model, estimated by the 'rmgarch' package in the statistical software R.

Finally, in the third step, we examine the dynamics conditional correlations (DCCs) of the estimated series. We estimated the average and standard deviation of conditional correlations between the commodities prices' daily return series. We then investigated whether the Russia-Ukraine conflict contributed to significant changes in the conditional correlations. The t-test was applied for both samples (pre- and post-conflict), with the assumption that variances were different, to examine the correlation averages before and after the aforementioned military conflict.

3.2 Data

The dataset consists of the daily spot and futures prices for corn, soybeans, wheat, and crude oil. Futures prices represent closing quotes for corn (ZC), soybeans (ZS), and soft red wheat (SRW) near contracts from the Chicago Mercantile Exchange (CME, 2022). Crude oil futures prices represent closing quotes in nearby contracts from the Brent ICE Futures Europe. The spot price analysis considered only the main producing and trading areas in Brazil, for example, Sao Paulo state for corn, Parana state for wheat, and Paranagua port for soybean, based on the Cepea (2022) spot price indexes. Brazilian futures prices are not used because of the absence of wheat futures contracts. In addition, Brazilian soybean contracts have low liquidity and their futures prices are not a better reference for this commodity, as pointed out by Trujillo-Barreras, Mallory & Garcia (2012). Agricultural price series were standardized in US$ dollars per bushel. We then applied a logarithm over all the price series.

The data sample considered the period from January 4, 2021, to June 15, 2022, with a total of 354 observations. This dataset allows us to examine the effects of the Russia-Ukraine most critical period and capture the pre- and post-conflict period, considering the 2021 harvest in the Northern Hemisphere, the 2021 and 2022 summer harvests in Brazil (for corn and soybeans), and the 2021 winter harvest in Brazil (for wheat and corn). We presume that this period minimizes possible seasonality effects in the price series behavior.

4. Results

Figure 1 shows graphs of daily futures prices and returns of futures prices for corn, soybeans, wheat, and crude oil in the CME group and ICE futures, respectively. Figure 2 shows graphs of daily spot prices and the return of spot prices for corn, soybeans, and wheat in Brazil.

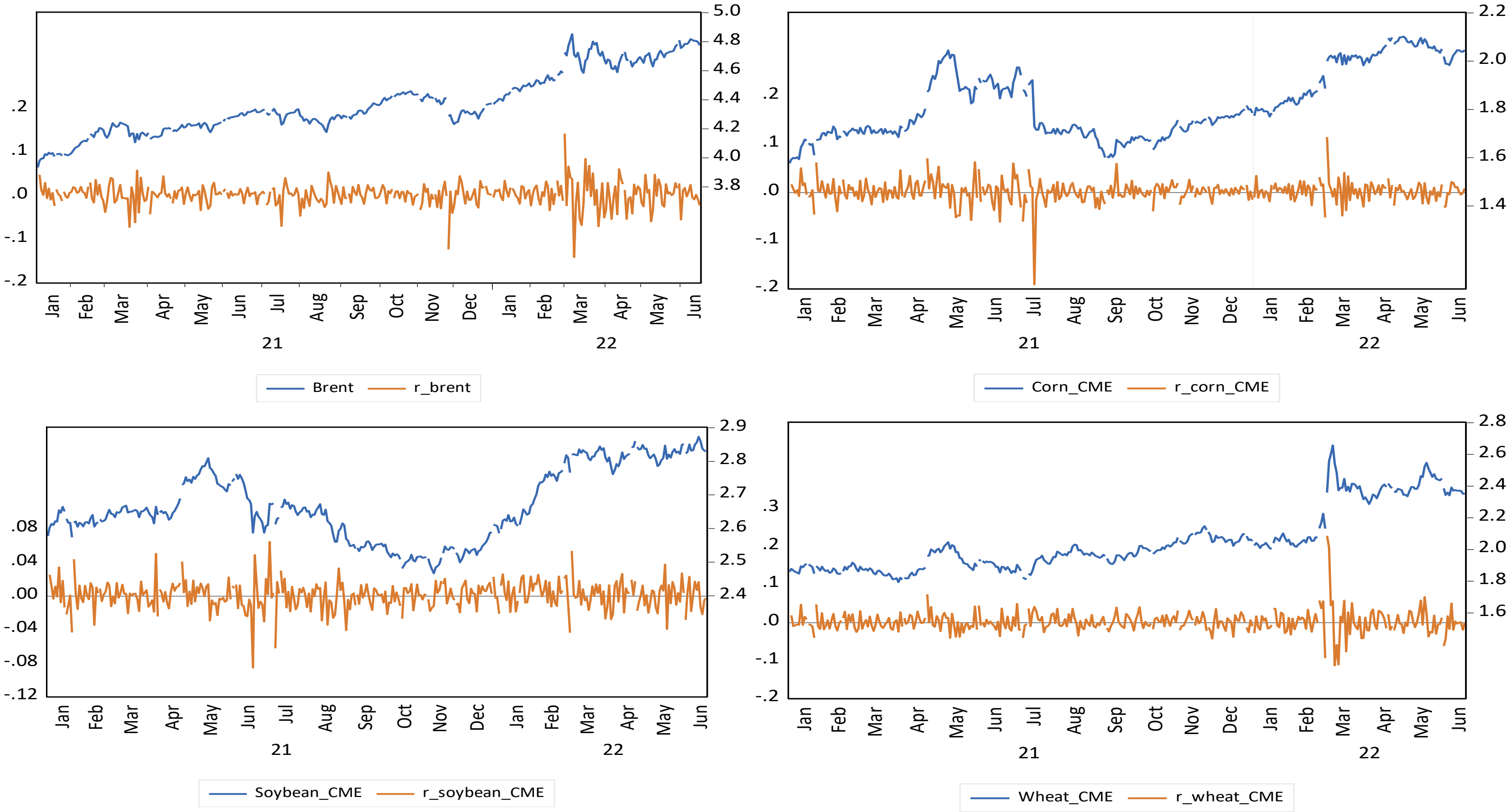

Figure 1. Commodities Prices and Return in Futures Market

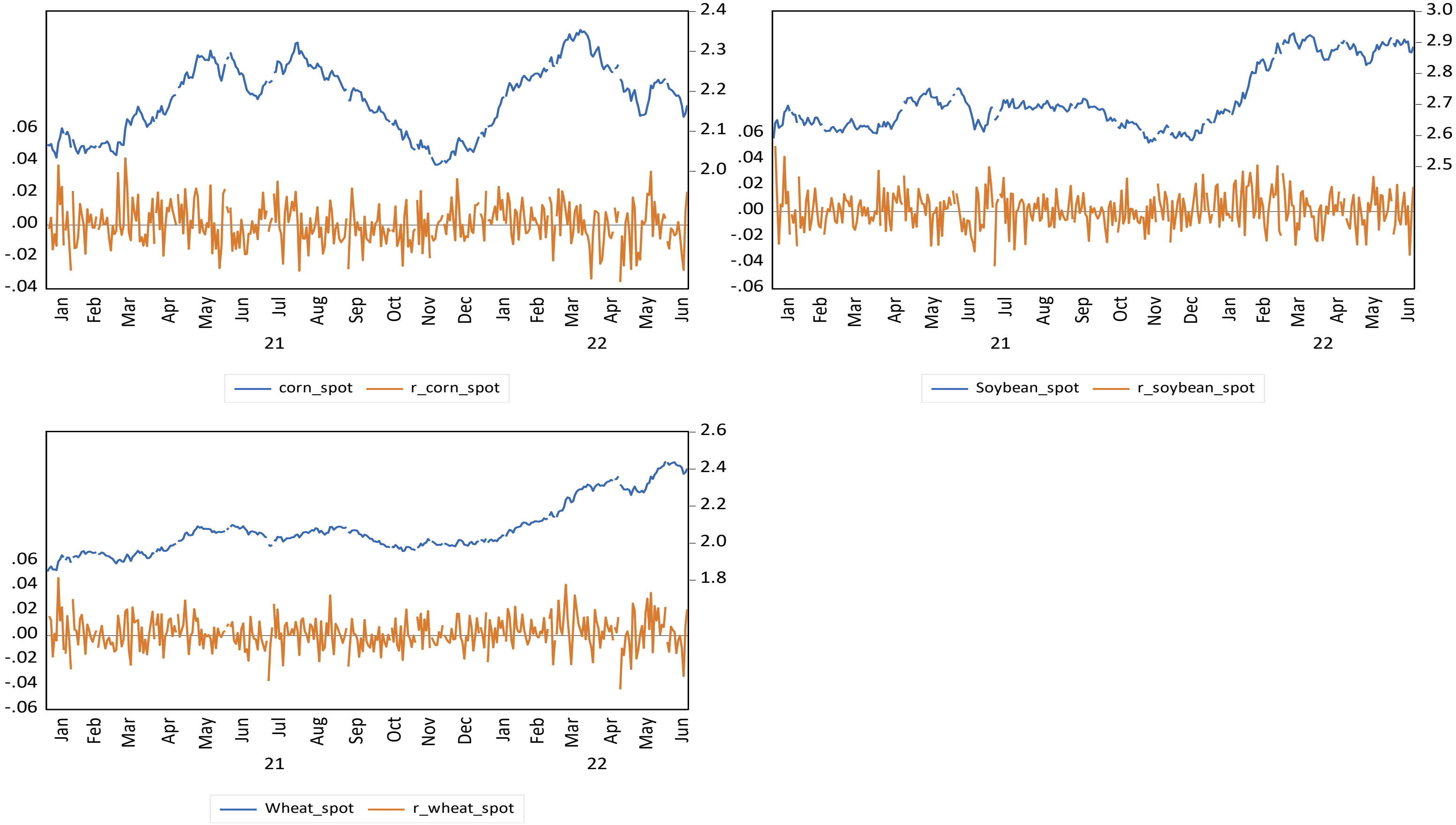

Figure 2. Commodities Prices and Return in Brazilian Spot Market

Table 1. Data Descriptive Statistics

	Obs.	Average	Max.	Min.	Std. Dev.	Skewn.	Kurt.	JB	ADF	Q(10)
Full sample										
Brent	353	0.0024	0.14	-0.14	0.026	-0.52	9.30	599.2*	-19.6*	14.6
Corn_CME	353	0.0013	0.11	-0.19	0.023	-1.39	18.78	3774.6*	-20.2*	29.0*
Corn_Spot	353	0.0003	0.04	-0.04	0.013	0.06	3.24	1.08	-16.5*	13.9
Soybean_CME	353	0.0007	0.06	-0.09	0.016	-0.37	6.29	167.2*	-20.7*	15.8
Soybean_spot	353	0.0008	0.05	-0.04	0.014	0.12	3.43	3.49	-18.6*	9.6
Wheat_CME	353	0.0014	0.23	-0.11	0.029	1.94	20.19	4569.8*	-16.9*	18.5**
Wheat_spot	353	0.0016	0.05	-0.04	0.013	0.05	3.78	9.1**	-18.4*	20.3
Before Russia-Ukraine Conflict										
Brent	277	0.0023	0.06	-0.12	0.020	-1.18	8.66	433.7*	-17.2*	6.5
Corn_CME	277	0.0012	0.07	-0.19	0.023	-2.05	20.83	3860.3*	-16.7*	32.2*
Corn_Spot	277	0.0007	0.04	-0.03	0.012	0.27	3.20	3.81	-15.2*	8.9
Soybean_CME	277	0.0008	0.06	-0.09	0.016	-0.48	7.15	210.0*	-17.7*	23.4*
Soybean_spot	277	0.0010	0.05	-0.04	0.013	0.17	3.65	6.3**	-16.8*	8.8
Wheat_CME	277	0.0010	0.07	-0.04	0.019	0.46	3.43	11.9*	-17.0*	15.7
Wheat_spot	277	0.0011	0.05	-0.04	0.011	0.15	3.70	6.8**	-17.2*	10.6
After Russia-Ukraine Conflict										
Brent	76	0.0027	0.14	-0.14	0.040	-0.10	5.44	18.9*	-9.1*	11.2
Corn_CME	76	0.0018	0.11	-0.05	0.022	1.23	10.12	179.5*	-12.2*	25.5*
Corn_Spot	76	-0.0014	0.03	-0.04	0.014	-0.30	2.89	1.21	-7.0*	5.9
Soybean_CME	76	0.0005	0.05	-0.04	0.017	0.02	3.64	1.32	-10.6*	9.5
Soybean_spot	76	0.0003	0.03	-0.03	0.014	-0.06	2.71	0.31	-8.0*	8.4
Wheat_CME	76	0.0029	0.23	-0.11	0.050	1.55	9.87	179.8*	-7.3*	9.6
Wheat_spot	76	0.0034	0.04	-0.04	0.016	-0.26	3.29	1.13	-7.8*	10.9

Notes: JB: Jarque-Bera normality test. ADF: Augmented Dickey Fuller stationarity test. Q(10): Ljung-Box test returns in lag of 10 serials autocorrelation. (*) p-value < 0.01, (**) p-value < 0.05.

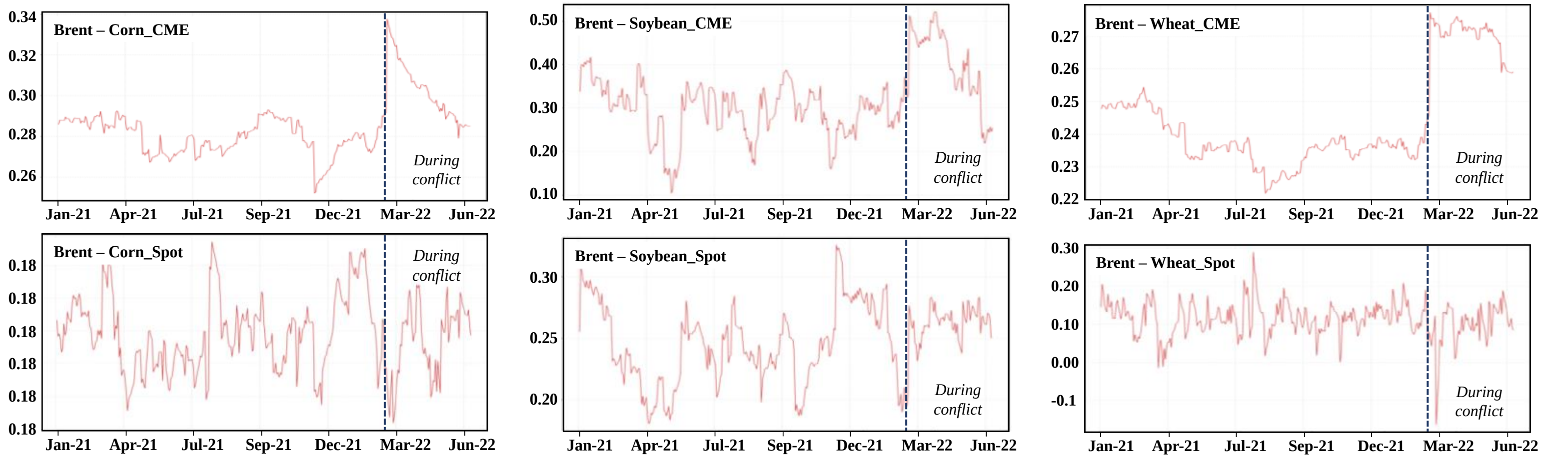

Figure 3. Dynamics Conditional Correlations (DCC) of Futures Crude-Oil Market (Brent)

It seems that the Russia-Ukraine conflict affected agricultural futures markets. This is noted by the increase in the standard deviation of returns in the post-conflict period, especially for wheat, corn, and crude oil. However, in Brazilian agricultural markets, especially soybean and corn, the effects are not evident. A possible explanation is the harvesting of soybeans and corn in Brazil from late February to March, which should minimize domestic price increases in the short run. Beyond that, commodities prices in Brazil were in a growing cycle until late 2021, which may explain why prices did not increase after the conflict.

Descriptive statistics, reported in Table 1 for three periods (full period, pre-, and post-conflict), allow a better illustration of these findings. The results indicate that the increase in price return average was greater for wheat (futures and spot) and crude oil (futures) as the conflict started. However, the average return on soybeans decreased for both the futures and spot markets, although they were still positive. For corn, the average spot price return was negative after the conflict.

The variance in price returns exhibited a generalized increase after the conflict in all markets except for corn in Brazil. The most significant effect was noted in the wheat and crude oil markets regarding the importance of Russia in both commodity exports. For corn in Brazil, prices achieved their positive records in 2021. This indicates why conflict has no significant effect in explaining a new bullish movement.

The distribution function of price returns shows that skewness was different from zero and kurtosis was greater than three, indicating long tails and extreme events, as expected. This suggests that most distribution functions are nonnormal. However, after the conflict, price return distributions exhibit skewness close to zero and kurtosis close to three, and the Jarque-Bera normality test points to a normal distribution in the series, suggesting that the conflict affects price behavior in these markets.

Following the analysis, the augmented Dickey-Fuller test (ADF) test indicated that all series were stationary, as expected for the price return series. In addition, the Ljung and Box test pointed out that there is no serial correlation (autocorrelation) in the price return series when considering 10 lags.

Considering the previous analysis, an estimation of the DCC-GARCH (1,1) model is conducted. Figures 3, 4, 5, and 6 show the dynamics conditional correlations between the assessed markets. Figure 3 shows the relationship between Brent crude oil and the agricultural markets. Figure 4 shows the relationship between the CME corn futures market and the other agricultural markets. Figure 5 shows the relationship between the CME soybean futures market and the rest of the agricultural markets (except for corn, as expressed in Figure 4). Finally, Figure 6 shows the relationship between the CME wheat futures market and the rest of the agricultural markets, except corn and soybean, expressed in Figure 4 and 5, respectively). In addition, numerical results of DCC model of the Brent, Corn, Soybean and Wheat markets are expressed in the Tables A.1, A.2, A.3 and A.4 in the manuscript Appendix. The detached areas in Figures 3, 4, 5, and 6 represent the conflict periods. Note that volatility spillovers are significant and positively related to the entire sample period.

Table 2 reports the average conditional correlations for the pre- and post-conflict periods. The t-test is significant in all cases, except for the linkages between corn futures and corn spot, and soybean futures and soybean spot.

Figure 3 shows a significant increase in the conditional correlations between crude oil and CME futures contracts. A structural break can be observed in the price return series after the conflict, where correlations reached their maximum values for futures agricultural prices, which were greater than in the pre-conflict period. This effect persists in wheat futures (Table 2), suggesting that volatility in this market is higher after the conflict outbreak. However, for soybean and corn futures, the correlations converge to the previous level after two months. Unlike the agricultural futures markets, there is no substantial difference in the volatility of the Brazilian spot market. The conditional correlations were similar before and after the conflict except for the wheat spot market, which exhibited a slight increase.

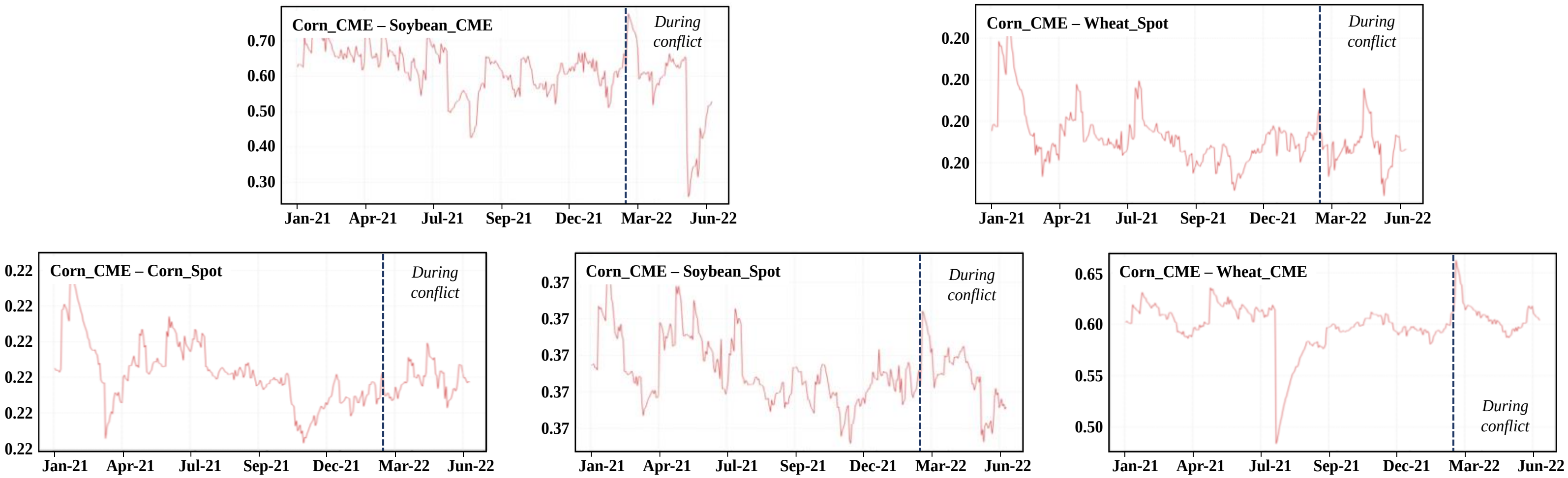

Figure 4. Dynamics Conditional Correlations (DCC) of Futures Corn Market (ZC – CME)

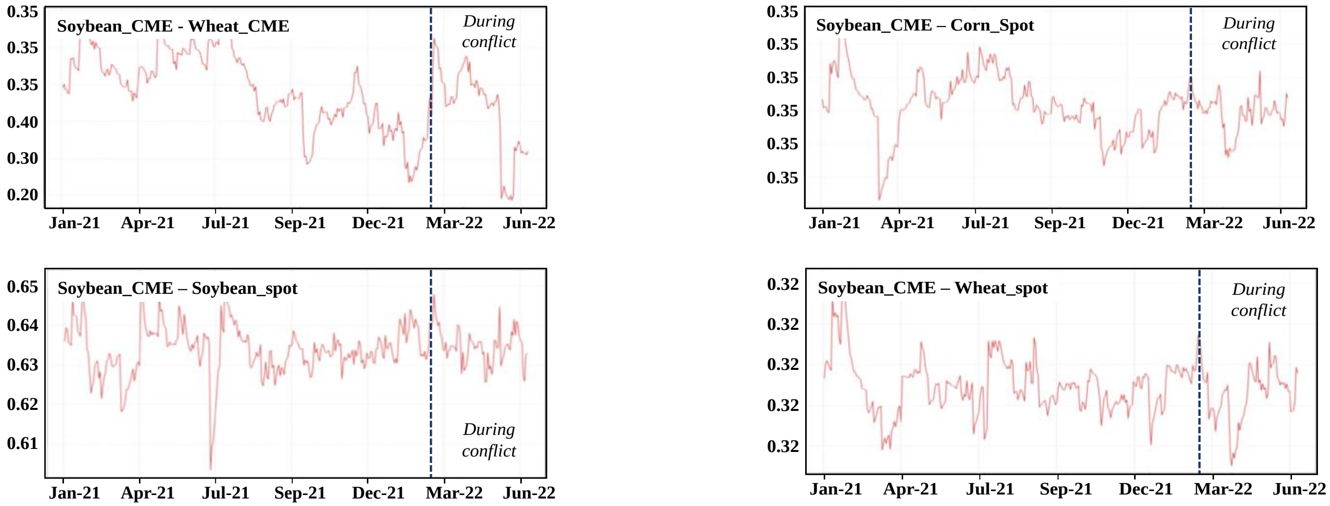

Figure 5. Dynamics Conditional Correlations (DCC) of Futures Soybean Market (ZS –CME)

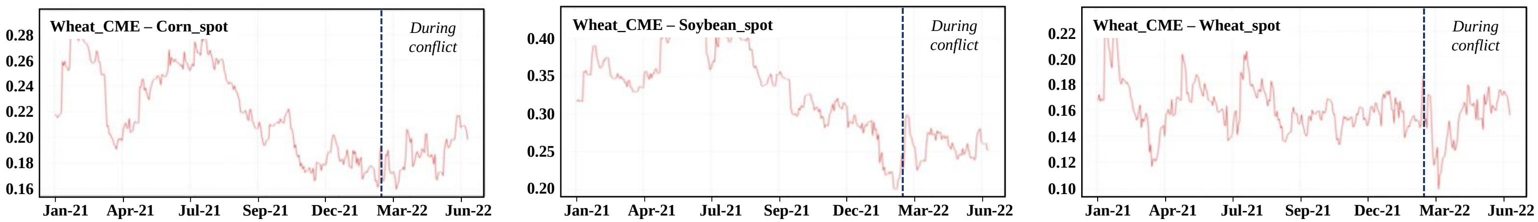

Figure 6. Dynamics Conditional Correlations (DCC) of Futures Wheat Market (SRW – CME)

The conditional correlations between the agricultural futures and spot markets (Figures 4, 5, and 6) provide new elements for discussion. Figure 4 shows that the conditional correlation increases between CME corn futures and other markets (futures and spot). However, this growth was not persistent, and the difference between the periods was not significant (Table 2). Further, the conditional correlation between CME soybean futures and other agricultural markets (Figure 5) remained constant or smaller, suggesting that there are no elements to point out that the Russia-Ukraine conflict changed the fluctuations in the global soybean market and its relationship with wheat and corn markets. The conditional correlations between CME wheat futures and spot markets (Figure 6) indicate an increase in volatility spillover (note that the relationships between wheat futures and corn futures, and wheat futures and soybean futures are expressed in Figure 4 and 5). The DCC differences between pre- and post-conflict periods indicate a reduction in volatility transmission to Brazilian agricultural markets (Table II). Contrary to our expectations, the Brazilian wheat spot market appears to be weakly affected by CME wheat futures. A possible explanation is that the Brazilian wheat market is less integrated with the commodity global market (import flows are irregular and mainly from Argentina), especially in comparison to the soybean and corn markets, where the country is a large exporter.

Overall, our findings indicate that the level of dependence between the considered agricultural markets changes over time. The increase in correlations after the conflict confirms the existence of contagion between the commodity markets. In most of the evaluated scenarios, the volatility spillover was also greater in the post-conflict period. Therefore, we can confirm the existence of a shock transmission in this period, especially between the crude oil and international agricultural commodities markets (expressed by CME futures contracts).

Table 2. Average Dynamics Conditional Correlations (DCC) Analysis

	Corn_CME	Corn_Spot	Soybean_CME	Soybean_spot	Wheat_CME	Wheat_Spot
Brent						
Before [a]	0.2795	0.1819	0.2938	0.2444	0.2373	0.1171
After [b]	0.3019	0.1819	0.3957	0.2602	0.2689	0.0988
Dif. DCC [c]	0.0223	0.0000	0.1019	0.0158	0.0316	-0.0184
t stats.	-13.03*	1.64	-9.84*	-5.61*	-32.59*	2.62**
Corn CME						
Before [a]		0.2188	0.6235	0.3682	0.5970	0.2053
After [b]		0.2188	0.5689	0.3682	0.6090	0.2053
Dif. DCC [c]		0.0000	-0.0546	0.0000	0.0120	0.0000
t stats.		2.92*	3.67*	2.32**	-5.36*	3.99*
Soybean CME						
Before [a]	0.6235	0.3491		0.6339	0.4898	0.3180
After [b]	0.5689	0.3491		0.6350	0.4313	0.3180
Dif. DCC [c]	-0.0546	0.0000		0.0011	-0.0585	0.0000
t stats.	3.67*	2.72*		-1.77	3.92*	2.05**
Wheat CME						
Before [a]	0.5970	0.2228	0.4898	0.3427		0.1625
After [b]	0.6090	0.1871	0.4313	0.2582		0.1537
Dif. DCC [c]	0.0120	-0.0356	-0.0585	-0.0845		-0.0088
t stats.	-5.36*	13.44*	3.92*	22.59*		3.59*

Notes: a: before the conflict; b: after the conflict; c: DCC difference; * significant at 1%.

Our results follow the findings of Just & Echaust (2022), especially considering the relationship between agricultural international markets. In addition, this study contributes to the conclusions of Umar et al. (2022), who pointed out crude oil as the major volatility transmitter over commodities markets after the Russia-Ukraine conflict. Finally, this study's evidence is related to the findings of Adekoya et al. (2022), who identify that the effects of the crude oil market after the conflict affected other financial markets, including agricultural derivatives.

5. Conclusions

This study evaluates the effects of the 2022 military conflict between Russia and Ukraine on the volatility transmission levels between agricultural commodities and crude oil markets. Additionally, the study investigated whether volatility spillover at the international level could be noted in Brazilian commodities markets, considering the importance of this country as a net agricultural exporter and its position as a developing country.

Overall, we found that volatility transmission in agricultural commodities markets increased substantially after military conflict. Our findings indicate a strong conditional correlation between crude oil and CME agricultural futures prices. The effect is persistent in linkage with the wheat market and loses relevance after two months for soybeans and corn. Nonetheless, for Brazilian spot prices, volatility transmission is weak for both linkages (crude oil and CME futures prices). One possible reason for this is the escalation of agricultural prices by 2021. Additionally, considering that spot prices were treated in US dollars and the Brazilian currency (Real) exhibited a strong devaluation since 2020, the exchange rate effect could suppress the real effect in these spot markets.

This study contributes to a recent and important topic that affect commodities prices worldwide. In addition, it provides new elements to the empirical literature on the evaluation of volatility connections in agricultural commodities markets, especially considering a crisis period and the connections between energy and agricultural markets. Further, the analysis considers the association with global markets to an emergent country and agricultural commodities exporters as Brazil, which can shed light on new insights and the effects of a global crisis in developing countries.

Finally, future contributions of this study can be proposed. For example, an improvement in the methodological approach to estimate conditional correlation, such as the use of Diebold & Yilmaz (2012) method or estimating multifractal regressions to examine the cross-correlation between prices. Additionally, the inclusion of different agricultural commodities and spot prices from different emerging markets can add new elements to the current literature.

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Appendix

Table A.1. DCC Model of the Brent Futures Market

	Brent-Corn (CME)	**Brent-Soybean (CME)**	**Brent-Wheat (CME)**	**Brent-Corn (spot)**	**Brent-Soybean (spot)**	**Brent-Wheat (spot)**
	Coef.	**Coef.**	**Coef.**	**Coef.**	**Coef.**	**Coef.**
	(Std. erro.)	**(Std. erro.)**	**(Std. erro.)**	**(Std. erro.)**	**(Std. erro.)**	**(Std. erro.)**
	Variance Equations					
ω_1	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_1	0.148*	0.148*	0.148*	0.148*	0.148*	0.148*
	(0.057)	(0.057)	(0.056)	(0.057)	(0.056)	(0.056)
β_1	0.801*	0.801*	0.801*	0.801*	0.801*	0.801*
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
ω_2	0.000	0.000*	0.000***	0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_2	0.162	0.097***	0.234***	0.000	0.051*	0.055*
	(0.403)	(0.053)	(0.129)	(0.000)	(0.004)	(0.004)
β_2	0.834*	0.773*	0.540*	0.999*	0.881*	0.849*
	(0.230)	(0.078)	(0.208)	(0.000)	(0.010)	(0.019)
	DCC Equation					
λ	0.003	0.036	0.002	0.000	0.012	0.039
	(0.008)	(0.029)	(0.006)	(0.000)	(0.020)	(0.060)
τ	0.955*	0.906*	0.988*	0.920*	0.923*	0.635*
	(0.021)	(0.062)	(0.023)	(0.073)	(0.033)	(0.147)
	Skew-N					
φ	4.628*	6.124*	6.747*	8.069*	7.598*	6.715*
	0.690	-1.091	-1.469	-2.134	-1.764	-1.399
Akaike	-9.855	-10.320	-9.546	-10.656	-10.553	-10.676
Bayes	-9.746	-10.210	-9.437	-10.546	-10.443	-10.567
Shibata	-9.857	-10.321	-9.548	-10.657	-10.554	-10.678
HQ	-9.811	-10.276	-9.502	-10.612	-10.509	-10.633
Log-Like	1749.407	1831.408	1694.869	1890.713	1872.543	1894.381

Note: ***, ** and * denote significance at the 10%, 5% and 1% levels, respectively.

Table A.2. DCC Model of the Corn Futures Market

	Corn - Soybean (CME)	**Corn - Wheat (CME)**	**Corn - Corn (spot)**	**Corn - Soybean (spot)**	**Corn - Wheat (spot)**
	Coef.	**Coef.**	**Coef.**	**Coef.**	**Coef.**
	(Std. erro.)	**(Std. erro.)**	**(Std. erro.)**	**(Std. erro.)**	**(Std. erro.)**
Variance Equations					
ω_1	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_1	0.162	0.162	0.162	0.162	0.162
	(0.405)	(0.404)	(0.404)	(0.406)	(0.405)
β_1	0.834*	0.834*	0.834*	0.834*	0.834*
	(0.230)	(0.230)	(0.230)	(0.230)	(0.230)
ω_2	0.000**	0.000***	0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

α_2	0.097***	0.234	0.000	0.051*	0.055*
	(0.052)	(0.129)	(0.000)	(0.004)	(0.004)
β_2	0.773*	0.540	0.999*	0.881*	0.849*
	(0.078)	(0.209)	(0.000)	(0.010)	(0.019)
DCC Equation					
λ	0.043***	0.006	0.000	0.000	0.000
	(0.023)	(0.014)	(0.000)	(0.000)	(0.000)
τ	0.875*	0.925	0.948*	0.936*	0.916*
	(0.076)	(0.097)	(0.235)	(0.264)	(0.251)
Skew-N					
φ	5.257*	5.614	7.520*	7.854*	6.405*
	(0.993)	-1.242	-2.017	-1.960	-1.339
Akaike	-11.002	-10.258	-10.906	-10.859	-10.935
Bayes	-10.892	-10.149	-10.797	-10.749	-10.825
Shibata	-11.003	-10.260	-10.908	-10.860	-10.936
HQ	-10.958	-10.215	-10.863	-10.815	-10.891
Log-Like	1951.844	1820.612	1934.972	1926.556	1939.971

Note: ***, ** and * denote significance at the 10%, 5% and 1% levels, respectively.

Table A.3. DCC Model of the Soybean Futures Market

	Soybean - Wheat (CME)	Soybean – Corn (spot)	Soybean - Soybean (spot)	Soybean - Wheat (spot)
	Coef.	Coef.	Coef.	Coef.
	(Std. erro.)	(Std. erro.)	(Std. erro.)	(Std. erro.)
Variance Equations				
ω_1	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
α_1	0.097***	0.097***	0.097***	0.097***
	(0.053)	(0.053)	(0.055)	(0.053)
β_1	0.773*	0.773*	0.773*	0.773*
	(0.077)	(0.078)	(0.079)	(0.078)
ω_2	0.000***	0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
α_2	0.234***	0.000	0.051*	0.055*
	(0.129)	(0.000)	(0.004)	(0.004)
β_2	0.540*	0.999*	0.881*	0.849*
	(0.208)	(0.000)	(0.009)	(0.019)
DCC Equation				
λ	0.034	0.000	0.006	0.000
	(0.041)	(0.000)	(0.014)	(0.000)
τ	0.932*	0.922*	0.779*	0.864**
	(0.109)	(0.295)	(0.200)	(0.401)
Skew-N				
φ	8.038*	9.391*	10.625*	7.533*
	-1.730	-2.600	-3.070	-1.596
Akaike	-10.493	-11.503	-11.747	-11.507
Bayes	-10.384	-11.393	-11.638	-11.397
Shibata	-10.495	-11.504	-11.749	-11.508
HQ	-10.450	-11.459	-11.704	-11.463
Log-Like	1862.070	2040.239	2083.380	2040.930

Note: ***, ** and * denote significance at the 10%, 5% and 1% levels, respectively.

Table A.4. DCC Model of the Wheat Futures Market

	Wheat – Corn (spot)	**Wheat - Soybean (spot)**	**Wheat - Wheat (spot)**
	Coef.	**Coef.**	**Coef.**
	(Std. erro.)	**(Std. erro.)**	**(Std. erro.)**
Variance Equations			
ω_1	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
α_1	0.234***	0.233***	0.234***
	(0.132)	(0.131)	(0.131)
β_1	0.540**	0.539**	0.540**
	(0.211)	(0.210)	(0.210)
ω_2	0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)
α_2	0.000	0.051*	0.055*
	(0.000)	(0.004)	(0.004)
β_2	0.999*	0.881*	0.849*
	(0.000)	(0.009)	(0.018)
DCC Equation			
λ	0.007	0.009	0.009
	(0.011)	(0.007)	(0.023)
τ	0.976*	0.983*	0.876*
	(0.034)	(0.006)	(0.074)
Skew-N			
φ	16.010*	13.446*	10.783*
	-6.630	-4.578	-3.074
Akaike	-10.676	-10.601	-10.679
Bayes	-10.566	-10.492	-10.569
Shibata	-10.677	-10.603	-10.68
HQ	-10.632	-10.558	-10.635
Log-Like	1894.23	1881.126	1894.793

Note: ***, ** and * denote significance at the 10%, 5% and 1% levels, respectively.