DYNAMIC CORRELATION BETWEEN SELECTED CEREALS TRADED IN COMMODITY EXCHANGE MARKET IN AP VOJVODINA

Dejan Živkov[1], Biljana Stankov[2], Milijana Roganović[3], Mirela Momčilović[4]

**Corresponding author E-mail: dejanzivkov@gmail.com*

A R T I C L E I N F O

Original Article

Received: *27 January 2022*

Accepted: *30 March 2022*

doi:10.5937/ekoPolj2202395Z

UDC 339.13.012:633.1(497.113)

Keywords:

agricultural commodities, dynamic conditional correlations, DCC-GARCH model

***JEL**: C32, Q02, Q14*

A B S T R A C T

This paper investigates the level of pairwise dynamic correlations between prices of four agricultural commodities – corn, wheat soybean and barley that are traded in Novi Sad commodity exchange market. We use DCC-GARCH model, which is specially designed for this type or research. The results of the estimated dynamic conditional correlations show that low and positive correlation exist between all the pairs of the selected agricultural commodities, where the highest correlation is recorded between wheat and barley (24%), corn-barley pair follows (20%), while all other dynamic correlations are below 20%. The results indicate that price movements of the selected agricultural cereals are independent, which means that price discovery of one agricultural commodity does not provide information about the price of another agricultural commodity. Therefore, our results strongly suggest that traders in this market do not rely on the price co-movements between particular agricultural assets when they plan their selling or buying strategies, but to analyze fundamental macroeconomic factors.

1 Dejan Živkov, Professor, Novi Sad School of Business, Vladimira Perića Valtera 4, Novi Sad, Republic of Serbia, Phone: +381601445598, E-mail: dejanzivkov@gmail.com, ORCID ID (https://orcid.org/0000-0003-2357-3250)

2 Biljana Stankov, Lecturer, Novi Sad School of Business, Vladimira Perića Valtera 4, Novi Sad, Republic of Serbia, Phone: +381605054644, E-mail: bilja.l.stankov@gmail.com , ORCID ID (https://orcid.org/0000-0001-8773-4143)

3 Milijana Roganović, Lecturer, Novi Sad School of Business, Vladimira Perića Valtera 4, Novi Sad, Republic of Serbia, Phone: +381641570331, E-mail: milijanadjordjevic@gmail.com, ORCID ID (https://orcid.org/0000-0002-8476-7086)

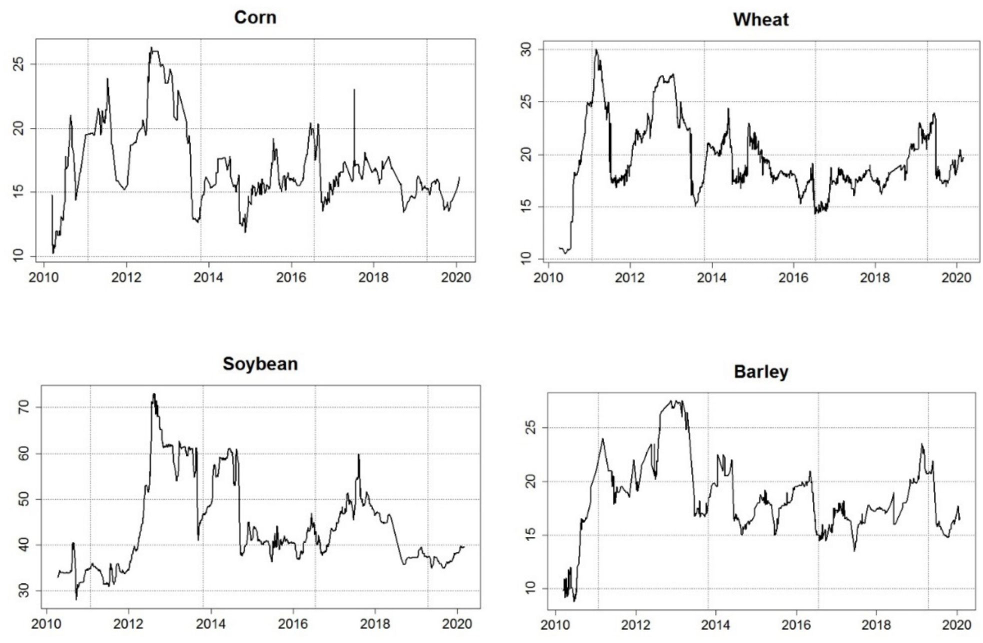
4 Mirela Momčilović, Lecturer, Novi Sad School of Business, Vladimira Perića Valtera 4, Novi Sad, Republic of Serbia, Phone: +38163280010, E-mail: bizniscentar@gmail.com , ORCID ID (https://orcid.org/0000-0001-5752-6992)

Introduction

Generally speaking, agricultural commodities are closely connected due to numerous reasons. It can be said that these commodities are close substitutes in demand, their production costs are similar and they compete for limited natural resources. In addition, increased financialization of agricultural markets in recent decades, in a form of herd and speculative behaviour, further enhanced interdependence between crop prices. Dawson and White (2002) listed several reasons why commonality between commodity futures (or cash) prices arises. They asserted that macroeconomic fundamentals, such as aggregate demand, inflation, and interest rates, are common factors in determination of commodity prices. Secondly, high correlations between prices of similar commodities may exist because some of them are substitutes or complements in supply or demand. de Nicola et al. (2016) contended that academics and policy makers have an interest to analyse agricultural commodity price co-movements due to potentially large welfare and policy implications. They explained that the presence of synchronized changes in the behaviour of agricultural commodity prices may cast doubts on the competitiveness and efficiency of these markets. Similarly, farmers that grow multiple crops may face themselves with strong income fluctuations owing to the synchronized changes in agricultural prices. As for countries which are dependent on import of agricultural commodities, a simultaneous increase in several commodity prices may generate inflation pressures in these economies, while agricultural commodity exporting countries may experience high volatilities in their export incomes.

Serbia is a country with relatively significant production in agricultural sector, which particularly applies for autonomous province of Vojvodina. According to Gulan (2014), the weight of agricultural production in Serbian GDP is relatively high, ranging between 11.8%-15.5% in the period 2002-2012. Đurić et al. (2017) and Marković et al. (2019) added that agricultural and food sector has an important role in the economic development of the Republic of Serbia, significantly participating in the structure of domestic exports. Having in mind aforementioned, this paper tries to determine a level of dynamic correlations between prices of four cereals – corn, wheat, soybean and barley, which are traded in commodity exchange market in Novi Sad. Several motives prompted us to do this research. Firstly, according to Li and Lu (2012), studies on correlation and cross-correlation in agricultural markets are rare in general, while most of them are related to North American futures contracts. To the best of our knowledge, none of the extant papers have tried to measure correlation between agricultural products traded in Serbian commodity exchange market, and this paper tries to fill this gap. The second motive is more practical. Namely, dynamic correlation coefficients gauge mutual correlation of two assets throughout the particular period and they are time-varying. This means that these measures carry significantly more information than Pearson correlation coefficient that is static by nature, and as such can offer only one average value of correlation for entire period. In addition, it is highly unlikely to assume that correlation is unchangeable throughout the time (see e.g. Onay and Ünal, 2012). Therefore, having on disposal a data about dynamic correlation is important for various reasons. First of all, dynamic mutual correlation is a primary input in the construction of risk-minimizing portfolio (see e.g. Lee et al., 2014; Asai, 2013; Kang and Yoon, in press). Even more importantly, dynamic correlation can provide useful information for Serbian farmers in a sense that existence of high positive correlation between two agricultural commodities would imply that rise (fall) of one agricultural product means rise (fall) of the other one in some time in the future, and *vice-versa*. This type of knowledge is very useful for agricultural producer when they make their decisions about when to sell their annual harvests. Figure 1 shows empirical dynamics of the selected cereals, and it can be seen that prices of these agricultural commodities are pretty much volatile, but visually, they follow relatively common dynamics. Therefore, the task of this paper is to determine how much price movements of these cereals are synchronized, i.e. whether visual price harmonization that can be seen in Figure 1 is supported by calculated dynamic correlation coefficients.

Figure 1. Empirical dynamics of the selected cereals



Source: Authors' calculations

In order to calculate pairwise dynamic correlations between the selected cereals, we use complex and sophisticated methodology – bivariate Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity model (DCC-GARCH) developed by Engle (2002). More precisely, we want to measure dynamic correlations as accurate as possible, so we, firstly, try to determine the best fitting DCC model. In that process, we estimate DCC-GARCH and DCC-EGARCH models, in combination with normal and Student t multivariate distributions. The former model is symmetric in the variance, while the latter model can measure asymmetric effect in the variance. The best fitting model is selected by Akaike information criterion, and this model is used subsequently to extract the dynamic conditional correlations. We apply this methodology, because Milani and Ceretta (2014) asserted that correlation is perhaps the most traditional way of measuring the association between two variables, whereas Živkov et al. (2016) contended that it could indicate a more direct interdependence between these two assets. Many recent papers found very appealing DCC-GARCH model for their researches (see e.g. Jones and Olson, 2013; Singhal and Ghosh, 2016; Hou and Li, 2016; Jiang et al., 2019).

Besides introduction, the rest of the paper has the following structure. Second section gives an overview of the existing literature. Third section explains used methodology. Fourth section presents dataset and descriptive statistics. Fifth section presents research results. Sixth section is reserved for the discussion of the results, while the last section concludes.

Literature review

Referring to Boroumand et al. (2014), very few academic papers investigated mutual correlation between agricultural commodities, and this section presents the findings of some papers that did this type of research. For instance, Gardebroek et al. (2016) employed a multivariate GARCH approach to assess the time evolution of conditional correlations and volatility transmission across corn, wheat, and soybeans price returns on a daily, weekly, and monthly basis. They claimed that daily interactions are probably driven by financial transactions in agricultural markets. However, they asserted that this evidence is not supported by increasing trend in the conditional correlations between commodities on a daily basis, whatsoever. Similar results, regarding interdependence (conditional correlations) between markets, they reported on a weekly and monthly basis. The paper of Bonato (2019) studied the dynamics of price correlations and spillover effects in the commodity market, considering the interaction within soft and grain commodities and between these commodities and oil. They found that soft commodities were segmented prior to 2008 and became correlated thereafter, but they claimed that the nature of the increase in correlation is only temporary. On the other hand, they reported significant and positive correlations within grains. The paper of Baffes and Haniotis (2016) considered arguments that cause the agricultural price cycle. Their research focused on six agricultural commodities (maize soybeans, wheat, rice, palm oil and cotton) in order to identify the key quantifiable drivers of their prices. They found that increases in real income negatively affect real agricultural prices, which is consistent with the Engel's Law. Energy prices affect agricultural commodities the most, which is expected, taking into account the energy-intensive nature of agriculture production. Stock-to-use ratios and ex-change rate movements have a lesser extent on agricultural commodities. The cost of capital influences prices only marginally, probably because it not only influences demand, but also evokes a supply response.

Li and Lu (2012) examined the cross-correlation properties of agricultural futures markets (soy bean, wheat, soy meal and corn) between the US and China. Their results showed that the cross-correlations between the two geographically distant markets for the selected agricultural commodities futures are significantly multifractal. In addition, they discovered that the cross-correlations in the short term are more strongly multifractal, but they are weakly in the long term. Dawson and White (2002) investigated interdependencies between several agricultural futures contracts – barley, cocoa, coffee, sugar and wheat on the LIFFE exchange market. Since barley and wheat are substitutes in demand and supply, they expected for these two to be related, while other pair-wise combinations are expected to be unrelated because they are neither complements nor substitutes. However, their results indicated that the prices of agricultural futures contracts are independent. In other words, there are no interdependencies between any two prices, that is, price discovery of one contract provides no information about others. The paper of Boroumand et al. (2014) researched the correlation structures of a large panel of agricultural commodities prices (cocoa, cotton, palm oil, hides of cattle, soya beans, corn, sugar and beef), covering the period between January 1990 and February 2014. They concluded that strong correlation exists between prices of palm oil, soya beans and corn. On the other hand, their findings suggested that prices of beef, sugar and cocoa are completely independent.

Methodology

For the construction of dynamic correlations, we use bivariate DCC model of Engle (2002). In particular, in order to be as accurate as possible in the estimation process, we consider two univariate GARCH specifications – simple GARCH(1,1) and asymmetric EGARCH(1,1) models, along with two multivariate distributions – normal and Student t. The univariate GARCH(1,1) and EGARCH(1,1) processes in the DCC framework have the form as in the equations (1) and (2), respectively:

$$\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{1}$$

$$ln(\sigma_t^2) = c + \beta\, ln(\sigma_{t-1}^2) + \gamma\left|\frac{\varepsilon_{t-1,i}}{\sqrt{\sigma_{t-1}^2}}\right| + \alpha\frac{\varepsilon_{t-1,i}}{\sqrt{\sigma_{t-1}^2}}, \tag{2}$$

where σ_t^2 is a conditional variance of the particular agricultural asset, whereas ε_t^2 describes squared residuals of the univariate GARCH models.

Symbol c denotes constant term, β parameter captures the persistence of volatility, α gauges an ARCH effect, while γ is the coefficient that measures asymmetric response of volatility to positive and negative shocks.

In order to avoid autocorrelation bias, all mean equations are estimated in the autoregression form of order 1, i.e. AR(1). DCC model of Engle (2002) involves two-stage estimation procedure of the conditional covariance matrix (H_t). In the first stage, each pair of considered agricultural commodities is estimated via GARCH or EGARCH models, and subsequently estimates of standard deviations, $\sqrt{\sigma^2_{ii,t}}$, are acquired. In the second step, asset-return residuals are standardized, i.e. $\nu_{i,t} = \varepsilon_{i,t}/\sqrt{\sigma^2_{ii,t}}$, where the $\nu_{i,t}$ is then used to estimate the parameters of the conditional correlation. According to Engle (2002) procedure, the multivariate conditional variance is specified as $H_t = D_t C_t D_t$. Where $D_t = diag(\sqrt{\sigma^2_{11,t}} \cdots \sqrt{\sigma^2_{nn,t}})$ and $\sigma^2_{ii,t}\sigma^2_{ii,t}$ represents the conditional variance, which is obtained from some form of a univariate GARCH model in the first stage. The evolution of correlation in the DCC model is presented as:

$$Q_t = (1 - a - b)\bar{Q} + \alpha \nu_{t-1}\nu'_{t-1} + \beta Q_{t-1}\,, \tag{3}$$

where a and b are nonnegative scalar parameters of DCC(1,1) model under condition $a + b < 1$. These parameters measure the effects of previous shocks and previous dynamic conditional correlations on current dynamic conditional correlations, respectively. Symbol $Q_t = [q_{nm,t}]$ describes n × n time-varying covariance matrix of residuals, where i ≠ j in our bivariate model, and n equals two. Symbol $\bar{Q} = E[\nu_t \nu'_t]$ signifies a n × n time-invariant variance matrix of ν_t. Q_t does not have unit elements on the diagonal, so it is scaled to obtain proper correlation matrix (C_t) according to the following form:

$$C_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \tag{4}$$

Accordingly, the element of C_t looks like:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} = \frac{(1-a-b)\bar{q}_{ij} + a\nu_{i,t-1}\nu_{j,t-1} + bq_{ij,t-1}}{\sqrt{[(1-a-b)\bar{q}_{ii} + a\nu^2_{i,t-1} + bq_{ii,t-1}]}\sqrt{[(1-a-b)\bar{q}_{jj} + a\nu^2_{j,t-1} + bq_{jj,t-1}]}} \tag{5}$$

where i ≠ j and in our bivariate model n is equal to 2. All DCC models were estimated by quasi maximum likelihood (QMLE) technique, which allows asymptotically consistent parameter estimates even if the underlying distribution is not normal, as asserted by Bollerslev and Wooldridge (1992).

Dataset

This paper uses daily prices of four agricultural cereals – corn, wheat, soybean and barley, which are traded in commodity exchange market in Novi Sad. We observe relatively long time-period, from March 2010 to March 2020. All empirical agricultural time-series are transformed into log-returns according to the expression $r_{i,t} = 100 \times \log(P_t/P_{t-1})$, where P_i denotes the closing prices of the selected assets. However, significant shortcoming of these data is the fact that they are not characterized by continuous trading, that is, trading process took place in limited number of days every month, in most 10 days. Also, during one trading day, several transactions were made at different prices. Therefore, we invest a lot of work in order to make usable these data for the software in which calculation were done[5]. In other words, before computational process, we have to calculate average weighted price for every single day in which several transactions were made at different prices. In this way, we get only one trading price per day, throughout the observed sample of 11 years.

After these settings, all agricultural time-series are synchronized according to the existing daily observations, because trading process in commodity market took place in different days for different cereals. More precisely, after synchronization, following synchronized pairs – corn-wheat, corn-soybean, corn-barley, wheat-soybean, wheat-barley and soybean-barley have 1964, 1492, 563, 1298, 478 and 370 daily observations, respectively. It can be noticed that pairs with barley have the lowest number of observations, and the reason lies in the fact that trading with barley happened in the least number of days. Table 1 contains descriptive statistics of log-returns of the selected agricultural commodities, i.e. first four moments, Jarque-Bera test of normality, Ljung-Box test statistics and augmented Dickey-Fuller test of stationarity. Figure 1 shows graphical illustrations of the agricultural log-returns.

Table 1. Descriptive statistics of log-returns of the selected cereals

	Mean	**Stan. dev.**	**Skewness**	**Kurtosis**	**JB**	**LB(Q)**	**LB(Q^2)**	**ADF**
Corn	0.019	2.721	0.287	36.210	90283.1	0.000	0.000	-64.386
Wheat	0.030	2.667	-0.968	27.083	47769.4	0.000	0.000	-15.729
Soybean	0.062	3.979	-1.847	21.736	5621.9	0.002	0.997	-15.439
Barley	0.138	5.074	-1.753	17.026	3222.2	0.153	0.753	-22.058

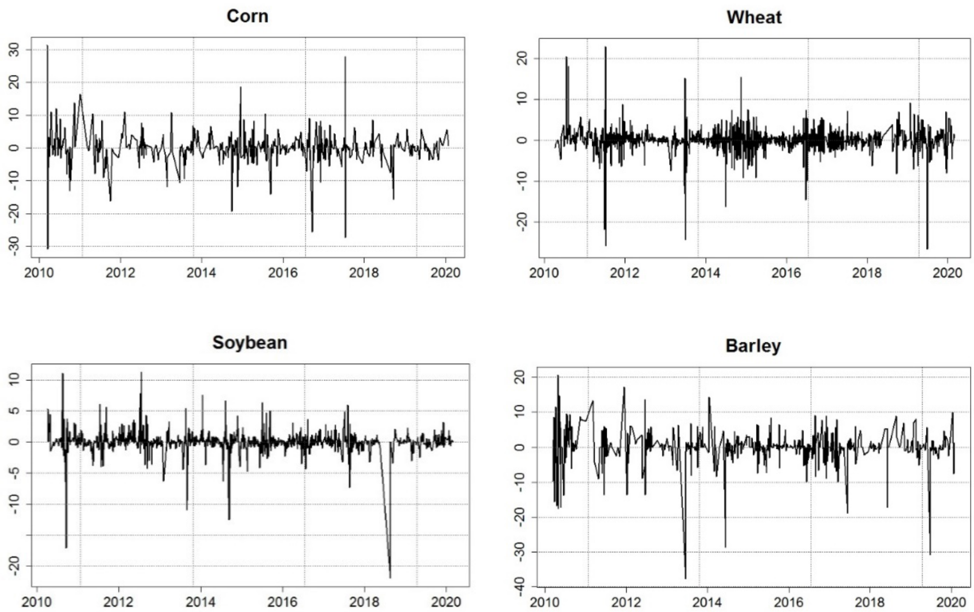
Notes: JB stands for Jarque-Bera coefficients of normality, LB(Q) and LB(Q^2) tests denote p-values of Ljung-Box Q-statistics of level and squared residuals for 20 lags. 1% and 5% critical values for ADF test with 5 lags, assuming only constant, are -3.433 and -2.863, respectively.

Source: Authors' calculations

5 We use OX metrics software for our computations.

According to Table 1, the riskiest agricultural commodity is barley, because it has the highest standard deviation. Most agricultural commodities have negative skewness, which means that most observations are placed left in regard to the mean, and all skewness values significantly deviate from zero, which is the value of the Gaussian distribution. Kurtosis value indicates the presence of fat tails, and it can be seen that all kurtosis values are very high, which means that extreme log-return measures are present. Figure 2 can verify this assertion. Both skewness and kurtosis coefficients significantly diverge from referent values of normal distribution, 0 and 3, which implies that none of the empirical agricultural commodities follow normal distribution. This is corroborated by the very high values of Jarque-Bera coefficients. The presence of serial correlation and heteroscedasticity in the empirical time-series is tested by Ljung-Box Q-statistics for level and squared residuals. All cereals, except barley, has the issue with autocorrelation, while corn and wheat have the problem with time-varying variance. These findings suggest that some form of ARMA-GARCH parameterization might be appropriate, because these models can resolve reported issues. In addition, spurious regression is evaded since ADF test suggests that all selected time-series do not contain unit root, i.e. all time-series are stationary.

Figure 2. Log-returns of the selected cereals



Source: Authors' calculations

Empirical results

This section presents the results of estimated DCC models and calculated dynamic correlations. As have been said earlier, in order to obtain reliable results, we strive to determine the best fitting model before calculation of dynamic correlations. Therefore, we choose between DCC-GARCH and DCC-EGARCH models in combination with multivariate normal and Student t distributions. The decisive criterion is the lowest Akaike information coefficient, and these values are presented in Table 2.

Table 2. Calculated AIC values

		Corn vs Wheat	Corn vs Soybean	Corn vs Barley	Wheat vs Soybean	Wheat vs Barley	Soybean vs Barley
DCC-GARCH	Normal	8.247	7.438	11.161	8.081	11.206	11.276
	Student t	7.751	6.837	10.166	7.026	10.218	10.072
DCC-EGARCH	Normal	8.291	7.396	11.641	8.064	11.501	11.702
	Student t	7.812	6.855	10.968	7.118	10.510	10.519

Source: Authors' calculations

We have six pairs because all agricultural commodities are combined with each other. As Table 2 reveals, all AIC values give an upper hand to DCC-GARCH model with multivariate Student t distribution. After determination of the best fitting DCC model, we present the results of estimated univariate GARCH and multivariate DCC parameters in Table 3.

Table 3. Estimated parameters for DCC-GARCH models

	Corn vs Wheat	Corn vs Soybean	Corn vs Barley	Wheat vs Soybean	Wheat vs Barley	Soybean vs Barley
Panel A: Univariate GARCH estimates						
	Corn	***Corn***	***Corn***	***Wheat***	***Wheat***	***Soybean***
c	0.139***	0.520***	3.865*	0.271	2.528	4.779
α	0.379***	0.642***	0.213	0.263	0.255***	0.161
β	0.697***	0.470***	0.589***	0.783***	0.656***	0.829**
	Wheat	***Soybean***	***Barley***	***Soybean***	***Barley***	***Barley***
c	0.127	0.324**	3.497**	0.625***	3.626	8.325
α	0.237***	0.561**	1.223***	1.083***	1.126***	0.221
β	0.794***	0.454***	0.241**	0.248***	0.286	0.715**
Panel B: DCC estimates						
Average ρ	0.041	0.193	0.200	0.071	0.243	0.159
a	0.007	0.024	0.000	0.021	0.000	0.000
b	0.938***	0.787***	0.908***	0.925***	0.748***	0.868
υ	3.891***	3.192***	2.635***	2.772***	2.588***	2.478***

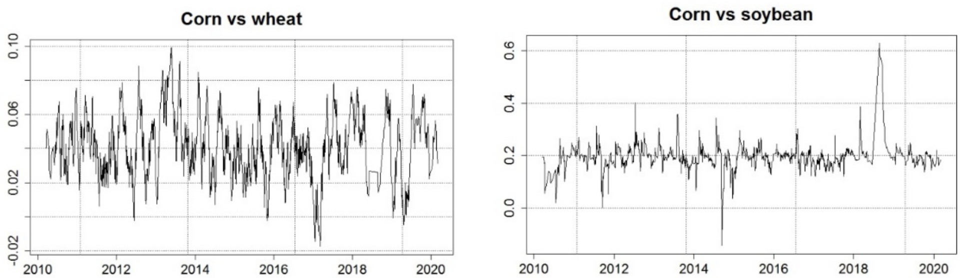
Note: ***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively.

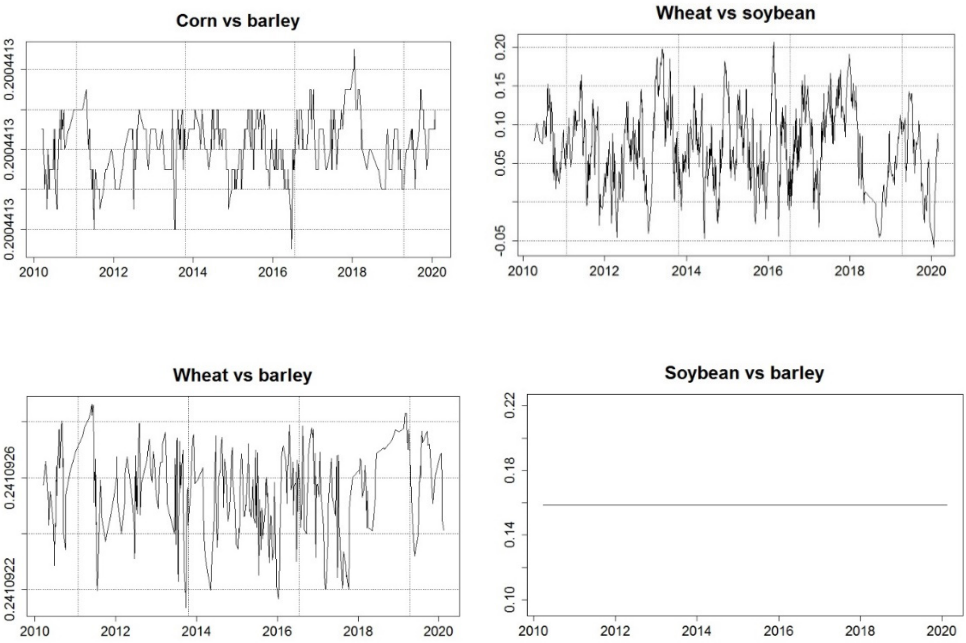
Source: Authors' calculations

Table 3 suggests that majority of the estimated parameters are highly statistically significant, but also some parameters are not significant. As for insignificant α coefficients, it means that shocks in time t-1 do not have an effect on conditional variance. In addition, in majority of estimated univariate GARCH models (Panel A), a high persistence of conditional volatility is observable, which means that $\alpha + \beta > 1$. This drawback could cause a non-stationary volatility in a single-regime GARCH models (see Frommel, 2010). In other words, our models probably bear some flaws, and the reason could line in the nature of the empirical data. In particular, due to relatively limited number of trading days in Novi Sad commodity exchange market, it is possible that high volatility persistence occurs.

As for DCC parameters (Panel b), all *a* parameters are insignificant, while all *b* parameters are highly statistically significant, except for soybean-barley pair. Insignificant *a* parameter implies that previous shocks do not have an influence on current dynamic conditional correlation. It should be said that estimation of statistically significant *b* parameters contributes crucially to the validity of dynamic conditional correlations, i.e. these correlations are then readable and can be interpreted. This contention is in line with Figure 3 presentation, which shows the plots of six dynamic conditional correlations. More specifically, it can be seen that five out of six DCCs are time-varying, while only for soybean-barley pair, DCC is static. The reason probably lies in the fact that *b* is estimated as statistically insignificant for soybean-barley pair, and this parameter is of utter importance for the creation of time-varying correlations. Symbol *υ* stands for the parameter of multivariate Student t distribution, and all these coefficients are highly statistically significant, which means that choice of this distribution is justifiable.

Figure 3. Estimated dynamic conditional correlations for the selected pairs of agricultural commodities





Source: Authors' calculations

Although the findings of the estimated dynamic conditional correlations clearly show that mutual correlations between the selected cereals are time-varying, these oscillations are not particularly significant, while in most instances they barely exist. In other words, according to plots in Figure 3, we find only in pairs of corn-wheat and wheat-soybean relatively significant fluctuations of dynamic correlations. More specifically, in the corn-wheat plot, DCCs oscillates 10% between the lowest and highest correlations, while in the wheat-soybean plot, the oscillations are more expressed, amounting 25% between the highest and the lowest value. However, looking at the corn-barley, wheat barley and soybean-barley plots, these oscillations are less than 1%. It is interesting to notice that all these correlations are estimated between barley and the other commodity grains, and barley has the least trading days in comparison to all other agricultural commodities. This means that lot of empirical observations is lost in the process of data synchronization, which could produce an estimation bias in DCC-GARCH models.

Besides, it is interesting to note that all dynamic correlations are not very high throughout the observed sample, as a matter of fact, they are pretty low. This is visible in Figure 3, while Panel B of Table 2 contains the exact average values of dynamic conditional correlations, and it can be seen that majority of DCCs are below 20%, which is very low. In other words, only wheat-barley pair has an average correlation above 20%, and it amounts 24%, whereas the lowest correlations are found for corn-wheat and wheat-soybean pairs, with the value of 4% and 7% respectively.

The findings of low correlations among agricultural commodities are not surprising, and can be related with other studies in this field. For instance, our results coincide very well with the paper of Gardebroek et al. (2016). These authors investigated dynamic correlation between three spot prices of corn, wheat and soybean, traded in the Chicago Board of Trade (CBOT). They asserted that despite the so called "financialization" of agricultural markets that happened in the past decades, a little evidence has been found that this was a major reason for a stronger interdependence in conditional returns and volatilities between agricultural commodities. They found volatility interactions in weekly and monthly returns, but not in daily returns. Their explanation is that former interactions are less likely driven by herding or speculative behaviour, but instead could be better explained by more fundamental factors such as interdependence across input and output markets and demand substitution. Also, these authors reported somewhat stronger correlation between corn and soybean, as we did, and they explained these findings by the fact that corn and soybeans have strong structural connections in land, fuel and feed markets.

In addition, we also can find the connection between our results and the paper of Bonato (2019). This author researched the changes in the dynamics of price correlations and spillover effects in the agricultural commodity market, using eight major US-traded futures prices (corn, soybeans, wheat, and soybean oil for grain commodities, and coffee, cotton, sugar, and cocoa for soft commodities). They revealed that only soft commodities were segmented prior to 2008 and became correlated thereafter, but the nature of this increase in correlation is only temporary. On the other hand, correlations within grain commodities, which were already significant and positive, remained relatively stable between 2002 and 2017, which indicates that this group has been less affected by the 2008 commodity market turmoil. Lastly, we find an explanation in the study of Dawson and White (2002) why wheat-barley combination has the highest average dynamic correlation among all the pairs. They examined long-run interdependencies between the agricultural futures contracts of barley, cocoa, coffee, sugar, and wheat, traded in the LIFFE exchange market, using Johansen's cointegration procedure. They reported long-run connection between wheat and barley because these commodity grains are substitutes in demand and supply and, thus, they are expected to be related, which coincides with our results. On the other hand, they found other pair-wise combinations as unrelated because they are neither complements nor substitutes in either production or consumption.

Discussion of the results

This section tries to explain the implications of the results as well as to see how the results can be used in practical purposes. According to the results, all dynamic correlations are positive and relatively low, with very limited scope of oscillations. From the market point of view, this means that price dynamics of the selected agricultural grains is independent, which implies that discovery of the price of one agricultural commodity does not provide information about the price of another agricultural commodity. This results strongly indicate that participants in Novi Sad commodity exchange market, sellers and buyers, cannot rely on the price co-movements between particular agricultural assets when they plan their selling or buying strategies. Dawson and White (2002) added that low correlation between agricultural assets signals that traders in market probably put a greater effort to assess the effect of macroeconomic fundamentals on agricultural prices than to determine their selling strategies by following the dynamics of other agricultural commodities. Knowing the nature of Novi Sad spot commodity exchange market, this finding is not unexpected. In other words, the participants in this market are local farmers that act as sellers with short position and various traders that take long position with the purpose to use agricultural commodities in further production process or to resell them in the global market. Therefore, our suggestion for traders in Novi Sad exchange market is to pay more attention on the analysis of macroeconomic factors and global movements of agricultural commodities, whereas dynamic correlations of agricultural prices in Novi Sad exchange market can be disregarded, because they do not provide relevant and useful information for traders' strategies.

Another conclusion that can be drawn from low correlation findings is that speculators do not participate in Novi Sad exchange market. Speculative activities certainly contribute to the liquidity of the market and the convergence of the prices, but interest of speculators is not to use agricultural commodities for real purposes, but to make a profit in price differences. Since Novi Sad commodity exchange do not trade with futures contracts, speculative activities are not present in this market, which implies that macroeconomic factors, domestic and global, play a key role in determination of agricultural prices. We can assert that the absence of speculations in this market also means the absence of herd and panic behaviour in this market. This contention indirectly means that traders on this market tend to specialize and focus their activities in some particular commodity of their interest, and this is the reason why relatively small number of trading transactions exist in one year.

Lastly, it should be mentioned that existence of low correlation between the assets are the basic precondition for the successful portfolio diversification. In other words, combination of agricultural assets from Novi Sad exchange market in various portfolios could be potentially beneficial in the risk minimizing process. However, the problem arises because this market does not trade with futures contracts that would be used for these purposes, but only with real transactions that imply physical delivery of the purchased commodities. Therefore, continuously low correlation between agricultural commodities in Novi Sad exchange market cannot be used in portfolio construction and risk-minimizing efforts.

Summary and conclusion

This paper investigates the level of pairwise dynamic correlations between prices of four agricultural commodities – corn, wheat soybean and barley, that are traded in Novi Sad commodity exchange market, observing the period of 11 years. For the research purposes, we use complex and elaborate methodological approach – DCC-GARCH model of Engle (2002). Before the estimation process, we have to adjust the empirical time-series and make them usable for the software. In other words, relatively low number of trading days is characteristic for all agricultural commodities, whereas some empirical data are lost in the process of time-series synchronization. This is particularly true for pars with barley. As a consequence, possible estimation bias could be present, particularly for pairs with barley.

The results of the estimated dynamic conditional correlations show that low and positive correlation exist between all the pairs of the selected agricultural commodities. In other words, the highest correlation is recorded between wheat and barley, and it amounts on average 24%, corn-barley pair follows with 20%, while all other dynamic correlations are below 20%. In addition, the oscillations of dynamic correlations are not particularly significant, while in most cases they barely exist. More precisely, only corn-wheat and wheat-soybean pairs have relatively significant fluctuations of dynamic correlations, with 10% and 25%, respectively. Our results concur very well with the finding of other studies, which also found relatively low correlation or no correlation at all between agricultural commodities. These findings indicate that price movements of the selected agricultural cereals are independent, meaning that price discovery of one agricultural commodity does not provide information about the price of another agricultural commodity. Therefore, we can firmly assert that traders in Novi Sad exchange market do not rely on the price co-movements between particular agricultural assets when they plan their selling or buying strategies. Novi Sad commodity exchange do not trade with futures contracts, thus speculative activities are not present in this market. This implies that price movements in this market do not happen as an aftermath of speculations or increased liquidity, but rather macroeconomic factors (domestic and global) play a key role in determination of these prices.

This study provides an insight about the nature of dynamic correlations between the selected agricultural commodities in Novi Sad exchange market, and these results can be interesting for traders in this market. Also, the paper explains what is the relevance of the results and how (whether) they can be used in practical purposes. Due to the existence of possible estimation bias in some estimated dynamic correlations that is probably caused by discontinuous trading in this market, future papers can address this topic, applying different methodological approaches. Extended research in this subject will confirm or refute our results, contributing significantly to the robustness of overall findings.

Conflict of interests

The authors declare no conflict of interest.

References

1. Asai, M. (2013) Heterogeneous Asymmetric Dynamic Conditional Correlation Model with Stock Return and Range. *Journal of Forecasting*, *32*(5), 469-480. doi: 10.1002/for.2252
2. Baffes, J., & Haniotis, T. (2016) What Explains Agricultural Price Movements? *Journal of Agricultural Economics*, *67*(3), 706–721. doi: 10.1111/1477-9552.12172
3. Bollerslev, T., & Wooldridge, J. M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews, 11*(2), 143–172. doi: 10.1080/07474939208800229
4. Bonato, M. (2019) Realized correlations, betas and volatility spillover in the agricultural commodity market: What has changed? *Journal of International Financial Markets, Institutions and Money*, 62, 184-202. doi: 10.1016/j.intfin.2019.07.005
5. Boroumand, R. H., Goutte, S., Porcher, S., & Porcher, T. (2014) Correlation evidence in the dynamics of agricultural commodity prices. *Applied Economics Letters*, *21*(17), 1238–1242. doi: 10.1080/13504851.2014.922742
6. Dawson, P. J., & White, B. (2002) Interdependencies between agricultural commodity futures prices on the LIFFE. *The Journal of Futures Markets*, *22*(3), 269–280. doi: 10.1002/fut.2217
7. De Nicola, F., De Pace, P., & Hernandez, M. A. (2016) Co-movement of major energy, agricultural, and food commodity price returns: A time-series assessment. *Energy Economics*, 57, 28–41. doi: 10.1016/j.eneco.2016.04.012
8. Đurić, D., Ristić, J., Đurić, D., & Vujanić, I. (2017) Export of agricultural and food products in the function of economic growth of republic of Serbia. *Economics of Agriculture*, *64*(3), 887-900. doi: 10.5937/ekopolj1703887d
9. Engle, R. E. (2002) Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics*, *20*(3), 339‒350. doi: 10.1198/073500102288618487
10. Frommel, M. (2010). Volatility Regimes in Central and Eastern European Countries' Exchange Rates. *Finance a úver-Czech Journal of Economics and Finance*, *60*(1), 2-21.
11. Gardebroek, C., Hernandez,, M. A., & Robles, M. (2016) Market interdependence and volatility transmission among major crops. *Agricultural Economics*, *47*(2), 141–155. doi: 10.1111/agec.12184
12. Gulan, B. (2014). *Stanje i perspektive poljoprivrede i sela u Srbiji*. Republika Srbija, Beograd: Privredna komora Srbije. [*in English*: Gulan, B. (2014) *Condition and perspectives of agriculture and village in Serbia*. Republic of Serbia, Belgrade: Economic Chamber of Serbia.]
13. Hou, Y., & Li, S. (2016). Information transmission between U.S. and China index futures markets: An asymmetric *DCC GARCH* approach. *Economic Modelling*, 52, 884-897. doi: 10.1016/j.econmod.2015.10.025

14. Jiang, Y., Jiang, C., Nie, H., & Mo, B. (2019) The time-varying linkages between global oil market and China's commodity sectors: Evidence from *DCC*-GJR-*GARCH* analyses. *Energy*, 166, 577-586. doi: 10.1016/j.energy.2018.10.116
15. Jones, P. M., & Olson, E. (2013) The time-varying correlation between uncertainty, output, and inflation: Evidence from a *DCC-GARCH* model. *Economics Letters*, *118*(1), 33-37. doi: 10.1016/j.econlet.2012.09.012
16. Kang, S. H., & Yoon, S. M. (2020). Dynamic correlation and volatility spillovers across Chinese stock and commodity futures markets. *International Journal of Finance & Economics*, *25*(2), 261-273.
17. Lee, Y-H., Fang, H., & Su, W-F. (2014) Effectiveness of Portfolio Diversification and the Dynamic Relationship between Stock and Currency Markets in the Emerging Eastern European and Russian Markets. *Finance a úvěr-Czech Journal of Economics and Finance*, *64*(4), 296-311.
18. Li, Z., & Lu, X. (2012) Cross-correlations between agricultural commodity futures markets in the US and China. *Physica A: Statistical Mechanics and Its Applications*, *391*(15), 3930–3941. doi: 10.1016/j.physa.2012.02.029
19. Marković, M., Krstić, B., & Rađenović, Ž. (2019) Export competitiveness of the Serbian agri-food sector on the EU market. *Economics of Agriculture*, *66*(4), 941-953. doi: 10.5937/ekopolj1904941m
20. Milani, B., & Ceretta, S. P. (2014). Dynamic Correlation between Share Returns, NAV Variation and Market Proxy of Brazilian ETFs. *Engineering Economics, 25*(1), 21–30. doi: 10.5755/j01.ee.25.1.4274
21. Onay, C., & Ünal, G. (2012) Cointegration and Extreme Value Analyses of Bovespa and the Istanbul Stock Exchange. *Finance a úvěr-Czech Journal of Economics and Finance*, *62*(1), 66-90.
22. Singhal, S., & Ghosh, S. (2016) Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-*DCC-GARCH* models. *Resources Policy*, 50, 276-288. doi: 10.1016/j.resourpol.2016.10.001
23. Živkov, D., Njegić, J., & Pavlović, J. (2016). Dynamic correlation between stock returns and exchange rate and its dependence on the conditional volatilities – the case of several Eastern European countries. *Bulletin of Economic Research*, *68*(S1), 28-41. doi: 10.1111/boer.12059