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What Bayesian quantiles can tell about volatility transmission between the major agricultural futures?

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Abstract: This paper investigates an idiosyncratic volatility spillover effect between the four agricultural futures – corn, wheat, soybean, and rise. In order to avoid biased measurements of the volatilities, we use the Markov switching generalized autoregressive conditional heteroskedasticity (MS-GARCH) model. The created volatilities are imbedded in the Bayesian quantile regression framework which can produce accurate quantile estimates. We report that soybean and wheat receive relatively high levels of volatility shocks from the other markets, and that excludes soybean and wheat as primary investment assets in a portfolio. On the other hand, rice receives the lowest amount of volatility shocks from all other agricultural futures. The reason could be the policy of rice price stability that is conducted by countries in the Asia and Pacific region. This result favours rice futures, from the four commodities, as the primary asset in a portfolio. All other futures are suitable to be an auxiliary asset in a portfolio with rice, because rice receives the weakest volatility shocks spillover effect from the other three markets.

Keywords: bidirectional volatility spillovers; regime-switching volatilities; Monte Carlo estimation

The increased price volatility of the international agricultural markets has become an important topic in the last two decades. This is particularly true from the food price crisis period in 2006–2007, at both conceptual and empirical levels among scholars, traders and politicians (Matoškova 2011; Grófová and Srnec 2012). As a consequence of the increased volatility in the agri-food markets, it quickly became apparent that this volatility can easily transfer from one agricultural market to another. Various authors tried to find an explanation why this was happening. For instance, Huang et al. (2012) asserted that one reason could be a tremendous increase in the financialization of commodity futures markets, which started in the early-2000s, since agricultural commodity markets became more integrated due to globalisation. On the other hand, Sanjuan-Lopez and Dawson (2017) listed three possible hypotheses. Firstly, they argued that land allocation for grains production is relatively fixed, and because of that, shocks from one crop price may spill over into others. Secondly, they pointed out that commodity futures markets are somewhat segmented from other financial markets, such as stock markets, which produces less downside risk. Consequently, international investors who want to reduce risk *via* diversification on commodity futures markets could increase the co-movement between agricultural commodity futures in the process of portfolio rebalancing. The last reason is related to a market contagion. This can result from herd behaviour, since information about prices in one market can be transmitted immediately to other markets electronically due to automated trading. Knowledge of the true nature of volatility spillovers between commodity markets represents an important issue for international investors since it affects their possible hedging strategies and the pricing of commodity instruments (Kirkulak-Uludag and Lkhamazhapov 2017).

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Generally speaking, volatility transmission in financial and commodity markets was a subject of attention in relatively few papers, while the volatility spillover effect between agricultural markets was even less researched. The following rare papers studied this topic in the field of agricultural commodities. For instance, Beckmann and Czudaj (2014) investigated volatility spill-over effect between corn, cotton, and wheat futures, using GARCH-in-mean vector autoregression (VAR) model, and concluded that short-run volatility transmission process exists in the agricultural futures markets. Sanjuan-Lopez and Dawson (2017) researched futures markets for corn, soybeans, and wheat. Their Baba, Engle, Kraft and Kroner (BEKK-GARCH) findings showed that past wheat shocks affect soybean volatility and vice versa; past corn shocks affect wheat volatility; and past corn volatility affects wheat volatility and vice versa. Hamadi et al. (2017) examined the level of interconnectedness across corn, wheat, soybeans and soybean oil in terms of return volatility spillover. They reported significant bidirectional volatility spillover effects, and concluded that there is more spillover from soybeans and soybean oil markets to corn and wheat markets, than the other way around.

Having in mind the aforementioned, the goal of this study is to thoroughly investigate the idiosyncratic volatility spillover effects between the four major agricultural futures markets – corn, wheat, soybean, and rice. We decided to analyse futures prices instead of spot prices, since futures prices incorporate all available information by definition, and thus are more appropriate for the volatility spillover measurement than real prices (Qu and Xiong 2019). In this process, we especially want to emphasize the way in which the idiosyncratic dynamic volatility of the agricultural futures is measured. The reason why this issue should be addressed lies in the fact that many empirical time-series are characterized by the presence of structural breaks. Traditional GARCH class model is frequently used to model conditional volatility, but it cannot recognize structural breaks in empirical time-series. If this is the case, the sum of estimated GARCH coefficients is close to or even exceeds one, according to Masood et al. (2017), and this drawback implies estimation of a non-stationary volatility. Frommel (2010) explained that this nuisance leads to overestimation of volatility persistence and misspecification of the GARCH model. In order to circumvent this problem and to measure conditional volatility as accurately as possible, we use several GARCH type models – simple GARCH, Glosten-Jagannathan-Runkle (GJRGARCH), exponential (EGARCH) and Markov switching GARCH (MS-GARCH). The GJR-GARCH and EGARCH models measure asymmetry in the volatility, while the MS-GARCH model can capture the structural breaks endogenously. In particular, the MS-GARCH model combines the traditional GARCH model with the Markov switching process, and for our computation purposes, we apply the MS-GARCH model of Gray (1996).

In addition, equally important for international investors is to distinguish the size of volatility spillover effects in different market conditions. In order to address this issue, we follow Xiao et al. (2019) and combine the conditional volatility time-series with the quantile regression (QR) framework. To be more specific, we use the Bayesian QR technique, which is more sophisticated type of QR methodology, since it uses the MCMC (Markov Chain Monte Carlo) algorithm in the estimation process that produces exact inference about the quantile parameters. In other words, Bayesian QR methodology in comparison with the traditional ordinary least square (OLS) QR estimation approach decreases the length of the credible intervals and increases accurateness of the quantile estimates.

By combining the MS-GARCH model and Bayesian QR methodology, we put an emphasis on the reliability of estimated QR parameters. Firstly, we avoid biased measures of conditional volatilities employing MS-GARCH model, and secondly, we produce accurate and trustworthy QR parameters using MCMC algorithm. To the best of our knowledge, this is the first time that these two non-traditional and complex techniques are mixed together in a single research process.

METHODOLOGY

Isolating idiosyncratic volatility. Before we construct the conditional volatilities, we first isolate the common factor in the agricultural futures that is related to broader market developments. In this way, we make a basis to capture an idiosyncratic volatility that carries only characteristic features of each examined market. In order to properly decompose the returns to a market-related component and an idiosyncratic component, we refer to the paper of Bali and Cakici (2008). These authors extracted idiosyncratic residuals by employing a single factor model in the following way:

$$r_{i,t} = C + \Theta r_{m,t} + \varepsilon_{i,t} \tag{1}$$

where: $r_{i,t}$ and $r_{m,t}$ – returns of individual stock market (i) and global market (m); t – time.

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We proxy global market by the U.S. S&P500 index. C and Θ are common regression parameters, while $\varepsilon_{i,t}$ describes regression residuals that are free of noises from the global market. These residuals are used to create idiosyncratic volatilities in the next stage of our computation process.

Markov switching GARCH model. In order to preserve space, we present only econometric specification of the Markov switching GARCH[1] model in this subsection. We assume an autoregressive AR(1) process for the conditional mean of all selected agricultural futures, with residuals of the model following the normal distribution $\varepsilon_t \mid I_{t-1} \sim N(0,h_{it})$, where: I_{t-1} – information set at time $t-1$ and h_{it} – time varying conditional volatility. According to Frommel (2010), regime switching models can switch some or all parameters of the model according to the Markov process, which is governed by a state variable (S_t). Czapkiewicz et al. (2018) asserted that the state variable S_t evolves according to a first-order Markov chain, with transition probability $p_{ij} = Pr(S_t = j \mid S_{t-1} = i)$. For our purposes, we assume two possible states – low volatility and high volatility regimes. The dynamics of this process is given by the transition matrix $\boldsymbol{P}$, and p_i – the probability of switching from state 1 to state 2. These probabilities are grouped together into a transition matrix according to the Equation (2):

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} \tag{2}$$

If the regimes are stable, switching probabilities should be relatively high. We set the conditional variance to follow a GARCH (1,1) process according to the following equation:

$$h_t = \omega_{S_t} + \alpha_{S_t}\varepsilon_{t-1}^2 + \beta_{S_t}h_{t-1} \tag{3}$$

where: ω_{S_t} – state dependent constant, whereas ε_{t-1,S_t}^2 and h_{t-1,S_t} are ARCH and GARCH effects under regime S_t. The non-negativity of h_t is ensured by setting following restrictions: $\omega_{S_t} \geq 0$, $\alpha_{S_t} \geq 0$ and $\beta_{S_t} \geq 0$. Volatility persistence in state i is measured by $\alpha_i + \beta_i$.

However, it should be noted that GARCH model estimation in a regime switching context with state-dependent past conditional variances is unfeasible. This happens because conditional variance depends not only on the observable information set I_{t-1} and on the current regime S_t, but also on all past states S_{t-1}, which is essentially impossible to estimate. Therefore, in order to circumvent this shortcoming, we use the Markov switching GARCH model of Gray (1996) who proposed to integrate out the unobserved regime path S_{t-1} in GARCH term, using the conditional expectation of the past variance. According to Marcucci (2005), Gray (1996) used information observable at time $t-2$ to integrate out the unobserved regimes as in the Equation (4):

$$\begin{aligned} h_{t-1} = E_{t-2}\left(h_{t-1}^{(j)}\right) = p_{1,t-1}\left[\left(\mu_{t-1}^{(1)}\right)^2 + h_{t-1}^{(1)}\right] + \\ + \left(1-p_{1,t-1}\right)\left[\left(\mu_{t-1}^{(2)}\right)^2 + h_{t-1}^{(2)}\right] - \\ - \left[p_{1,t-1}\mu_{t-1}^{(1)} + \left(1-p_{1,t-1}\right)\left(\mu_{t-1}^{(2)}\right)\right]^2 \end{aligned} \tag{4}$$

where: $j = 1, 2$; $\mu_t^{(j)}$ – conditional mean or location parameter; and E_{t-2} – expected value of second lag.

To estimate the model we use the maximum likelihood methodology, as follows in Equation (5) below. In Equation (5) : L – log likelihood function; r_t – log-returns.

Bayesian quantile regression. After creating the regime switching conditional volatilities, we insert these time-series in the Bayesian quantile regression framework[2]. In its original concept, QR methodology extends the mean regression model to conditional quantiles of the response variable. Accordingly, this technique provides a more detailed view of the interlink between the dependent variable and the covariates, because it can estimate how a set of covariates affects different parts of the distribution of regressand (Živkov et al. 2019). QR methodology has been found appealing by many researchers from various theoretical disciplines (Dybczak and Galuščak 2013; Maestri 2013; Živkov et al. 2014; Vilerts 2018).

$$L = \sum_{t=1}^{T} \log\left[p_{1t}\frac{1}{\sqrt{2\Pi h_{1t}}}\exp\left\{-\frac{\left(r_t-\mu_{1t}\right)^2}{2h_{1t}}\right\} + \left(1-p_{1t}\right)\frac{1}{\sqrt{2\Pi h_{2t}}}\exp\left\{-\frac{\left(r_t-\mu_{2t}\right)^2}{2h_{2t}}\right\}\right] \tag{5}$$

[1]Markov switching GARCH model is estimated via "MSGARCH" package in "R" software.

[2]Bayesian quantile parameters were calculated via "bayesQR" package in "R" software.

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In order to explain the Bayesian QR methodology, we start with the standard linear model as in the Equation (6):

$$y_i = \mu(x_i) + \varepsilon_i \tag{6}$$

where: y_i and x_i – both continuous variables.

In Equation (6), each of the selected four agricultural futures can be either the dependent or the independent variable, because all agricultural futures can either receive or transmit volatility shocks. According to Benoit and van den Poel (2017), the regression coefficient in case of all quantiles can be found by solving the Equation (7):

$$\hat{\beta}(\tau) = \arg\min \sum_{i=1}^{n} \rho_\tau \left(y_i - x_i'\beta\right); \quad \beta \in \Re \tag{7}$$

where: $\tau \in (0,1)$ – any quantile of interest, while $\rho_\tau(z) = z(\tau - I(z<0))$ and $I(\cdot)$ stand for the indicator function. The quantile $\hat{\beta}(\hat{o})$ is called the τ^{th} regression quantile; while in the case where: $\tau = 0.5$, it corresponds to the median regression.

The QR parameters are then estimated by the conventional Bayesian procedure, which implies the usage of the MCMC algorithm (Ari et al. 2019). This procedure generates exact estimates of the quantile parameters $\hat{\beta}(\hat{o})$. Crucial advantage of the Bayesian quantile regression as compared to the conventional QR approach is the fact that 95% Bayesian credible interval contains the true parameter value in 95% of the time.

DATASET AND CREATION OF REGIME-DEPENDENT CONDITIONAL VOLATILITIES

This paper comprises daily closing prices of four agricultural futures (corn, soybean, wheat, and rice), which are traded on Chicago Mercantile Exchange CME Group. All closing prices of the selected futures are transformed into log returns according to the expression: $r_{i,t} = 100 \times (P_{i,t}/P_{i,t-1})$; where: $P_{i,t}$ – the closing price of the particular assets. The sample ranges from January 1, 2007 to September 30, 2019, and all the time-series are collected from the Investing.com website (Investing.com 2019). All collected time-series are synchronized according to the existing observations.

First task in our computational process is to construct conditional volatility series from idiosyncratic residuals as accurately as possible. Therefore, we need to find out which GARCH specification fits the empirical agricultural time-series the best. Table 1 presents Akaike information criterion (AIC) values for the estimated GARCH models, and it can be seen that the MS-GARCH model has an upper hand in all four cases. This means that all four agricultural time-series are "polluted" with multiple structural breaks, and MS-GARCH model can successfully recognize this intrinsic feature. In order to make a parallel presentation of the best and worst fitting models, we show in Table 2 the estimated parameters for the MS-GARCH model and the single regime GARCH model, with the latter serving as a benchmark. It is obvious that the simple GARCH model has higher persistence ($\alpha + \beta$) of the variance, comparing to this persistence in both regimes of the MS-GARCH model in all the cases.

Table 2 discloses that all the futures are dominantly in low volatility regime, which means that low volatility regime is more stable and lasts longer. This is verified by their values of regime probabilities (P_{11} and P_{22}) and also by Figure 1. As can be seen, the probability of staying in low volatility regime for these three futures is around 90%, while only in around 10% of cases they are in high volatility regime.

Figure 2 presents plots that couple the daily-based dynamic volatilities derived from the single regime GARCH and MS-GARCH models. Merely from a visual inspection of all the plots it can be concluded that the single regime volatilities have higher mean, standard deviation, and kurtosis values than the regime-switching counterparts.

Table 1. Akaike information criterion (AIC) values for four GARCH specifications

	Corn	Wheat	Soybean	Rice
GARCH	4.0198	4.2209	3.5178	3.6251
GJRGARCH	4.0197	4.2197	3.5170	3.6241
EGARCH	4.0095	4.2194	3.5161	3.6209
MS-GARCH	3.9554	4.1287	3.4784	3.5996

GARCH – generalized autoregressive conditional heteroscedasticity; GJRGARCH – Glosten-Jagannathan-Runkle GARCH; EGARCH – exponential GARCH; MS-GARCH – Markov switching GARCH

Source: Authors' calculation

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Table 2. Parameter estimates of the GARCH and MS-GARCH models

			Corn	Wheat	Soybean	Rice
GARCH		c	0.039***	0.050*	0.023***	0.152**
		α	0.078***	0.067***	0.063***	0.100***
		β	0.918***	0.932***	0.928***	0.892***
		$\alpha + \beta$	0.996	0.999	0.991	0.992
		LL	–6 365.4	–6 684.1	–5 570.7	–5 740.3
MS-GARCH	regime 1– low volatility regime	c_1	0.036***	0.023***	0.012***	0.000
		α_1	0.062***	0.024***	0.028***	0.005*
		β_1	0.913***	0.960***	0.951***	0.987
		$\alpha_1 + \beta_1$	0.975	0.984	0.979	0.992
	regime 2 – high volatility regime	c_2	4.244**	3.676**	5.875***	0.176**
		α_2	0.214*	0.291*	0.284	0.069*
		β_2	0.781***	0.677***	0.691	0.909***
		$\alpha_2 + \beta_2$	0.995	0.988	0.975	0.978
		P_{11}	0.96	0.92	0.89	0.90
		P_{22}	0.04	0.08	0.11	0.10
		LL	–6 212.5	–6 593.9	–5 458.4	–5 671.0

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$; GARCH – generalized autoregressive conditional heteroscedasticity; MS-GARCH – Markov switching GARCH;. P_{11} and P_{22} are probabilities of staying in regime 1 and regime 2 in MS-GARCH model; LL – log-likelihood
Source: Authors' calculation

Table 3 reveals descriptive statistics of the GARCH and MS-GARCH idiosyncratic conditional volatilities, and it can be noticed that all four moments of conditional volatilities are improved significantly in the MS-GARCH model, compared to the values in the GARCH model. Mean and deviation from the mean are lower in the MS-GARCH model. In addition, all kurtosis coefficients exceed heavily the ref-

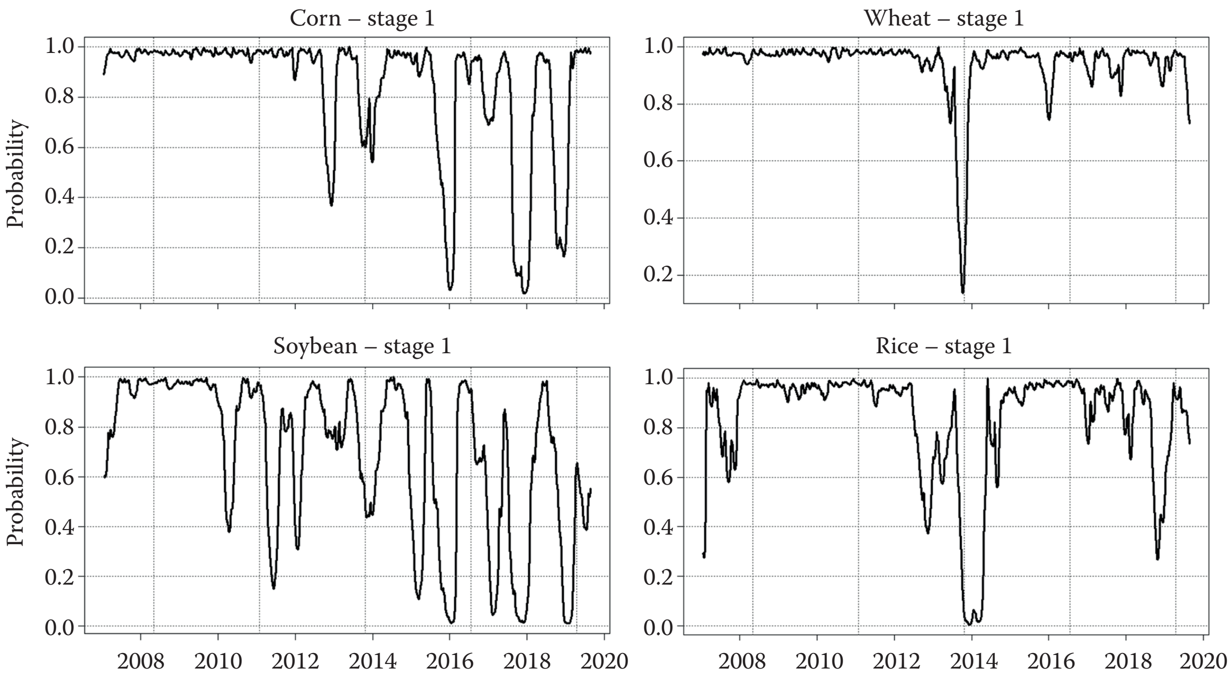

Figure 1. Smooth probabilities of low volatility regime for the agricultural futures

Source: Authors' calculation

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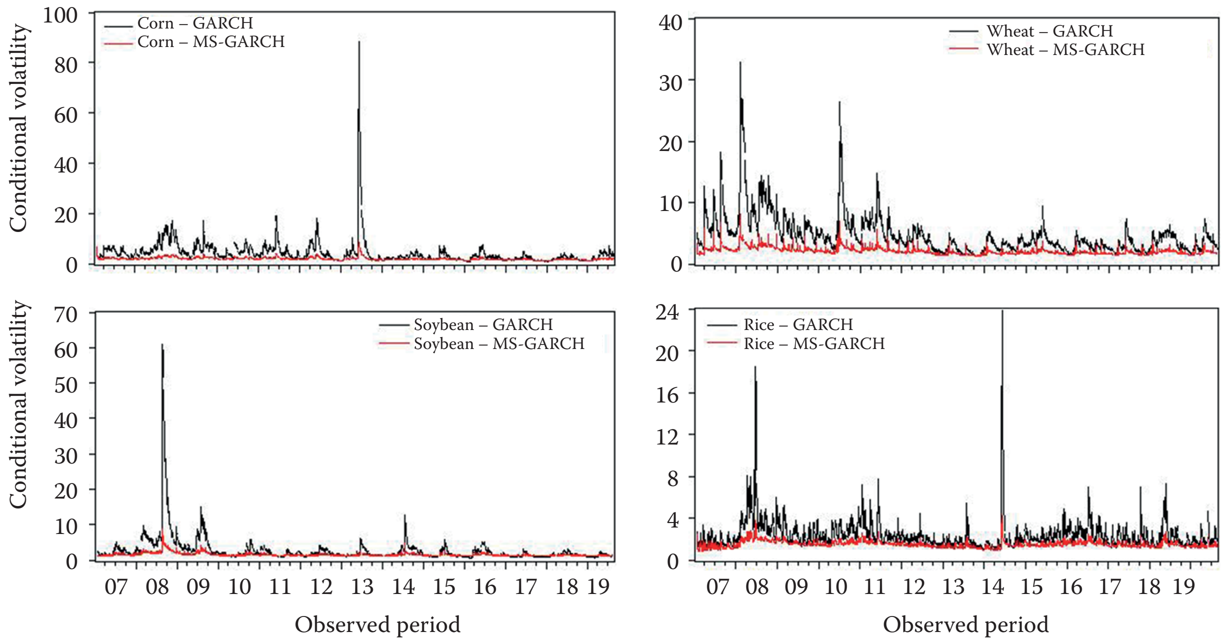

Figure 2. Calculated dynamic conditional volatilities of the agricultural futures

Y-axis – the value of conditional volatility of each agricultural commodity; X-axis – the observed period; GARCH – generalized autoregressive conditional heteroscedasticity; MS-GARCH – Markov switching GARCH
Source: Authors' calculation

erence value of the normal distribution (equal to 3), which indicates significant presence of extreme values and outliers in distribution of conditional volatilities. However, in the MS-GARCH model, kurtosis values are significantly lower. Figure 2 undoubtedly indicates that all single regime volatilities are permeated by high peaks throughout the sample, and this characterizes the all agricultural futures. In addition, Table 3 shows that all volatility time-series are heavily skewed to the right, which is expected, since we work with volatilities. These facts justify the use of QR method, because the MCMC QR estimator is a powerful tool in recognizing the deviations from normality and it gives reliable parameter estimates in the extreme value environment.

We can check the validity of the estimated Bayesian QR parameter by using a visual inspection of the convergence of the MCMC chains, which shows the evolution of the MCMC draws over the iterations. We use 6 000 iterations for our computations. Figure 3 portrays the trace-plots of the MCMC chain of median quantiles $\hat{\beta}(\hat{o}) = 0.5$ of the selected agricultural futures. It can be seen that all trace-plots have a good performance, which means that the effect of the initial values of the MCMC chains wears off very rapidly, while the MCMC sampler quickly moves to the stationary distribution. In addition, trace-plots are very similar across all quantiles, thus we present only median quantiles trace plots in Figure 3. All other trace plots can be obtained by request. These findings sug-

Table 3. Descriptive statistics of the GARCH and MS-GARCH conditional volatilities

	GARCH					MS-GARCH				
	mean	S.D.	skewness	kurtosis	JB	mean	S.D.	skewness	kurtosis	JB
Corn	4.259	4.946	7.997	98.670	1 242 331.0	1.916	0.621	3.425	24.558	67562.3
Soybean	2.663	3.724	8.177	94.402	1 138 440.0	1.485	0.487	4.231	35.779	151 329.9
Wheat	4.690	3.300	3.110	17.356	32 320.9	2.062	0.583	2.390	14.406	20 195.4
Rice	2.401	1.361	5.594	59.217	433 818.4	1.503	0.318	1.270	7.504	3 530.8

GARCH – generalized autoregressive conditional heteroscedasticity; MS-GARCH – Markov switching GARCH; JB – Jarque-Bera test of normality
Source: Authors' calculation

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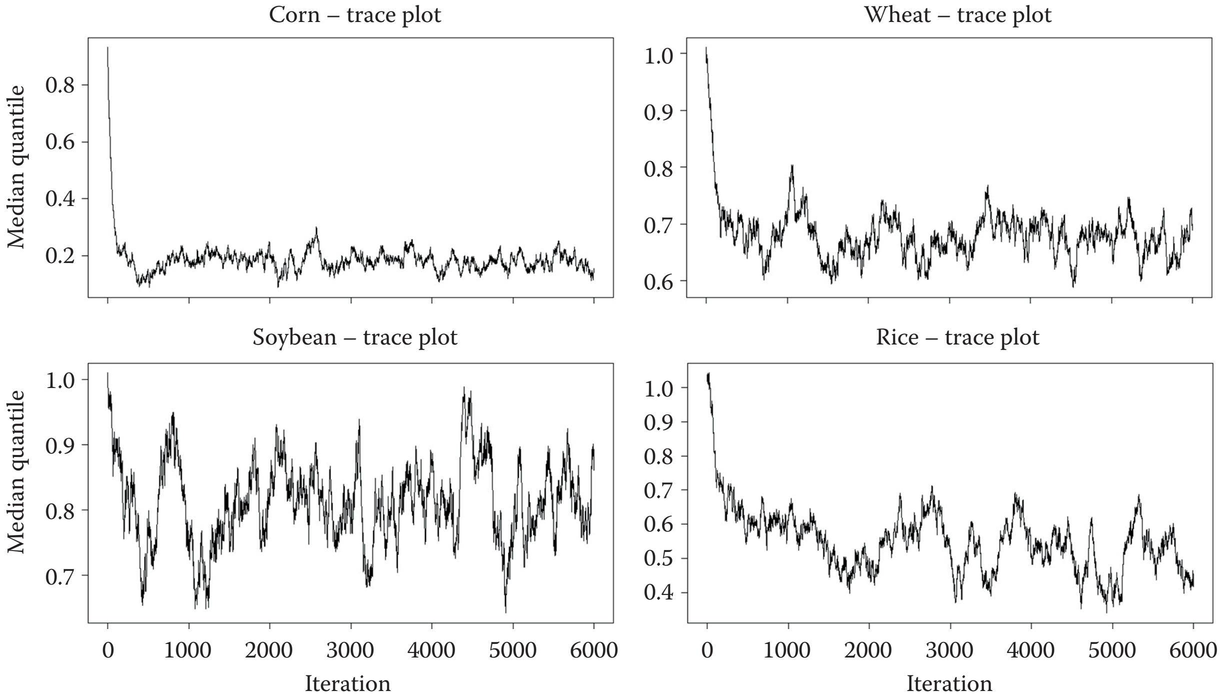

Figure 3. Trace plots for median quantile of the selected agricultural futures

Y-axis depicts the value of calculate trace plots for the median quantile; X-axis stands for the number of iterations in Markov chain

Source: Authors' calculation

gest that all estimated Bayesian quantile parameters are highly statistically significant and reliable.

RESEARCH RESULTS

This section presents the results of an idiosyncratic volatility spillover effect between the four agricultural futures in different market conditions. Since we analyse volatility spillovers, our quantiles represent the conditions of low volatility (left-tail quantiles), moderate volatility (median quantile) and high volatility (right-tail quantiles). Our goal is to check is there a bidirectional volatility transmission effect among the all selected agricultural futures. This is a viable assumption, because futures markets are highly integrated and investors can easily transfer from one market to another due to electronic automated trading. Owing to this fact, volatility shocks can easily transfer across the markets. Table 4 contains the pairwise estimated Bayesian quantile parameters, while Figure 4 presents their graphical illustrations.

The results in Table 4 are heterogeneous and they indicate that quantile estimates grow larger with the increase of quantiles, which is expected. This means that stronger volatility spillover effect is detected in the periods of market turmoil, when volatility is increased. In particular, we find very slim volatility spillover effect from corn to soybean when volatility in soybean market is very low, and it amounts 5%. However, when volatility in soybean market is high or very high, which is represented by 0.75^{th} and 0.95^{th} quantiles, the rise of volatility by 100% in corn market transmits to soybean market by 71% and 130%, respectively. When the nexus is reversed, we detect relatively high risk spillover effect from soybean to corn even in very low volatility conditions in corn market, amounting to 43%, and this influence gradually increases with the rise of volatility in corn market, reaching 88% and 73% when volatility is at its peak. These results are in line with the paper of Gozgor and Memis (2015) who reported strong bidirectional volatility transmission between the soybeans and corn markets. They explained that strong nexus between corn and soybean probably comes from the fact that both corn and soybean are used in the biofuel production.

Wheat has stronger impact on corn in very low volatility conditions (19%) compared to the corn —› wheat transmission effect, where: corn impacts wheat with 2.5%. On the other hand, corn has stronger risk spillover effect on wheat in 0.95^{th} quantile than the other way around. These findings are similar to the previous relation, i.e. the corn-soybean connection. In addition,

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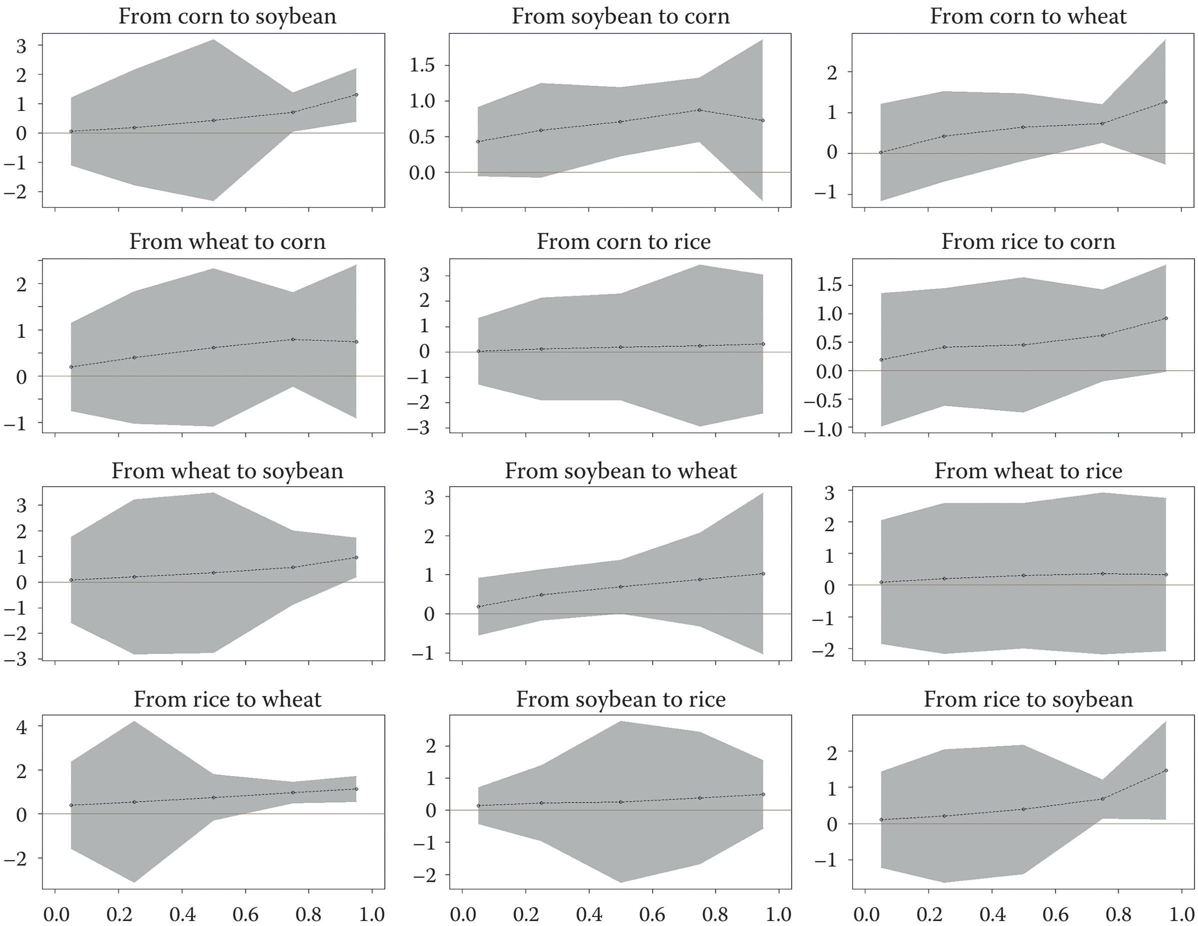

Figure 4. Graphical illustration of the estimated Bayesian quantile parameters

Y-axis describes the value of the estimated Bayesian quantile parameters; X-axis denotes particular quantile parameters that are estimated; the shaded area portrays the credible intervals at 95% probability

Source: Authors' calculation

Table 4. Bayesian quantile estimates for the volatility transmission effect between the agricultural futures

Bayesian quantile estimates									
0.05th	0.25th	0.5th	0.75th	0.95th	0.05th	0.25th	0.5th	0.75th	0.95th
very low	low	moderate	high	very high	very low	low	moderate	high	very high
		corn —› soybean					**soybean —› corn**		
0.052	0.184	0.430	0.711	1.300	0.428	0.589	0.709	0.876	0.729
		corn —› wheat					**wheat —› corn**		
0.025	0.420	0.645	0.738	1.261	0.193	0.401	0.617	0.795	0.744
		corn —› rice					**rice —› corn**		
0.035	0.112	0.198	0.245	0.314	0.187	0.416	0.454	0.619	0.921
		wheat —› soybean					**soybean —› wheat**		
0.082	0.200	0.359	0.566	0.966	0.190	0.486	0.692	0.880	1.030
		wheat —› rice					**rice —› wheat**		
0.096	0.211	0.298	0.362	0.331	0.393	0.541	0.750	0.971	1.130
		soybean —› rice					**rice —› soybean**		
0.147	0.225	0.259	0.387	0.491	0.105	0.209	0.390	0.675	1.468

Source: Authors' calculation

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we find that soybean has higher volatility spillover effect on wheat in all quantiles, without exception, compared to how wheat affects soybean. Regarding the interlink between corn, soybean, and wheat, our results coincide very well with the study of Hamadi et al. (2017) who reported stronger spillover effect running from soybeans to corn and wheat than conversely. According to Table 4, corn, soybean, and wheat are the agricultural commodities that receive and transmit relatively high levels of volatility shocks among themselves. Baldi et al. (2016) offered a probable explanation for this phenomenon. They asserted that the reason could lie in so-called commodity financialization phenomenon, which has been caused by a massive increase in investments in commodities in the last two decades. These activities play an important role in investors' portfolio diversification strategies, but also increase integration between commodity markets, rise levels of correlation, and induce volatility spillovers between markets.

On the other hand, we find interesting results with regards to rice futures. Table 4 suggests that rice futures receive disproportionately lower level of risk transmission from other three agricultural futures, while the effect of rice on corn, soybean, and wheat is relatively high, and it particularly applies for rice —› wheat and rice —› soybean pairs. In other words, corn has the lowest volatility impact on rice, whereas wheat and soybean follow, and this effect amounts to 31, 33 and 49%, respectively, in very high volatility conditions. In moderate volatility conditions, this impact is significantly smaller, amounting 20, 30 and 26% for 100% volatility increase in corn, soybean and wheat markets, respectively. It can be seen that this influence is far lower than the size of volatility spillover effects which other three agricultural futures experience between each other and from rice as well. To be more specific, some of the highest volatility transmissions come from the rice market, and in the highest quantile, rice idiosyncratic volatility shocks impact corn with 92%, wheat with 113% and soybean with 147%. In moderate market conditions, this effect is also relatively high and amounts to 45, 75 and 39% regarding the rice —› corn, rice —› wheat and rice —› soybean relations, respectively. According to our results, it seems that rice futures are the most resistant on the volatility shocks that originate from other agricultural markets. Timmer (2014) offered a possible explanation why rice prices are relatively stable throughout the time. He argued that rice remains a major food source for most of the population in the Asia and Pacific region. Therefore, owing to the rapid economic growth, most countries in the Asia and Pacific region became capable of conducting aggressive food price stabilisation policies, which provide food to the poor. According to this author, these policies make rise prices resilient to external shocks, which also includes volatility spillovers from other agricultural markets.

The implications of the findings could be as follows. First, volatility spillover effect reflects the arrival of information in the market, according to Ross (1989). We find that soybean and wheat futures markets endure the most intense spillover effect from other markets, which means that these two markets receive the highest rate of information flow from the other markets. This high sensitivity of wheat and soybean to the shocks from other markets prevents these commodities from being primary investment instruments in a portfolio. On the other hand, the volatility transmission effect can also carry a message which commodities are suitable to combine, because Lee et al. (2014) asserted that if volatility from one financial market transmits to another in high intensity, then the assets from such markets cannot be included in the same portfolio with the other asset. This means that corn cannot be coupled with soybean, when corn is an auxiliary asset in a portfolio. The same applies for rice when this asset plays an auxiliary role in portfolios with corn, wheat and soybean. However, when rice stands as a primary asset in a portfolio, then corn, wheat and soybean could play an auxiliary role, because rice futures receive the lowest amount of volatility shocks from these three markets.

CONCLUSION

This paper tries to determine the level of idiosyncratic volatility spillover effects between the major agricultural futures – corn, soybean, wheat, and rice. In order to perform this task, we first isolate the common factor in the agricultural futures markets that is related to a broader market, and then use the MS-GARCH model to construct idiosyncratic regime switching conditional volatilities. This model produces unbiased and accurate measure of uncertainties in the agricultural futures markets. In the next step, we embed these regime-switching volatilities in the Bayesian QR framework, which is also a robust methodology in terms of reliability of results.

According to our findings, the spillover effect is the strongest in high volatility conditions in all markets without exception. Soybean and wheat are the ag-

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ricultural commodities that receive relatively high levels of volatility shocks from the other markets. These findings exclude soybean and wheat as primary investment assets in a portfolio. On the other hand, rice receives the lowest amount of volatility shocks from all other agricultural futures. The reason could be the policy of rice price stability that is conducted by countries in the Asia and Pacific region, since rice is a major food source for most of the population in this region. This result favours rice futures, from all four commodities, as the primary asset in a portfolio. Due to the fact that rice receives the weakest volatility shocks spillover effect from the other three markets, all other futures are suitable to be an auxiliary asset in a portfolio with rice.

Our results could be useful for various market participants and policymakers who analyse and trade in the agricultural markets, and who design their portfolios with the agricultural futures. Also, our paper gives a starting point for the future research, in terms of intense and origins of the agricultural market volatilities. In addition, future studies might address the connection between speculators' activities in the agricultural markets and the size of volatility in these markets.

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