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Full Length Article

Short and long-term volatility transmission from oil to agricultural commodities − The robust quantile regression approach

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Abstract

This paper investigates permanent and transitory spillover effects from Brent oil futures to four agricultural futures − corn, wheat, soybean and canola. We construct permanent and transitory volatilities *via* component GARCH model, considering six different distribution functions. Created volatility time-series are embedded in the robust quantile regression framework. Transitory effect from oil market has slightly stronger influence on the agricultural commodities than its permanent counterpart, which is a sign that short-term information flow has more intense effect than fundamental factors. The results indicate that the best diversification instrument in combination with oil is soybean futures, since it is the least subject to oil volatility shocks.

JEL classification: C22; C51; O13

Keywords: Oil and agricultural futures; Volatility spillover effect; Component GARCH; Robust quantile regression

1. Introduction

After a food price surge in 2006, considerable attention has been raised among academics and practitioners about the question whether and how crude oil influences agricultural commodities. Dahl et al. (in press) asserted that the prices of oil and agricultural commodities experienced huge oscillations over the last decade due to numerous global events, such as global financial crises, changes in global demand and supply, introduction of new regulations to fight climate change, etc. In particular, in January 2006, price of crude oil was $61 per barrel, up to July 2008 it was over $140 per barrel, while in November 2008 price of crude oil was under $50 per barrel. Another oil price upswing was recorded in February 2012, when the price of crude oil was beyond $120 per barrel, whereas up to December 2015, oil was sold below $40 per barrel. Agricultural commodities displayed similar volatile behaviour. For instance, the price of the US corn futures in January 2006 was below $220 cents per bushel, in June 2008 it was well over $700 cents per bushel, while in November 2008, the price was significantly below $400 cents per bushel. In March 2011, these contracts reached again very high prices over $720 cents per bushel, whereas in a couple of years later, the price of corn futures plummeted for the second time in less than 5 years period, going slightly over $400 cents per bushel. Other agricultural futures also had very erratic dynamics, as Fig. 1 shows.

It is important to say that oil and agricultural markets are heavily connected in a number of ways. Regarding this fact, we provide a wide list of potential conduits in the following. First of all, agricultural production is energy intensive, which

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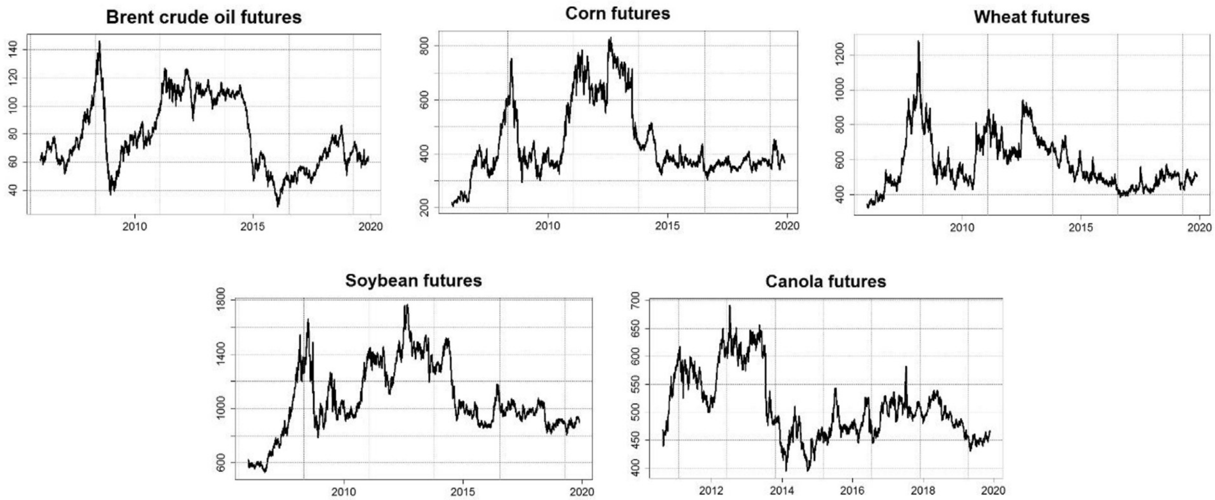

Fig. 1. Price dynamics of Bren oil and agricultural commodity futures.
Notes: Prices of canola futures are available from August 2010, while all other futures are observed from January 2006. Prices of Brent crude oil futures are expressed in USD per barrel, prices of corn, wheat and soybean futures are in USD cents per bushel, while prices of canola futures are expressed in Canadian dollars per tonne.

means that an increase in crude oil price results in higher cost of inputs that eventually cause higher prices of these commodities. Secondly, oil and agricultural products are related *via* ever growing biofuel production in a sense that high crude oil prices lead to high food prices, since biofuel is a cheaper substitute in that occasions (see Chang et al., 2019). Yang et al. (2008) stated that 38% of corn and 22% of wheat price increase was related to biofuels in the 2005−2008 period. Thirdly, Živkov, Kuzman and Subić (2019a) stated that increased economic growth in most populated countries, such as China and India, causes higher food and energy consumption, since these factors reinforce each other. Fourthly, economic forces have also been found in the literature as important factors that spark the commodity markets comovement. For instance, commodity financialization phenomenon needs to be considered, because oil and agricultural products are increasingly regarded as financial assets by market participants, since they can serve well as alternative investments and instruments for hedging and portfolio diversification purposes. Gilbert (2010) added that dollar exchange rate has to be mentioned as an important and consistent causal factor for the dynamics of oil and agricultural commodities, but this effect is relatively small comparing to other factors. At the end, Frankel (2014) asserted that economic activity, easy monetary policy and speculation have a role in explanation for recent increases in the prices of oil and most of agricultural commodities.

Due to numerous aforementioned reasons, it can be expected that these commodities recorded substantial rise of price volatility in the past two decades. Cashin and McDermott (2001) noticed very well that there has been a decline in real commodity prices by 1.3%, but a rise in their volatility in the period over 140 years. They asserted that the increase in volatility are more important than concerns about the long-run downward trend, because sharp movements in commodity prices can have profound consequences on terms of trade, real incomes and fiscal positions of commodity exporting countries. Despite the fact that many papers researched the interdependence between oil and agricultural commodities, relatively little studies were dedicated to volatility spillover phenomenon, according to Nazlioglu et al. (2013).

Therefore, this paper tries to investigate the extent of volatility transmission process from Brent crude oil futures to the four agricultural futures − corn, wheat, soybean and canola. We focus on these five agricultural futures because of the two reasons. First of all, all these five futures commodities exhibited large price swings in the observed period (see Fig. 1). Secondly, all chosen agricultural commodities can be used as a feedstock for biofuels. In particular, corn is used in ethanol production, wheat is a “second-generation” biofuel in that the parts used for biofuels are not eaten, whereas soybean and canola have a great potential for biodiesel production. Having in mind that prices of crude oil inevitably affect the production of these biofuels, and biofuels are heavily dependent on the supply of agricultural commodities, it can be assumed that there is a firm market connection in a form of volatility transmission between energy and agricultural markets.

Our contribution to the literature is based on the use of several innovative approaches, which can shed a new light about the nature of volatility transmission between oil and agricultural commodities. By first, we decompose time-varying volatility process into two segments − transitory and permanent, which is done by the component GARCH (CGARCH) model. In such way, we can assess the strength of the volatility transmission process in both short-run (transitory part) and long-run (permanent part), which has never been done before. Taking this approach, we can highlight an existence of heterogeneous information flows, which are associated with different factors that affect the nexus in different time-horizons. To the best of our knowledge, only two papers − Morales-Zumaquero and Sosvilla-Rivero (2018) and Wong (2019) investigated permanent and transitory volatility spillover effect, and their researches were directed to stock and exchange rate markets. This means that a plenty of room exists in the international literature to carry out an investigation about the transitory and permanent volatility nexus between oil and different agricultural commodities.

In addition, we want to calculate volatility time-series as accurate as possible, since problem may occur in this process when empirical data have no-normal characteristics, such as strong skewness and heavy tails. In order to address this issue, we combine CGARCH type model with several traditional and non-traditional distribution functions − normal (*N*), Student-t (*St*), generalized error distribution (*GED*), normal inverse gaussian distribution (*N*IG), generalized hyperbolic distribution (*GHYP*) and Johnson SU distribution (*JSU*). This approach is in contrast to the abundance of studies that have used only the GARCH model with the ordinary normal distribution in the process of volatility time-series creation. Chen et al. (2008) explained that the major weakness of the ordinary GARCH-normal type model is that it assumes a specific functional form before any estimations are made, which could be a crucial mistake that can produce biased coefficient estimates and standard errors. Primary motivation behind the usage of several alternative and non-traditional distributions is the fact that they could have theoretical advantages over the common normal distribution in modelling the tail distribution of oil and agricultural commodities, and as such, can potentially improve the assessment of these time-series (see e.g. Kresta & Tichy, 2012; Lyu et al., 2017).

After the creation of transitory and permanent part of volatilities of the all empirical time-series, we measure the magnitude of the unidirectional volatility transmission effect by inserting these volatilities into the recently developed sophisticated econometric methodology − robust quantile regression (QR) of Wichitaksorn et al. (2014). In particular, this new quantile regression technique uses a likelihood-based approach for the quantile parameter estimation, considering several new skewed distributions − Normal, Student-t, Laplace, Contaminated normal and Slash distribution. It should be said that when researchers use traditional quantile regression methodology, they usually disregard the choice of proper density function, because QR assess quantile parameters, which makes irrelevant the choice of the best fitting distribution. However, if QR is estimated under the optimal distribution function then it increases robustness of the estimated quantile parameters, which is crucial for the reliability, because it provides unbiased and trustworthy results. This means that the robust QR methodology decreases the length of credible intervals and increases the accurateness of quantile estimates, in comparison with the traditional quantile regression approach of Koenker and Bassett (1978).

A primary motivation to use quantile regression method stems from two reasons. Firstly, QR can portray much better and with much more accuracy the relationship between the variables. In other words, if empirical time-series are characterized by non-Gaussian features, which is an attribute of all selected agricultural commodities (see Fig. 1), quantile regression would provide a more robust and consequently more efficient estimates. In that regard, it should also be added that quantile regression estimator is robust to outlying observations of the dependent variable, which is also an intrinsic characteristic of all agricultural commodities due to their erratic dynamics. Secondly, the QR methodology is an appeal approach for our research because we cover relatively long sample, which is permeated with numerous ups and downs of the agricultural commodity prices. Due to that reason, QR can give different estimation solutions to each quantile, which reflect different levels of agricultural price volatilities. In other words, QR can successfully capture the heterogeneity of the volatility transmission effect from Brent crude oil futures to the selected agricultural futures. Therefore, we can assert that combination of the CGARCH method with the robust QR model can ensure accuracy in estimates, but also it can provide a rich spectrum of information about the magnitude of the spillover effect in the states of low, moderate and high volatility in short- and long-term horizons. Generally speaking, quantile regression methodology has been found appealing by many researchers from various theoretical disciplines (see e.g. Goy & Johnes, 2015; He et al., 2020; Maestri, 2013; Shawtari et al., 2017; Vilerts, 2018).

In order to be more thorough in the analysis, we refer to the paper of You et al. (2017) and estimate the robust quantile parameters in different subsamples. The goal is to see what is the difference in magnitude of volatility transmission in states of low, moderate and high volatility, when subperiods of pronounced boom and bust are observed. We avoid arbitrariness in determination of subsamples by utilizing modified ICSS algorithm of Sans'o et al. (2004). This particular methodology can detect exact structural break dates that are used subsequently to divide full sample of agricultural time-series into several subsamples.

Besides introduction, the rest of the paper is constructed as follows. Second section presents brief literature review. Third section explains used methodologies − CGARCH model, robust QR and modified ICSS algorithm. Forth section is reserved for dataset and construction of the permanent and transitory volatilities. Fifth section contains the results for full sample and two subsamples. The last section offers discussion of the results and conclusion.

2. Brief literature review

There is a vast number of papers that investigated the nexus between oil and agricultural prices, but it seems that studies on risk transfer between oil and agricultural commodities are still scarce, whereby this causal link remains unclear. Therefore, it calls for more attention.

Some of the existing papers that studied this topic is Nazlioglu et al. (2013), who researched volatility transmission between oil and several agricultural commodities − wheat, corn, soybeans, and sugar. They found no risk transmission between oil and agricultural commodity markets in the pre-crisis period, whereas oil market volatility spills on the agricultural markets in the post-crisis period, with the exception of sugar. Barbaglia et al. (2020) analysed volatility spillovers among large number of energy, agriculture and biofuel commodities via the vector auto regressive (VAR)model. They reported bidirectional volatility spillovers between energy, biofuel and agricultural commodities. Using a rolling window approach, they found that volatility spillovers experience large swings over time, whereby volatility spillovers become weaker when energy prices drop. The paper of Fernandez-Diaz and Morley (2019) examined the degree of interdependence between three agricultural commodity prices, crude oil price returns, macroeconomic variables and the S&P GSCI commodity returns index, using cDCC model. They detected volatility spillover between crude oil and maize, but not among oil with soybean and sugar markets. They asserted that an increasing interdependence between crude oil and maize price returns could be induced by the introduction of biofuel policies. Chiou-Wei et al. (2019) analysed the interactions between energy and agricultural commodity markets by focusing on five major commodities: oil, natural gas, soybean, corn, and ethanol. Their results indicated that there were statistically significant volatility correlations among the five markets. In particular, they found that agricultural commodity markets and ethanol market had the highest volatility connection while natural gas market had the lowest connection with the other markets. They argued that these results are in line with the fact that economic policy promoted more connections between oil, ethanol, corn, and soybean.

Chang et al. (2019) researched the relationship and the interactions on price and volatility between the agricultural and energy industries. Using multivariate conditional volatility diagonal BEKK models, they found that volatility spillovers exist between these markets. Shahzad et al. (2018) considered the joint behaviour of energy and agricultural commodities from the risk point of view. They documented a varying levels of bi-directional spillover effect, running from crude oil to commodity markets or vice versa, which strongly intensify during periods of financial turmoil or uncertainty. They contended that the strongest asymmetric tail dependence takes place between the oil and soybean markets and between the oil and maize markets. The study of Hau et al. (2020) investigated volatility dependence between global crude oil and China's agriculture futures by employing a quantile-on-quantile method. They showed that the volatility dependence between crude oil and China's agricultural futures are heterogeneous across quantiles, whereby the absolute volatility spillover exhibits an overall increasing trend with higher quantiles of agricultural volatility. They stated that crude oil volatility has a positive effect on the high quantiles of agricultural futures' volatility, and it reduces the agricultural volatility at low quantiles. In addition, they contended that the dependence is asymmetric under different market conditions. Yip et al. (2020) researched the spillovers of the forward-looking volatility between crude oil and the most actively traded agricultural commodities (corn, wheat and soybean). They observed both static and dynamic aspects and how they are linked to the low and high oil's volatility regimes. As for static analysis, they reported that on average, the crude oil implied volatility index has a neutral relationship with agricultural commodity implied volatility indices in the absence of crises. On the other hand, dynamic analysis showed that the net volatility spillover effect from crude oil to all agricultural commodities tends to decrease when crude oil remains in its low volatility regime. Conversely, this effect experiences an increasing trend when crude oil remains in its relatively high volatility regime.

3. Research methodologies

3.1. Component GARCH model

The goal of this paper is to determine the level of permanent and transitory spillover effect from Brent crude oil futures to the selected agricultural commodity futures. In order to decompose conditional volatility into permanent and transitory parts, we estimate the selected time-series with the component GARCH model.[1] The mean and GARCH processes are described in equations (1)–(3). We assume an AR (1) process for the conditional mean in all examined assets in order to overcome autocorrelation bias, while residuals of the model follow some form of identical and independent distribution function – $\varepsilon_t \sim i.i.d.(0, \sigma_t^2)$. We want to estimate permanent and transitory components of volatility as accurate as possible, so we consider six different distribution functions in CGARCH model, with aim to find the optimal one. In other words, we consider three traditional distribution functions – normal $\varepsilon \sim N(0, h_t)$, Student-t $\varepsilon \sim St(0, h_t, \nu)$ and generalized error distribution $\varepsilon \sim GED(0, h_t, \nu)$, and three complex, unconventional heavy tailed distributions – normal inverse Gaussian distribution $\varepsilon \sim NIG(0, h_t, \nu, \kappa)$ of Barndorff-Nielsen (1997), generalized hyperbolic distribution $\varepsilon \sim GHYP(0, h_t, \nu, \kappa)$ of Barndorff-Nielsen (1977) and Johnson SU distribution $\varepsilon \sim JSU(0, h_t, \nu, \kappa)$ of Johnson (1949). ν and κ are shape and skew parameters, respectively. Three unconventional distributions (*NIG*, *GHYP*and *JSU*) are applied because we assume the presence of heavy tails in the empirical distributions, and these functions can recognize better heavier tails than the normal distribution. This is because the non-normal distributions are often skewed and asymmetric, whereby one tail is heavy, and the other one is semi-heavy or more Gaussian-like (see Živkov, Manić, Đurašković nd Kovačević, 2019b).

$$r_t = a_0 + a_1 r_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim i.i.d.\left(0, \sigma_t^2\right) \tag{1}$$

$$q_t = \phi_1 + \phi_2 (q_{t-1} - \phi_1) + \phi_3 \left(\varepsilon_t^2 - \sigma_t^2\right) \tag{2}$$

$$\sigma_t^2 = q_t + \phi_4 \left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \phi_5 \left(\sigma_{t-1}^2 - q_{t-1}\right) \tag{3}$$

where r_t stands for log returns of Brent oil futures and the selected agricultural futures and r_{t-1} is an autoregressive term. $a_0$and a_1 are parameters in the mean equation. Symbol ε_t

[1] Estimation of component GARCH model with different alternative distributions was done *via* the ‘rugarch’ package in ‘R’ software.

stands for an independently and identically distributed error terms of the selected commodities, while σ_t^2 denotes the conditional variance. $q_t$represents the long-run component of the conditional variance, which reflects shocks to economic fundamentals and describes the long-run persistent behaviour of the variance. It converges to the long-run time-invariable volatility level $\phi_1$with a magnitude of ϕ_2. The CGARCH model is stable if the AR coefficient (ϕ_2) of permanent volatility exceeds the coefficients ($\phi_4 + \phi_5$) in the transitory component, which implies that short-run volatility converges faster than the long-run volatility. The closer the parameter of the $\phi_2$is to one, the slower $q_t$approaches to ϕ_1, and the closer it is to zero the faster it approaches to ϕ_1. In other words, parameter $\phi_2$gauges the long-run persistence. The coefficient $\phi_3$indicates how shocks affect the permanent component of volatility. The expression $\sigma_{t-1}^2 - q_{t-1}$indicates to the short-run component and suggests the degree of memory in transitory component. Term $\varepsilon_{t-1}^2 - q_{t-1}$measures the initial impact of a shock to the transitory component.

3.2. Robust quantile regression

Assuming the general quantile regression, Yu and Moyeed (2001) proposed a Bayesian modelling approach by using the asymmetric Laplace distribution (ALD). However, ALD is not differentiable at zero, which could cause problems of numerical instability, according to Morales et al. (2017). Therefore, the Laplace density represents a pretty strong assumption in a quantile regression model in both the classical or Bayesian framework. In order to circumvent this drawback, Wichitaksorn et al. (2014) developed a generalized class of skew densities (SKD) for the analysis of QR that provides competing solutions to the ALD-based formulation. More specifically, the procedure of the robust skew density class distributions construction involves mixing a skew-normal distribution of Fernandez and Steel (1998) and the symmetric class of scale mixture of normal distributions of Andrews and Mallows (1974). Morales et al. (2017) explained that $y$has a skewed distribution (SKD) with location parameter μ, scale parameter σ, skewness parameter $p \in (0,1)$and weight function $\kappa(\bullet)$, if $y$can be presented stochastically as $y = \mu + \sigma\kappa(U)^{1/2}Z$, where Zfollows skewed normal distribution (SKN), $Z \sim SKN(0,1,p)$. Also, it should be noted that $P(y \le \mu) = p$and $P(y > \mu) = 1 - p$, which allows a direct application to quantile regression problems, according to Morales et al. (2017). If $U$is integrated out, then the marginal probability density function (pdf), of $y$is given as in equation (4):

$$f\left(y|\mu,\sigma,p\right) = \int_0^\infty \frac{4p(1-p)}{\sqrt{2\pi k(u)\sigma^2}} exp\left\{-2p_p^2\left(\frac{y-\mu}{k^{\frac{1}{2}}(u)\sigma}\right)\right\} dH(u|\nu) \tag{4}$$

ν is a scalar parameter indexing the distribution of $U$and $Z \sim N(0,1)$, with Uindependent of Z. From the expression (4), several skewed and thick-tailed distributions can be derived, regarding different specifications of the weight function $\kappa(\bullet)$and probability density functions: $pdf\ h(u|\nu)$. These functions are Student-t, Laplace, slash distribution and contaminated Normal distribution, and their mathematical specifications are presented in Table 1.

This study tries to estimate the complex spillover effect, regarding permanent and transitory parts of volatilities that goes from Brent futures towards agricultural futures. In that process, we use robust quantile regression[2] approach. Therefore, the conditional quantile function of y at quantile τ, given regressor x and some form of distribution function (F_u) of the errors, can be defined as in equation (5):

$$Q_y(\tau|x) = \beta_0 + \beta_1 x + F_u^{-1}(\tau) \tag{5}$$

where β_0 and β_1 are the parameters to be estimated. In our case, y stands for permanent or transitory component of agricultural volatility, while $x$denotes permanent and transitory component of Brent oil volatility. Morales et al. (2017) stated that the quantile regression estimation of the particular quantile parameter β_τ can be achieved by minimization of equation (6):

$$\widehat{\beta}(\tau) = \text{argmin} \sum_{i=1}^{n} \rho_\tau(y_i - x_i^{\prime}\beta);\ \beta \in \Re \tag{6}$$

where $\tau \in (0,\ 1)$ is any quantile of interest, while $\rho_\tau(z) = z(\tau - I(z < 0))$ and $I(\bullet)$ represents the indicator function. It is important to mention that connection exists between the minimization of the sum in (6) and the maximum likelihood theory. In other words, minimization of equation (6) is equivalent to maximize the likelihood function when data follows some form of distribution function, observed in the family of zero conditional quantile SKD, as presented in Table 1.

3.3. Modified ICSS algorithm

Due to the fact that we consider relatively long time-span, which comprises the periods of market tranquillity and turbulence, we want to assess the magnitude of permanent and

Table 1
Mathematical formulations of the skewed distributions.

Distribution	$f(y\|\mu,\sigma,p,\nu)$
Skewed Student t (SKT)	$\frac{4p(1-p)\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{2\pi\sigma^2}}\left\{\frac{4}{\nu}p_p^2\left(\frac{y-\mu}{\sigma}\right)+1\right\}^{-\frac{\nu+1}{2}}$
Skewed Laplace (SKL)	$\frac{2p(1-p)}{\sigma} exp\left\{-2\rho_p\left(\frac{y-\mu}{\sigma}\right)\right\}$
Skewed slash (SKS)	$\nu\int_0^1 u^{\nu-1}\phi_{skd}\left(y\middle\|\mu,u^{-\frac{1}{2}}\sigma,p\right)du$
Skewed contaminated normal (SKCN)	$\nu\phi_{skd}\left(y\middle\|\mu,\gamma^{-\frac{1}{2}}\sigma,p\right) + (1-\nu)\phi_{skd}(y\|\mu.\sigma,p$

Note: See Morales et al. (2017).

[2] Estimation of robust quantile regression was done *via* the 'lqr' package in 'R' software.

transitory volatility transmission effect in these distinctively different subperiods. Also, since we estimate robust quantile parameters, they can provide us with a knowledge about the size of the effect in conditions of low, moderate and high volatility in these subperiods. In this way, an additional picture can be gained about the size of volatility spillover effect when agricultural markets are in calm periods or when they are in mode of intense stress. This can be an important information regarding the investors' actions in oil and agricultural futures markets. Referring to Kirkulak-Uludag and Lkhamazhapov (2017), we try to determine exact breaking points between the subperiods, which are characterized by different volatility levels, and to avoid arbitrariness at the same time, we use sophisticated method of structural breaks detection – the modified iterative cumulative sum of squares (ICSS) of Sans'o et al. (2004). This methodology resolves the issue of oversized break detection, which is an intrinsic feature of a basic ICSS algorithm of Inclan and Tiao (1994). In other words, modified ICSS can recognize explicitly the fourth moment properties of the time series and it also assumes that data is independent and identically distributed with zero mean and constant variance. Applying a non-parametric adjustment based on Bartlett kernel, the modified ICSS algorithm is presented as in equation (7):

$$modified\ ICSS = \sup_k \left| T^{-0.5} G_k \right|, \tag{7}$$

where $G_k = \hat{\lambda}^{-0.5}[C_k - (k/T)C_T]$; $\hat{\lambda} = \hat{\gamma}_0 + 2\sum_{l=1}^{m}[1 - l(m+1)^{-1}]\hat{\gamma}_l$; $\hat{\gamma}_l = T^{-1}\sum_{t=l+1}^{T}(\tau_t^2 - \hat{\sigma}^2)(\tau_{t-1}^2 - \hat{\sigma}^2)$; $\hat{\sigma}^2 = T^{-1}C_T$. Following the procedure of Newey and West (1994), our lag truncation parameter is set to be $m = 0.75T^{1/3}$. The asymptotic distribution of the modified ICSS statistics under general conditions is given by $\sup_l |W^*(l)|$ and the 95th percentile critical value for the asymptotic distribution of the modified ICSS statistics is 1.4058.

4. Dataset and the construction of permanent and transitory volatilities

This study uses the daily futures[3] prices of Brent crude oil and four major agricultural commodities – corn, wheat, soybean and canola, traded in Chicago Mercantile Exchange (CME). Brent crude oil is chosen rather than WTI because this energy commodity is the most traded oil in the current global oil market. Therefore, Brent oil portrays the evolution of the global oil prices in the best way. In addition, we consider futures prices rather than spot prices of the selected assets, because futures prices by definition incorporate all available information and thus provide a more realistic volatility spillover effect measurement in comparison with the spot prices, as Cipra (2010) and Natanelov et al. (2011) contended. The closing futures prices of Brent oil and the agricultural commodities are transformed into the log returns according to the expression: $r_{i,t} = 100 \times \log(P_{i,t}/P_{i,t-1})$. All samples range from January 2006 to October 2019 except for canola, which commences from August 2010. All time-series are collected from the *investing.com* website. We synchronize all agricultural futures with Brent oil futures according to the existing observations.

Table 2 presents descriptive statistics of the empirical log-returns time-series. The basic statistics encompasses first for moments, robust third and fourth moments, LB(Q) tests for level and squared empirical log-returns as well as DF-GLS test for stationarity. Kim and White (2004) asserted that standard measures of skewness and kurtosis are based on averages, and as such, they can be sensitive to the presence of one or few outliers in time-series, which makes their reliability doubtful. Due to this reason, we include robust third (SK_R) and fourth moments (KR_R) in the descriptive statistics, since we want to find out whether the usage of an optimal distribution function contributes to the model's goodness-of-fit. Robust third and fourth moments are based on quantiles rather than averages. Bowley (1920) and Crow and Siddiqui (1967) defined robust skewness and kurtosis, respectively, and these measures can be calculated as in equations (8) and (9).

$$SK_R = \frac{Q_3 + Q_1 - 2 \times Q_2}{Q_3 - Q_1} \tag{8}$$

$$KR_R = \frac{Q_4 + Q_0}{Q_3 - Q_1} \tag{9}$$

where following quantiles are defined as: $Q_0 = \tau^{0.025}$, $Q_1 = \tau^{0.25}$, $Q_2 = \tau^{0.5}$, $Q_3 = \tau^{0.75}$ and $Q_4 = \tau^{0.95}$.

Table 2 reveals that soybean has the highest average annual price rise, whereas wheat has the highest average annual price drop. Standard deviation indicates that oil and wheat have the highest average risk. It is also noticeable that the majority of assets are left-asymmetric, whereas all assets are fat-tailed in comparison with the Gaussian distribution. It can be seen that all SK_Rcoefficients oscillate around zero, while all KR_Rcoefficient are significantly lower than their empirical counterparts. LB(Q) and LB (Q^2) tests suggest the presence of autocorrelation and heteroscedasticity in the empirical time-series, which means that some form of ARMA-GARCH model might be appropriate. DF-GSL test suggests that all the assets are stationary, and thus suitable for the CGARCH estimation. Jarque-Bera coefficients of normality are not presented in Table 2, because, based on the skewness and kurtosis coefficients, it is clear that none of the empirical time-series follows normal distribution.

In order to create transitory and permanent part of volatility for every selected asset as accurate as possible, we estimate CGARCH model with six different distribution functions.

[3] All observed futures are the expiring futures contracts. It should be said that before expiration date, traders have three options. 1) Offsetting the position, which means that trader can realize all profits or losses associated with that position without taking physical or cash delivery of the asset. 2) Rollover, which means that trader moves his position from the front month contract to another contract further in the future. 3) Settlement applies if trader did not offset or rollover his position prior to contract expiration. In this situation, the contract will expire and the trader will go to the settlement.

Table 2
Descriptive statistics of the selected assets.

	Annual mean	Standard deviation	Skewness	Kurtosis	Robust skewness	Robust kurtosis	LB(Q)	LB(Q^2)	DF-GLS
Brent oil	1.512	2.119	0.008	6.760	−0.038	2.430	0.000	0.000	−25.245
Corn	−1.260	2.031	−0.537	25.312	−0.009	3.700	0.004	0.000	−9.938
Wheat	−4.032	2.144	0.034	7.091	0.007	3.153	0.006	0.000	−61.369
Soybean	2.016	1.605	−0.817	26.539	−0.006	3.281	0.000	0.000	−11.844
Canola	0.089	1.139	−1.470	16.731	−0.067	2.342	0.003	0.000	−45.775

Notes: JB describes p-value of Jarque-Bera coefficients of normality, LB(Q) and LB(Q^2) tests present p-values of Ljung-Box Q-statistics of level and squared residuals for 20 lags. DF-GLS is Dickey-Fuller generalized lest squares test with 10 lags assuming only constant, and 1% and 5% critical values are −2.566 and −1.941, respectively.

Table 3
AIC and relative likelihood values for CGARCH models with different distributions.

	Brent oil		Corn		Wheat		Soybean		Canola	
	AIC	RL	AIC	RL	AIC	RL	AIC	RL	AIC	RL
Normal	4.0672	0.9783	4.0296	0.9523	4.2070	0.9802	3.5089	0.9607	2.9625	0.9428
Std	4.0269	0.9982	3.9319	1	4.1680	0.9995	3.4288	0.9999	2.8497	0.9975
GED	4.0315	0.9959	3.9469	0.9925	4.1776	0.9947	3.4403	0.9942	2.8817	0.9816
NIG	4.0239	0.9997	3.9364	0.9978	4.1682	0.9994	3.4303	0.9992	2.8522	0.9962
GHYP	4.0242	0.9996	3.9330	0.9994	4.1675	0.9997	3.4289	0.9999	2.8446	1
JSU	4.0233	1	3.9335	0.9992	4.1669	1	3.4287	1	2.8482	0.9982

Notes: AIC denotes Akaike information criterion, while RL abbreviation stands for relative likelihood. RL is calculated as: $RL = e^{(AIC_O - AIC_{NO})/2}$. AIC_O is the optimal AIC, while AIC_{NO} denotes all other nonoptimal AIC numbers.

Table 3 reveals which density function is the optimal one for every considered asset. For that purpose, we calculate AIC values and relative likelihood (RL) indicator.

Model with the lowest AIC is the best one, while RL shows how worse is nonoptimal model comparing to the optimal one. AIC values indicates that, in four out of five cases non-traditional distributions, such as JSU and GHYP, have an upper hand, while only in the case of corn, traditional Student-t distribution is found to be the best fitting one. According to Table 3, the differences between the models are tiny, however, every improvement in model specification can contribute to better measurement of conditional volatilities, which makes our approach justifiable.

Table 4 contains the values of parameters estimated with the best-fitting CGARCH model. It can be seen that majority of the parameters are highly statistically significant, whereas the $\phi_2$coefficient of the lagged permanent volatility is relatively large and highly significant at 1% level for all the assets. This suggests a presence of long-run volatility persistence. Fig. 2 clearly shows that permanent component of volatility is larger and more persistent than the temporary component in all the plots. In particular, we find conspicuous peaks of permanent volatility in all the plots in Fig. 2. For corn, very high permanent volatility is recorded around 2013, and the reason lies in the sharp increase in corn prices due to devastating drought in 2013 in the US. As for wheat and soybean, we find very high permanent volatility around 2008. It can be argued that numerous factors, such as weak US dollar, rising global incomes, trade restrictions by major grain suppliers, panic buying by several large importers as well as record oil prices, could be immediate causes of rising wheat and soybean prices that had occurred before the global financial crisis (see Fig. 1). Also, very high permanent volatility is found in the case of Brent between 2008 and 2009, and the reason for that finding is very sharp drop of oil prices that happened after the onset of the global financial crisis, as can be seen in Fig. 1. It should be said that all $\phi_2$coefficients are very close to one, which signals that permanent volatility converges to its mean very slowly.

The parameter of transitory component (ϕ_4) gauges the initial impact of a shock to the CGARCH transitory component, and it is most expressed in canola market. The parameter $\phi_5$indicates the degree of memory in the transitory component

Table 4
Estimated CGARCH parameters.

	Brent oil	Corn	Wheat	Soybean	Canola
ϕ_1	0.008***	0.045***	0.009***	0.023***	0.001***
ϕ_2	0.998***	0.990***	0.998***	0.990***	0.999***
ϕ_3	0.030***	0.072***	0.020***	0.046***	0.008***
ϕ_4	0.043***	0.048**	0.050***	0.000	0.108***
ϕ_5	0.917***	0.072	0.858***	0.721	0.806***
Diagnostic tests					
LB(Q)_20	0.76	0.73	0.78	0.51	0.29
LB (Q^2)_20	0.95	0.81	0.92	0.97	0.99
LB(Q)_30	0.57	0.47	0.15	0.32	0.50
LB (Q^2)_30	0.89	0.69	0.55	0.49	0.52
Li-Mak[a] (20)	6.95 (0.25)	1.60 (0.77)	6.54 (0.29)	5.66 (0.39)	4.16 (0.98)
Robust skewness	−0.043	−0.000	0.007	−0.006	−0.073
Robust kurtosis	2.410	3.358	3.153	3.258	2.241

Notes: LB(Q) and LB(Q^2) tests denote p-values of Ljung-Box Q-statistics of level and squared residuals for 20 and 30 lags. Li-Mak (20) is Li and Mak (1994) test statistic for the squared standardized residuals at 20 lags, and p-values are in parenthesis. ***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively.

[a] Li and Mak test statistics is calculated via 'WeightedPortTest' package in 'R' software.

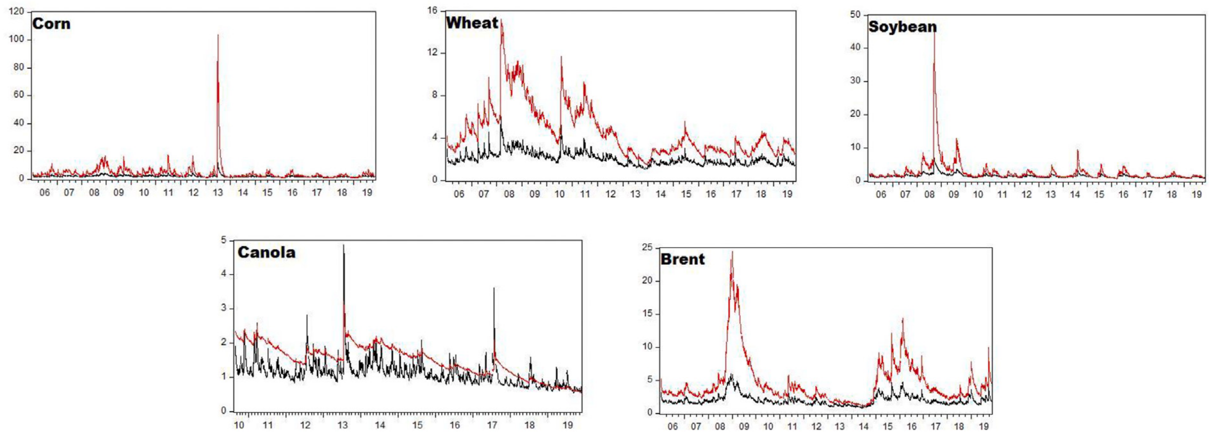

Fig. 2. Estimated dynamic permanent and transitory volatilities of the selected assets.
Note: Red and black lines denote permanent and transitory volatilities, respectively.

and it is significant in three out of five cases. Due to the fact that the permanent component parameter (ϕ_2) is greater than the sum of the transitory components ($\phi_4 + \phi_5$), this indicates that mean reversion is slower in the long run, which makes our models stable. On the other hand, it is obvious that transitory volatility tends to be mean reverting. The mean reversion of transitory volatility is verified by DF-GLS test, which shows that all transitory volatilities have no unit root. Calculated DF-GLS values of the assets are as follows − Brent oil (−2.529), corn (−4.230), soybean (−3.061), wheat (−3.410) and canola (−3.803).

Diagnostic LB(Q) and LB (Q^2) tests for 20 and 30 lags confirm the absence of autocorrelation and heteroscedasticity in all the models' residuals. In order to be more through in the analysis, we additionally compute Li and Mak (1994) test statistics for the squared standardized residuals at 20 lags, because this measure is more robust when residuals from GARCH model are in question. Li-Mak test also confirms the absence of heteroscedasticity in squared residuals in all CGARCH models. An addition, we also calculate $SK_R$and KR_Rcoefficients for models' residuals, and it can be seen that all KR_Rcoefficients of the models are better (lower) than their empirical counterparts. This means that the usage of the best-fitting distribution in CGARCH models recognises in better way heavy tails in the selected time-series.

The next task in our computational process involves determination of the best-fitting SKD of the particular agricultural futures in the robust QR framework, taking into account both transitory and permanent segments of volatility. Table 5 presents the AIC values for the estimated robust quantile regression models under five different skewed distributions − Normal, Student-t, Laplace, Slash and Contaminated normal distribution. We fit robust QR with different distribution functions, performing a median regression ($\tau^{0.5}$). According to AIC measures in Table 5, it can be concluded that in seven out of eight cases, the best robust QR model is with the Slash distribution, whereas only in the case of wheat with permanent volatility the advantage goes to Student-t distribution. In order to preserve space, we present in Fig. 3 model residuals with the theoretical shape of every distribution function only for permanent volatility of corn as dependent variable. Visual presentation of the fitted model residuals for all other agricultural futures can be obtained by request.

5. Research results

5.1. Full sample analysis

This subsection reveals the full sample results of transitory and permanent spillover effects from oil futures market towards agricultural futures commodities, estimated *via* robust quantile regression. Table 6 contains these results, while Fig. 4 presents the quantile plots. In order to be more detailed in the analysis, we also checked for the presence of seasonality effect in daily commodity prices by inserting four dummy variables that represent daily seasonal effects, where Monday is observed as a reference. After the dummy variables are added in the models, the values of $\phi_4$and $\phi_5$parameters change very little, which means that dummy variables have a negligible effect on the coefficient of ARCH and GARCH terms. In other words, seasonal effect is not found in daily data of the selected assets and we proceeded with the creation of transitory and permanent volatilities without dummy variables in the models.

By segmenting total conditional volatilities into transitory and permanent parts, we can assess what is the nature of short-run volatility relationships, which is influenced by market sentiments and investor behaviour, and what is the extent of long-run connection, which is caused by fundamental factors. It can be seen that majority of the estimated quantile parameters are statistically significant, whereas the magnitude of these parameters increases gradually with the rise of quantiles. This is an indication that volatility transmission between the markets is more intense in periods of increased market turbulence, which happens most likely due to rising financialization of commodity markets in the last two decades. Numerous authors reported rising shock and volatility

Table 5
Estimated AIC values for the quantile regression under different SKD.

Agricultural futures	Type of volatility	Types of different SKD				
		Normal	Student-t	Laplace	Slash	Cont. Normal
Corn	Transitory	12938.2	6397.5	6707.0	6340.9	6994.9
	Permanent	21925.1	7021.5	9846.9	6687.4	15113.9
Wheat	Transitory	10491.2	5181.3	5452.4	5135.4	5331.9
	Permanent	13905.9	8149.6	8237.8	8162.0	8647.9
Soybean	Transitory	10280.0	2923.7	3610.1	2891.6	4576.3
	Permanent	15717.5	75.3	4370.4	−657.3	9253.3
Canola	Transitory	551.3	−6182.7	−5440.9	−6278.8	−3688.9
	Permanent	−4304.4	−14069.6	−12817.6	−14244.5	−9237.0

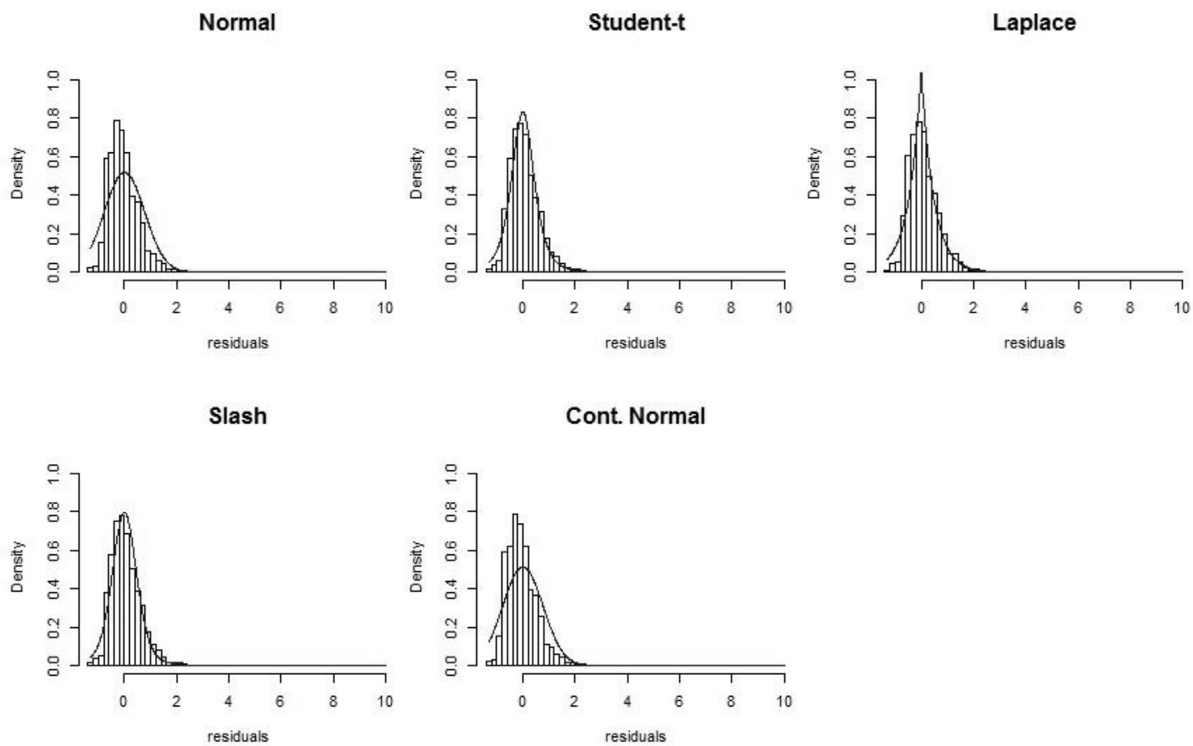

Fig. 3. Fitted distributions of the estimated residuals of corn permanent volatility.

Table 6
Estimated transitory and permanent volatility quantile parameters − full sample.

Estimated parameter	Type of volatility	Estimated robust quantiles						
		0.05	0.20	0.35	0.50	0.65	0.80	0.95
Panel A. Dependent variable − Corn futures								
β_2	Transitory	−0.000	0.072***	0.144***	0.211***	0.286***	0.350***	0.360***
	Permanent	−0.002	0.052***	0.089***	0.119***	0.197***	0.326***	0.457***
Panel B. Dependent variable − Wheat futures								
β_2	Transitory	0.065***	0.128***	0.189***	0.257***	0.292***	0.301***	0.317***
	Permanent	0.062***	0.138***	0.217***	0.290***	0.292***	0.269***	0.318***
Panel C. Dependent variable − Soybean futures								
β_2	Transitory	−0.001	0.010	0.060***	0.149***	0.217***	0.273***	0.410***
	Permanent	−0.011**	−0.017*	0.022**	0.116***	0.139***	0.150***	0.231***
Panel D. Dependent variable − Canola futures								
β_2	Transitory	−0.073***	−0.058***	−0.060***	−0.065***	−0.066***	−0.071***	−0.101***
	Permanent	−0.030***	−0.043***	−0.038***	−0.041***	−0.047***	−0.052***	−0.055***

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

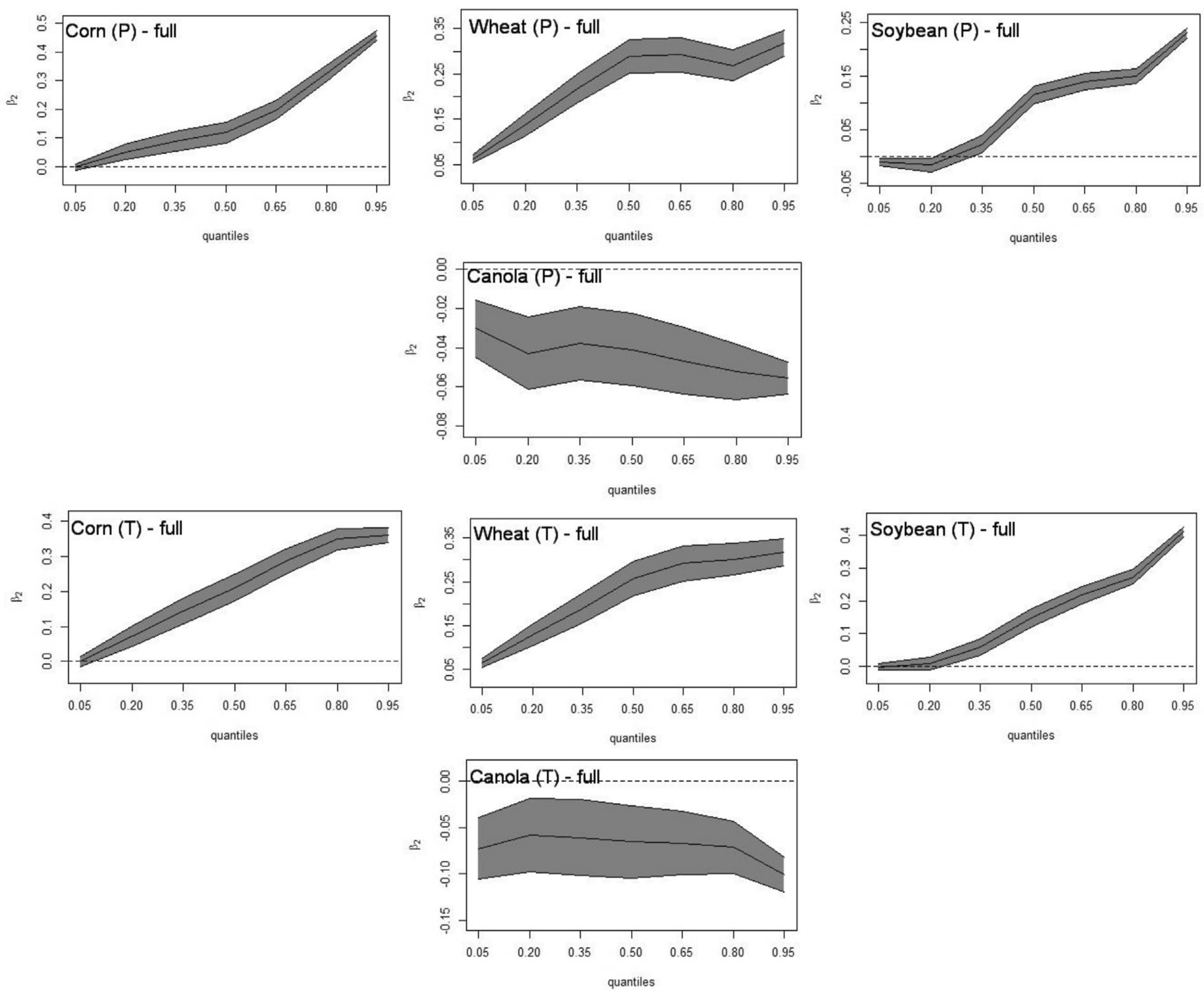

Fig. 4. Plots for permanent and transitory spillover effect for full sample
Note: Letters 'P' and 'T' in brackets indicate permanent and transitory transmission effect.

spillover effect between the financial and commodity markets in the periods of increased market turmoil (see e.g. Abdullah et al., 2016; Chen et al., 2018). This pattern applies to all selected agricultural commodities as well as to both types of volatilities.

Our results in Table 6 indicate that the level of the spillover effect is not particularly high over the quantiles, while in the canola case, this effect is even negative across all the quantiles. Negative spillover parameters suggest that increase in oil volatility actually decreases volatility in canola futures markets, which is good for hedging purposes. In low volatility terms ($\tau^{0.05}$ and $\tau^{0.2}$), we record very low volatility transmission effect, whereby wheat receives the largest spillover effect from oil in the amount that goes around 13%. This means that 100% increase in oil volatility causes 12.8% and 13.8% rise in transitory and permanent volatility in wheat futures market, respectively. In moderate volatility conditions ($\tau^{0.35}$, $\tau^{0.5}$and $\tau^{0.65}$), the spillover effect oscillates around 20−30% in cases of corn and wheat, while for soybean, it is between 10 and 20%. As for high volatility conditions ($\tau^{0.8}$ and $\tau^{0.95}$), this effect is around 30% for corn and wheat and 20% for soybean in the full sample analysis. These findings of relatively low volatility transmission effect concur with some existing papers. For instance, Behmiri et al. (2019) estimated several dynamic correlations in a multivariate DCC-GARCH model between oil, natural gas, and eight more commodities in the agriculture and metals markets. They reported that dynamic correlations are larger between energy and metal than in the case energy-agricultural commodities. In addition, Dahl et al. (in press) investigated spillover effects among markets of crude oil and ten major agricultural commodities by employing the Diebold and Yılmaz (2012) methodology and found that the largest net receivers of volatility spillover effect from oil market are wheat, canola, cotton, and sugar, which receives on average 11.08%, 5.31%, 3.95%, and 3.28%, respectively, which is not high amount at all.

Regarding the transmission effect between different types of volatilities across the quantiles, our results indicate that in most cases the short-run (transitory) transmission effect is higher than the long-run (permanent) effect, and that particularly applies to corn, soybean and canola. According to Ross (1989), synonymous for information transfer is volatility spillover effect, and he claimed that the variance of price changes is directly linked to the rate of information flow to the market. This means that short-term information flow that comes from oil futures markets has stronger volatility shock transmission effect on agricultural futures markets than fundamental factors. Our finding fit very well with the assertion of Behmiri et al. (2019), who explained that higher speculative activity in the energy markets is associated with stronger dynamic conditional correlations between energy and agriculture, which is probably an aftermath of greater presence of non-commercial traders in the energy markets. Besides, some authors, such as Wang and Wang (2019) who researched commodity and stock markets, found an evidence that volatility spillover effect is manly driven by short-term spillovers.

In particular, Table 6 reports that significant difference between transitory and permanent spillover effect in corn futures market is visible at $\tau^{0.5}$and $\tau^{0.65}$quantiles, and it amounts about 10%. This means that in moderate volatility conditions, transitory (short-run) volatility transmission effect between oil and corn futures markets is stronger, than the permanent (long-run) connection, which is caused by fundamental factors. In other quantiles, except the last one ($\tau^{0.95}$), transitory spillover effect is also stronger but not as obvious as in the $\tau^{0.5}$and $\tau^{0.65}$quantiles. When corn futures market is in very high volatility mode, then fundamental factors have an upper hand over transitory factors, since β_2 permanent parameter amounts 0.46 in comparison with 0.36, which is the size of a transitory parameter. In the case of wheat, transitory and permanent spillover effects are relatively equable, which indicates that short-term and long-term volatility shocks that come from oil market hit wheat market in relatively equal manner. In soybean market, transitory volatility shocks are more dominant in regard to permanent shocks, and this is recorded from $\tau^{0.35}$quantile onwards. In the canola case, transitory effect is slightly higher in all the quantiles, whereby all the canola parameters bear negative sign.

5.2. Subsample analysis

Due to the fact that we cover relatively long sample that is permeated with numerous ups and downs of agricultural prices, we want to see what is the difference when the short- and long-run volatility spillover effects are observed in different subperiods that are characterized by the lowest and highest risk (see e.g. Nomikos & Pouliasis, 2015). In this way, it can be seen is there a difference in magnitude of spillover effect between volatile and tranquil subperiods and whether there is need for some hedging strategies to overcome the existing risk transmission from oil to agricultural markets. Some authors, such as Nazlioglu et al. (2013) and Dahl et al. (in press) also analysed the spillover effect in different subsamples, but our approach differentiate from these papers in a way that we use mathematical algorithm to detect exact breaking points between subsamples, and thus avoid arbitrariness in the determination of subperiods. In particular, we use modified ICSS algorithm of Sansó et al. (2004) to detect multiple structural breaks in agricultural log-return time-series. Detected breaks are used as dividing points between subsamples. Table 7 presents subperiods bounded with exact dates and accompanying levels of standard deviation for each subperiod. The levels of standard deviations are used to choose two subsamples with the lowest and highest risk. Fig. 5 contains empirical log-return plots of the agricultural futures with the detected structural breaks.

It is obvious that the highest risk is detected in the first half of the observed sample relative to the second half in all the plots in Fig. 5. This is expected finding, since all agricultural futures prices recorded very volatile behaviour up to 2014, due to previously mentioned reasons, such as weak US dollar, rising global incomes, trade restrictions by major grain suppliers, commodity financialization, very explicit oil price swings, etc., while from 2014, the volatility of all agricultural grains subsides significantly. This feature of the selected agricultural prices is very visible in Fig. 1, and this is the main economic reason for the structural break identification in Fig. 5.

Tables 8 and 9 contain estimated robust quantile parameters, which measure transitory and permanent volatility transmission effect in the subsamples with the highest and lowest volatility, respectively. In order to preserve space, we do not present quantile plots for the subsamples. Based on the results from Table 7, we choose first and third subsamples for corn, which depict the subsamples with the highest and lowest standard deviation. We disregard second subsample of corn futures, because this subsample is too short, while its very high risk is clearly an aftermath of outliers. For soybean, chosen subsamples are second and third, whereas for canola, the subsamples are first and third. As for wheat, we do not need to choose between subsamples, because only two subsamples are detected.

Table 8 presents robust QR parameters estimated in the high volatility subperiod, and it can be seen that these coefficients are higher comparing to the full sample parameters. This particularly applies to corn, wheat and soybean futures,

Table 7
Exact break points and standard deviations of the selected agricultural commodities.

Corn		Wheat		Soybean		Canola	
S.D.	Periods	S.D.	Periods	S.D.	Periods	S.D.	Periods
2.203	1/1/06 – 6/28/13	2.667	1/1/06–10/12/11	1.344	1/1/06 – 3/3/08	1.315	1/1/06–8/18/15
6.288	6/29/13 – 9/13/13	1.677	10/13/11 – 11/30/19	3.046	2/4/08–10/13/09	1.093	8/19/15 – 8/18/17
1.419	9/14/13 – 11/30/19			1.303	10/14/09–11/30/19	0.669	8/19/17 – 11/30/19

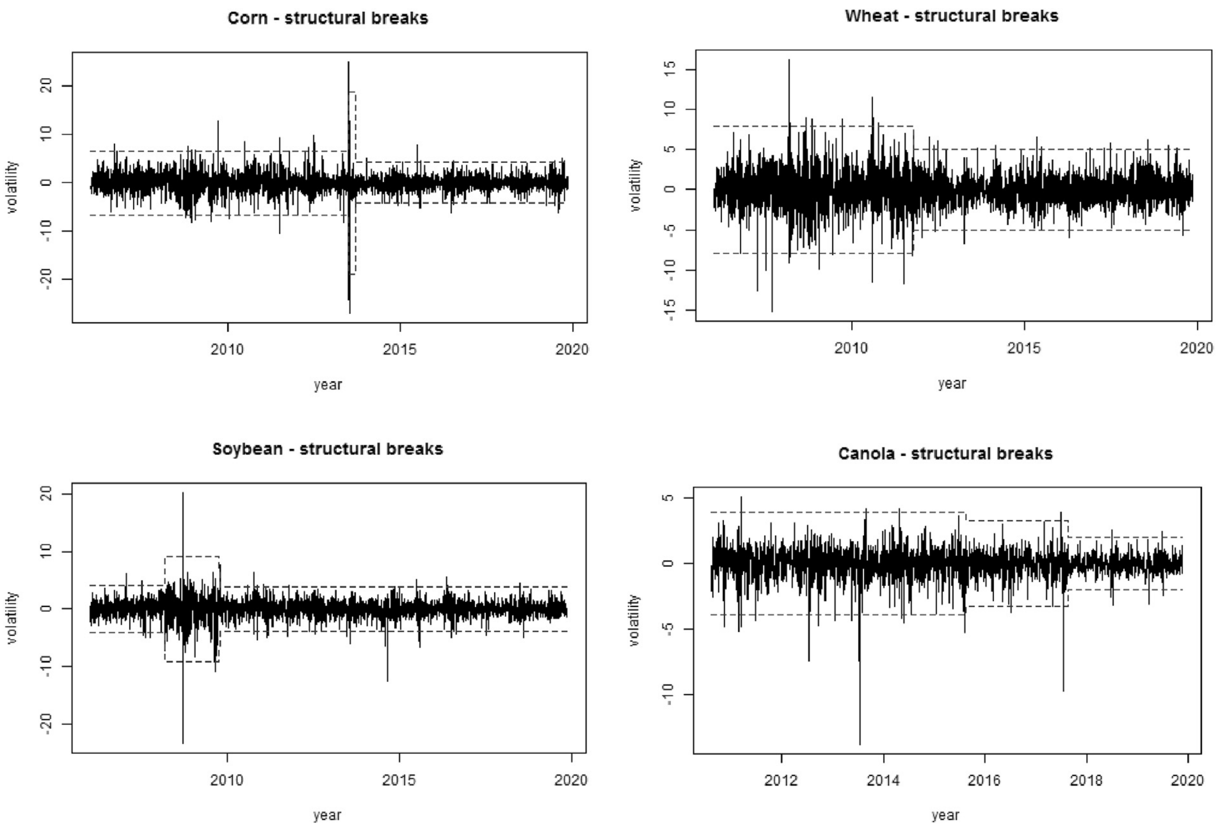

Fig. 5. Detected structural breaks *via* modified ICSS algorithm
Note: Doted lines denote bands of ±3 standard deviations, where change points are estimated by the modified ICSS algorithm.

Table 8
Estimated transitory and permanent volatility quantile parameters – crisis subsample.

Estimated parameter	Type of volatility	Estimated robust quantiles						
		0.05	0.20	0.35	0.50	0.65	0.80	0.95
Panel A. Dependent variable – Corn futures								
β_2	Transitory	0.282***	0.292***	0.322***	0.354***	0.376***	0.382***	0.367***
	Permanent	0.155***	0.159***	0.204***	0.293***	0.367***	0.437***	0.512***
Panel B. Dependent variable – Wheat futures								
β_2	Transitory	0.308***	0.285***	0.266***	0.300***	0.335***	0.324***	0.368***
	Permanent	0.295***	0.288***	0.253***	0.295***	0.308***	0.302***	0.308***
Panel C. Dependent variable – Soybean futures								
β_2	Transitory	0.144***	0.138***	0.121**	0.116*	0.230**	0.314***	0.532***
	Permanent	0.075***	0.051	0.013	0.013	0.031	0.065*	0.151***
Panel D. Dependent variable – Canola futures								
β_2	Transitory	0.013	−0.006	−0.008	−0.007	−0.010	−0.024	−0.040**
	Permanent	0.016*	0.007	−0.008	−0.021*	−0.028**	−0.027***	−0.022***

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

while canola robust QR parameters are either very small or statistically insignificant. In addition, it is evident that the estimated parameters are particularly higher in lower quantiles (from $\tau^{0.05}$to $\tau^{0.5}$), and this finding is evident for corn, wheat and soybean markets. This indicates that even in low volatility conditions in the crisis subperiod, the volatility spillover effect from oil to agricultural futures markets is relatively high, which requires some use of hedging activities for those investors who combine both oil and the listed agricultural commodities in their portfolios. On the other hand, the spillover effect in high volatility conditions (from $\tau^{0.65}$to $\tau^{0.95}$), is not much higher in high volatility subsample in comparison with the full sample, which is characteristic for corn, wheat and soybean. Also, it should be said that the transitory effect is stronger than the permanent effect in the crisis period, similarly as in a full sample analysis, which means that short-term information flow causes greater volatility spillover impact than fundamentals. This is particularly obvious in the soybean case, since permanent QR parameters in the soybean case are either low or statistically insignificant.

Table 9
Estimated transitory and permanent volatility quantile parameters — calm subsample.

Estimated parameter	Type of volatility	Estimated robust quantiles						
		0.05	0.20	0.35	0.50	0.65	0.80	0.95
Panel A. Dependent variable — Corn futures								
β_2	Transitory	−0.008	−0.011	0.005	0.026	0.045*	0.057*	0.085***
	Permanent	−0.005	−0.009	−0.003	0.005	0.013	0.011	0.051**
Panel B. Dependent variable — Wheat futures								
β_2	Transitory	0.070***	0.045***	0.047**	0.037*	0.019	0.014	0.011
	Permanent	0.054***	0.039***	0.037**	0.025	−0.006	−0.051*	−0.090***
Panel C. Dependent variable — Soybean futures								
β_2	Transitory	−0.025***	−0.032*	−0.035*	−0.033*	−0.041*	−0.074***	−0.100***
	Permanent	−0.016***	−0.028**	−0.032**	−0.028*	−0.025***	−0.048***	−0.095***
Panel D. Dependent variable — Canola futures								
β_2	Transitory	−0.083***	−0.075***	−0.068**	−0.065**	−0.061***	−0.068***	−0.076***
	Permanent	−0.049***	−0.056***	−0.072***	−0.076***	−0.079***	−0.089***	−0.096***

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

Table 10
Average daily trading volumes in the selected agricultural futures markets in 2019.

	Corn futures	Wheat futures	Soybean futures	Canola futures
Daily trading volumes	410,567.5	120,895.8	212,009.9	22,522.6

Source: https://stooq.com

As for the calm subperiod, Table 9 suggests that all estimated robust QR parameters are low (below 10%), statistically insignificant or negative, and these features are applicable for all the agricultural futures. This is a clear sign that in bearish subperiod in agricultural markets, the risk transmission from oil futures to agricultural futures is almost non-existent. This pattern applies to both short- and long-run volatility transmissions, which implies that none of hedging strategies is needed in tranquil periods.

Looking at the results for both crisis and tranquil subperiods, our findings are in line with Nazlioglu et al. (2013), who reported that volatility responses of wheat, corn, soybeans, and sugar markets to risk shocks in oil markets seem to be significant only for the post-crisis period. They offered a probable explanation, claiming that investors augment their efforts to find safe havens in crisis periods, which increases the financialization of the agricultural commodity markets, and consequently it drives the short run volatility in agricultural markets. They also contended that these responses are not permanent and die off in relatively short amount of time, which also coincide with our findings, since transitory spillover effect is stronger than the permanent.

6. Conclusion and discussion of the results

This paper investigates transmission of transitory and permanent part of volatilities from Brent oil futures market to four agricultural futures markets — corn, wheat soybean and canola. In the two-step procedure, we first estimate transitory and permanent volatilities in the optimal CGARCH model, and then these volatilities are embedded in the robust quantile regression. In addition, we also perform subsample analysis, observing two diametrically opposite subsamples in terms of risk in each agricultural commodity market, i.e. with the highest and lowest standard deviations. Precise division of the full sample is done with the help of modified ICSS algorithm.

Estimated robust quantile parameters indicate a time-varying nature of the connections, in a sense that they grow larger as volatility in agricultural markets increases. In particular, the full-sample findings suggest that volatility shocks that originate in the oil futures market spill over towards corn, wheat and soybean futures markets, while in the canola case, a rise in oil volatility actually decreases volatility in canola market. This is a clear indication that canola is not a recipient of volatility from the oil market, which makes canola potentially a good asset for diversification in a portfolio with the oil. However, based only on quantile estimates, this is superficial assessment. This is because canola futures market is relatively small and illiquid, comparing to other agricultural futures markets (see Table 10). Due to potential difficulties in converting canola futures into cash, we cannot say that canola futures are good hedging (diversification) tool for investors in combination with oil. On the other hand, negative canola quantile parameters could rather indicate that estimated negative robust QR parameters are, most likely, a consequence of low trading volumes in this market. More specifically, due to low liquidity in the canola futures market, volatility shocks from the oil market cannot come to the fore in full swing in this market. Besides, canola futures are little bit specific because they are priced in Canadian dollars, which additionally puts canola in unfavourable position, since investment in canola futures requires exchange rate transaction costs.

Therefore, having in mind aforementioned, we can say that the best diversification instrument in combination with oil is soybean futures, since it is the least susceptible to oil volatility shocks, taking into account both corn and wheat futures, whereas soybean futures are also very liquid, as Table 10 shows. Our conclusion is derived from the basic principle that says if volatility from one financial market transmits to another one in high intense, then these assets should not be combined together in a single portfolio. In other words, according to the short-term and long-term volatility transmission results in the full-sample, soybean futures have the best diversification potential of all selected grains.

However, the subsample analysis reveals that soybean, but also corn and wheat, can be used as suitable diversification instruments in the portfolio with oil, but only in the periods which are classified as tranquil. In this case, soybean becomes a very suitable hedging asset, since robust QR parameters are negative, whereas corn and wheat also become convenient because the quantile parameters are very low. On the other hand, in the crisis subperiod, corn, wheat and soybean receive significant amount of volatility shocks from oil market, even in conditions of low volatility, which is depicted by the lowest quantiles. Therefore, investors in crisis period should abandon oil-agricultural futures combination, and seek some other assets which will serve as more appropriate safe haven.

By splitting conditional volatilities in the permanent and transitory parts, we can assess which factor – market sentiments (short-term investor behaviour) or long-run fundamental factors, that come from the oil market, have stronger effect on the volatility of the agricultural futures. According to the results, it seems that transitory effect has slight upper hand than its permanent counterpart, which is a sign that short-term information flow has more influential effect than fundamental factors. These results coincide with the findings of other authors.

We believe that the results from this paper could help market participants to understand what lies behind the transmission effect between oil and agricultural futures, and how they should behave in different market conditions, i.e. should they retain long position in the markets or should they seek new investment opportunities.

Conflict of interest:

We have no conflict of interest to report.

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