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HOW DO OIL PRICE CHANGES IMPACT THE MAJOR AGRICULTURAL COMMODITIES IN DIFFERENT MARKET CONDITIONS AND IN DIFFERENT TIME-HORIZONS?

Abstract: *This paper investigates how do oil price changes affect the major agricultural commodities (barley, corn, rice, soybean and wheat) in the different time-horizons and in the different market conditions. For computation purposes we employ a wavelet-based quantile approach. We find strong transmission effect from oil only in the tail quantiles in the longer time-horizons, which is especially true for barley, corn and soybean. It is an indication that the agricultural commodities are affected by oil in the periods of increased market turbulence, regardless of whether it is characterized by increasing or decreasing prices of these commodities. Barley and corn experience the spillover effect in the periods of the rising agricultural prices, and this impact reaches almost 30% in the long-term horizon. The wavelet cross-correlation results provide strong evidence that corn and soybean lead oil in midterm and long-term horizons.*

Key words: *agricultural commodities, oil, quantile regression, wavelets*.

JEL Classification: C22, C63, Q13, Q41

1. Introduction

Increased volatility dynamics in the energy and agricultural commodity markets as well as strong interconnections between these markets raised a widespread interest from policy makers, various market participants and academic community in the last two decades. According to International Grains Council (IGC), a dramatic

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upswing in the cereal prices occurred during the period 2000–2008, particularly during the 2007/2008 food crisis. For instance, wheat price rose from 107 US$ per ton on January 3, 2000 to 532 US$ per ton on March 12, 2008, while at the same time-period corn price increased from 90 US$ per ton to 241 per ton. Santeramo and Lamonaca (2019)asserted that grains percentage price change in period 2006-2008is among the largest changes in the agricultural commodity history. On the other hand, major price-spikes and increased volatility were also recorded on the crude oil market during the last two decades owing to the heterogeneous global events such as the 2001 Dot-com bubble burst, 2003 Iraqi war, 2008-2009 world financial crisis (WFC), and 2015-2016 oil price plunge, (see e.g. Frank and Hesse, 2009;Mirović et al., 2017). As an illustration, the Brent crude oil spot price closed at around 10 US$ per barrel in January 1999, while it reached record high of 140 US$ per barrel in July 2008, and plummeted again at 30 US$ per barrel by the begging of 2016.

Mensi et al. (2014) explained the intertwining connection between the agricultural and energy markets. Firstly, oil is an essential input in the agricultural production, e.g. transportation and food processing, since it can raise the costs of mechanical cultivation and energy-related inputs like fertilizers and pesticides. Secondly, bioethanol and biodiesel are energy alternative and were recently developed as an answer to rising oil prices[1]. These biofuels are extracted from corn and soybean, thus an increase in oil price can induce increased corn and soybean prices. Thirdly, increased economic growth in emerging and developing countries, in particular China and India, is often accompanied by the growth in the population of these countries, which causes higher food and energy consumption, since these factors reinforce each other. Therefore, having a clear picture about how the oil price changes affect grain commodities would be of great interest for farmers, major grain producing countries as well as various market participants, such as traders, investors and portfolio managers which combine oil and agricultural commodities.

It should be said that most of the existing literature(see e.g. Wu and Zhou, 2016;Cao and Xing, 2018) is mainly focused on low frequency observations(daily or weekly data)due to the fact that long-term observations often imply serious sample reduction problem, which is accompanied by the valuable information loss. In addition, it should be added that various market participants have diverse expectations, risk profiles, informational sets, etc., and thus they pursue heterogeneous objectives, which can be achieved at different time-horizons. It is well known that institutional investors and policy makers are a part of low-frequency (long-term) agents, whereas speculators and market makers belong to high-frequency (short-term) participants.

[1]According to Renewable Fuels Association (RFA) world ethanol production reached roughly 65 million tons in 2009, whereby the United States (US), Brazil, and the European Union (EU) take approximately 54%, 34%, and 5% of global share, respectively.

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Having in mind aforementioned, this paper investigates thoroughly the interdependence between spot oil returns and five spot agricultural commodity returns – barley, corn, rice, soybean and wheat. In order to gauge spillover effect from oil to agricultural commodities, we couple two different methodologies – quantile regression (QR) and wavelet decomposition analysis. These two approaches together can provide a holistic picture, since QR methodology can explore conditional dependence at the different quantiles including the states of downturn (lower quantiles), normality (intermediate quantiles), and upturn (upper quantiles) markets.In that manner, QR enables us to find out whether the spillover effect from oil towards agricultural commodities differs across the distribution of the dependent variable. On the other hand, the wavelet technique gives researchers an opportunity to grasp the dependence structure of two variables, regarding the different time-horizons. Wavelet technique is model-free approach and is relatively new tool in economic studies, whereby it is very powerful in generating a data structure that contains segments of various lengths. In particular, it circumvents the problem of sample size reduction, while the computation is done without wastage of valuable information. Many recent studies applied wavelet methodology to analyse various economic phenomena at different time-horizons (see e.g. Barunik and Vacha, 2013; Lee and Lee, 2016; Živkov et al., 2018; Živkov et al., 2019a).In addition, in order to enhance analytical contribution of this paper, we calculate wavelet cross-correlation, as complementary analysis, which can examine the lead/lag relationship between oil and the selected agricultural commodities at various time-horizons. To the best of our knowledge, this paper is the first one that uses wavelet-QR methodology to thoroughly inspect the nexus between oil and agricultural commodities.

Besides introduction, the rest of the paper is structured as follows. Second section gives brief literature review. Third section explains used methodologies – quantile regression and wavelet approach. Fourth section introduces dataset, while fifth section presents the results of wavelet-based quantiles and wavelet cross-correlation. The last section concludes.

2. Brief overview of the previous studies

The literature on the relations between oil and agricultural commodities have expanded rapidly in the last decade. However, according to Nazlioglu et al. (2013) the nature of this causal link thus far remains unclear. For instance, Fernandez-Perez et al. (2016) examined the contemporaneous interactions among energy (oil and ethanol)

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and agricultural commodities (corn, soybean, and wheat) in the United States using SVAR methodology. Their results indicated that crude oil has a unidirectional contemporaneous impact on the agricultural commodities. Saghaian (2010) analysed the cointegration relationships between crude oil and corn, soybean and wheat prices and the results indicated that causality running from oil prices to these agricultural commodity prices. Nazlioglu et al. (2013) examined volatility transmission between oil and selected agricultural commodity prices (wheat, corn, soybeans, and sugar). They found that there is no risk transmission between oil and agricultural commodity markets in the pre-crisis period, while oil market volatility spills on the agricultural markets, with the exception of sugar, in the post-crisis period. The manuscript of Alghalith (2010) analysed the impact of oil price uncertainties on food prices in Trinidad and Tobago and found that an increase in oil price and its volatility yields a higher food price. She asserted that higher risk in the oil market induces a higher food price, indicating that there exists a risk transfer mechanism between the two commodity markets. Similar results reported Lucotte (2016), who examined the dynamics of co-movements between crude oil and food pricesvia correlations of VAR forecast errors at different horizons (pre-commodity-boom (1990–2006) and a post-boom period (2007–2015). The results indicated strong positive co-movements between crude oil and food prices in the aftermath of the commodity boom, while no statistically significant co-movements are observed over the pre-boom period.

3. Methodology

3.1. Quantile regression approach

Complex dependence structure between oil and the agricultural commodities, which considers different market conditions, can be captured only by a more sophisticated tool than the linear regression. Therefore, we utilize a quantile regression approach by Koenker and Bassett (1978).According to Dybczak and Galuščák (2013), quantile function provides a more precise and accurate result when normality conjecture is severely violated and when data contain numerous outliers. In other words, this methodology is particularly useful when the dependence structure is constructed in some non-Gaussian settings. A good characteristic of QR is that it does not have a restrictive conjecture that the error terms are identically distributed at all points of the conditional distribution, which means that no parametric distributional form (e.g. Normal, Student, Poisson) needs to be assumed due to a semiparametric nature of quantile regression method.

Assuming that y is linearly dependent on x, then τ^{th} conditional quantile function of y is given in the following manner:

$$Q_y(\tau|x) = inf\{b|F_y(b|x) \geq \tau\} = \sum_k \beta_k(\tau)x_k = x'\beta(\tau), \quad (1)$$

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where b denotes an element of the conditional distribution function of y given x. $F_y(b|x)$denotes the conditional distribution function of y given x, while parameter $\beta(\tau)$ for $\tau \in (0,1)$defines the dependence relationship between vector x and the τ^{th} conditional quantile of y. x' represents $n \times 1$ vector, which contains constant and independent variable. This research endeavours to examine unidirectional spillover effect from oil returns towards selected agricultural returns, regarding τ^{th} quantile of the dependent variable distribution, whereby y stands for agricultural returns, while x portrays oil returns.

The coefficients β(τ) for a given τ are estimated by minimizing the following objective function, that is, the average of asymmetrically weighted absolute errors with weight φ on positive errors and weigh $(1-\varphi)$ on negative errors:

$$Min\frac{1}{T}\left[\varphi\sum_{y_t\geq x'\beta}|y_t - x'\beta(\tau)| + (1-\varphi)\sum_{y_t<x'\beta}|y_t - x'\beta(\tau)|\right] \quad (2)$$

Expression (2) implies the minimization of the sum of asymmetrically weighted absolute error terms, where positive and negative residuals are weighted differently depending on the quantile chosen.

3.2. Wavelet methodology

Wavelets are signal processing methodology that can decompose time series into their time-frequency components. Wavelets can ensure an appropriate trade-off between resolution in the time and frequency domains, unlike traditional Fourier analysis, which only stresses the frequency domain at the expense of the time domain (see Poměnková et al., 2019). Wavelet theory knows two basic wavelet functions: the father wavelet (ϕ)and the mother wavelet (ψ). More precisely, the father wavelets augment the representation of the smooth or low frequency parts of a signal with an integral equal to 1, whereas the mother wavelets can describe the details of high frequency components with an integral equal to 0. The long-term trend over the scale of the time series is portrayed by the father wavelet, while the mother wavelet delineates fluctuations in the trend. These functions can be expressed as in equation (3):

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(\frac{t-2^Jk}{2^J}\right), \qquad \psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^jk}{2^j}\right) \quad (3)$$

According to the expression (3), the scale or dilation factor is 2^j, whereas the translation or location parameter is 2^jk. As much as j grows, so does the dilation factor 2^j, which is a measure of the width of the functions $\phi_{J,k}(t)$and$\psi_{j,k}(t)$, and it affects the underlying functions to get shorter and more dilated. Besides, when j

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increases, the translation steps automatically get larger in order to accommodate the level of scale parameter 2^j.

The most commonly used wavelets are the orthogonal ones, and the approximation to a continuous signal series *y(t)*in$L^2(R)$is given as following:

$$y(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \quad (4)$$

where symbol J stands for the number of multi-resolution components or scales, and k ranges from 1 to the number of coefficients in the corresponding component.

For our research purposes, we utilize the maximum overlap discrete wavelet transformation (MODWT), which is based on a highly redundant non-orthogonal transformation. We employ multi resolution analysis with 6 levels of time scales using MODWT with Daubechies least asymmetric (LA) wavelet filter of length L= 8, which is also known as LA(8) wavelet filter. Chen and Lin (2016)argued that LA(8) wavelet filter has been widely used and applied in the financial literature because it has been shown that LA(8) provides the best performance for the wavelet time series decomposition.

3.3. Wavelet cross-correlation

Additionally, we use the wavelet cross-correlation to examine the lead–lag relationship on a scale-by-scale basis between the oil price and the selected agricultural commodities. Cross-correlation reveals which time series leading, and which one lagging across the wavelet scales. From the theoretical point of view, cross-correlation observes two time series, which are generated on the basis of a synchronous information flow. In that sense they would have a symmetric lagged correlation function, $\rho_\tau = \rho - \tau$, wherebythe symmetry is violated only by purely stochastic deviations, which are insignificantly small. When deviations between $\rho_\tau$and $\rho - \tau$ become significant, the asymmetry in the information flow takes place, whereby it can be concluded that the leading variable has predictive power on the lagging time variable. According to Chen and Lin (2016), the MODWT cross-correlation, for scale j and lag μ can be presented as follows:

$$\rho_{x,y,j,t,\tau} = \frac{COV(\hat{D}_{x,j,t},\hat{D}_{y,j,t+\mu})}{\left(Var(\hat{D}_{x,j,t})Var(\hat{D}_{y,j,t+\mu})\right)^{1/2}}, \quad (5)$$

where by cross-correlation takes value $-1 \leq \rho_{x,y}(\mu_j) \leq 1$.

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4. Dataset

This study considers the daily spot prices of OPEC[2] oil and spot price indices of the five major agricultural commodities – barley, corn, rice, soybean and wheat. We consider OPEC oil becauseOPEC produces about 40 percent of the world's crude oil, while OPEC's oil exports represent about 60 percent of the total petroleum traded internationally (see US Energy Information Administration). Spot prices of OPEC oil as well as of all the agricultural indices are transformed into log returns according to the expression:$r_{i,t} = 100 \times (P_{i,t}/P_{i,t-1})$. OPEC oil time-series is retrieved from quantl.com, while agricultural indices are collected from the International Grains Council website. Our data sample comprises the period from January 2003 to September 2018, which is permeated with numerous ups and downs in both oil and agricultural markets. All return series are synchronized according to the existing observations. In the quantile regression framework, we use wavelet decomposed series, where we observe six wavelet scales, which can provide an insight about the oil-agricultural nexus in different time horizons. These horizons correspond to: scale 1 (2-4 days), scale 2 (4-8 days), scale 3 (8-16 days), scale 4 (16-32 days), scale 5 (32-64 days) and scale 6 (64-128 days). First four scales are treated as the short-term dynamics, midterm is represented by fifth scale, while sixth scale correspond to the long-term. Descriptive statistics for row empirical series is presented in Table 1, while Figure 1 presents wavelet decomposed series of OPEC oil for six scales. Due to brevity, we only present wavelet details for OPEC oil in Figure 1, while plots of wavelet decomposed agricultural series can be obtained by request.

Descriptive statistics contains first four moments and Jarque-Bera test of normality. Table 1 suggests that all asset returns have positive mean, which means that their prices, on average, have growing trend. OPEC oil has the highest volatility, while soybean and corn follow. Skewness signs are mixed, whereby most of the returns for the OPEC oil, corn and soybean are left-skewed, while other assets are predominantly right-skewed. Kurtosis heavily exceeds the reference value of the normal distribution (equal to 3) for the all considered assets, whereas barley and soybean have extremely large kurtosis values. These findings indicate the presence of heavy tails compared to the Gaussian distribution.

[2]The OPEC Crude Oil Basket includes: Girassol (Angola), Saharan Blend (Algeria), Oriente (Ecuador), Basra Light (Iraq), Iran Heavy (Islamic Republic of Iran), Kuwait Export (Kuwait), Es Sider (Libya), Bonny Light (Nigeria), Arab Light (Saudi Arabia), Qatar Marine (Qatar), Murban (UAE) and Merey (Venezuela).

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Table 1. Descriptive statistics of returns for the selected commodities

	Mean	St. dev.	Skewness	Kurtosis	JB
OPEC oil	0.023	1.655	-0.059	6.963	2653
Barley	0.018	0.896	0.250	33.426	156299
Corn	0.010	1.380	-0.133	5.940	1470
Rice	0.019	0.527	1.216	72.432	814698
Soybean	0.008	1.442	-0.403	6.006	1635
Wheat	0.010	0.864	0.203	6.031	1578

Notes: JB stands for p-value of Jarque-Bera coefficients of normality.

Due to findings of extreme empirical values, wavelet-based quantile approach could bea suitable choice due to the following reasons. Firstly, the wavelet method successfully tackles extreme movements and numerous outliers in empirical signals (see e.g. Živkov et al, 2019b). Secondly, the quantile regression estimators are fairly robust to deviations from normality and it performs very well in the extreme value environment. This is the case because quantile functionsprovide information about the average dependence as well as the extreme tail dependence. Due to very high kurtosis values, JB test statistics discard normality hypothesis.

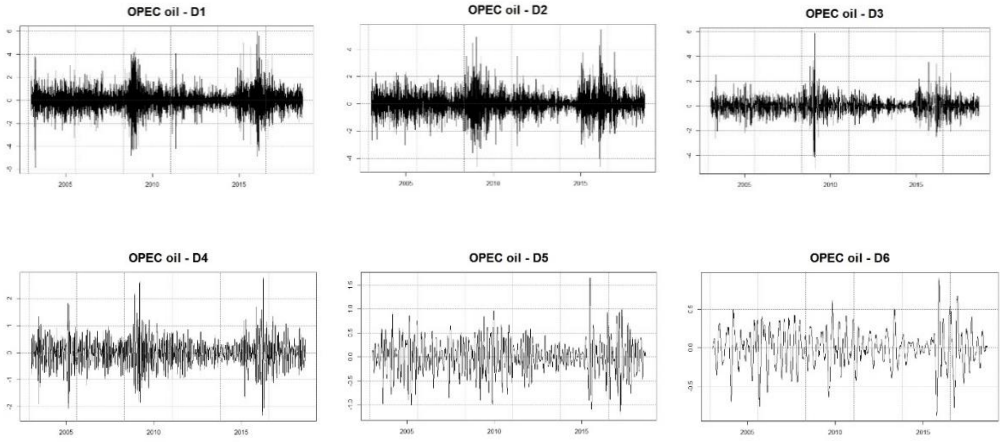

Figure 1. Wavelet details of OPEC oil returns

5. Empirical results

5.1. Results of wavelet-based quantiles

This section contains quantile regression results of spillover effect from OPEC oil to the five agricultural commodities, based on the wavelet decomposed series up to sixth scale. Table 2 presents QR results for the seven quantiles from 0.05 to 0.95.

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We report the presence of vast heterogeneity across all wavelet-based quantiles, which justifies the usage of this approach. Considering this methodology, we can estimate how oil price changes impact the selected agricultural commodities in various market conditions and in different time-horizons. These conditions are calm, normal and turbulent financial periods. Looking at Table 2, it is evident that vast majority of estimated parameters are positive and statistically significant across seven quantiles and six wavelet scales. It means that prices of oil and agricultural commodities follow common dynamics, i.e. when oil prices rise the same happens with the prices of agricultural commodities, and *vice-versa*. The only exception is oil vs. rice combination, in which most of the QR parameters are not statistically significant.

Also, the estimated QR parameters are relatively high, which indicates that they have an economic significance. More specifically, it is evident that tail quantiles are higher than median ones, regarding all oil-cereal pairs. Similar findings reported Shahzad et al. (2018), whocontended that spillover effect, which runs from crude oil to commodity markets, strongly intensifies itself during periods of financial turmoil or uncertainty. Hence, our results undoubtedly speak in favour that extreme dependence is present between oil and the selected grains. Another interesting finding is also the fact that QR parameters rise, more or less consistently, with an increase of wavelet scales across all selected pairs, except for oil-rise pair. This is an indication that oil has higher impact on agricultural commodities in the longer time-horizons, regardless of which market condition is in question.

As for the individual dependence structure between the selected pairs, it can be seen that all QR parameters in the case of oil-barley are highly statistically significant, and take values approximately between 5% and almost 30%, depending on scales and quantiles. The results indicate that the tail quantile parameters are relatively equable in short-term horizons, which suggests that changes in the oil price, affect the barley returns with almost the same force, in both crisis and prosperity periods. On the other hand, we find that right upper tail quantile parameters are significantly higher than its left counterparts in themed term and long-term. In the midterm, this difference amounts more that 10%, while in the long term it is more than 5%. Also, it is noticeable, that median, near-median and near-tail QR parameters are much lower, comparing to the both left and right tail quantile parameters. This occurrence repeats itself across all wavelet scales, whereas this discrepancy becomes more pronounced at higher wavelet scales. These findings send a clear message that in extreme market conditions, regardless of which type (downturn or upturn), the oil shocks affect the barley price changes with much more severity than in the moderate or relatively moderate market conditions, throughout all time-horizons.

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Table 2. Estimated QR parameters between oil and the agricultural commodities

Wavelet details	Quantile estimates						
	0.05-th	0.2-th	0.35-th	0.5-th	0.65-th	0.8-th	0.95-th
Panel A: OPEC oil → barley							
D1	0.1054***	0.0684***	0.0526***	0.0495***	0.0545***	0.0604***	0.1110***
D2	0.0940***	0.0492***	0.0489***	0.0471***	0.0481***	0.0582***	0.1046***
D3	0.0937***	0.0634***	0.0585***	0.0633***	0.0638***	0.0681***	0.0815***
D4	0.1371***	0.1131***	0.1037***	0.0832***	0.0907***	0.0889***	0.1446***
D5	0.1876***	0.1142***	0.1021***	0.1017***	0.1001***	0.1538***	0.2986***
D6	0.2264***	0.0799***	0.0479***	0.0545***	0.0540***	0.1392***	0.2749***
Panel B: OPEC oil → corn							
D1	0.1574***	0.0555***	0.0325*	0.0304**	0.0370***	0.0356	0.1256***
D2	0.1299***	0.1000***	0.0855***	0.0906***	0.1017***	0.1189***	0.1540***
D3	0.2130***	0.1314***	0.1043***	0.0965***	0.1077***	0.1218***	0.1764***
D4	0.1043***	0.1014***	0.0899***	0.0812***	0.0764***	0.0882***	0.1272***
D5	0.2399***	0.1121***	0.0985***	0.1029***	0.1269***	0.1549***	0.1957***
D6	0.1866***	0.1269***	0.1031***	0.0858***	0.0968***	0.1397***	0.2878***
Panel C: OPEC oil → rice							
D1	-0.0160	0.0052	0.0039	0.0031	0.0033	0.0031	0.0036
D2	-0.0122	0.0029	0.0036	0.0029	0.0020	0.0032	-0.0025
D3	0.0054	0.0060	0.0061**	0.0069***	0.0064**	0.0079***	-0.0046
D4	0.0149	0.0115***	0.0063*	0.0045	0.0098***	0.0171***	0.0015
D5	-0.0380***	-0.0215***	-0.0041	-0.0024	-0.0080*	-0.0116	-0.0127
D6	0.0983***	0.0188	0.0210***	0.0196***	0.0063	0.0380***	0.1344***
Panel D: OPEC oil → soybean							
D1	0.1248***	0.0354*	0.0433**	0.0518***	0.0569***	0.0662***	0.1026***
D2	0.1852***	0.1213***	0.1053***	0.1129***	0.1095***	0.1154***	0.1528***
D3	0.2003***	0.1745***	0.1373***	0.1519***	0.1632***	0.1880***	0.2135***
D4	0.2004***	0.1586***	0.1515***	0.1324***	0.1248***	0.1297***	0.1836***
D5	0.2004***	0.1586***	0.1515***	0.1324***	0.1248***	0.1297***	0.1836***
D6	0.1410***	0.1262***	0.1425***	0.0754***	0.0683***	0.1057***	0.2153***
Panel E: OPEC oil → wheat							
D1	0.0506***	0.0240**	0.0133	0.0041	0.0117	0.0228	0.0466***
D2	0.0758***	0.0367***	0.0489***	0.0479***	0.0533***	0.0592***	0.0993***
D3	0.1428***	0.0855***	0.0658***	0.0633***	0.0624***	0.0679***	0.1237***
D4	0.1479***	0.1169***	0.1033***	0.0960***	0.0907***	0.1124***	0.1606***
D5	0.0326***	0.0869***	0.0876***	0.0692***	0.0813***	0.0787***	0.1507***
D6	0.1074***	0.0231	0.0673***	0.0650***	0.0877***	0.0480**	0.0665*

All QR spillover parameters are highly statistically significant in the oil-corn case, and these parameters, in the most cases, are slightly higher in comparison with oil-barley counterpart. In this case, high QR parameters came to the fore at lower scales, i.e. scale D3, which depicts short range period (8-16 days). We find relatively

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high left tail parameter at this scale of 21% and 17.6% in the right tail. The midterm and long-term tail QR parameters are double the size than the median and near-median QR parameters, which is similar results, comparing with the previous cereal. However, one difference is that midterm left tail parameter is higher than the right one, which is not the case with barley. The midterm left tail parameter is higher than the long-term left tail parameter, which suggests that oil shocks has the greatest impact on corn in 32-64 days' time-horizon (24%) in periods when markets are under severe stress. On the other hand, oil shocks affect corn even stronger in the long-term horizon in the periods when markets booming, and that amounts 29%. Our results coincide with the findings of Elmarzougui and Larue (2013), who asserted that the ethanol boom strengthened the relation between corn and oil prices. They also argued that corn prices systematically respond to the oil price shocks.

The oil vs. rice pair is the only one in which statistically insignificant parameters dominates across all wavelet scales. It is a sign that the oil price changes have very little or no effect at all on the rice price. Shahzad et al. (2018) asserted that the dependence between oil and rice appears to co-move asymmetrically, unlike the dependence between oil and most of the agricultural commodities. This contention we confirm in some extent by finding negative statistically significant QR parameters in the left tail of the rice distribution in the fifth wavelet scale. Somewhat stronger spillover effect we report only at left and right tail at the sixth wavelet scale, whereby the oil impact on rice reaches 10% in crisis periods and 13.4% in periods of market prosperity.

The oil-soybean combination is overwhelmingly characterized by highly statistically significant quantile parameters, which have the highest value, comparing to QR parameters of all other pairs. For instance, the oil impact on soybean in extreme market conditions reaches 20% even at short-time horizons, and remains that strong throughout the midterm and the long-term horizons. Nazlioglu et al. (2013) stated that various global factors can be responsible for the short run volatility in the agricultural markets. They listed the risk in energy markets, but also the financial factors such as exchange rates, futures markets, speculation, and interest rates changes. Besides, it can be seen that the impact is also strong in the moderate market conditions, which is represented by the median QR parameters. These parameters are 15% in the third wavelet scale and 13% in the fourth and fifth wavelet scales, which is the highest level comparing to all other oil-cereal combinations. Mensi et al. (2014) explained that possible link between oil and cereals, particularly corn and soybean, can be found in increased production of biofuels since 2006, because bioethanol comes from corn while that of biodiesel is extracted from soybeans. Our finding coincides with this assertion, since corn quantile parameters are the second largest, right after soybean's parameters. Shahzad et al. (2018) also contended that the most bidirectional spillover

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effects occur between the oil and corn, and oil and soybean markets. The tail QR parameters are high in midterm and long-term horizons, and they go around 20%.

Spillover effects from oil towards wheat is moderate, regarding the median, near-median and near-tail quantile parameters.On the other hand, tail quantile parameters are significantly lower than barley, corn and soybean counterparts, while short-range median QR parameters range between 4.8-9.6%. Similar to the barley case, we find stronger right tail spillover effect than the left one, which indicates that this impact is stronger in periods of market boom than market bust.

5.2. Results of wavelet cross-correlation

In order to broaden our analysis in terms of interdependence between oil and the selected commodities as well as to add more credibility into the overall results, we calculate wavelet cross-correlations. This methodology can identify causality interlinks between the selected assets at different time-intervals.

Knowing which variable leads and which one lags is important for various market participants and investors which are interested in commodity market trading, since it shows how well two markets are connected and how one market reacts on information from the other market. If interlink exists between two markets then traders and investors may use the past information from a leading variable to forecast future dynamics of a legging one.

Wavelet cross-correlation function gauges the similarity of two waveforms and a function of a time-lag applied to one of them. We consider 36daily lags between observed and fitted values from the same linear combination at each of the wavelet scales. In such way, we can examine whether there exists any pulling effect between the OPEC oil and the selected cereals at contrasting time lags. Table 3 gives exact cross-correlation values, while Figure 2 presents wavelet cross-correlation plots.

These results can be interpreted in the following way. Since OPEC oil is the first variable in the computation process, and all grains are the second ones, then the left side of the plots presents lagged correlation for oil, while the right one stands for the agricultural commodities. If cross-correlation curve is skewed significantly in the left side of the graph, then it implies that first time-series is leading the second time-series, and *vice-versa*. If both the 95% confidence levels are above the horizontal axes, it is considered as a significant positive wavelet cross-correlation. Conversely, if the both 95% confidence levels are below the horizontal axes, it is considered as a significant negative wavelet cross-correlation.

Our results show that the cross-correlation coefficients for the all selected pairs moves around zero in first two wavelet scales, which depicts very short time-horizons. It means that in very short time there is no lead-lag effect between the assets. This is expected and coincides with the findings of other researchers, who also

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reported zero cross-correlation in low frequency levels (see e.g. Tiwari et al, 2013). However, in the higher scales, starting from the scale D3, it can be seen that the cross-correlation parameters are significantly higher in one side, considering lower lag level (lag ±5).

Table 3. Wavelet cross-correlations between OPEC oil and the selected cereals

		Negative lagged correlations				Positive lagged correlations			
		-20	-15	-10	-5	5	10	15	20
Oil vs barley	D1	0.017	0.001	0.006	0.015	0.013	0.020	0.003	0.022
	D2	0.002	0.018	0.048	0.022	0.002	-0.001	-0.012	0.033
	D3	-0.016	0.014	-0.014	-0.057	-0.108	0.015	0.005	0.006
	D4	-0.005	-0.081	-0.136	0.088	-0.059	-0.131	0.045	0.035
	D5	-0.162	-0.165	-0.036	0.136	0.172	0.035	-0.098	-0.153
	D6	0.049	0.088	0.131	0.166	0.147	0.110	0.075	0.032
Oil vs corn	D1	0.004	-0.038	0.013	-0.001	-0.008	0.032	-0.005	-0.003
	D2	-0.004	-0.035	-0.015	-0.021	0.013	0.006	0.012	0.051
	D3	-0.033	0.007	0.038	-0.137	-0.101	-0.004	0.020	0.010
	D4	-0.024	0.046	-0.066	-0.107	0.078	-0.040	-0.005	-0.080
	D5	-0.131	-0.163	-0.087	0.044	0.190	0.103	-0.035	-0.101
	D6	-0.106	-0.040	0.033	0.102	0.218	0.220	0.188	0.131
Oil vs rice	D1	0.009	-0.042	-0.017	0.011	-0.048	-0.012	-0.020	0.009
	D2	0.016	-0.045	-0.007	-0.003	-0.024	0.015	0.009	0.009
	D3	0.005	0.000	-0.002	-0.012	-0.030	-0.005	0.039	-0.054
	D4	0.055	0.027	-0.027	0.005	-0.048	-0.029	0.022	-0.013
	D5	0.075	0.132	0.119	0.052	-0.083	-0.090	-0.052	-0.011
	D6	0.129	0.135	0.121	0.091	0.008	-0.037	-0.066	-0.077
Oil vs soybean	D1	-0.011	0.018	0.024	0.004	-0.019	0.034	-0.016	-0.011
	D2	0.015	-0.010	-0.009	-0.013	-0.042	-0.006	0.009	0.015
	D3	0.012	0.011	0.031	-0.137	-0.161	0.002	0.039	0.012
	D4	-0.013	-0.014	-0.105	-0.035	0.038	-0.142	0.015	-0.013
	D5	-0.158	-0.248	-0.078	0.134	0.233	0.080	-0.089	-0.158
	D6	0.111	-0.052	0.028	0.115	0.222	0.213	0.176	0.111
Oil vs wheat	D1	0.004	-0.016	0.010	-0.020	0.003	0.031	-0.009	-0.027
	D2	-0.012	0.009	0.015	0.003	-0.015	0.013	-0.002	0.008
	D3	-0.023	0.034	-0.014	-0.098	-0.118	0.033	-0.001	-0.018
	D4	0.063	0.005	-0.198	-0.078	0.082	-0.075	-0.036	-0.020
	D5	-0.088	-0.217	-0.197	-0.042	0.224	0.155	0.003	-0.104
	D6	-0.014	-0.001	0.014	0.043	0.094	0.090	0.078	0.062

For instance, barley leads oil in the third and fifth wavelet scales, while situation is reversed in the fourth and sixth scales. Lead-lag dependencies are not so obvious for the oil-rice case in all frequency scales, since the cross-correlation

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parameters predominantly oscillates around zero. It is interesting to note that, for the cases oil-corn and oil-soybean in midterm and long-term, right cross-correlation parameters are twice as big as the left ones, which strongly suggests that these cereals lead oil in the longer time horizons. These results concur with the assertion of Mensi et al. (2014), who claimed that probable reason for the relatively strong nexus between oil, corn and soybean lies in a fact that these cereals have been used increasingly in a production of biofuels since 2006. Also, Fernandez-Perez et al. (2016) claimed that corn and soybean have a greater impact on ethanol than the other way around. As for the oil-wheat case, we find strong leading role of wheat at lag 5, which is particularly conspicuous in midterm.

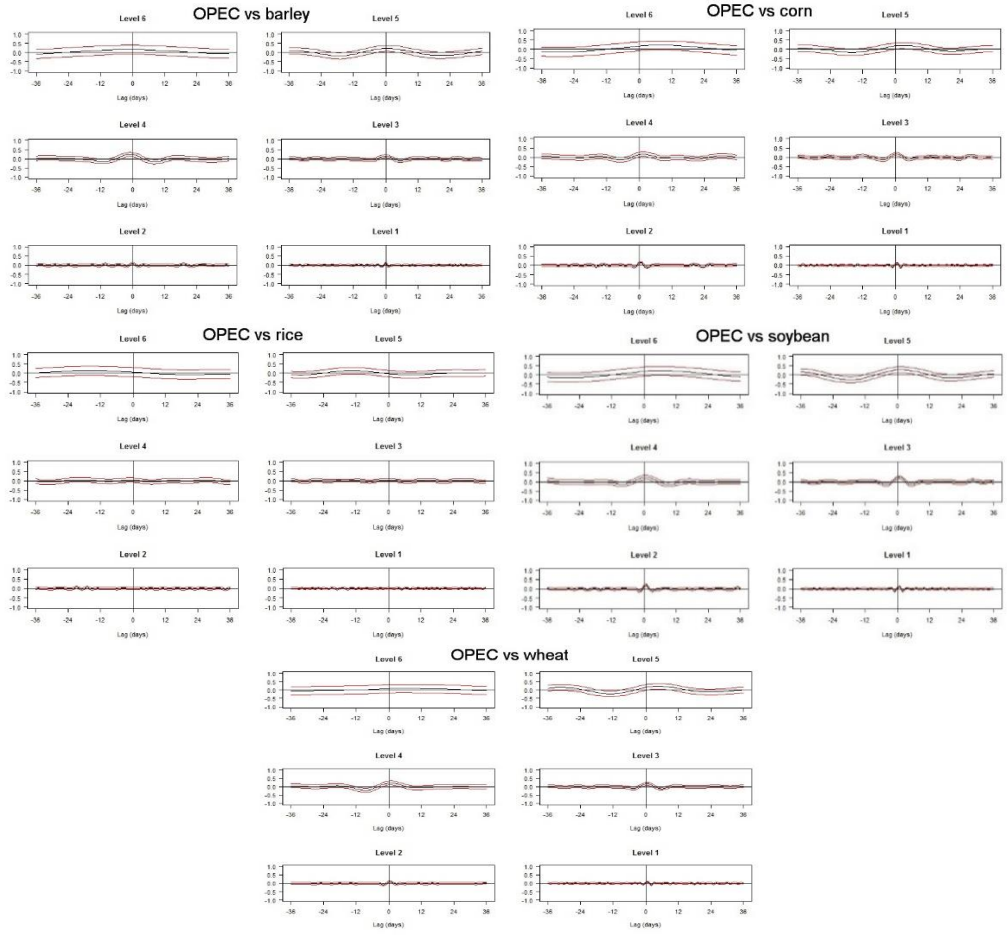

Figure 2. Wavelet cross-correlation plots

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6. Conclusion

This paper tries to uncover how oil price changes affect the five major agricultural commodities (barley, corn, rice, soybean and wheat)in different market conditions and in different time-horizons. For this task, we combine quantile regression approach with the wavelet signal-decomposing methodology.

The obtained results suggest a complex interdependence between oil and the cereals. More specifically, we find strong transmission effect only in tail quantiles in longer time-horizons, which is particularly true for barley, corn and soybean. It means that these agricultural commodities are affected by oil in periods of increased market turbulence, regardless of whether it is characterized by the rising or falling prices of these commodities. For instance, barley and corn are affected more by oil in periods of rising agricultural prices, and this impact reaches almost 30% in the long-term horizon. For the soybean case, this impact is also the strongest in tail quantiles, but it is not so intense because it goes around 20%.However, in the soybean case, relatively strong spillover effect occurs in shorter time-horizon (between 8-16 days), which is much earlier than for barley and corn counterparts. Due to the findings of relatively significant spillover effect in the tail quantiles for three out of five agricultural commodities, it could signal to a herd behavior. Sari et al. (2012) asserted that grains are largely favored by risk averse investors, thus it is possible that risk-averse investors feel a sense of security in following the crowd, which causes the herd behavior in grains and produce extreme movements in the tails of the grains' distributions.

Wavelet cross-correlation results provide strong evidence that corn and soybean lead oil in midterm and long-term horizons. For these results, followed by the strong spillover effect, a rational explanation could be found in an increased biofuel production in recent years. Namely, corn and soybean enter as raw materials in a biofuels production, and this production was largely supported primarily by major policy changes in the United States and the European Union during the 2000s (see Lucotte, 2016). Therefore, corn and soybean are intrinsically and deeply intertwined with oil, and this nexus will grow even stronger as oil and grain markets become more unstable and volatile.

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