



## **Does Agricultural Commodity Price Co-move with Oil Price in the Time-Frequency Space? Evidence from the Republic of Korea**

**Xiangcai Meng\***

Solbridge International School of Business, Woosong University, Uam-ro 128 (Samsung-dong), Dong-gu, Daejeon, 34613, Republic of Korea. \*Email: [xiangcaimeng@solbridge.ac.kr](mailto:xiangcaimeng@solbridge.ac.kr)

### **ABSTRACT**

As the strategies and behaviors of oil and agricultural market participants change across frequencies and over time, this paper extends the literature on the associations between oil and agricultural commodity price fluctuations from the time domain to the time-frequency sphere with the continuous wavelet approach and quarterly data from the Republic of Korea. Our results reveal strong volatilities of oil price at high frequencies from early 1970s to late 2010s, and its interactions with farming product prices indeed vary in the time-frequency space. In particular, grain price strongly co-moves with oil price with in-phase patterns at high frequencies from 1970 to 1985 and at low frequencies from 1986 to 2000, respectively, and it leads oil price after 1985. Moreover, vegetable price exhibits high common power with oil price with in-phase patterns across frequencies from 1960 to 1995, it is led by oil price at low frequencies in our sample. Our analysis implies that considering the time-frequency dynamics of oil and farming product prices is important for market participants and investors to optimally diversify their portfolios and manage the associated risks.

**Keywords:** Crude Oil, Agricultural Commodity, GARCH Model, Wavelet Power Spectrum, Squared Wavelet Coherence, Phase Difference

**JEL Classifications:** C63, E31, Q11, Q18, Q43

### **1. INTRODUCTION**

The significant surge in agricultural commodity prices from 2006 to 2008 and its subsequent dramatic collapse have ignited lots of studies to examine the determinants of commodity price fluctuations in the agricultural sector, among many factors, crude oil price is considered as one of the most important elements in affecting agricultural price variations (Pal and Mitra, 2017; Ahmadi et al., 2016; Fowowe, 2016; Abbott et al., 2008; 2009). Because rising oil price resulted from increasing economics activities usually boosts the demand for food and hence the prices of many agricultural commodities (Baumeister and Kilian, 2014; Hochman et al., 2012). Moreover, increasing oil price drives up the demand for biofuels, leading a positive shift in the prices of corn, soybeans and other agricultural products (Rafiq and Bloch, 2016; Natanelov et al., 2011). In addition, higher oil price raises the agricultural production costs and hence the prices of farming products (Zhang and Qu, 2015; Tyner, 2010).

As oil and agricultural market participants have different objectives over time and behave heterogeneously across frequencies, the

relationships between oil price and agricultural commodity price would be quite different in the time-frequency space. However, most of existing empirical studies only evaluated their interactions in the time space (e.g., Wang et al., 2014; Nazlioglu and Soytaş, 2012; 2011; Chen et al., 2010; Mutuc et al., 2010; Farzanegan and Markwardt, 2009), and the frequency dimension is completely ignored, which is a big gap in the literature, as understanding their time-frequency-wise interactions is of great importance for market participants to optimally diversify their portfolios and governments to choose the appropriate timing, magnitudes, and frequencies of policy interventions.

The main target of this paper is to empirically investigate the dynamic relationships between oil price changes and agricultural commodity price fluctuations in the time-frequency space. In particular, we ask the following questions: What are the volatility features of oil price across frequencies and over time? How would their local correlations and lead-lag relationships vary in the time-frequency space? How about their phase patterns? We employ the continuous wavelet coherence approach with a quarterly dataset from the Republic of Korea, which is one of the world's leading

energy importers<sup>1</sup> and about 98% of its fossil fuel consumptions is relied on imports, to address these issues.

The estimated GARCH model shows high persistency in the conditional volatilities of crude oil price, while the wavelet power spectrum reveals strong power of crude oil price mainly at high frequencies after 1970. Moreover, the wavelet coherence analysis exhibits several interesting results. First, grain price strongly co-moves with oil price with in-phase patterns at high frequencies from 1970 to 1985 and at low frequencies from 1985 to 2000, respectively, and it is led by oil price before 1985 but not after. Second, vegetable price has high common power with oil price with in-phase patterns at high frequencies from 1970 to 1990 and at low frequencies from 1975 to 1995, respectively, and it is oil price that leads vegetable price at low frequencies. Third, the price of special crops strongly co-moves with oil price at high frequencies with anti-phase patterns around 1990 and at low frequencies with in-phase patterns from 1975 to 2009, and oil price always leads special crops price. In addition, other farming product prices also exhibit high common power with oil price across frequencies with heterogeneous lead-lag relationships and mixed-phase patterns.

This study contributes to the existing literature from three different perspectives. First, this is the first paper that analyzes the dynamic interactions between oil price changes and agricultural commodity price fluctuations in the time-frequency space, which not only unveils some new facts, but also bridges the gap in the literature. Second, different from previous studies focusing on the effects of oil price on the aggregate economy or the whole industry, this paper concentrates on six categories of specific agricultural commodities in the Republic of Korea: Grain, vegetable, fruit, live products, special crops, and secondary product. Third, we employ the continuous wavelet approach rather than the traditional vector autoregression (VAR) model or impulse response analysis to examine the heterogeneous interactions between oil and agricultural commodity price interactions across frequencies and over time.

The remainder of this paper is organized as follows. Section 2 briefly reviews the literature. Section 3 describes the wavelet methodology. Section 4 presents the data and conducts preliminary analysis. Section 5 discusses the empirical results. Section 6 concludes the paper and discusses the policy implications.

## 2. LITERATURE REVIEW

As one of the most important raw materials and fundamental energies, oil is of great importance to production and its price changes affect almost all aspects of the economy (He et al., 2012). The existing literature on the characters of oil price changes could be classified into four categories in general.

The first category of investigation examines the effects of oil price shocks on the aggregate economy (e.g., Nusair, 2016; Allegret

et al., 2014; Cavalcanti and Jalles, 2013; Ou et al., 2012; Iwayemi and Fowowe, 2011; Aydin and Acar, 2011; Tang et al., 2010; Rafiq et al., 2009; Hamilton, 2005; Uri, 1996), these studies show that surging oil prices usually reduce output, increase unemployment, and lead to higher inflation volatilities, however, the magnitudes of these effects change with the economies and sample periods under consideration.

The second stream of literature investigates the effects of oil price changes on energy industries. Reboredo et al. (2017) find that the dependence between oil and renewable energy returns increases from the short run to the long run from 2006 to 2015. Moreover, significant and positive associations between oil price and gas sector were found by Scholtens and Yurtsever (2012) and Panagiotidis and Rutledge (2007), but Ewing et al. (2002) showed that gas sector was only indirectly affected by oil sector, while oil sector is both directly and indirectly affected by gas sector. In addition, Mohammadi (2009) and El-Sharif et al. (2005) demonstrate that the long-term associations between oil sector and other energy sectors are fairly weak in the US and UK, respectively.

The third class of research studies the impact of oil price changes on metal industries (e.g., Reboredo and Ugolini, 2016; Wang and Chueh, 2013; Nazlioglu, 2011; Nazlioglu and Soytas, 2011). Some of these studies find that oil price increases are positively associated with the prices of industrial metals (Wang and Chueh, 2013; Hammoudeh and Yuan, 2008; Narayan et al., 2008), while other investigations show that oil price has no effect on precious metal prices (Soytas et al., 2009), and no consensus has been achieved.

The fourth group of study examines the interactions between oil price changes and agricultural commodity markets. Within a structural VAR framework, Ahmadi et al. (2016) show that oil price shocks indeed affect agricultural market volatilities and different products respond heterogeneously depending on the nature of shocks. Zhang and Qu (2015) find that mature agricultural future markets display co-movements with crude oil in the long run, and government intervention affects their interactions through employing ARMA and ARJI-GARCH models. Moreover, some studies show that oil price affects the fluctuations of corn, soybean, and cotton markets (e.g., Nazlioglu, 2011; Mutuc et al., 2010) and the effects of oil price changes vary across economies and over time (e.g., Ji and Fan, 2016; Liu, 2014; Wang et al., 2014; Nazlioglu, 2011; Nazlioglu and Soytas, 2011; Tyner, 2008). One common feature of this literature is that they only investigated the effects of oil price changes over time without considering the frequency dimension, thus little is known about the impact of oil price fluctuations across frequencies and over time.

Last but not the least, to the best of our knowledge, only one paper (Pal and Mitra, 2017) examines the associations between oil and food prices in the time-frequency space with wavelet analysis, but our paper differs from it in three aspects. First, the focus of Pal and Mitra (2017) is to study the interactions between oil and world food prices, whereas our target is to characterize the relationships between oil and agricultural commodity prices across frequencies and over time. Second, rather than employing overall world food

<sup>1</sup> The Republic of Korea was ranked as the 4<sup>th</sup> largest oil importing country according to the total amount of crude oil imported in barrels per day in 2015, and the 9<sup>th</sup> largest energy consumer in 2015 according to the BP Statistical Review of World Energy 2016.

indexes, our paper employs more concrete price measures for six different categories of agricultural products: Grain, vegetables, fruits, live products, special crops, and secondary product. Third, instead of discussing the general impact of oil price on world food market, we concentrate on a investigating the roles of oil price fluctuations in the agricultural markets of a specific country, i.e., the Republic of Korea.

### 3. EMPIRICAL METHODOLOGY

Fourier analysis could examine the cyclical nature of a stationary time series in the frequency domain, but it is hard to study transient relations and to identify structural changes (Aguar-Conraria and Soares, 2011). Wavelet analysis overcomes these limitations and could investigate the statistical properties of non-stationary time series (Fan and Gençay, 2010; Gençay et al., 2002; Ramsey, 2002; Percival and Walden, 2000).

A family of wavelet functions  $\varphi_{s,\tau}(t)$  can be obtained by scaling and translating a mother wavelet  $\varphi$

$$\varphi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \varphi\left(\frac{t-\tau}{s}\right), s, \tau \in \mathbb{R}, s \neq 0 \tag{1}$$

Where  $\tau$  is a translation parameter defining the centered location,  $s$  is a dilation factor determining the length, and  $1/\sqrt{s}$  preserves unit energy, i.e.,  $\|\varphi_{s,\tau}\|^2=1$ . The minimum requirement for a square integrable function  $\varphi(t)$  to be a mother wavelet is to fulfill the admissibility condition (Percival and Walden, 2000; Bruce and Gao, 1996; Gençay et al., 2002);

$$C_\varphi = \int_0^\infty \frac{|\phi(f)|^2}{f} df < \infty \tag{2}$$

Where  $\phi(f)$  is the Fourier transform of  $\varphi(t)$  (Daubechies, 1992), implying that  $\int_{-\infty}^{+\infty} \varphi(t) dt = 0$  and  $\int_{-\infty}^{+\infty} \varphi^2(t) dt = 1$ .

As in Goupillaud et al. (1984), a complex wavelet, delivering a complex transform with information on both amplitude and phase, is specified as:

$$\varphi^M(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{t^2}{2}} \tag{3}$$

Where  $\omega_0$  indicates the central frequency and is set to six to provide a balance between time and frequency (Grinsted et al., 2004; Aguilar-Conraria et al., 2008; Rua and Nunes, 2009).

The continuous wavelet transform (CWT) of a time series  $x(t)$  with respect to  $\varphi$  is a function  $W_x(s,\tau)$  derived from projecting  $x(t)$  onto the family  $\{\varphi_{s,\tau}\}$ ,

$$W_x(s,\tau) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{s}} \varphi^*\left(\frac{t-\tau}{s}\right) dt \tag{4}$$

and the admissibility condition allows us to recover the raw time series  $x(t)$  from its CWT,

$$x(t) = \frac{1}{C_\varphi} \int_0^\infty \left[ \int_{-\infty}^{+\infty} W_x(s,\tau) \varphi_{\tau,s}(t) d\tau \frac{ds}{s^2} \right] \tag{5}$$

Where  $s>0$ . Moreover, the energy of the raw time series is preserved,

$$\|x\|^2 = \frac{1}{C_\varphi} \int_0^\infty \left[ \int_{-\infty}^{+\infty} |W_x(s,\tau)|^2 \right] \frac{d\tau ds}{s^2} \tag{6}$$

and a Parseval type identity is maintained,

$$\langle x, y \rangle = \frac{1}{C_\varphi} \int_{-\infty}^{+\infty} \left[ W_x(s,\tau) W_y^*(s,\tau) \right] \frac{d\tau ds}{s^2} \tag{7}$$

Where  $\langle x, y \rangle \in L^2(\mathbb{R})$ ,  $L^2(\mathbb{R})$  is the set of square integrable functions,  $\langle x, y \rangle = \int_{-\infty}^{+\infty} x(t) y^*(t) dt$  is the inner product of  $x(t)$  and  $y(t)$ .

As in Hudgins et al. (1993) and Torrence and Compo (1998), the cross wavelet transform of two different time series  $x(t)$  and  $y(t)$  is

$$W_{xy}(s,\tau) = W_x(s,\tau) W_y^*(s,\tau) \tag{8}$$

Where  $W_x(s,\tau)$  and  $W_y(s,\tau)$  indicate the CWT of  $x(t)$  and  $y(t)$ , respectively, while the superscript \* indicates a complex conjugate. The cross wavelet power is defined as  $|W_{xy}(s,\tau)|$ , measuring the local covariance of the two time series at each frequency.

The wavelet coherence is measured by the ratio of the cross spectrum to the product of the individual spectrum of each series,

$$R^2(s,\tau) = \frac{\left| S\left(s^{-1} W_{xy}(s,\tau)\right) \right|^2}{S\left(s^{-1} |W_x(s,\tau)|^2\right) S\left(s^{-1} |W_y(s,\tau)|^2\right)} \tag{9}$$

Where  $R^2(s,\tau) \in [0,1]$ , measuring the local correlation in the time-frequency space, higher  $R^2(s,\tau)$  indicates strong correlation (Torrence and Webster, 1999).  $S$  denotes a smoothing parameter in both time and scale and is,

$$S(W) = S_s(S_\tau(W(s,\tau))) \tag{10}$$

Where  $S_s$  and  $S_\tau$  indicate smoothing in scale and time, respectively. Moreover, the phase difference, indicating the delays of the oscillations between the two time series, is,

$$\chi_{xy}(s,\tau) = \tan^{-1} \left( \frac{\Im \left\{ S \left[ s^{-1} W_{xy}(s,\tau) \right] \right\}}{\Re \left\{ S \left[ s^{-1} W_{xy}(s,\tau) \right] \right\}} \right) \tag{11}$$

Where  $\Im$  and  $\Re$  are the imaginary and real parts of the smoothed crossspectrum (Torrence and Webster, 1999), respectively. A zero phase difference indicates that two time series move together at the specified time-frequency. If  $\chi_{xy} \in (0,\pi/2)$ ,  $x(t)$  and  $y(t)$  are positively correlated while  $y(t)$  leads  $x(t)$ . If  $\chi_{xy} \in (-\pi/2,0)$ ,  $x(t)$  and  $y(t)$  are anti-phase while  $x(t)$  is leading. In addition,  $x(t)$  is leading if  $\chi_{xy} \in (\pi/2,\pi)$ , while  $y(t)$  is leading if  $\rho_{xy} \in (-\pi, -\pi/2)$ .

## 4. DATA

The oil price is measured by the spot crude oil price of west texas intermediate, which is extracted from the Federal Reserve Bank of St. Louis (FRED). As in Zhang and Qu (2015), we choose six categories of agricultural commodities including grain (GRAN), vegetables (VEGT), fruits (FRUT), live products (LIVT), special crops (SPCR), and secondary product (SEDP), the price indexes of these commodities are extracted from the statistical database of Korea Statistical Information Service (KOSIS), and the sample period is from Quarter 01, 1959 to Quarter 04, 2012, which is chosen because of data availability.

To investigate the dynamic relationships between oil price changes and agricultural commodity price fluctuations across frequencies and over time, the growth rates relevant time series are calculated based on the seasonally adjusted data. The summary statistics of the calculated series are reported in Table 1, where we observe that the standard deviation of oil price is the largest, indicating that it experienced the most turbulent variations. Except the fruit price, oil and the other commodity prices all exhibit positive skewness. Moreover, the high values of Kurtosis indicate that the distributions of all time series have sharp peaks and fat tails. In addition, the Jarque-Bera statistics show that the normal assumption is rejected for all time series except fruit price at the 1% significance level.

As all variables under consideration are subject to structural changes in our sample period, these series could not be analyzed directly before considering their unit root properties (Fang and You, 2014). We employ break point unit root test to examine their stationarity, and the results are reported in Table 2. The null hypothesis of having a unit root could be rejected for all the

series involved at the 1% significance level, implying that these time series are all stationary after correcting for structural breaks. Moreover, Table 3a and Table 3b report the results of Johansen test, where we find that crude oil price and these agricultural commodity prices are all difference stationary, and no evidence of cointegration is detected.

Before conducting the wavelet analysis, it is important to examine the volatility properties of crude oil prices, we employ the GARCH type of modeling to address this issue. Table 4 presents the results of estimated GARCH parameters and ARCH errors at all predetermined lags. The autoregressive GARCH components show a high level of persistence in the conditional volatilities of crude oil price, indicating that once oil price uncertainty is augmented, it will not recede quickly, and all AR components are significant up to lag 2. After examining the unit root, cointegration, and volatility properties in the pure time domain, we proceed to assess their co-movements in the time-frequency sphere.

## 5. EMPIRICAL RESULTS

To characterize the dynamic interactions between oil price changes and agricultural commodity price fluctuations across frequencies and over time, we proceed to analyze the empirical results of continuous wavelet analysis in this section.

### 5.1. The Wavelet Transform

The wavelet power spectrums of oil and six agricultural commodity price changes are exhibited in Figure 1, where the horizontal and vertical axes indicate time and frequency, respectively. The yellow regions represent where the time series under consideration

**Table 1: Descriptive statistics of the variables**

Statistic	OILP	GRAN	VEGT	FRUT	LIVT	SPCR	SEDP
Mean	2.3814	2.6680	3.3077	2.8426	2.6497	2.5462	2.2897
Median	0.5601	1.6667	2.7027	3.5124	0.8667	1.1940	0.4193
Maxim.	128.45	61.111	87.179	36.842	25.000	50.000	30.986
Minim.	-47.943	-31.034	-30.431	-30.891	-12.295	-26.667	-19.502
Std. Dev.	13.708	8.0414	8.0414	13.056	6.3437	6.4276	5.9970
Skewn.	3.5625	1.6093	1.6093	-0.2857	0.9281	2.0993	1.1608
Kurtos.	36.559	17.267	17.267	3.3273	3.9238	18.529	9.5028
Jarq. Ber.	10543	1916.2	197.28	3.8854	38.511	2318.3	427.09

Notes: (1) OILP indicates the spot crude oil price, west texas intermediate (WTI); (2) GRAN represents grains; (3) VEGT and FRUT indicate vegetables and fruits, respectively; (4) LIVT and SPCR indicate live products and special crops, respectively; (6) SEDP indicates secondary product; (5) These statistics are calculated using the sample period from Quarter 01, 1959 to Quarter 04, 2012

**Table 2: The breakpoint unit root test**

Variable	Trend specification	Critical value**	t-statistic	Probability*
OILP	(II, II)	-4.4436	-15.876	<0.01
GRAN	(II, II)	-4.4436	-5.2776	<0.01
VEGT	(II, II)	-4.4436	-14.457	<0.01
FRUT	(II, II)	-4.4436	-15.694	<0.01
LIVT	(II, II)	-4.4436	-12.315	<0.01
SPCR	(II, II)	-4.4436	-14.876	<0.01
SEDP	(II, II)	-4.4436	-15.888	<0.01

Notes: (1) The null hypothesis under the Breakpoint unit root test is: The time series under consideration has a unit root; (2) The "Break Type" is specified as "Innovation Outlier;" (3) In "Trend Specification," the first "II" indicates that "Basic" is specified as "Intercept only," while the second "II" indicates that "Breaking" is specified as "Intercept only;" (4) The "Breakpoint selection" is specified as "Dickey-Fuller min-t;" (5) For "Lag length," the method is "Schwarz criterion" and "Max. lags" is 14; (6) \*\* indicates the test critical values at the 5% level; (7) \* is the Vogelsang (1993) asymptotic one-sided P values

**Table 3a: The rank test (trace)**

Hypoth. Num. of CEs	Engienvalue	Trace statistic	Critical value	Probability**
OILP and GRAN				
None*	0.2229	78.069	15.495	0.0000
At most 1*	0.1127	25.118	3.8415	0.0000
OILP and VEGT				
None*	0.2325	105.31	15.495	0.0001
At most 1*	0.2110	49.757	3.8415	0.0000
OILP and FRUT				
None*	0.2158	101.24	15.495	0.0001
At most 1*	0.2126	50.197	3.8415	0.0000
OILP and LIVT				
None*	0.2233	74.011	15.495	0.0000
At most 1*	0.0949	20.949	3.8415	0.0000
OILP and SPCR				
None*	0.2238	78.997	15.495	0.0000
At most 1*	0.1156	25.806	3.8415	0.0000
OILP and SEDP				
None*	0.2268	78.554	15.495	0.0000
At most 1*	0.1102	24.527	3.8415	0.0000

Notes: (1) In testing, a linear trend is included, and the lag interval included is 1–4; (2) The trace test indicates 2 cointegrating equations at the 0.05 level; (3) \* denotes rejection of the hypothesis at the 0.05 level; (4) \*\*MacKinnon-Haug-Michelis (1999) P values

**Table 3b: The rank test (maximum eigenvalue)**

Hypo. Num. of CEs	Engienvalue	Maxi.-Eige stat	Critical value	Probability**
OILP and GRAN				
None*	0.2229	52.950	14.265	0.0000
At most 1*	0.1127	25.118	3.8415	0.0000
OILP and VEGT				
None*	0.2325	55.556	14.265	0.0000
At most 1*	0.2110	49.757	3.8415	0.0000
OILP and FRUT				
None*	0.2158	51.046	14.265	0.0000
At most 1*	0.2126	50.197	3.8415	0.0000
OILP and LIVT				
None*	0.2233	53.062	14.265	0.0000
At most 1*	0.0949	20.949	3.8415	0.0000
OILP and SPCR				
None*	0.2238	53.189	14.265	0.0000
At most 1*	0.1156	25.808	3.8415	0.0000
OILP and SEDP				
None*	0.2268	54.027	14.265	0.0000
At most 1*	0.1102	24.527	3.8415	0.0000

Notes: (1) In testing, a linear deterministic trend is included, and the lags interval included is 1–4; (2) The maximum-eigenvalue test indicates 2 cointegrating equations at the 0.05 level; (3) \*denotes rejection of the hypothesis at the 0.05 level; (4) \*\*MacKinnon-Haug-Michelis (1999) P values

exhibit strong variations, and the thick black contour refers to the five percent significance level estimated from the Monte Carlo simulations.

Several interesting facts are revealed from the time-frequency decompositions of crude oil price and agricultural commodity prices. First, Figure 1a shows that the volatilities of OILP are very high at the timescale of 1–24 quarters around early 1970s, late 1980s, mid 1990s, and late 2010s, respectively. Second, Figure 1b and Figure 1c demonstrate that the variations of GRAN and VEGT are very high at the timescale of 1–20 quarters before early 1970s and mid 1980s, respectively. Third, FRUT exhibits high power mainly at the timescale of 2–16 quarters in the sample period as shown in Figure 1d, while LIVT shows strong variations across different frequencies before 2000 as Figure 1e shows. Fourth, Figure 1f demonstrates that SPCR has high power at high frequencies from 1959 to 1966 and at low frequencies from 1970

to 1981, respectively. Fifth, Figure 1g shows that SEDP exhibits strong 42 variations at the timescale of 1–12 quarters before 1985 and after 43 2000, respectively.

The analysis of wavelet power spectrums could not provide any guidance on the dynamic interactions between oil price and agricultural commodity prices in the time-frequency space, therefore, we turn to the wavelet coherence analysis to understand their co-movements and lead-lag relationships in the next section.

## 5.2. The Wavelet Coherence

The estimation results of wavelet coherence on the relationships between oil and agricultural commodity price changes are exhibited in Figure 2, where the yellow regions indicate the two variables under consideration exhibit strong co-movements, and the thick black contour is the five percent significance level estimated from Monte Carlo simulation.

The time-frequency dynamics between oil and grain price changes are illustrated in Figure 2a, where we observe that GRAN strongly co-moves with OILP with in-phase patterns at the timescale of 4–24 quarters from 1970 to 1985 as well as at the timescale of over 32 quarters from 1985 to 2000, respectively. Moreover, OILP leads GRAN before 1985, but it is GRAN that leads OILP after 1985. This result is consistent to the findings of Liu (2014) and Vacha et al. (2013), who showed high correlation between

oil and wheat prices. Figure 2b shows the interactions between oil and vegetable price fluctuations across frequencies and over time, where we observe that VEGT exhibits high common power with OILP with in-phase patterns at the timescale of 1–10 quarters from late 1960s to late 1980s as well as at the timescale of over 48 quarters from 1975 to 1995, respectively. In addition, OILP leads VEGT at low frequencies over time and at high frequencies before 1985, but it is VEGT that leads OILP at high frequencies after 1985, and this finding conforms to the observations of Pal and Mitra (2017), where strong local correlations between oil and vegetable prices were revealed.

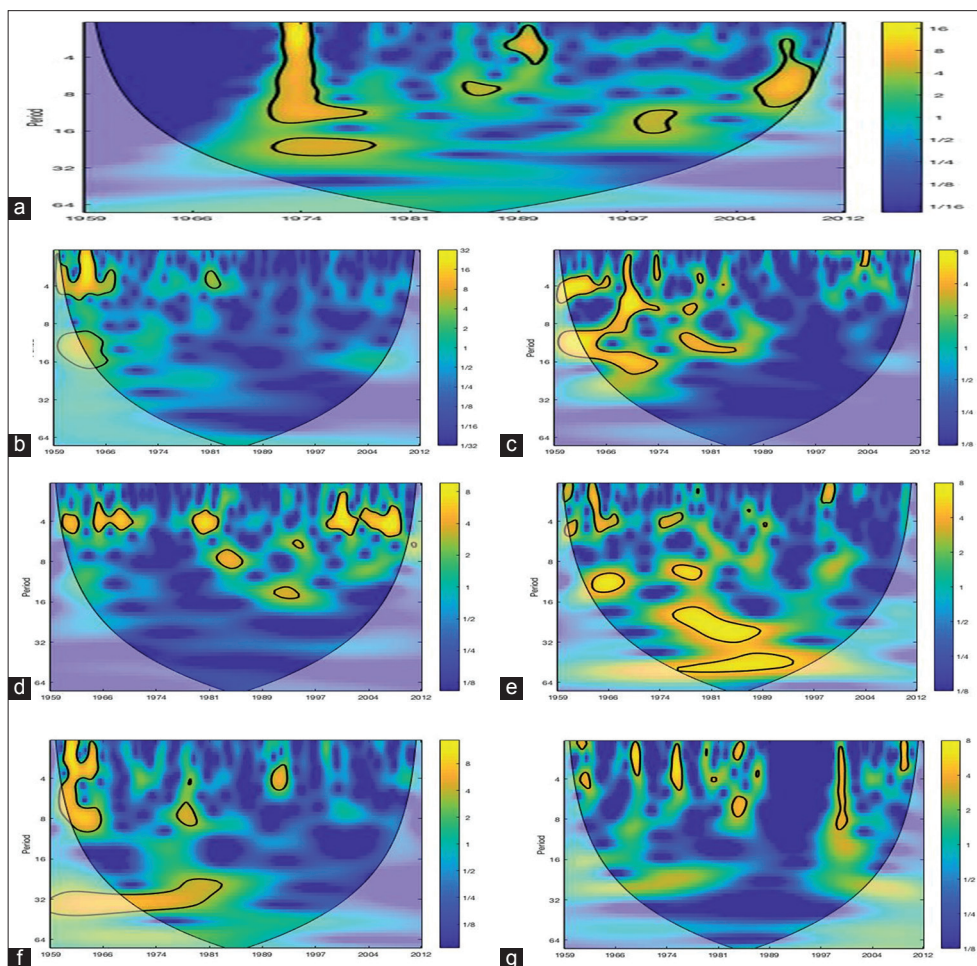
**Table 4: The estimation results of the GARCH model**

Variable	Coeff.	Std. Err	z-statistic	P
Mean equation				
AR(-1)	1.3202	0.0539	24.480	0.0000
AR(-2)	-0.3320	0.0532	-6.235	0.0000
Variance equation				
ARCH(-1)	2.5142	0.3431	7.3276	0.0000
ARCH(-2)	0.4828	0.3449	1.4000	0.1615
GARCH(-1)	0.3868	0.1202	3.2188	0.0013
GARCH(-2)	-0.0838	0.0384	-2.1848	0.0289

Notes: (1) The dependent variable is the level of spot crude oil price; (2) The estimation method is ML-ARCH; (3) The optimization method is Eviews legacy, the legacy method is Marquardt; (4) The AIC is 3.1911; (5) The Schwarz criterion is 3.3169; (6) The Hannan-Quinn criterion is 3.2419.

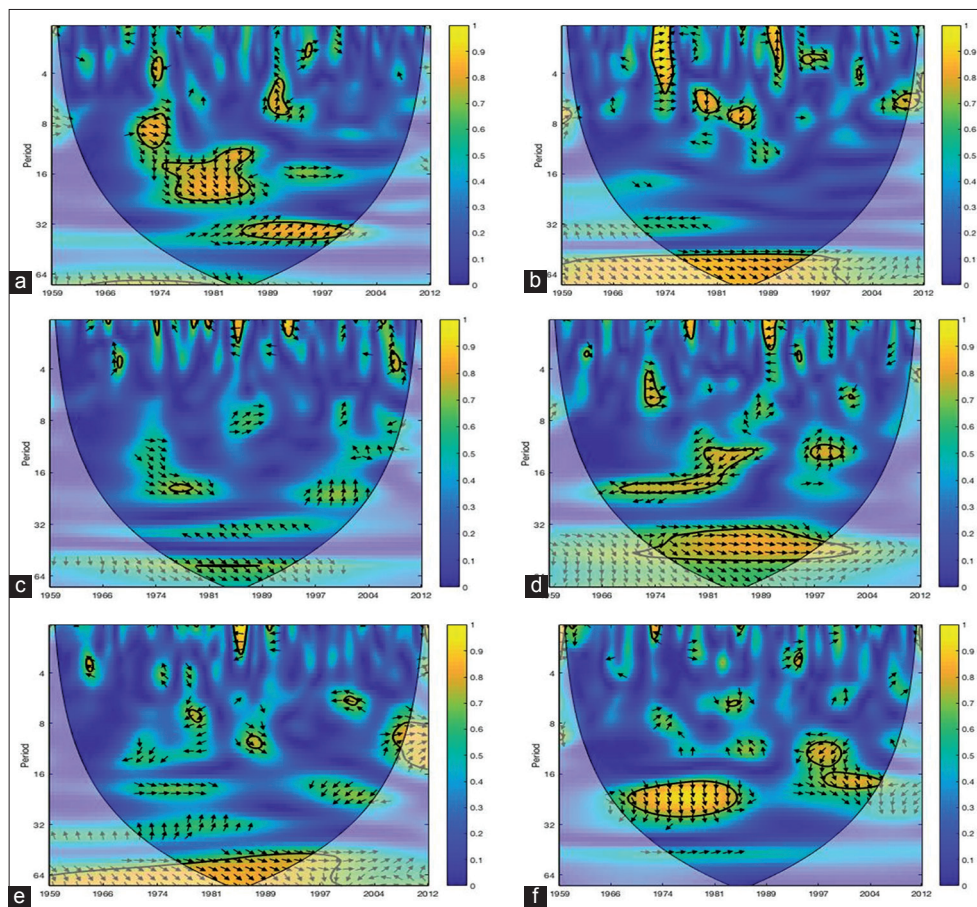
Figure 2c shows the dynamic interactions between oil and fruit price changes in the time-frequency sphere, where we find that OILP and FRUT have high common power with mixed-phase patterns mainly at high frequencies during 1970s and 1980s. Furthermore, it is OILP that leads FRUT across frequencies in the sample. The time-frequency relationships between oil and live products price fluctuations are exhibited in Figure 2d, where we observe that LIVT strongly co-moves with OILP at the timescale of 4–20 quarters with mixed-phase patterns from 1970 to 2000 and

**Figure 1:** Continuous wavelet transform (CWT) of OILP and indexes. (a) CWT of OILP, (b) CWT of GRAN. (c) CWT of VEGT. (d) CWT of FRUT. (e) CWT of LIVT. (f) CWT of SPCR. (g) CWT of SEDP.



Notes: (1) The horizontal axis indicates time (quarterly), the vertical axis represents the period (frequency); (2) The black line refers to the cone of influence, and the blue contour defines the 5% significance level of the wavelet power spectrum; (3) The color code of power changes from blue (lower power) to yellow (high power)

**Figure 2:** The wavelet coherence (WTC) of OILP and Indexes. (a) WTC: OILP and GRAN. (b) WTC: OILP and VEGT. (c) WTC: OILP and FRUT. (d) WTC: OILP and LIVT, (e) WTC: OILP and SPCR. (f) WTC: OILP and SEDP.



Notes: (1) The horizontal axis indicates time, the vertical axis represents the scale; (2) The black line refers to the cone of influence, and the yellow regions indicate where the two variables exhibit strong co-movements or high common power; (3) The color code of power changes from blue (lower power) to yellow (high power)

at the timescale of more than 32 quarters with in-phase patterns from mid 1970s to late 2000s, respectively. Moreover, OILP leads LIVT across frequencies before 1995 and at low frequencies after 1995, while LIVT leads OILP at high frequencies after 1995.

The varying relationships between oil and special crop price changes are showed in Figure 2e, where we find that SPCR strongly co-moves with OILP at the timescale of 1–12 quarters with anti-phase patterns around 1990 and at the timescale of over 48 quarters with in-phase patterns from mid 1970s to late 2000s, respectively. Moreover, it is OILP that leads SPCR across frequencies and over time. Figure 2f reveals the dynamic interactions between oil and secondary product price fluctuations, where we observe that SEDP strongly co-moves with OILP at the timescale of 12–32 quarters with anti-phase patterns from 1970 to 2005, meanwhile, OILP always leads SEDP across frequencies and over time.

The wavelet analysis in this section shows that not only the local correlations between crude oil and agricultural commodity price fluctuations, but also their phase patterns and lead-lag relationships change across frequencies and over time, which is consistent with the findings of Pal and Mitra (2017) and Han et al. (2015), which

also demonstrate that agricultural commodities were employed as financial assets during the 2007–2009 financial crisis, and our analysis about the time-frequency interactions between oil and agricultural prices provides more information on the dynamics of different categories of farming products, which should be of interest to government, central banks, investors, and policy makers in the agricultural sectors.

## 6. CONCLUSION

This paper investigates the dynamic interactions between oil price and agricultural commodity price fluctuations across frequencies and over time through employing the continuous wavelet approach with quarterly data from the Republic of Korea.

The estimated GARCH model and CWT consistently show that the volatilities of crude oil price are very high and quite persistent in our sample period. Moreover, the wavelet coherence analysis demonstrates that the degree of co-movement between oil and agricultural commodity price fluctuations indeed change across frequencies and over time. In particular, grain price strongly co-moves with oil price with in-phase patterns at high frequencies before 1985 and at low frequencies after 1985, and it leads oil price

after 1985 but not before. In addition, the prices of vegetable, fruit, live products, special crops, and secondary product all display strong co-movements with oil price with heterogeneous lead-lag relationships and mixed-phase patterns, indicating that the local correlations between crude oil and agricultural commodity prices vary in the time-frequency sphere.

The results of our analysis have interesting implications for governments, central banks, and policy makers in the agricultural sector. For governments, we find that the grain price strongly co-moves with oil price and it leads oil price after 1985, thus certain public spending should be devoted to monitoring the grain price fluctuations, such that government can forecast the oil price changes and make appropriate adjustments on its grain and oil storages to mitigate the price volatilities. For central banks, we show that agricultural product prices strongly co-move with oil price across frequencies and over time, contractionary monetary policies could be adopted to deal with the inflations caused by oil price surges. For policy makers in the agricultural sector, we observe that the prices of vegetable and fruit strongly co-move with that of oil, and it is oil price that leads them at high frequencies, so short-run agricultural subsidies to the producers of vegetables and fruits could be provided in the presence of oil price shocks to prevent dramatic price fluctuations. In addition, as agricultural commodity prices are very sensitive to oil price changes, the domestic agricultural commodity reserve should be improved and agricultural commodity future markets could be strengthened to effectively resist the global oil price fluctuations (Zhang and Qu, 2015).

## REFERENCES

- Abbott, P.C., Hurt, C., Tyner, W.E. (2009). What's Driving Food Prices? March 2009 Update (No. 48495). Farm Foundation.
- Aguiar-Conraria, L., Azevedo, N., Soares, M.J. (2008), Using wavelets to decompose the time–frequency effects of monetary policy. *Physica A: Statistical Mechanics and its Applications*, 387(12), 2863-2878.
- Aguiar-Conraria, L., Soares, M.J. (2011), Oil and the macroeconomy: Using wavelets to analyze old issues. *Empirical Economics*, 40(3), 645-655.
- Ahmadi, M., Behmiri, N.B., Manera, M. (2016), How is volatility in commodity markets linked to oil price shocks? *Energy Economics*, 59, 11-23.
- Allegret, J.P., Couharde, C., Coulibaly, D., Mignon, V. (2014), Current accounts and oil price fluctuations in oil-exporting countries: The role of financial development. *Journal of International Money and Finance*, 47, 185-201.
- Aydin, L., Acar, M. (2011), Economic impact of oil price shocks on the Turkish economy in the coming decades: A dynamic CGE analysis. *Energy Policy*, 39(3), 1722-1731.
- Baumeister, C., Kilian, L. (2014), Do oil price increases cause higher food prices? *Economic Policy*, 29(80), 691-747.
- Bruce, A., Gao, H.Y. (1996), *Applied Wavelet Analysis with S-plus*. New York: Springer-Verlag Inc.
- Cavalcanti, T., Jalles, J.T. (2013), Macroeconomic effects of oil price shocks in Brazil and in the United States. *Applied Energy*, 104, 475-486.
- Chen, S.T., Kuo, H.I., Chen, C.C. (2010), Modeling the relationship between the oil price and global food prices. *Applied Energy*, 87(8), 2517-2525.
- Daubechies, I. (1992), *Ten Lectures on Wavelets*. SIAM: Society for Industrial and Applied Mathematics.
- El-Sharif, I., Brown, D., Burton, B., Nixon, B., Russell, A. (2005), Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. *Energy Economics*, 27, 819-830.
- Ewing, B.T., Malik, F., Ozfidan, O. (2002), Volatility transmission in the oil and natural gas markets. *Energy Economics*, 24, 525-538.
- Fan, Y., Gençay, R. (2010), Unit root tests with wavelets. *Econometric Theory*, 26(5), 1305-1331.
- Fang, C.R., You, S.Y. (2014), The impact of oil price shocks on the large emerging countries' stock prices: Evidence from China, India and Russia. *International Review of Economics and Finance*, 29, 330-338.
- Farzanegan, M.R., Markwardt, G. (2009), The effects of oil price shocks on the Iranian economy. *Energy Economics*, 31(1), 134-151.
- Fowowe, B. (2016), Do oil prices drive agricultural commodity prices? Evidence from South Africa *Energy*, 104, 149-157.
- Gençay, R., Selçuk, F., Whitcher, B. (2002), An introduction to wavelets and other filtering methods in finance and economics. *Waves in Random Media*, 12(3), 399-399.
- Goupillaud, P., Grossman, A., Morlet, J. (1984), Cycle-octave and related transforms in seismic signal analysis. *Geoexploration*, 23(1), 85-102.
- Grinsted, A., Moore, J.C., Jevrejeva, S. (2004), Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear Processes in Geophysics*, 11(5/6), 561-566.
- Hamilton, J.D. (2005), *Oil and the Macroeconomy*. The New Palgrave Dictionary of Economics. 2nd ed. New York: Palgrave Macmillan.
- Hammoudeh, S., Yuan, Y. (2008), Metal volatility in presence of oil and interest rate shocks. *Energy Economics*, 30(2), 606-620.
- Han, L., Zhou, Y., Yin, L. (2015), Exogenous impacts on the links between energy and agricultural commodity markets. *Energy Economics*, 49, 350-358.
- He, K., Yu, L., Lai, K.K. (2012), Crude oil price analysis and forecasting using wavelet decomposed ensemble model. *Energy*, 46(1), 564-574.
- Hochman, G., Kaplan, S., Rajagopal, D., Zilberman, D. (2012), Biofuel and food commodity prices. *Agriculture*, 2(3), 272-281.
- Hudgins, L., Friehe, C.A., Mayer, M.E. (1993), Wavelet transforms and atmospheric turbulence. *Physical Review Letters*, 71(20), 32-79.
- Iwayemi, A., Fowowe, B. (2011), Impact of oil price shocks on selected macroeconomic variables in Nigeria. *Energy Policy*, 39(2), 603-612.
- Ji, Q., Fan, Y. (2016), How do China's oil markets affect other commodity markets both domestically and internationally? *Finance Research Letters*, 19, 247-254.
- Liu, L. (2014), Cross-correlations between crude oil and agricultural commodity markets. *Physica A: Statistical Mechanics and its Applications*, 395, 293-302.
- MacKinnon, J.G., Haug, A.A., Michelis, L. (1999). Numerical distribution functions of likelihood ratio tests for cointegration. *Journal of Applied Econometrics*, 563-577.
- Mohammadi, H. (2009), Electricity prices and fuel costs: Long-run relations and short-run dynamics. *Energy Economics*, 31, 503-509.
- Mutuc, M., Pan, S., Hudson, D. (2010), *Response of Cotton to Oil Price Shocks*. Orlando, FL: The Southern Agricultural Economics Association Annual Meeting.
- Narayan, P.K., Narayan, S., Smyth, R. (2008), Are oil shocks permanent or temporary? Panel data evidence from crude oil and NGL production in 60 countries. *Energy Economics*, 30(3), 919-936.
- Natanelov, V., Alam, M.J., McKenzie, A.M., Van Huylbroeck, G. (2011), Is there co-movement of agricultural commodities futures prices and crude oil? *Energy Policy*, 39(9), 4971-4984.
- Nazlioglu, S. (2011), World oil and agricultural commodity prices: Evidence from nonlinear causality. *Energy Policy*, 39(5), 2935-2943.
- Nazlioglu, S., Soytas, U. (2011), World oil prices and agricultural



- commodity prices: Evidence from an emerging market. *Energy Economics*, 33(3), 488-496.
- Nazlioglu, S., Soytaş, U. (2012), Oil price, agricultural commodity prices, and the dollar: A panel co integration and causality analysis. *Energy Economics*, 34(4), 1098-1104.
- Nusair, S.A. (2016), The effects of oil price shocks on the economies of the Gulf Co-operation council countries: Nonlinear analysis. *Energy Policy*, 91, 256-267.
- Ou, B., Zhang, X., Wang, S. (2012), How does China's macro-economy response to the world crude oil price shock: A structural dynamic factor model approach. *Computers and Industrial Engineering*, 63(3), 634-640.
- Pal, D., Mitra, S.K. (2017), Time-frequency contained co-movement of crude oil and world food prices: A wavelet-based analysis. *Energy Economics*, 62, 230-239.
- Panagiotidis, T., Rutledge, E. (2007), Oil and gas markets in the UK: Evidence from a co integrating approach. *Energy Economics*, 29, 329-347.
- Percival, D.B., Walden, A.T. (2000), *Wavelet Methods for Time Series Analysis*. Cambridge Series in Statistical and Probabilistic Mathematics. Vol. 4. Cambridge: Cambridge University Press.
- Rafiq, S., Bloch, H. (2016), Explaining commodity prices through asymmetric oil shocks: Evidence from nonlinear models. *Resources Policy*, 50, 34-48.
- Rafiq, S., Salim, R., Bloch, H. (2009), Impact of crude oil price volatility on economic activities: An empirical investigation in the Thai economy. *Resources Policy*, 34(3), 121-132.
- Ramsey, J.B. (2002), *Wavelets in economics and finance: Past and future*. *Studies in Nonlinear Dynamics and Econometrics*, 6(3), 1-27.
- Reboredo, J.C., Rivera-Castro, M.A., Ugolini, A. (2017), Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. *Energy Economics*, 61, 241-252.
- Reboredo, J.C., Ugolini, A. (2016), The impact of downward/upward oil price movements on metal prices. *Resources Policy*, 49, 129-141.
- Rua, A., Nunes, L.C. (2009), International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance*, 16(4), 632-639.
- Scholtens, B., Yurtsever, C. (2012), Oil price shocks and European industries. *Energy Economics*, 34, 1187-1195.
- Soytaş, U., Sari, R., Hammoudeh, S., Hacıhasanoğlu, E. (2009), World oil prices, precious metal prices and macroeconomy in Turkey. *Energy Policy*, 37(12), 5557-5566.
- Tang, W., Wu, L., Zhang, Z. (2010), Oil price shocks and their short-and long-term effects on the Chinese economy. *Energy Economics*, 32, S3-S14.
- Torrence, C., Compo, G.P. (1998), A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society*, 79(1), 61-78.
- Torrence, C., Webster, P.J. (1999), Interdecadal changes in the ENSO-monsoon system. *Journal of Climate*, 12(8), 2679-2690.
- Tyner, W.E. (2008), The US ethanol and biofuels boom: Its origins, current status, and future prospects. *BioScience*, 58(7), 646-53.
- Tyner, W.E. (2010), The integration of energy and agricultural markets. *Agricultural Economics*, 41(s1), 193-201.
- Uri, N.D. (1996), Changing crude oil price effects on US agricultural employment. *Energy Economics*, 18, 185-202.
- Vacha, L., Janda, K., Kristoufek, L., Zilberman, D. (2013), Time-frequency dynamics of biofuel-fuel-food system. *Energy Economics*, 40, 233-241.
- Vogelsang, J. T. (1993). *Essays On Testing for Nonstationarities and Structural Change in Time Series Models*, Unpublished Ph.D. Dissertation, Princeton University, Princeton, NJ.
- Wang, Y., Wu, C., Yang, L. (2014), Oil price shocks and agricultural commodity prices. *Energy Economics*, 44, 22-35.
- Wang, Y.S., Chueh, Y.L. (2013), Dynamic transmission effects between the interest rate, the US dollar, and gold and crude oil prices. *Economic Modelling*, 30, 792-798.
- Zhang, C., Qu, X. (2015), The effect of global oil price shocks on China's agricultural commodities. *Energy Economics*, 51, 354-364.
- Abbott, P.C., Hurt, C., Tyner, W.E. (2008), *What's Driving Food Prices?* (No. 37951). Farm Foundation.