The Inter-connectivity between Fuel and Food Markets: Evidence from Biodiesel Market in the United States

Tetsuji Tanaka [a,*] and Jin Guo [a,1]

[a] *Department of Economics, Setsunan University, 17-8 Ikedanakamachi, Neyagawa, 572-8508, Osaka, Japan*

Abstract

The previous literature does not appropriately focus on the United States, one of the largest biodiesel producers, mingling price series in different countries. It employs spot and futures price series, although financial markets hold heterogeneous characteristics with non-commercial traders (i.e. speculators) who amplify price volatility by placing various types of positions (e.g. long and short positions with leveraged contracts and options). The present article is the first to apply the partial wavelet coherence and the Diebold-Yilmaz Connectedness Index in biodiesel price transmission research, concentrating on non-futures markets in the United States. Our research investigates the price inter-connectivity between biodiesel, highway diesel, crude oil and soybean, using the aforementioned state-of-the-art econometric techniques. The outcomes predominantly exhibit consistency between the two methodologies, implying the robustness of the results. Our main results are as follows: First, significant-high coherence for biodiesel-soybean, biodiesel-highway diesel and highway diesel-crude oil is identified in the short and long term. Second, crude oil and biodiesel prices are net transmitters, while soybean and highway diesel prices are net receivers. Finally, the crude oil market is the source of spillovers among the four markets strongly influencing the highway diesel market.

[*] Corresponding author.
E-mail address: tetsuji.tanaka@econ.setsunan.ac.jp (T.Tetsuji).

[1] Both authors contributed equally to this work.

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Highlights:

- **The "fuel vs food" topic is a growing interest with the decarbonization movement**
- **Two state-of-the-art econometric methods are applied to biodiesel price analysis**
- **Unconventionally, local prices in the United States are used.**
- **Energy and food markets are connected in the short and long term**

1. Introduction

Biofuel has attracted international attention over the past two decades as a carbon-neutral fuel that is useful to reduce carbon dioxide emissions. From 2000 to 2019, biodiesel production grew as much as 50 times in the world (EIA, 2021). Several existing studies focus on biodiesel markets in European countries since the region accounted for an outstanding share of the global biodiesel production (Hassoueh et al., 2012; Abdelradi and Serra, 2015; Serra and Gil, 2012). Although the United States is the world's second-largest biodiesel producer, its biodiesel markets have not been investigated in an appropriate manner. Kristoufek et al. (2012, 2014) use futures prices from the Chicago Board of Trade (CBOT) and the Intercontinental Exchange (ICE) together with the spot price of biodiesel in Germany. Hence, they do not, strictly speaking, concentrate on the biodiesel market relationships in the United States. In addition, futures markets encompass a sufficient number of non-commercial traders (i.e. speculators) who could proliferate market volatilities, placing long- and short-positions with leveraged contracts. The heterogeneity of market characteristics between financial and non-financial markets needs to be carefully considered when discussing the interaction between food and fuel prices that might generate different results. The existing studies analyzing the U.S. markets focus on futures and spot prices (Kristoufek et al. 2012, 2014; Vacha et al., 2013).

Another issue is that some advanced econometric techniques have been underutilized in the previous literature. The wavelet coherence has gained immense popularity, particularly in the area of financial commodity markets and macroeconomics. The model enables us to continuously identify the statistical significance of the time and frequency domains, the degree of effects, and the lead-lag relationship, which suits time-series price inter-connectivity analyses and is applied to biofuel and related commodity markets by Vacha et al. (2013) for the first time. The partial wavelet coherence that controls for the effects of third variables on the pairwise connectedness is first employed for the current subject by Kristoufek et al. (2016) that analyze the futures prices connections among bioethanol, crude oil, gasoline and corn markets. Accordingly, the partial wavelet model has never been applied to the price relationships between biodiesel and other relevant goods. Besides, the Diebold-Yilmaz Connectedness Index (DYCI) originated in Diebold and Yilmaz (2012, 2014) is also a newly developed method to simultaneously interrogate the correlations between various variables, making it possible to discover the pass-through source of variables relationships. Though this approach is also becoming more common in financial market analyses, no paper applies it in the "food versus fuel" research.

This article fills the aforementioned knowledge gap by employing the partial wavelet continuous transform and DYCI to explore the inter-relationships among biodiesel, highway diesel, soybean and crude oil non-futures prices in the United States, spanning from April 2007 to December 2020. Our research is the first to apply the above two methods to price connectivity analysis between biodiesel and relevant goods. The results from the two techniques function as a robustness check, reinforcing the trustworthiness.

The paper is structured as follows. Section 2 presents the existing literature on the topic. The methodology and data are explained in section 3, followed by section 4 that reports on the empirical results. Section 5 describes policy implications based on our outcomes. Finally, section 6 summarises the paper with future research themes.

2. Literature review

Copious existing studies on price links between biofuels and food goods primarily focused on bioethanol price linkages with the price of relevant commodities, and research on price spillovers between biodiesel and agricultural goods is relatively scarce. This section overviews the past analyses of price relationships between biodiesel and foods.

Several papers tackle the issue in European regions. Hassouneh et al. (2012) concentrate on Spanish energy and food markets using the co-integration and vector error correction (VEC) methods, which argues that the prices of biodiesel, sunflower oil, and crude oil maintain the long-run connectivity although sunflower oil price does not affect biodiesel price in the short run. Abdelradi and Serra (2015) examined the price volatility transmissions between biodiesel, rapeseed oil and crude oil in European countries, using GARCH models. Significant asymmetries are discovered in volatility spillovers between pure biodiesel and rapeseed oil prices. Cabrera and Schultz (2016) analyze price and volatility risk originating in linkages between Germany's energy and agricultural commodity prices using VEC models. They find that prices move together and preserve an equilibrium in the long term, while correlations are positive with persistent market shocks for most of the sample period. Concerns about biodiesel being the cause of high and volatile agricultural commodity prices are rather unjustified. Serra and Gil (2012) analyze the connectedness between diesel and crude oil prices in Spain, showing symmetric dependence by which both extreme increases and decreases in the crude oil price are equally likely to be passed on to consumers. Busse et al. (2012) examine the liaisons between diesel and biodiesel prices and between soy oil, rapeseed oil, and biodiesel prices in Germany. They find that the long-term relationships between biodiesel and diesel prices and between biodiesel, rapeseed oil, and soy oil prices exist.

Some past research papers shed light on biodiesel markets in other regions. Kristoufek et al. (2012) applied a minimal spanning tree and hierarchical tree to investigate the interconnections among various fuel and agricultural commodities of futures prices from the Chicago Board of Trade and the Intercontinental Exchange and German biodiesel spot price. They conclude that biodiesel price is associated with energy prices but not with its feedstock price. Vacha et al. (2013) use the wavelet coherence method on ethanol, biodiesel, gasoline, diesel, crude oil, corn, wheat, soybean, sugarcane and rapeseeds oil. It is found that biodiesel price is correlated with German diesel price during stable (non-crisis) period at a low frequency while biodiesel price co-moves with soybean and rapeseed oil prices in the long run. The mutual dependency between biofuels and related goods are analyzed by Kristoufek et al. (2012). This article uncovers that biodiesel and German diesel are mutually dependent, bioethanol and biodiesel hold mutual responsiveness with fossil fuels, and their connectedness is price-dependent. Further, they discover that biodiesel price is intensely influenced by German diesel and soybean prices. To sum, most articles find that biodiesel price correlates with feedstock prices in the long run though the relationship is not always established in the short run. In addition, biodiesel price tends to co-move with fuel prices. Kristoufek et al. (2014) use the two-stage least squares procedure to probe biodiesel market transmissions using German spot biodiesel and agricultural futures prices from the CBOT. They discovered that the strength of spillovers increased during the global food crisis period around 2008.

Even though state-of-the-art econometric techniques such as the wavelet transform and DYCI have gained immense popularity in recent years in financial commodity markets and macroeconomics , they are not fully applied to the price correlation in biofuel research. Only two existing articles employ the wavelet coherence methodology applying to biofuel price interdependency on food prices. Vacha et al. (2013) are the first to apply the technique to discover the interaction between biofuels and related goods. The partial wavelet model that allows us to consider third variable effects on the pair is employed by Kristoufek et al. (2016), concentrating on bioethanol markets. The DYCI has never been utilized in either bioethanol or biodiesel markets.

To conclude, to the best of our knowledge, there is no publication focusing on non-futures price inter-connectivity analysis between biodiesel and related goods in the United States. Additionally, no article discovers the long- and short-term impacts between those commodities using the DYCI method and the partial wavelet coherence framework.

3. Methodology and Data

In this section, we describe in detail the empirical methods applied to the present study. Methodologically, we focus on two mathematical tools: the multivariate wavelet technique introduced by Aguiar-Conraria and Soares (2014) and the time domain connectedness measures proposed by Diebold and Yilmaz (2012, 2014). The reader who is not interested in the technical details may skip to segment 4, where we interpret the empirical results of our analysis.

3.1. Multivariate wavelet analyses

To examine the dynamic interaction and lead-lag relationship among soybean, biodiesel, highway diesel and crude oil across time and frequency domain, we employ the multiple wavelet coherency, partial wavelet coherency, partial wavelet phase-difference, and partial wavelet gain.

First, following Aguiar-Conraria and Soares (2014), the continuous wavelet transform (CWT) of a time series $x(t) \in L^2(\mathbb{R})$ can be represented by

$$W_x(\alpha,\beta)=\frac{1}{\sqrt{|\beta|}}\int_{-\infty}^{\infty}x(t)\overline{\psi}\left(\frac{t-\alpha}{\beta}\right)dt\,. \tag{1}$$

Note that wavelet ψ [1] is the function of two variables $W_x(\alpha,\beta)$ where β is the scaling factor controlling the width of the wavelet, while α is a translation parameter describing the location of the wavelet ($\alpha,\beta\in\mathbb{R}$ and $\beta\neq 0$). The window of function[2] $W_x(\alpha,\beta)$ becomes larger with corresponding lower frequency for $|\beta|>1$. Meanwhile, the window becomes narrower with higher frequency for $|\beta|<1$. If the wavelet function ψ is complex, the wavelet transform W_x is also complex-valued. Based on the CWT, we can derive the wavelet power spectrum (WPS) as: $(WPS)_x = W_x\overline{W_x}=|W_x|^2$. The WPS gives us a measure of the variance distribution of univariate time series.

Second, to be able to investigate the dynamic correlation between fuel and food price returns, we need to introduce a bivariate framework of wavelet analysis. For the bivariate case, the cross-wavelet transform of two time-series $y(t)$ and $x(t)$, denoted by W_{yx}, is defined as $W_{yx}=W_y\overline{W_x}$ and its absolute value $|W_{yx}|$ is referred to as the cross-wavelet power (CWP). The CWP of two time-series reflects the covariance between two time-series along both time scales and frequency. Based on the CWP, we can derive the complex wavelet coherency δ_{yx}, by

$$\delta_{yx}=\frac{\theta(W_{yx})}{\sqrt{\theta(|W_y|^2)}\sqrt{\theta(|W_x|^2)}}, \tag{2}$$

where θ represents a smoothing operator in both scale and time. For simplicity, we introduce the

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[1] The specific wavelet we use in this paper is the Morlet wavelet defined by $\psi^M(t)=\frac{1}{\pi^{1/4}}e^{i\omega_0 t}e^{-t^2/2}$. See Aguiar-Conraria and Soares (2014) for a discussion of some important properties of this wavelet.

[2] For simplicity, we will omit (α,β) in the next formulae.

notation θ_{yx} to replace $\theta\left(W_{yx}\right)$ and use σ_y and σ_x to denote $\sqrt{\theta\left(\left|W_y\right|^2\right)}$ and $\sqrt{\theta\left(\left|W_x\right|^2\right)}$, respectively. Hence, Eq. (2) can simply become $\delta_{yx} = \frac{\theta_{yx}}{\sigma_y \sigma_x}$. The absolute value of δ_{yx} is called the wavelet coherency, which can be defined by $R_{yx} = \left|\delta_{yx}\right|$. The wavelet coherence is the ratio of cross-spectrum to the product of the spectrum of each individual series.

Given a complex-valued wavelet, Aguiar-Conraria and Soares (2014) also provide a phase difference tool to clarify the information about the possible delays of the oscillations between two time series. The wavelet-coherence phase difference is determined as follows:

$$\gamma_{yx} = \operatorname{Arc\,tan}\left(\frac{\Im\left\{W_{yx}\right\}}{\Re\left\{W_{yx}\right\}}\right), \text{ with } \gamma_{yx} \in \left[-\pi, \pi\right], \tag{3}$$

where the smoothed real ($\Re$) and imaginary ($\Im$) parts should have been estimated in Eq. (2). We identify the lead-lag relationship between $y(t)$ and $x(t)$ at each time and frequency by using the value of the phase difference. Specifically, a phase difference of zero indicates that the two series co-move: when $\gamma_{yx} \in \left[0, \pi/2\right]$, the two series move in-phase (positively related) with $y(t)$ leading $x(t)$. Yet, when $\gamma_{yx} \in \left[-\pi/2, 0\right]$, we say that $x(t)$ leads $y(t)$. On the other hand, the two series are in an anti-phase relationship (negatively related) when $\gamma_{yx} \in \left[-\pi, -\pi/2\right]$ and $\gamma_{yx} \in \left[\pi/2, \pi\right]$, while $y(t)$ leads $x(t)$ in the former and $x(t)$ leads $y(t)$ in the latter. Finally, we apply the technique of wavelet partial coherency which helps identify the resulting wavelet coherency between two time series $y(t)$ and $x(t)$ after eliminating the influence of the controlling variable $z(t)$. Following Aguiar-Conraria and Soares (2014), the complex partial wavelet coherency between y and x, after controlling for z, is given by

$$\delta_{yx,z} = \frac{\delta_{yx} - \delta_{yz}\overline{\delta_{xz}}}{\sqrt{\left(1-R_{yz}^2\right)\left(1-R_{xz}^2\right)}}, \tag{4}$$

where δ_{yz} and δ_{xz} are defined in a similar manner to δ_{yx}, while and R_{yz} and R_{xz} are calculated in a similar manner to R_{yx}. The absolute value and the angle of $\delta_{yx,z}$, will, respectively, be called the partial wavelet coherency and the partial wavelet phase-difference between the series y and x, after controlling for z, and be denoted by $R_{yx,z}$ and $\gamma_{yx,z}$ [3]. Further, Mandler and Scharnagl (2014) generalize the concept of wavelet gain and define the partial wavelet gain, which can be interpreted as a regression coefficient in the regression of y on x after controlling for other variables. Following Mandler and Scharnagl (2014), the partial wavelet gain $G_{yx,z}$ is indicated by

$$G_{yx,z} = \frac{\left|\delta_{yx} - \delta_{yz}\overline{\delta_{xz}}\right|}{\left(1-R_{xz}^2\right)}\frac{\sigma_y}{\sigma_x}. \tag{5}$$

The partial wavelet gain provides the magnitude of impact among variables at each time and frequency.

3.2. DYCI measures

We also use a time domain connectedness measure to examine the directional return connectedness and build a network among the prices of food, biofuels, and fossil fuels. Following Diebold and Yilmaz (2012, 2014), we consider 4 variables $VAR(k)$ system, defined as follows:

[3] To save space, we do not express the definition of $R_{yx.z}$ and $\gamma_{yx.z}$ but these are available from the authors on request.

$$z_t = \sum_{i=1}^{k} \phi_i z_{t-i} + u_t , \tag{6}$$

where a 4×1 vector of the variables at time t is denoted by z_t, including soybean, biodiesel, highway diesel and crude oil. ϕ_i expresses the autoregressive coefficients of dimension 4×4 and u_t stands for serially uncorrelated innovations of the VAR system. If the VAR model above is a covariance stationary, the Eq. (6) can be rewritten as an infinite moving average process: $z_t = \sum_{i=0}^{\infty} \Phi_i u_{t-1}$, where the coefficient matrix Φ_i obey the recursion: $\Phi_i = \phi_1 \Phi_{i-1} + \phi_2 \Phi_{i-2} + \cdots + \phi_p \Phi_{i-p}$, and for $i < 0$, $\Phi_i = 0$. To make the order irrelevant to the results of the variance decomposition, we add the *H*-step-ahead forecast errors for $H = 1, 2, \ldots$, suggested by Koop et al. (1996) and Pesaran and Shin (1998). As such, the generalized variance decomposition becomes:

$$\lambda_{ij}^{g}(H) = \frac{1}{\sigma_{jj}} \frac{\sum_{h=0}^{H-1} \left(\xi_i' \Phi_h \sum \xi_j \right)^2}{\sum_{h=0}^{H-1} \left(\xi_i' \Phi_h \sum \Phi_h' \xi_j \right)}, \tag{7}$$

where the connectedness matrix $\lambda_{ij}^{g}(H)$ is the contribution of the *j*th variable to the forecast error variance of the element *i*th at horizon *h*. $\sum$ marks the covariance matrix of errors in the VAR model. σ_{jj} is the standard deviation of the innovation for the *j*th equation, whereas the 4×1 selection vector is represented by ξ_i with the *i*th element equal to 1, and 0 otherwise.

The advantage of the DYCI approach is that it provides the direction of pairwise connectedness, which enables understanding of the spillovers between variables. We use $\tilde{\lambda}_{ij}^{g}(H)$ to represent the directional connectedness from variable j to variable i which is defined as:

$$C_{i\leftarrow j}(H)=\frac{\lambda_{ij}^{g}(H)}{\sum_{j=1}^{N}\lambda_{ij}^{g}(H)}=\tilde{\lambda}_{ij}^{g}(H). \tag{8}$$

For simplification, it is denoted as $C_{i\leftarrow j}(H)$. Note that the own and cross-variable variance contribution sums to 1 under the generalized decomposition with $\sum_{j=1}^{N}\tilde{\lambda}_{ij}^{g}(H)=1$ and $\sum_{i,j=1}^{N}\tilde{\lambda}_{ij}^{g}(H)=N$. Since one of our purposes is to estimate the total connectedness (T.C.), we sum up the pairwise connectedness and construct the T.C. as:

$$TC(H)=\frac{\sum_{i,j=1(i\neq j)}^{N}\tilde{\lambda}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\lambda}_{ij}^{g}(H)}\times 100. \tag{9}$$

This shows the impact of connectedness across variables on the total forecast error variance. More, it is important to investigate the spillover effect and identify which variables are transmitting a shock to others and which are receiving a shock from others. The directional connectedness (D.C.) to the variable *i* from all other variables *j* is given by:

$$DC_{i\leftarrow\bullet}(H)=\frac{\sum_{j=1(i\neq j)}^{N}\tilde{S}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{S}_{ij}^{g}(H)}\times 100. \tag{10}$$

With the reverse, the directional connectedness from variable *i* to all other variables *j* is calculated as:

$$DC_{\bullet\leftarrow i}(H)=\frac{\sum_{j=1(i\neq j)}^{N}\tilde{S}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{S}_{ji}^{g}(H)}\times 100. \tag{11}$$

Based on Eq. (10) and Eq. (11), we then obtain the net total connectedness (N.C.) from variables *i* to all other variables *j* as follows:

$$NC_i(H) = C_{\bullet\leftarrow i}(H) - C_{i\leftarrow\bullet}(H) \tag{12}$$

The NC indicates whether variables are net transmitters or receivers of shocks when the value is positive and when it is negative.

Finally, for a closer look into specific variables, it is also of interest to identify the net pairwise directional connectedness (NPDC) between two variables *i* and *j*, which can be set as:

$$NPDC_{ij}(H) = C_{j\leftarrow i}(H) - C_{i\leftarrow j}(H). \tag{13}$$

This makes us to better understand the transmission mechanism between two specific variables.

4. Empirical Results

The primary objective of this current paper is to examine the price pass-through mechanism between biodiesel, highway diesel, crude oil and soybean. While the attention paid in our research is to the linkage between biodiesel and soybean, we also include highway diesel and crude oil as a substitutive good and production factor of diesel, respectively. We collected monthly price data series for crude oil, biodiesel, highway diesel, and soybean in the United States to analyze their relationships with the sample period spanning April 2007 to December 2020. The crude oil and soybean prices data are from the Energy Information Administration and the Federal Reserve Economic Data, respectively. We obtained biodiesel and highway diesel price data from the USDA Economic Research Service.

All series are seasonally adjusted by using the X-13-ARIMA method[4]. R_t represents the monthly price returns calculated as the logarithmic first difference of prices: $R_t = \ln(p_t) - \ln(p_{t-1})$. The price at time t is shown with p_t. Table 1 reports the summary statistics and preliminary tests of price returns for biodiesel, soybean, highway diesel and crude oil. According to it, the positive value of mean for biodiesel and soybean are observed, while the mean values for highway diesel and crude oil are negative. On average, soybean data provided the highest returns. The lowest yield is displayed by the crude oil data. We also see that the standard deviation value of crude oil is larger than others, indicating more volatility. Furthermore, all the variables are negatively skewed indicating a high probability of negative returns. In term of kurtosis, crude oil and highway diesel are leptokurtic, which suggests that distributions of these two variables have fat tails. Also, all returns are not normally distributed at a 1% significance level based on the Jarque-Bera (J-B) normality test. Further, the results of the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) unit root test demonstrate that all price returns are stationary. Finally, the results from the autoregressive conditional heteroscedasticity (ARCH)-Lagrange multiplier (L.M.) test (Engle, 1982) suggest that the ARCH effects in return series apply for all the prices. On the other hand, the Breusch-Godfrey (B-G) L.M. test (Breusch, 1978; Godfrey, 1978) indicate evidence of serial correlation in soybean and crude oil. These results show some potential non-linearities in the series and provide the reasonability and necessity of applying wavelet-based analysis.

Table 1. Descriptive statistics and preliminary tests

[4] X-13-ARIMA (autoregressive integrated moving average) as developed by the US Census Bureau is one of the most popular methods for seasonal adjustment.

	Biodiesel	Soybean	Highway diesel	Crude oil
Mean $\times 10^3$	0.91	3.287	-0.733	-1.925
Std.Dev.	0.050	0.069	0.047	0.120
Skewness	-0.513	-0.637	-0.713	-0.888
Kurtosis	3.839	5.428	6.880	17.555
J-B test	11.996***	51.403***	116.767***	1469.089***
ADF test	-9.130***	-6.989***	-7.654***	-9.059***
KPSS test	0.056	0.095	0.042	0.041
ARCH test	5.485***	8.370**	5.225**	42.295***
B-G LM test	1.010	7.483**	0.142	5.070***
Observations	164	164	164	164

Note: ** and *** denote rejection of the null hypothesis at the 5% and 1% significance levels. The lag length selection is based on Schwarz Bayesian information criteria (SBIC) in the ADF and KPSS tests. We use 2 lags in both the ARCH test and B-G LM test

The monthly price returns of each variable are depicted in Fig. 1(a) on the left side, together with their wavelet power spectrum in Fig. 1(b) on the right side. The wavelet power spectrum indicates the magnitude of the variance for each return series and provides a first assessment of the behavior of each variable in the time and frequency domain. Here, all the returns are separated into two time-scale sections: short-term variation (high frequency) of 1 to 4 months, long-term variation (low frequency) of 4 to 8 months. From 5,000 times Monte Carlo simulations applying phase-randomized surrogates we expose the critical values. For the cones of influence (COI) we used a black outline which points out the area affected by edge effects.

Since Grinsted et al. (2004) argued that the results outside the COI region may not be reliable, we discuss the wavelet power specters inside the COI in this study. First, looking at soybean price in Fig 1(b.1), it is noted that the zones of volatility are largely dense in the time frame 2008-2012, especially at 1-2 months frequencies. Second, in the case of biodiesel in Fig. 1(b.2), we observe that the price returns exhibit high volatility at both high and low frequencies and appear from late 2008 to 2015. Third, in terms of highway diesel price in Fig 1(b.3), we identify two large regions of high volatility at either 1-4 or 4-8 months and they appear throughout the whole sample periods. Finally, the crude oil return in Fig 1(b.4) shows the high volatility of crude oil return can be identified in short-term frequencies band, occurring 2008-2010 and 2018-2019. The wavelet power spectrums are consistent with the corresponding time plots in Fig.1(a.1)–Fig.1(a.4). It is important to point out that the relatively volatile periods for these four price returns roughly coincide with the 2007-2008 global food crisis and the 2008-2009 financial crisis.

After identifying the volatility of all the price returns across time and frequency domains, we further explore their co-movement and lead-lag relationship based on multivariate wavelet analysis in the next section.

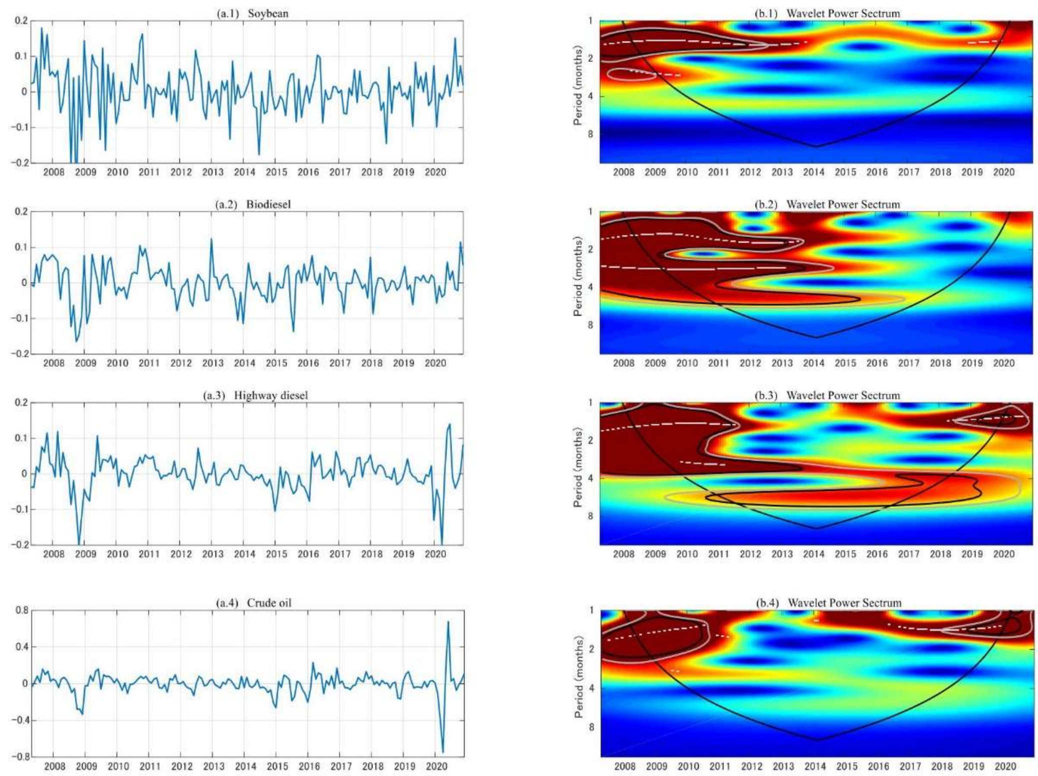


Fig. 1. Price-return plot and wavelet power spectrum for soybean, biodiesel, highway diesel and crude oil price returns.

Note: (a.1)-(a.4) convey the trend of the each return. (b.1)-(b.4) are the wavelet power spectrum of each return. The black and gray contour represent the 5% and 10% significance level, respectively. The strength of wavelet power and the local volatility is shown by colors ranging from blue (lowest) to red (highest). The broken white line indicates the maximum of the local wavelet power spectrum for each variable.

5. Empirical results

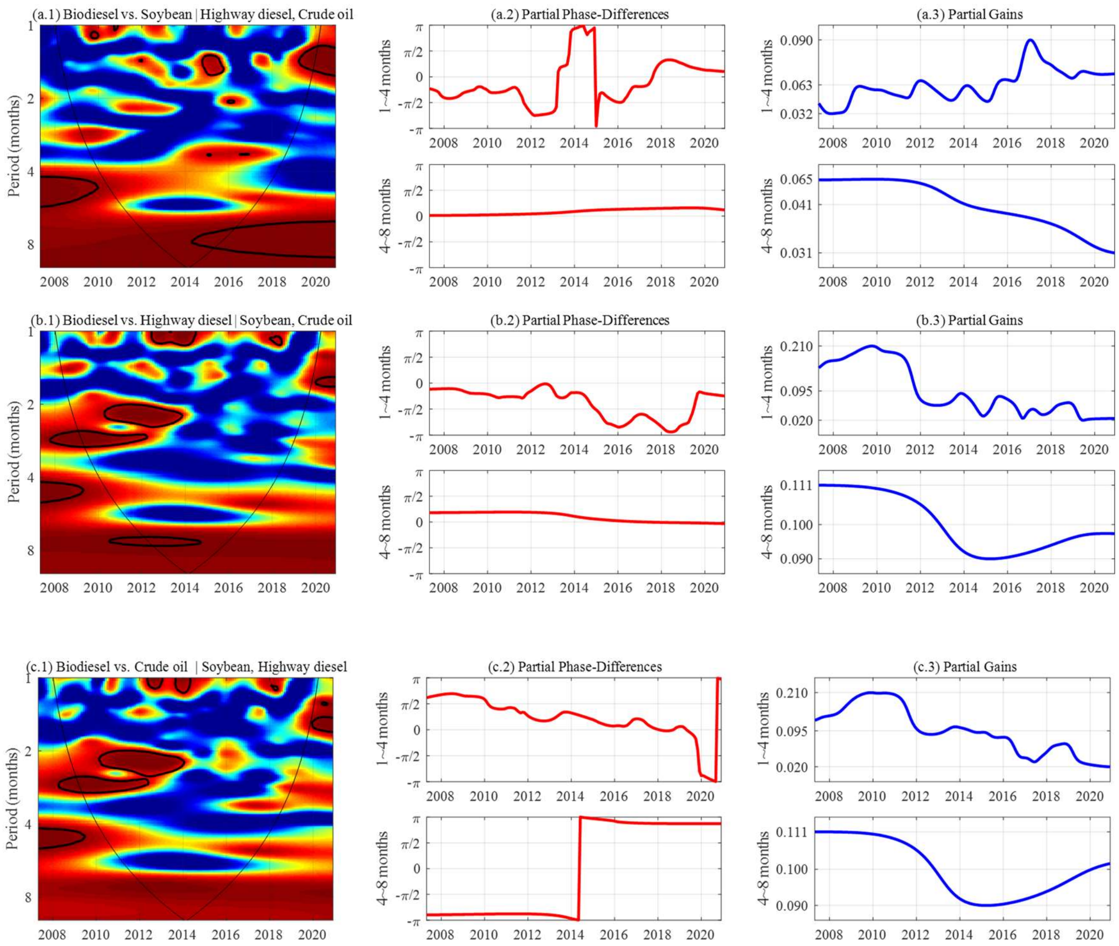
5.1 Wavelet analysis

In this subsection, the time-varying interaction and lead-lag relationship amongst biodiesel, soybean, highway diesel and crude oil returns are analyzed by partial wavelet coherence combined with the partial phase difference and partial wavelet gains[5]. The results of the partial coherency between each pair of variables over time and for different frequency domains are described from Fig. 2 (a.1) to Fig. 2 (f.1). The statistically significant coherence regions are represented by the red area with the black contour.

First, it is worth mentioning that the persistence of strong coherence regions at 4-8-month frequency band can be identified in the pairs of biodiesel-soybean, biodiesel-highway diesel and highway diesel-crude oil. This indicates a strong correlation exists among these three pairs of variables in the long-term scales. Specifically, the regions with significantly high coherence can be observed running from 2014 to 2016 for biodiesel-soybean in Fig. 2 (a.1). Moreover, according to the partial phase-difference in Fig. 2 (a.2), we can find that the phase differences are between 0 and $\pi/2$, indicating biodiesel positively lead soybean. In addition, the partial wavelet gains in Fig. 2 (a.3) show that the corresponding coefficient is close to 0.04 for the significant coherences. On the other hand, the partial coherence between biodiesel and highway diesel (Fig.2 (b.1)) is particularly strong between the beginning of 2012 to the middle of 2014. In this significant range, the phase difference in Fig. 2 (b.2) is between 0 and $\pi/2$, implying a positive relationship between two variables, with biodiesel leading. Meanwhile, the partial wavelet gains in Fig. 2 (b.3) decreased from 0.1 to 0.09 in this period. Finally, the region of high partial coherency between highway diesel and crude in Fig.2 (f.1) is observable across most of the sample. For the statistically significant region, the corresponding partial phase differences in Fig. 2 (f.2) are between 0 and $-\pi/2$, suggesting that crude oil positively lead highway diesel in the long term. Moreover, the partial wavelet gain (Fig.2 (f.3)) indicates that the coefficient of the period of coherence is from 0.09 to 0.1.

[5] The definition of the frequency band, significance level, COI and used color code are similar to the wavelet power spectrum analysis.

Turning our attention to the results for the high frequency (short-term), some different patterns emerge. More specifically, according to Fig. 2 (a.1), the partial coherency between biodiesel and soybean become stronger after 2014, especially in 2015 and 2019. What's more, we find that many pairs of variables, such as biodiesel-highway diesel in Fig. 2 (b.1), biodiesel-crude oil in Fig. 2 (c.1) and soybean-highway diesel in Fig. 2 (d.1), have shared a similar high coherency region running from 2009 to 2014. Also, the results of soybean-crude oil in Fig. 2 (e.1) exhibit that high coherence extends from 2017 to 2019. By contrast, the significantly high coherence between highway diesel and crude oil in Fig. 2 (f.1) can be identified throughout the sample period in the short term. It is interesting to note that the partial phase-difference exhibit time-variation and that the partial wavelet gains fluctuated dramatically across the sample period for all the variables pairs in the short term.



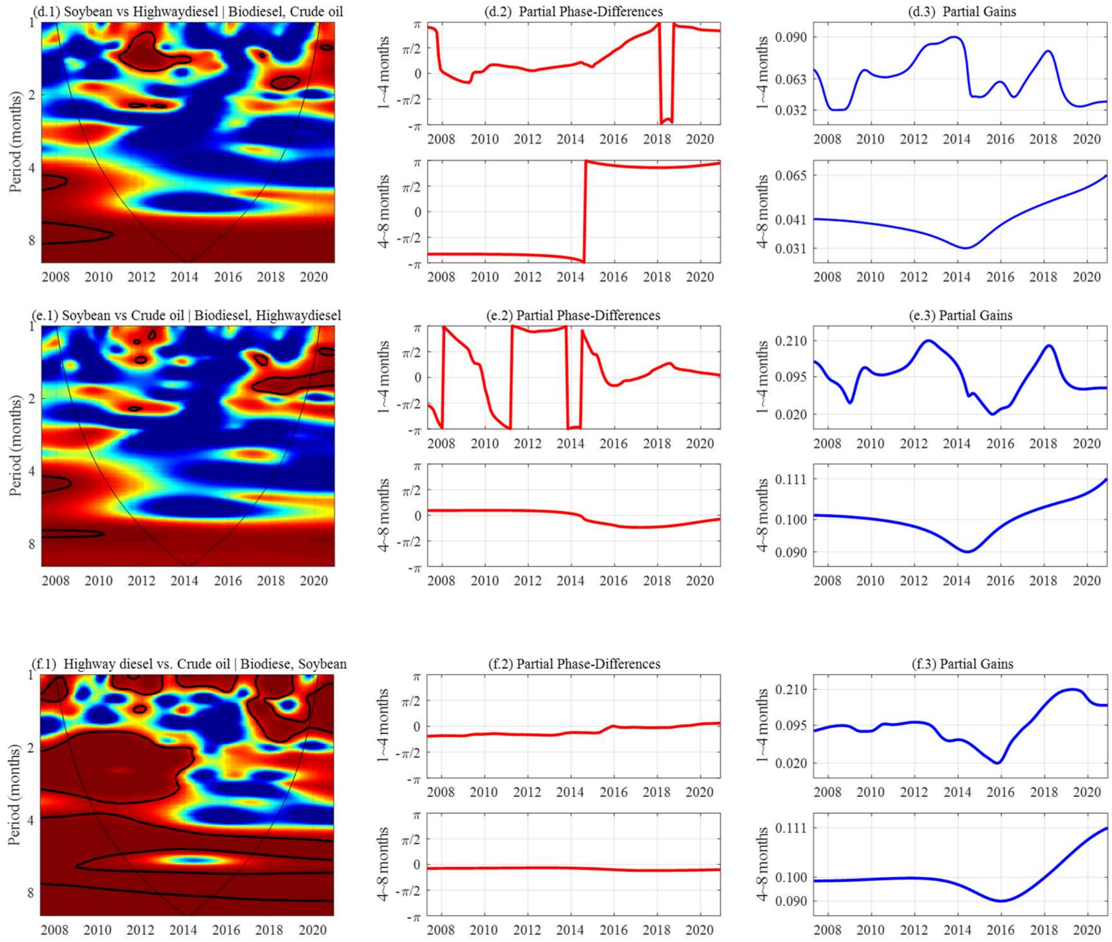


Fig 2. Empirical results of partial wavelet analysis

Note: On the left: partial wavelet coherence. In the center: partial phase-difference. On the right: partial wavelet gain. The color code for coherence ranges from blue (low coherence) to red (high coherence). The black contour designates the 5% significance level.

The wavelet analysis above provides noticeable evidence that the significant-high coherence for biodiesel-soybean, biodiesel-highway diesel and highway diesel-crude oil can be identified both in short term and in long term.

5.2 Dynamic connectedness analysis

The above wavelet analysis provides us with an overview of coherence and causality across the food and fuel market but does not examine in detailed the degree of connectedness and the spillover effect among the returns of biodiesel, soybean, highway diesel and crude oil. Based on the DYCI approach , we further conduct the dynamic spillover analysis. As the final model specification, a two lags VAR model is applied to estimate the connectedness index in our analysis[6].

First, Table 2 shows the static connectedness index across all variables. The off-diagonal elements capture shocks from (to) others and diagonal elements denote shocks of their own. We can see the total connectedness index (TCI) in the system is 41.18% suggesting that the interdependence between food and fuel markets is significant. More importantly, the results of directional spillovers from all variables to one specific variable vary from 27.90% for soybean to 55.9% for highway diesel. This indicates that highway diesel is the most affected by shocks from others while soybean is the least affected by the shock from others. On the other hand, regarding the contribution to others, crude oil has the highest total contribution (51.70%) to others and soybean has the lowest total contribution (23.10%) to others. The results of the net spillover provide evidence that soybean and highway diesel are the net recipient, meanwhile, biodiesel and crude oil are the net transmitters, respectively. Based on the connectedness index table, we can also obtain a net pairwise spillover matrix for all pairs.

Table 2. The total static connectedness index among biodiesel, soybean, highway diesel and crude oil.

[6] Our results indicate that the two-lag VAR model with a 10-step-ahead forecast horizon and the 24-month rolling sample provides the best performance based on SBIC. Full results are available upon request from the authors.

	Biodiesel	Soybean	Highway diesel	Crude oil	From others
Biodiesel	61.60	12.50	13.20	12.72	38.40
Soybean	15.91	72.15	7.00	4.94	27.90
Highway diesel	15.66	6.17	44.08	34.08	55.90
Crude oil	11.25	4.38	26.85	57.53	42.50
Contribution to others	42.80	23.10	47.00	51.70	164.70
Net spillovers	4.40	-4.80	-8.90	9.20	TCI= 41.18

Note: The FEVD is based upon a monthly VAR model for order 2. The return connectedness index is estimated by using and a 10-step-ahead forecast horizon and a 24-month rolling sample. “Net spillovers” are the difference between the “contributions to others” and the “from others”.

To construct the visualization of how the individual variables interact with each other, we plot a graph of the network among variables in Fig. 3.

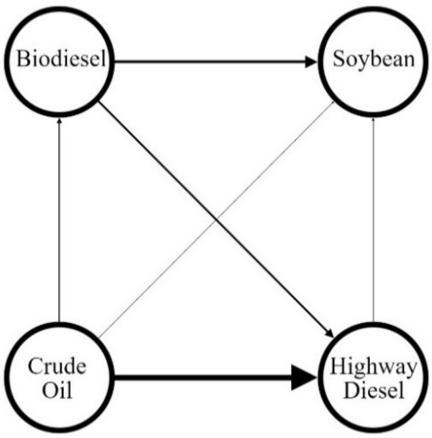


Fig. 3. The connectedness network for biodiesel, soybean, highway diesel and crude oil.

Note: The direction of arrows represents net pairwise directional connectedness between variables. The weight of the lines explains the strength of pairwise directional connectedness from strongest (bold line) to weakest (fine line).

The direction of arrows explains the net directional connectedness between variables and the bold line demonstrates greater spillover than the fine line. It is clear from Fig. 3 that crude oil is a net transmitter of shocks to the other three variables whilst soybean is a net receiver of shocks from the other variables. Specifically, the results provide evidence that the degree of spillover from crude oil to highway diesel is larger than that “to others”. Also, our results indicate that biodiesel returns impact the ones of soybean and highway diesel. Moreover, we can identify that the magnitude of the return transmission from biodiesel to soybean is stronger than that to highway diesel. In general, these findings are consistent with long-term results in wavelet analysis which suggested that biodiesel have a significant effect on either soybean or highway diesel, meanwhile, crude oil has a great influence on the highway diesel.

Although the results of static connectedness index provide an overall picture of the average spillovers among the variables, it does not exhibit the time-varying connectedness. To further investigate the net return spillover between each pair of variables, we conduct rolling-sample spillover analysis. For dynamic connectedness estimation, a 24-month rolling-sample window is utilized to obtain the net pairwise return spillovers. Fig. 4 describes the net pairwise connectedness across all pairs in the period May 2009 - December 2020 In general, as observed, the net pairwise connectedness exhibits variation across different pairs of variables over time. First, when we look at the pairwise connectedness index of biodiesel-soybean, the net spillovers are almost all positive, suggesting that shocks from the biodiesel market caused a change in the soybean market for most of the period. This finding is consistent with the long-term result in the partial wavelet analysis which stipulates that biodiesel positively lead soybean[7].To be noted that soybean becomes a net transmitter from the middle of 2015 to the end of 2017. This information confirms our results presented in Fig. 2 (a.1) and Fig. 2 (a.2): soybean positively leads biodiesel

[7] Although the concept of causality is not exactly similar to shock transmission, the dynamic connectedness index estimates bolster the causal relationship for the significant periods in wavelet analysis.

in the short-term frequency band in the significant coherence from 2015 to 2017. Second, from the plots of dynamic net pairwise connectedness between biodiesel and highway diesel, it results that biodiesel is a net transmitter, whereas highway diesel is a net recipient in the period 2009-2016. Subsequently, highway diesel becomes the net transmitter while biodiesel is the net recipient from 2017 to 2020. These results approximate our findings of partial wavelet coherence and relative phase in long term (Fig. 2 (b.1) and Fig. 2 (b.2)) to indicate that biodiesel positively lead highway diesel before 2016 and the reverse lead-lag relationship exists after 2017.

Third, in the case of highway diesel-crude oil, it is obvious that crude oil is the net transmitter and highway diesel is the net receiver during almost all under examination periods. This coincides with the conclusions in the wavelet analysis which suggest crude oil plays a leading role in transmitting shocks to highway diesel over the long term.

Finally, according to Fig. 4, the net pairwise connectedness of biodiesel-crude oil, soybean-highway diesel and biodiesel-crude oil share some common features. Such as, the time-varying connectedness of these three pairs fluctuated much more during the entire sample period compared to the other three pairs. Particularly, in the period before 2012, the former variable is the primary transmitter, whereas the latter variable is the net receiver. However, we find the reverse transmission of shocks running from the latter variable to the former variable in almost all of the period from 2013 to 2020. This interesting finding implies the probability that a structural change or specific regime shift occurred in 2013.

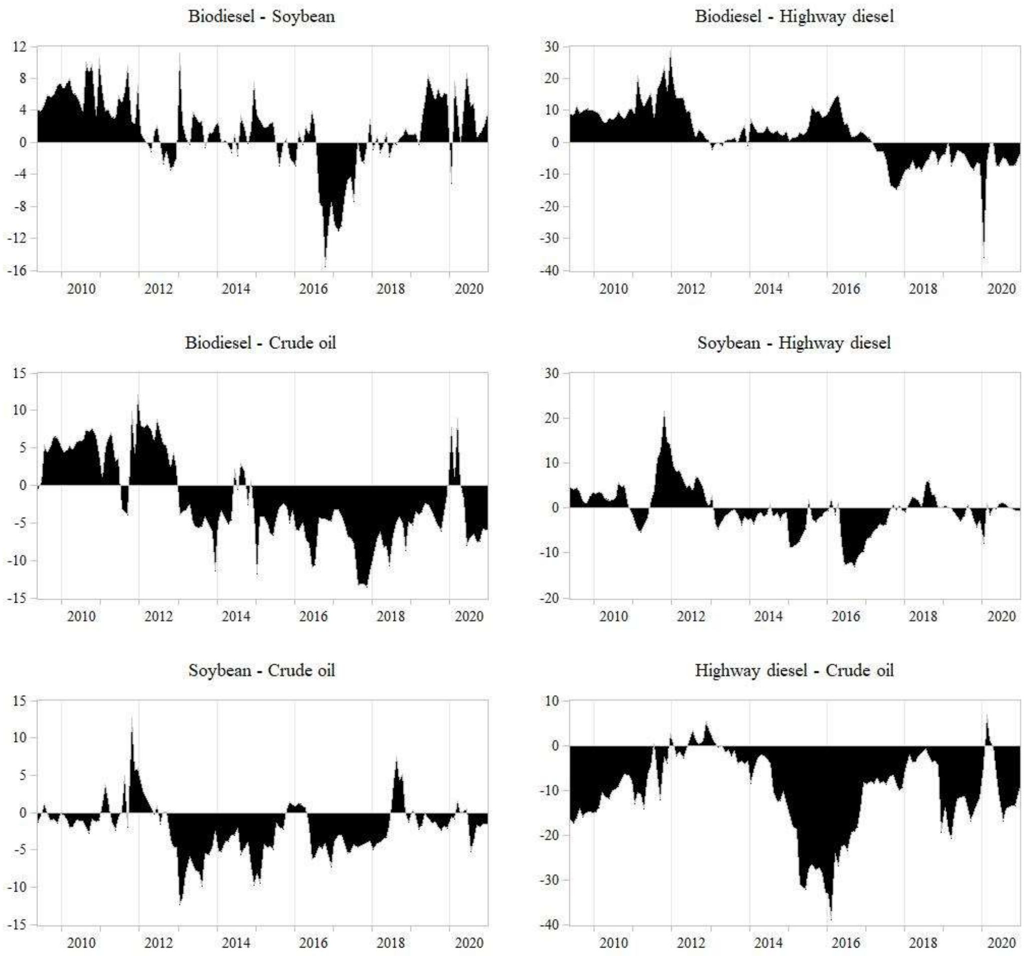


Fig. 4. Net pairwise returns spillovers among biodiesel, soybean, highway diesel and crude oil.

Note: The dynamic net pairwise connectedness is estimated by using the FEVD on 10-step-ahead forecasts and the 24-month rolling sample. Positive values indicate a net transmitter of return spillovers; negative values specify a net receiver.

Overall, the outcomes of using the DYCI measure are nearly similar to those using the wavelet framework. Therefore, our empirical results prove to be highly robust to the two types of methods.

6. Conclusion, policy implications and future research

Our research utilized the partial wavelet coherence and DYCI approach to analyze the connectedness between biodiesel and its related markets in the United States. The majority of the results obtained from the experiments shows consistency between the two methods. The primary outcomes are as follows. First, the significant-high coherence for biodiesel-soybean, biodiesel-highway diesel and highway diesel-crude oil is identified both in the short and long term. Second, crude oil and biodiesel prices are net transmitters, while soybean and highway diesel prices are net receivers. Finally, the crude oil market is the causal source among the markets concerned, particularly affecting the highway diesel market.

Several policy implications are drawn based on the experimental results as follows.

- In our analysis, both the wavelet transform and DYCI method prove that biodiesel price induces soybean price movements, which might suggest that the biodiesel production led by the governmental policies reinforces the relationship between biodiesel price and soybean price. Soybean is used not only as food but also as livestock feed. Because the United States is the second-largest soybean exporter to various nations such as China and Japan (FAOSTAT, 2021), domestic meat prices in such importing countries could be affected by biofuel policies in the United States, as demonstrated by Guo and Tanaka (2020). They argue that the U.S. farm-gate price of soybean significantly influences the international soybean price. It should be reserved that extended biodiesel production in the United States could exacerbate food price fluctuations in both domestic and global markets while the policy strategy has the potential to reduce carbon dioxide emissions and enhance its national energy security during an emergency.
- Another primary result is that the crude oil market is the source of the spillovers among the four markets. More specifically, transmission directions from crude oil to

biodiesel, highway diesel or soybean are confirmed by the DYCI method. Crude oil price directly affects soybean price while indirectly alters soybean price through highway diesel and biodiesel prices. Accordingly, stabilizing crude oil prices leads to the steadiness of the other three markets. Currently, the Strategic Petroleum Reserve held by the U.S. government reaches 621 million barrels in July 2021 (EIA, 2021) equivalent to approximately 34 days of consumption in the country.[8] An increase in the petroleum emergency reserve would extend the capacity of buffering shocks against highway diesel, biodiesel and soybean markets through price transmissions.

- Shale oil production accounting for more than half of U.S. crude oil production is also associated with petroleum price fluctuations (Owyang and Shell, 2018). For example, governor Gavin Newson announced on 23 April 2021 that the California government plans to ban hydraulic fracking by 2024 and phase out oil extraction by 2025 to create a decarbonized transport system and a healthier future for children. If many states of the United States adopt such measures, the country would need to depend more on foreign oil supply with lowering the level of petroleum self-sufficiency, which could lead to higher risk exposure of domestic crude oil markets. Therefore, the other three markets (i.e. biodiesel, highway diesel, and soybean markets) would also face more significant uncertainty.
- There exists a considerable number of speculators, especially in the futures market of crude oil. For instance, the ratio of non-commercial positions to the total of commercial and non-commercial positions for Brent crude oil at the Chicago Board of Trade has ranged between 10% and 50% since 2011. Futures market price movements influence other non-financial commodity markets such as farm-gate,

[8] The daily consumption of petroleum reaches 18.19 million barrels (U.S. Energy Information Administration, 2021).

wholesale and retail markets. The Tobin tax's implementation on agricultural markets was discussed in the policy circle to reduce volatility in agricultural commodity prices. The tax is imposed usually on short-term trading to dampen the enthusiasm of financial markets. Although the current analysis does not focus on financial commodity markets, spot or futures price of crude oil would have close relationships with the local crude oil prices, which suggest that inhibiting speculative activities could stabilize local crude oil price movements to a certain extent. Based on the result that crude oil price volatility is strongly transmitted to biodiesel, highway diesel and soybean prices, introducing the Tobin tax to the crude oil spot or/and futures market is likely to suppress the volatilities of those markets. However, such market intervention of administrative bodies often causes market inefficiency, so it is indispensable to consider the balance between the benefit and cost of the policy practice.

In conclusion, it is worth mentioning future research topics. As indicated in the Literature review section, despite that a substantial number of economists have tackled the issue of the price correlations in biofuel markets until today, the underlying factors behind the closeness of price connections have been left uninvestigated. For instance, the intensity of inter-connectivity might be affected by biofuel production. More specifically, it could be hypothesized that the larger biofuel production leads to the higher intensity of the relationships with producing factors such as corn, sugar and soybean. Besides, the price of carbon dioxide emission might influence the linkages. Research on the themes will contribute to the policy-making process, filling the missing knowledge gap on the mechanism of energy and food securities.

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