Information Flow Between Crude Palm Oil and Crude Oil Futures

M Jeong†, S Kim† and E Yi*,†
1 Department of Industrial Engineering & Center for Finance and Technology, Yonsei University, Seoul 03722, Republic of Korea
2 Korea Exchange, Seoul 07329, Republic of Korea
3 Pritzker School of Law, Northwestern University, Chicago, IL 60611, United States
† These co-first authors contributed equally to this work.
* E-mail: eojinkorea@nlaw.northwestern.edu (E.Y.)

Abstract. This study finds asymmetric information flow from the crude palm oil (CPO) futures to the West Texas Intermediate (WTI) crude oil futures market despite the CPO futures market’s low liquidity and small market capitalization. Our finding is robust regardless of the 2019 Coronavirus outbreak and the asymmetric information flow becomes even unilateral considering the exchange rate risk on the Malaysian Ringgit. Finally, we explain the asymmetric information flow from the CPO futures to WTI futures market given that the impact of speculation on market efficiency crowds out that of liquidity.

1. Introduction
Beginning with the Directive on Biofuels for Transport (May 2003), the European Union (EU) attempts to increase biofuel and renewable energy usage for a cleaner environment with the Directive on the promotion of Renewable Energy Sources (June 2009) [1–3]. Since then, the crude palm oil (CPO) market, the leading commodity in edible oil and biofuels, has been growing rapidly. In particular, the economic expansion of China and India (the major CPO importers), that of Indonesia (the largest producer and exporter), and the EU-driven environmental policies have dramatically promoted usage of CPO [4]. However, as CPO production could cause deforestation and contribute to environmental changes, the EU amended its directives and issued new policies, e.g., the Commission Delegated Regulation (EU) 2019/807, to reduce CPO imports from Southeast Asian countries [5,6]. Accordingly, the CPO market keeps getting attention from academics, industrial entities, and regulatory authorities.

The CPO futures market has less liquidity than the West Texas Intermediate (WTI) futures market, the global benchmark of the crude oil market, and it is well documented that markets become more efficient with increased liquidity [7]. From another perspective, after the financialization of the crude oil market in 2000, the pricing mechanism of the WTI futures market was affected by speculation [8]. When the herding behavior, caused by speculative trading activities, becomes widespread, market price is distorted and market efficiency decreases because of information unrelated to fundamentals [9]. Considering that more efficient markets have leadership on information discovery against less efficient markets [10], this study aims to (i) uncover the information flow between the CPO and WTI futures markets and (ii) identify the impact of liquidity and speculative transactions on the information flow particularly with the 2019 Coronavirus (COVID-19) as a natural experimental setting. The COVID-19 outbreak initiated a demand shock lowering the speculative transactions in oil markets [11,12].
Moreover, we investigate the role of the currency risk of Malaysian Ringgit (MYR), the trading currency of CPO futures, due to its impacts on oil prices [13].

2. Methodology and data

2.1. Transfer entropy

Several approaches investigate information flow between different assets: the Granger causality test [14,15], information shares [16], and common factor weights [17]. We used transfer entropy [18], which is free from restrictions on model structure [12,15,19], and calculated the histogram-based transfer entropy defined on equally spaced bins [15], where appropriate bin width \( h \) was determined using Freedman–Diaconis’ rule [20,21]. Effective transfer entropy was further considered to correct the bias from the finite sample size.

Transfer entropy from system \( Y \) to \( X \) is defined as follows [18]:

\[
TE_{Y \rightarrow X} = \frac{H(X_{t+1} | X_t^{(k)}) - H(X_{t+1} | X_t, Y_t^{(l)})}{M}
\]

where \( X_t^{(k)} = \{X_t, X_{t-1}, \ldots, X_{t-(k-1)}\} \) and \( Y_t^{(l)} = \{Y_t, Y_{t-1}, \ldots, Y_{t-(l-1)}\} \) are two random processes given by the \( k \) and \( l \) dimensional delay vectors, respectively. \( H(X_{t+1} | \cdot) \) is conditional entropy, implying the degree of uncertainty for predicting \( X_{t+1} \) for a given information \( \cdot \). Thus, transfer entropy is the effect of \( Y_t^{(l)} \) on predicting \( X_{t+1} \).

Effective transfer entropy is calculated by subtracting the arithmetic mean of the randomized transfer entropy values, \( TE_{Y(i) \rightarrow X} \) for \( i = 1,2,\ldots,M \), from the estimated transfer entropy as follows [22]:

\[
E TE_{Y \rightarrow X} = TE_{Y \rightarrow X}(k, l) - \frac{1}{M} \sum_{i=1}^{M} TE_{Y(i) \rightarrow X}(k, l)
\]

where \( Y(i) \) indicates the randomly shuffled variable \( Y \) and \( M \) is the number of random shuffling.

2.2. Data

We retrieved the price of CPO futures, particularly for front-month contracts, traded in Bursa Malaysia as a benchmark [23]. For the WTI futures, the price of front-month contracts in the New York Mercantile Exchange was collected. For both commodity futures, daily prices were obtained from Bloomberg, and the dataset covered February 1, 2019, to April 30, 2021. In addition, we separately analyzed the subsample covering from May 2020 to April 2021 (Pandemic period) to examine the impact of low speculative transactions with COVID-19. We excluded the turmoil period (February 2020 to April 2020) in the subsample as the World Health Organization’s pandemic declaration caused heterogeneous behavioral bias in both markets [12].

Table 1 shows descriptive statistics for the log-returns of our samples. In the subsample, the skewness of WTI was positive whereas that of CPO was negative, implying that after the pandemic declaration, investors in the CPO futures market are still risk-averse and those in WTI are changed to be risk-loving [24]. The kurtosis of WTI during the whole sample period was extremely high compared to that in the subsample, indicating that many outliers exist, especially in the turmoil period excluded in the subsample. Moreover, after the pandemic, the skewness and kurtosis of CPO became closer to 0 and 3, respectively, similar to those of the Gaussian distribution. This suggests that the CPO futures market became more efficient [25,26] after the pandemic outbreak.\(^1\)

\(^1\) To investigate the market efficiency more accurately, more formal approaches should be considered, such as variance ratio test [27], Hurst exponent [12,28], quantum harmonic oscillator [29–31], etc.
Table 1. Descriptive statistics of log-returns of CPO and WTI futures.

|                | Min.  | Max.   | Mean              | Std.   | Skewness | Kurtosis |
|----------------|-------|--------|-------------------|--------|----------|----------|
| **Panel A. Overall** |       |        |                   |        |          |          |
| CPO            | -0.1025 | 0.0518 | $1.200 \times 10^{-3}$ | 0.0183 | -0.5135 | 5.4489   |
| WTI            | -0.6017 | 0.3196 | $2.422 \times 10^{-4}$ | 0.0488 | -3.0554 | 52.8861  |
| **Panel B. Pandemic period** |       |        |                   |        |          |          |
| CPO            | -0.0482 | 0.0509 | $2.881 \times 10^{-3}$ | 0.0180 | -0.1673 | 3.0381   |
| WTI            | -0.0859 | 0.1861 | $4.543 \times 10^{-3}$ | 0.0277 | 0.9168  | 10.3619  |

3. Results and discussion

Table 2 summarizes the estimation results of effective transfer entropy between the CPO and WTI futures markets when the CPO futures price is MYR denominated. In Panel A, there exist mutual information flows but net information flow is asymmetric: information flow from CPO to WTI futures dominates that of the other way around. Panel B shows that the cause–effect relationship was not changed and even became stronger after the outbreak of COVID-19. Effective transfer entropy from the CPO to WTI futures is still positive and dominates the other way around regardless of pandemic outbreak. However, the WTI futures market started to provide significantly more information toward the CPO futures market as compared to before due to low speculative trading activities after the COVID-19 crisis.

Table 2. Effective transfer entropy between WTI and CPO futures markets (CPO futures in MYR).

|                | TE    | Std. Err. | p-value | ETE   |
|----------------|-------|-----------|---------|-------|
| **Panel A. Overall (num. of bins = 153)** |       |           |         |       |
| WTI $\rightarrow$ CPO | 2.3748 | 0.0525    | 0.0233  | 0.0166 |
| CPO $\rightarrow$ WTI  | 2.5370 | 0.0457    | 0.0000  | 0.0505 |
| **Panel B. Pandemic period (num. of bins = 32)** |       |           |         |       |
| WTI $\rightarrow$ CPO | 2.1286 | 0.0786    | 0.0000  | 0.0809 |
| CPO $\rightarrow$ WTI  | 2.0256 | 0.0659    | 0.0000  | 0.1046 |

Table 3 shows effective transfer entropy between the CPO and WTI futures markets when the CPO futures price is USD denominated. In all records, the effective transfer entropy in table 3 is lower than that in table 2, and some information flows were not effective anymore with currency risk: evidence for the role of foreign exchange rate in the CPO futures market as a channelling actor for accommodating macroeconomic fluctuations [13,32]. However, transfer entropy from the CPO to WTI futures were effective even with the currency risk regardless of the pandemic outbreak. Put differently, the CPO futures strongly holds its leadership for providing information to the WTI futures regardless of currency channel in the period of high efficiency in the WTI futures market, dominated by low speculative trading activities.

Table 3. Effective transfer entropy between WTI and CPO futures markets (CPO futures in USD).

|                | TE    | Std. Err. | p-value | ETE   |
|----------------|-------|-----------|---------|-------|
| **Panel A. Overall (num. of bins = 153)** |       |           |         |       |
| WTI $\rightarrow$ CPO | 2.3658 | 0.0543    | 0.0167  | 0.0000 |
| CPO $\rightarrow$ WTI  | 2.4998 | 0.0474    | 0.0000  | 0.0193 |
| **Panel B. Pandemic period (num. of bins = 32)** |       |           |         |       |
| WTI $\rightarrow$ CPO | 2.0352 | 0.0725    | 0.0000  | 0.0000 |
| CPO $\rightarrow$ WTI  | 1.9504 | 0.0629    | 0.0000  | 0.0113 |
Prior studies documented that market becomes more efficient with higher liquidity [7] and more efficient markets have leadership on information discovery [10]. However, after the financialization of the crude oil market, the WTI futures market was strongly influenced by speculative trading activities [8]. Speculation causes herding behavior, which results in distorted market prices and lowers market efficiency [9]. Hence, asymmetric information flow from the CPO to WTI futures market can be explained by lower efficiency in the WTI futures market, despite the liquidity of WTI futures being way higher.

4. Conclusion
This study provides evidence that the CPO futures market has leadership on information discovery against the WTI futures market despite having lower liquidity and smaller market capitalization. Moreover, our finding is robust regardless of the COVID-19 outbreak, and asymmetric information flow from the CPO futures to WTI futures market even becomes unilateral considering the currency risk of MYR. Speculation in the WTI futures market causes herding behavior, resulting in price distortion and low market efficiency. Finally, we explain that the impact of speculation on market efficiency crowds out that of liquidity, leading to the asymmetric information flow from the CPO to WTI futures markets.

References
[1] Klessmann C, Lamers P, Ragwitz M and Resch G 2010 Design options for cooperation mechanisms under the new European renewable energy directive Energy Policy 38 4679–4691
[2] Lind A, Rosenberg E, Seljom P, Espegren K, Fidje A and Lindberg K 2013 Analysis of the EU renewable energy directive by a techno-economic optimisation model Energy Policy 60 364–377
[3] Stichnothe H, Schuchardt F and Rahutomo S 2014 European renewable energy directive: Critical analysis of important default values and methods for calculating greenhouse gas (GHG) emissions of palm oil biodiesel Int. J. Life Cycle Assess. 19 1294–1304
[4] Snaith S, Kellard N M and Ahmad N 2018 Open outcry versus electronic trading: Tests of market efficiency on crude palm oil futures J. Futures Markets 38 673–695
[5] Krustiyati A, Janisriwati S, Christine N and Huda M K 2020 Observing European Union rejection of Indonesia’s crude palm oil exports from the most favored nation and quantitative restriction principles J. Adv. Res. L. Econ. 9 905–912
[6] Fernández-Tirado F, Parra-López C and Romero-Gámez M 2021 A multi-criteria sustainability assessment for biodiesel alternatives in Spain: Life cycle assessment normalization and weighting Renew. Energy 164 1195–1203
[7] Chordia T, Roll R and Subrahmanyam A 2008 Liquidity and market efficiency J. Financ. Econ. 87 249–268
[8] Joo K, Suh J H, Lee D and Ahn K 2020 Impact of the global financial crisis on the crude oil market Energy Strategy Rev. 30 100516
[9] Froot K A, Scharfstein D S and Stein J C 1992 Herd on the street: Informational inefficiencies in a market with short-term speculation J. Fin. 47 1461–1484
[10] Eom C, Jung W, Choi S, Oh G and Kim S 2008 Effects of time dependency and efficiency on information flow in financial markets Phys. A 387 5219–5224
[11] Norouzi N 2021 Post-COVID-19 and globalization of oil and natural gas trade: Challenges, opportunities, lessons, regulations, and strategies Int. J. Energy Res. 45 14338–14356
[12] Joo K, Jeong M, Seo Y, Suh J H and Ahn K 2021 Shanghai crude oil futures: Flagship or burst? Energy Rep. 7 4197–4204
[13] Zhang Y, Fan Y, Tsai H and Wei Y 2008 Spillover effect of US dollar exchange rate on oil prices J. Policy Model. 30 973–991
[14] Granger C W J 1969 Investigating causal relations by econometric models and cross-spectral methods Econometrica 37 424–438
[15] Jang S M, Yi E, Kim W C and Ahn K 2019 Information flow between Bitcoin and other investment assets Entropy 21 1116
[16] Hasbrouck J 1995 One security, many markets: Determining the contributions to price discovery *J. Fin.* 50 1175–1199
[17] Gonzalo J and Granger C 1969 Estimation of common long-memory components in cointegrated systems *J. Bus. Econ. Stat.* 13 27–35
[18] Schreiber T 2000 Measuring information transfer *Phys. Rev. Lett.* 85 461–464
[19] Yi E, Cho Y, Sohn S and Ahn K 2021 After the Splits: Information Flow between Bitcoin and Bitcoin Family *Chaos, Solitons & Fractals* 142 110464
[20] Freedman D and Diaconis P 1981 On the histogram as a density estimator: L2 theory *Probab. Theor. Rel.* 57 453–476
[21] Ahn K, Lee D, Sohn S and Yang B 2019 Stock market uncertainty and economic fundamentals: An entropy-based approach *Quant. Fin.* 19 1151–1163
[22] Sandoval L 2014 Structure of a global network of financial companies based on transfer entropy *Entropy* 16 4443–4482
[23] Lean H H and Smyth R 2015 Testing for weak-form efficiency of crude palm oil spot and future markets: New evidence from a GARCH unit root test with multiple structural breaks *Appl. Econ.* 47 1710–1721
[24] Patton A J 2004 On the out-of-sample importance of skewness and asymmetric dependence for asset allocation *J. Financ. Econ.* 2 130–168
[25] Fama E F 1965 The behavior of stock-market prices *J. Bus.* 38 34–105
[26] Fama E F 1970 Efficient capital markets: A review of theory and empirical work *J. Fin.* 25 383–417
[27] Lo A W and Mackinlay A C 1988 Stock market prices do not follow random walks: Evidence from a simple specification test *Rev. Financ. Stud.* 1 41–66
[28] Jang H, Song Y and Ahn K 2020 Can government stabilize the housing market? The evidence from South Korea *Phys. A* 550 124114
[29] Ahn K, Choi M, Dai B, Sohn S and Yang B 2018 Modeling stock return distributions with a quantum harmonic oscillator *Europhys. Lett.* 120 38003
[30] Lee G H, Joo K and Ahn K 2020 Market efficiency of the crude palm oil: Evidence from quantum harmonic oscillator *J. Phys.: Conf. Ser.* 1593 012037
[31] Ryu I, Jang H, Kim D and Ahn K 2021 Market efficiency of US REITs: A revisit *Chaos, Solitons & Fractals* 150 111070
[32] Hadi A R A, Huridi M H, Zaini S M and Zainudin Z 2019 Is Ringgit Really Influenced by Crude Oil Price? Evidence From Commodity and Bank Lending Markets *Contemp. Econ.* 13 407

Acknowledgments
This work was supported by the NRF grant funded by the Ministry of Science and ICT (Republic of Korea, No. 2021R1A2C1008652) and Technology Innovation Program ATC+ (20014125, Development of Intelligent Management Solution for Nuclear Decommissioning Site Characterization) funded by the Ministry of Trade, Industry & Energy (MOTIE, Republic of Korea).